# Journal of Medical Internet Research

Journal Impact Factor (JIF) (2022): 7.4
Volume 16 (2014), Issue 6 ISSN 1438-8871 Editor in Chief: Gunther Eysenbach, MD, MPH

## Contents

## Viewpoints

Review

# The Effectiveness of Electronic Screening and Brief Intervention for Reducing Levels of Alcohol Consumption: A Systematic Review and Meta-Analysis

Kim Donoghue[1], BSc (Hons), PhD; Robert Patton[1], BSc (Hons), MSc, PhD; Thomas Phillips[1], RMN, MSc; Paolo Deluca[1], PhD; Colin Drummond[1], MB ChB, MD, FRCPsych

Institute of Psychiatry, Addictions Department, King's College London, London, United Kingdom

**Corresponding Author:**
Kim Donoghue, BSc (Hons), PhD
Institute of Psychiatry
Addictions Department
King's College London
Addiction Sciences Building
4 Windsor Walk
London, SE5 8BB
United Kingdom
Phone: 44 207 848 0437
Fax: 44 207 848 0839
Email: kim.donoghue@kcl.ac.uk

## Abstract

**Background:** Electronic screening and brief intervention (eSBI) has been shown to reduce alcohol consumption, but its effectiveness over time has not been subject to meta-analysis.

**Objective:** The current study aims to conduct a systematic review and meta-analysis of the available literature to determine the effectiveness of eSBI over time in nontreatment-seeking hazardous/harmful drinkers.

**Methods:** A systematic review and meta-analysis of relevant studies identified through searching the electronic databases PsychINFO, Medline, and EMBASE in May 2013. Two members of the study team independently screened studies for inclusion criteria and extracted data. Studies reporting data that could be transformed into grams of ethanol per week were included in the meta-analysis. The mean difference in grams of ethanol per week between eSBI and control groups was weighted using the random-effects method based on the inverse-variance approach to control for differences in sample size between studies.

**Results:** There was a statistically significant mean difference in grams of ethanol consumed per week between those receiving an eSBI versus controls at up to 3 months (mean difference –32.74, 95% CI –56.80 to –8.68, $z$=2.67, $P$=.01), 3 to less than 6 months (mean difference –17.33, 95% CI –31.82 to –2.84, $z$=2.34, $P$=.02), and from 6 months to less than 12 months follow-up (mean difference –14.91, 95% CI –25.56 to –4.26, $z$=2.74, $P$=.01). No statistically significant difference was found at a follow-up period of 12 months or greater (mean difference –7.46, 95% CI –25.34 to 10.43, $z$=0.82, $P$=.41).

**Conclusions:** A significant reduction in weekly alcohol consumption between intervention and control conditions was demonstrated between 3 months and less than 12 months follow-up indicating eSBI is an effective intervention.

***(J Med Internet Res 2014;16(6):e142)*** doi:10.2196/jmir.3193

**KEYWORDS**

alcohol drinking; intervention studies; Internet; computers; meta-analysis

## Introduction

The hazardous and harmful use of alcohol is a global problem, contributing 4.6% of the total global burden of disease, with the highest rates reported in the European and American regions (17.3% and 14.2%, respectively) [1]. It is well documented that those with problem alcohol use seldom seek help [2]; this may be due to problems accessing treatment, or an unwillingness to do so, or failure of clinicians to identify their problem [3]. There is a large body of research to support the effectiveness of opportunistic screening and brief intervention (SBI) in reducing alcohol consumption and other alcohol-related outcomes in a number of health care settings, including primary care [4,5] and the emergency department [6,7]. A brief intervention typically comprises a single face-to-face session, ranging from 5-30 minutes in duration, and up to a maximum of 4 sessions aimed at providing information and advice that is designed to achieve a reduction in hazardous/harmful alcohol consumption [4]. Despite the effectiveness of SBI, there are a number of barriers to its widespread implementation in health care settings. Health care staff report that they lack the time and resources to carry out training and delivery of SBI in routine practice and that they lack the skills and knowledge necessary to do so [8,9].

The widespread use of computers, the Internet, and smartphones has led to the development of electronic systems to deliver SBI that can potentially address some of the barriers to implementation of traditional face-to-face SBI. Electronic SBI (eSBI) has the potential to offer greater flexibility and anonymity for the individual and reach a larger proportion of the in-need population. For both adults and adolescents, eSBI (computer-, Web-, and phone-based) can offer effective delivery of interventions in both educational and health care settings that may prove to be more acceptable than more traditional (face-to-face) approaches [10-12]. Also, eSBI can offer a more cost-effective alternative to face-to-face interventions. Previous studies have shown that 1 in 8 individuals respond to SBI; therefore, large numbers of people need to be screened to obtain a time-limited effect in reduction in alcohol consumption [4,5]. With the advent of mobile and e-technologies potentially increasing the population coverage of SBI, the potential cost of delivery can be reduced because the main cost is incurred during development of the intervention with limited additional costs associated with its delivery [13]. Evidence from recent systematic reviews has found eSBIs to be effective in reducing alcohol consumption [14,15]. However, these reviews did not address the effect of length of follow-up on alcohol outcomes. Cunningham and colleagues [16,17] conducted a randomized controlled trial of the effectiveness of an Internet-based intervention for alcohol misuse. They found that at 3- and 6-month follow-ups, those who had received the intervention had a greater reduction in alcohol consumption compared to controls. However, at 12-month follow-up the beneficial effects of the intervention were no longer apparent.

The current study aims to conduct a systematic review and meta-analysis of the available literature to determine the effectiveness of eSBI over time in nontreatment-seeking hazardous/harmful drinkers.

## Methods

### Search Strategy

A systematic search of the literature was conducted to identify randomized controlled trials investigating the effectiveness of eSBI to reduce alcohol consumption. Relevant studies were identified through searching the electronic databases PsychINFO, Medline, and EMBASE in May 2013. The search strategy was adapted from the search terms used for the National Institute for Health and Care Excellence (NICE) guideline systematic review for the effectiveness of acamprosate/naltrexone [18], and the search terms used for the Cochrane systematic review for the effectiveness of SBI for alcohol misuse [4], combined with additional search terms specific to electronic interventions to ensure a comprehensive search of the available published literature. The search terms used for this review are listed in Table 1. No date or language restrictions were applied. In addition, the reference lists of relevant review articles and key papers were hand searched. Unpublished literature was considered to be beyond the scope of this review.

**Table 1.** Electronic database search terms.

| Search term topic | Search terms |
| --- | --- |
| **Terms for alcohol use** | |
| | 1. alcohol-related disorder.mp. |
| | 2. alcohol drinking.mp. |
| | 3. (alcohol and (use$ or abuse or misuse or dependen$ or drink$ or intoxication$ or disorder$ or consumption)).mp. |
| | 4. exp Alcoholism/ or (alcoholi$).mp. |
| | 5. ((hazard$ or binge or heavy or harmful or risk$) and drink$).mp. |
| | 6. 1 or 2 or 3 or 4 or 5 |
| | 7. limit 6 to abstracts |
| | 8. (drinker$1 or (drink$ adj2 use$1) or ((alcohol$ or drink$) adj5 (binge$ or disorder$ or harm$ or hazard$ or heavy or high risk or intoxicat$ or misus$ or problem$))). ti.ab. |
| | 9. 7 or 8 |
| **Terms for e-formats** | |
| | 10. exp Text Messaging/ or ((text-messag$) or (SMS) or (short message service) or (text adj messag$)).mp. |
| | 11. ((phone adj application$) or (phone adj app)).ti,ab,kw. |
| | 12. ((social-network) or ( social network) or (social-media) or (social-media)).ti,ab,kw. |
| | 13. skype.ti,ab,kw. |
| | 14. exp telemedicine/ |
| | 15. facebook.ti,ab,kw. |
| | 16. ((personal adj digital adj assistant) or pda).ti,ab,kw. |
| | 17. (surf$ near4 internet$).ti,ab,kw. |
| | 18. (surf$ near4 web$).ti,ab,kw. |
| | 19. (virtual adj reality).ti,ab,kw. |
| | 20. Second life.ti,ab,kw. |
| | 21. User-computer interface/ |
| | 22. (consumer adj health adj informatics$).ti,ab,kw. |
| | 23. ((e adj health) or e-health or (electronic adj health)).ti,ab,kw. |
| | 24. (interactive adj ((health adj communicat$) or televise$ or video$ or technolog$ or multimedia)).ti,ab,kw. |
| | 25. ((bulletin adj board$) or bulletinboard$ or messageboard$ or (message adj board$)).ti,ab,kw. |
| | 26. (blog$ or web-log$ or weblog$ ).ti,ab,kw. |
| | 27. ((chat adj room$) or chatroom$).ti,ab,kw. |
| | 28. (online or on-line).ti,ab,kw. |
| | 29. exp internet/ or ((internet adj based) or internet-based).ti,ab,kw. |
| | 30. ((web adj based) or web-based).ti,ab,kw. |
| | 31. ((world adj wide adj web) or (world-wide-web) or WWW or (world-wide adj web) or (worldwide adj web) or website$).ti,ab,kw. |
| | 32. ((electronic adj mail) or email$ or email$).ti,ab,kw. |
| | 33. (((mobile or cellular or cell or smart) adj (phone$ or telephone$)) or smartphone).ti,ab,kw. |
| | 34. ((CD adj ROM) or cd-rom or cdrom or (compact adj dis$)).ti,ab,kw. |
| | 35. (decision adj (tree$ or aid$)).ti,ab,kw. |
| | 36. (Internet or (local adj area adj network)).ti,ab,kw. |
| | 37. (computer$ or microcomputer$ or laptop).ti,ab,kw. |
| | 38. exp Software-/ |
| | 39. exp Computer-Graphics/ |

| Search term topic | Search terms |
| --- | --- |
| | 40. exp Public-Health-Informatics/ |
| | 41. exp Audiovisual-Aids/ |
| | 42. exp Decision-Support-Techniques/ |
| | 43. exp Medical Informatics/ |
| | 44. exp Computer-Systems/ |
| | 45. (or/10-44) |
| **Brief interventions** | |
| | 46. alcohol reduction.mp. |
| | 47. brief intervention.mp. |
| | 48. early intervention.mp. |
| | 49. minimal intervention.mp. |
| | 50. alcohol therapy.mp. |
| | 51. Harm Reduction/ |
| | 52. screening.mp. |
| | 53. (counseling or counselling).mp. |
| | 54. controlled drinking.mp. |
| | 55. (brief counseling or brief counselling).mp. |
| | 56. physician based intervention.mp. |
| | 57. general practitioner intervention.mp. |
| | 58. Secondary Prevention/ |
| | 59. general practitioner’s advice.mp. |
| | 60. brief physician-delivered counseling.mp. |
| | 61. brief nurse-delivered counseling.mp. |
| | 62. identification.mp. |
| | 63. intervention.mp. |
| | 64. or/46-63 |
| **Terms for randomized controlled trial** | |
| | 65. exp clinical trial/ or (crossover procedure or double blind procedure or placebo$ or randomization or random sample or single blind procedure).sh. |
| | 66. exp clinical trial/ or cross-over studies/ or double-blind method/ or random allocation/ or randomized controlled trials as topic/ or single-blind method/ |
| | 67. exp clinical trial/ or (placebo or random sampling).sh. |
| | 68. (clinical adj2 trial$).tw. |
| | 69. (crossover or cross over).tw. |
| | 70. (((single$ or doubl$ or trebl$ or tripl$) adj5 blind$) or mask$ or dummy or singleblind$ or doubleblind$ or treble-blind$ or tripleblind$).tw. |
| | 71. (placebo$ or random$).mp. |
| | 72. (clinical trial$ or controlled clinical trial$ or random$).pt. or treatment outcome$.mp. |
| | 73. animals/ not human$.mp. |
| | 74. animal$/ not human$/ |
| | 75. (or/65-72) not (or/73-74) |
| | 76. and/9,45,64,75 |

### Selection Criteria

The inclusion criteria for this review were as follows:

1. Randomized controlled, parallel group trial comparing eSBI with a control condition (ie, care as usual, assessment only, nonintervention);
2. Participants were identified, through screening, as consuming alcohol to a hazardous level;
3. Measured alcohol reduction by independent reports of drinking quantity (eg, average consumption of alcohol per specified time period), including self-reports or reports from others of drinking frequency (eg, number of drinking occasions per specified time period), drinking intensity (eg, number of drinks per drinking day), or drinking within recommended limits (eg, official recommendations per specified time period), or levels of laboratory markers of reduced alcohol consumption, such as serum gamma-glutamyltransferase (GGT) or mean corpuscular volume (MCV); and
4. Trial arms had at least 10 participants.

We defined eSBI as an electronic intervention aimed at providing information and advice designed to achieve a reduction in hazardous/harmful alcohol consumption with no substantial face-to-face therapeutic component. SBI was defined as a brief intervention comprised of a single session, ranging from 5-45 minutes in duration, and up to a maximum of 4 sessions aimed at providing information and advice designed to achieve a reduction in hazardous/harmful alcohol consumption. Studies were not deemed eligible for inclusion if participants were alcohol dependent, mandated to complete eSBI, or a preselected specific group such as pregnant women. There were no restrictions on age.

### Identification of Included Studies

After each search, references were downloaded to the electronic bibliographic management software EndNote and duplicates were removed. Relevant titles were first identified and then abstracts were screened against inclusion criteria. If insufficient information was available in the abstract, the full text was retrieved. Eligibility was confirmed by at least one other member of the review group. The methodological quality of each study was assessed using the Scottish Intercollegiate Guidelines Network (SIGN) validated checklist [19]. Each question in the checklist covers an aspect of research methodology and was rated as present, absent or “can’t say” if inadequate information was available in the research article. An overall rating of quality was assigned to each article based on the checklist criteria:

1. High quality: Majority of criteria met with little risk of bias and conclusions unlikely to change by further research.
2. Adequate: Most of the criteria met with some risk of bias and conclusions may change in light of further research.
3. Low quality: Most criteria not met or significant flaws relating to key aspects of the study design and conclusions likely to change in light of future research.

### Data Extraction

A Microsoft Word-based form was used to extract data from eligible research papers. Data extraction was conducted independently by 2 members of the research team and consensus agreement reached by discussion between the 2 members if discrepancies arose. An intention-to-treat analysis was used wherever possible. If the study was a 3-arm trial, the control group sample size was divided by 2; if it was a 4-arm trial, it was divided by 3 to avoid double counting.

### Data Analysis

For the continuous variable (grams ethanol consumed per week) the mean difference was weighted using the random-effects method based on the inverse-variance approach to control for differences in sample size between studies. Alcohol consumption data are often not normally distributed. Because of this, some studies reported the sample median and range/interquartile range (IQR) and not the mean and standard deviation (SD). If appropriate data were not available in the published research papers, to calculate an effect size (ie, the mean, SD, and sample size), authors were contacted to request the required data. If the authors were unable to provide this data, the mean and SD were imputed from the median and range using the method proposed by Hozo et al [20]. If only the median and the IQR were available, the median was taken as an estimate of the mean and the IQR was divided by 1.35 (the distance in SDs from the mean). If appropriate data to estimate an effect size could not be obtained or imputed, the trial was not included in the meta-analysis. Some of the studies included in the meta-analysis had more than one trial arm. The number of participants in the control arm was divided by 2 for a 3-arm trial and by 3 for a 4-arm trial to avoid double counting and undue weighting.

Alcohol consumption, reported as the number of standard drinks per week, was converted into grams of ethanol per week using the definition for a standard drink reported in the research article. If this was not reported, the established standard for the country in which the research took place was used [21]. If alcohol consumption was reported per month versus per week, it was adjusted by multiplying by 52/12, or multiplied by 7 if reported as grams per day [4].

To check for the consistency of effects across studies, Cochran *Q* was calculated to determine the presence of heterogeneity and the magnitude was measured using $I^2$. The $I^2$ statistic was interpreted in the following way based on Higgins et al [22]: Research studies that produce statistically significant results may be more likely to be published than those with nonstatistically significant results, resulting in a “file-drawer” effect. Similarly, those studies that produce results in an opposite direction to that hypothesized and have a small sample size may be less likely to be published. This is referred to as publication bias and it was assessed using funnel plots and Egger’s weighted regression method. A significant Egger’s test indicates the possibility of the presence of publication bias.

The length of follow-up period can vary between individual studies and there may be more than one point of follow-up per study. Therefore, subgroup analysis was performed for up to 3 months, between 3 and less than 6 months, between 6 and less than 12 months, and 12 months or greater follow-up length postintervention.

## Results

### Study Characteristics

A total of 23 studies were deemed eligible for inclusion in this systematic review [16,17,23-44] (Figure 1); Tables 2 and 3 present the study characteristics. Sufficient data was available to allow analysis of just one variable: grams per week of ethanol consumed. If sufficient data to calculate means and SDs for this outcome were not reported in the published article, authors were contacted. Data were provided by the authors for 3 studies [17,39,41]. Data on alcohol consumption that could be transformed into grams per week of ethanol were not collected in 2 studies [25,27] and insufficient data to calculate the weighted mean difference (WMD) in grams of ethanol per week were reported in 4 studies [23,28,29,42]. Therefore, a total of 17 studies were included in the meta-analysis (1 study was published in 2 papers [16,17]. Most of these studies were conducted with student populations (13/17, 76%) and in the United States (10/17, 59%). All study interventions were either computer- or Web-based. The content of the interventions included an assessment followed by personalized and/or normative feedback. Control conditions generally consisted of an assessment with no further feedback, but 4 studies included general information on alcohol consumption for those in the control conditions [25,28,33,35]. There was some variation in the dose of the intervention with the reported time taken to complete the intervention ranging from less than 5 minutes [34] to 45 minutes [37]. The dose of exposure to the intervention could also be increased through repeated access during the study period [24] and/or a printed copy of the personalized feedback provided [26,31,36,38,40,43]. The attrition rate was highly variable between studies, ranging from 1% or 2% (eg, Hester et al [30]) up to more than 50% [42]

**Table 2.** Size and nature of study population and method of recruitment.

| Study ID[a] | Male, n (%) | Mean age (SD) | Population | Recruitment |
|---|---|---|---|---|
| **Araki et al, 2006 [23]** | 24 (100) | | Japan, employees of a manufacturing plant with available annual health check-up data | Not reported |
| eSBI (n=12) | | 44.3 (7.2) | | |
| Control (n=12) | | 43.8 (7.3) | | |
| **Blankers et al, 2011 [24]** | | | Netherlands, adult general population | Visitors to the Collaborating Substance Abuse Treatment (SATC) website |
| eSBI (n=68) | 40 (58.8) | 41.1 (9.6) | | |
| Control (n=69) | 35 (50.7) | 43.7 (9.3) | | |
| **Boon et al, 2011 [25]** | 450 (100) | | Netherlands, adults in the general population | Nationally representative online household survey |
| eSBI (n=230) | | 40.6 (15.2) | | |
| Control (n=220) | | 40.3 (15.1) | | |
| **Butler et al, 2009 [26]** | | | United States, undergraduate university students | Not reported |
| eSBI (n=30) | 11 (36.7) | 20.6 (1.48) | | |
| Control (n=26) | 9 (34.6) | 20.4 (1.49) | | |
| **Cunningham et al, 2009 [16]; Cunningham et al, 2010 [17]** | | | Canada, adults in the general population | Randomly selected from an on-going general population telephone survey |
| eSBI (n=92) | 53 (57.6) | 39.5 (13.5) | | |
| Control (n=93) | 45 (48.4) | 40.8 (13.4) | | |
| **Cunningham et al, 2012 [27]** | 118 (52.5) | 22.6 (12.2) | Canada, university students | Randomly selected using student email addresses |
| eSBI (n=211) | | | | |
| Control (n=214) | | | | |
| **Ekman et al, 2011 [28]** | | | Sweden, third-year university students | Email invitation to all third-year students |
| eSBI (n=330) | 152 (46.1) | N (%):18-20=43 (13), 21-25=264 (80), ≥26=23 (7) | | |
| Control (n=324) | 120 (37.0) | N (%) : 18-20=49 (15), 21-25=233 (72), ≥26=29 (9) | | |
| **Hansen et al, 2012 [29]** | | | Denmark, adults in the general population | Identified through the Danish Health Examination Survey, those identified as heavy drinkers were sent an email invitation to take part |
| eSBI PFI (n=476) | 271 (56.9) | median=61 | | |
| eSBI PBA (n=450) | 246 (54.7) | median=59 | | |
| Control (n=454) | 244 (53.7) | median=60 | | |
| **Hester et al, 2012 [30]** | | | United States, university students | Identified through advertisements in the college newspaper and around the campus |
| Exp 1: eSBI (n=65) | 41 (63.1) | 20.5 (1.80) | | |
| Exp 1: Control (n=79) | 49 (62.0) | 20.3 (1.63) | | |
| Exp 2: eSBI (n=42) | 23 (54.8) | 20.0 (1.52) | | |
| Exp 2: Control (n=40) | 23 (57.5) | 20.3 (2.09) | | |

| Study ID[a] | Male, n (%) | Mean age (SD) | Population | Recruitment |
|---|---|---|---|---|
| **Hester et al, 2005 [31]** | 32 (52.5) | Males=46.1 (13.8); females=45.2 (9.4) | United States, adult general population | Identified through advertisements in the media |
| eSBI (n=35) | | | | |
| Control (n=26) | | | | |
| **Kypri et al, 2009 [32]** | | | Australia, random sample of undergraduate university students | Students were sent a letter by mail followed by an email containing a Web link to the study questionnaire; up to 4 email reminders were sent |
| eSBI=1251 | 687 (54.9) | 19.7 (1.8) | | |
| Control=1184 | 645 (54.5) | 19.7 (1.8) | | |
| **Kypri et al, 2008 [33]** | | | New Zealand, users of a university student health service | Those leaving the student health service reception desk were consecutively approached and invited to participate |
| eSBI (n=138) | 67 (48.6) | 20.1 | | |
| Control (n=146) | 70 (47.9) | 20.1 | | |
| **Kypri et al, 2013 [34]** | | | New Zealand, Maori university students | Invited by email with up to 3 reminder emails |
| eSBI (n=939) | 35.7 | 20.2 (1.9) | | |
| Control (n=850) | 33.2 | 20.1 (2.2) | | |
| **Kypri et al, 2004 [35]** | 52 (50.0) | | New Zealand, users of a university student health service | Those checking into the reception of the student health service were invited to take part |
| eSBI (n=51) | | 19.9 (1.4) | | |
| Control (n=53) | | 20.5 (1.8) | | |
| **Lewis et al, 2007 [36]** | | 18.5 (2.04) | United States, university students enrolled in first-year orientation | All students enrolled for first-year orientation were invited to take part |
| eSBI specific (n=75) | | | | |
| eSBI neutral (n=82) | | | | |
| Control (n=88) | | | | |
| **Murphy et al, 2010 [37]** | | 18.6 (1.2) | United States, university students | Students enrolled in introductory classes were invited to take part |
| eSBI (n=45) | | | | |
| Control (n=42) | | | | |
| **Neighbors et al, 2004 [38]** | 104 (41.3) | 18.5 (1.24) | United States, university students from psychology classes | Students attending psychology classes were invited to take part |
| eSBI (n=126) | | | | |
| Control (n=126) | | | | |
| **Neighbors et al, 2010 [39]** | 208 (42.4) | | United States, incoming university freshmen students | Incoming university freshmen were invited to complete a Web-based survey sent via email and post |
| eSBI GSF (n=163) | | | | |
| eSBI GNSF(n=164) | | | | |
| Control (n=163) | | | | |
| **Neumann et al, 2006 [40]** | | | Germany, trauma center | Patients attending a trauma center were invited to take part after provision of initial care and resolution of significant pain |
| eSBI (n=561) | 449 (80.0) | median=30 | | |
| Control (n=575) | 449 (78.1) | median=31 | | |

| Study ID[a] | Male, n (%) | Mean age (SD) | Population | Recruitment |
|---|---|---|---|---|
| **Palfai et al, 2011 [41]** | | 18.6 (1.45) | United States, university students attending an introductory psychology class | Students attending an introductory psychology class were invited to take part |
| eSBI (n=56) | | | | |
| Control (n=63) | | | | |
| **Spijkerman et al, 2010 [42]** | | | Netherlands, volunteer members of an open access panel aged 15-20 | Registered members of an open access panel were invited to take part via email |
| eSBI NNF (n=192) | 74 (38.5) | 18.2 (1.55) | | |
| eSBI NF (n=193) | 82 (42.5) | 18.1 (1.54) | | |
| Control=190 | 69 (36.3) | 18.1 (1.59) | | |
| **Wagener et al, 2012 [43]** | | | United States, university students | Invited to participate via email using an online participant pool management system |
| eSBI (n=39) | 18 (46.2) | 20.3 (1.67) | | |
| Control (n=37) | 19 (51.4) | 20.3 (1.49) | | |
| **Walters et al, 2009 [44]** | | 19.8 (SD not reported) | United States, university students | University students invited via email, presentations, and posters at the university |
| eSBI (n=67) | | | | |
| Control (n=69) | | | | |

[a] eSBI: electronic screening and brief intervention; GNSF: gender-nonspecific; GSF: gender-specific; NF: intervention with normative feedback; NNF: intervention without normative feedback; PBA=personalized brief advice intervention; PFI=brief personalized feedback intervention.

**Table 3.** Characteristics of screening, experimental, and control interventions, and nature and timing of assessments.

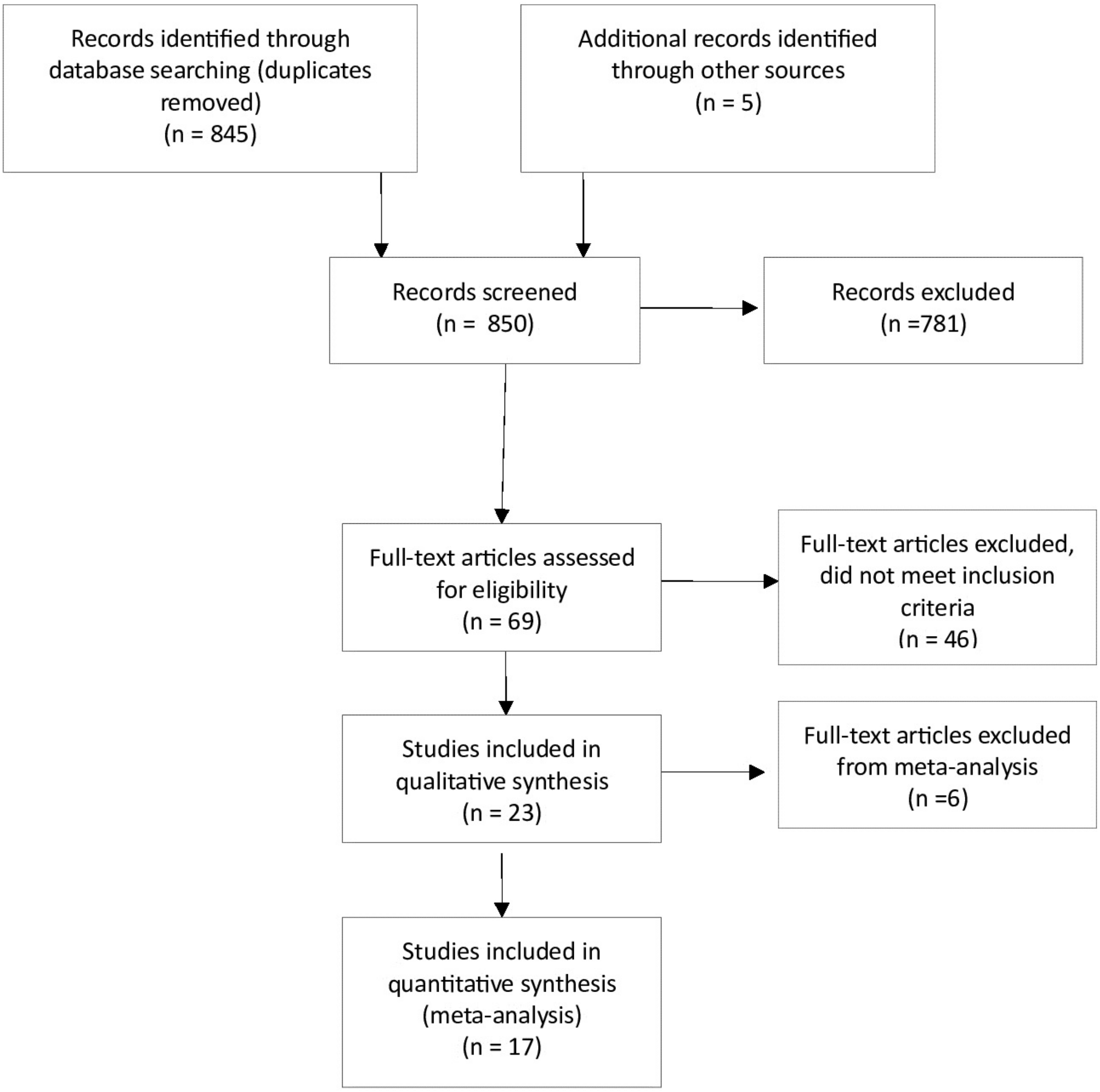
| Study ID | Screening cutoff[a] | eSBI details[a] | Control group | Dropouts at follow-up, n (%)[a] |
|---|---|---|---|---|
| Araki et al, 2006 [23] | Abnormal levels of gamma-glutamyl transpeptidase | Personalized feedback and advice sent via 2 emails 1 month apart; encouraged to ask questions via email | Assessment only | 2 mo: (1 participant was not included in the analysis but the group that they were randomized to was not reported) |
| Blankers et al, 2011 [24] | AUDIT score ≥8 and reported drinking average 14 standard drinks per week | Access to an online self-help program based on motivational interviewing and cognitive behavioral therapy principles, suggested daily use for 4 weeks | Assessment only | 3 mo: eSBI: 20 (29.4), control: 18 (26.1) |
| Boon et al, 2011 [25] | Exceeding Dutch guideline for low risk drinkers (>20 alcohol units per week or > 5 alcohol units on a single occasion on at least 1 day/week) | Single, 20-min brief personalized feedback session through website with the opportunity to print the feedback | Assessment and educational leaflet, instructed to read the leaflet for 20 min and could print the material | 1 mo: eSBI: 18 (7.8), control: 19 (8.6)<br>6 mo: eSBI: 22 (9.6), control: 25 (11.4) |
| Butler et al, 2009 [26] | ≥2 binge drinking occasions (≥5 drinks in 1 sitting for men and 4 or more for women) and 2 alcohol-related problems in the past 28 days Standard drink=14 g ethanol | Single, average 11-min session of computer-delivered personalized feedback and a paper copy to take home | Assessment only | 4 w: eSBI: 9 (30.0), control: 4 (15.4) |
| Cunningham et al, 2009 [16] and Cunningham et al, 2010 [17] | Score ≥4 on the AUDIT-C (standard drink=13.6 g ethanol) | Single, 10-min session completing Check Your Drinking online intervention of normative and personalized feedback | Assessment and a list of possible components to include in an intervention | 3 mo: eSBI=7 (7.6), control: 3 (3.2)<br>6 mo: eSBI: 7 (7.6), control: 8 (8.6)<br>12 mo: eSBI: 11 (12.0), control: 11 (11.8) |
| Cunningham et al, 2012 [27] | Score ≥4 on the AUDIT-C | Access to the Check Your Drinking University version online intervention of normative and personalized feedback; intervention could be accessed repeatedly | Assessment only | 6 w: eSBI: 59 (28.0), control: 75 (35.0) |
| Ekman et al, 2011 [28] | (1) Weekly alcohol consumption >120 g ethanol (women) or 180 g ethanol (men) in a typical week in the past 3 months and/or (2) engaged with heavy episodic drinking defined as consuming ≥48 g of ethanol (women) or ≥60 g of ethanol (men) on ≥2 occasions in the past month | Single session intervention of personalized normative feedback delivered via email | Assessment and brief feedback consisting of 3 statements | 3 mo: eSBI: 125 (37.9), control: 113 (34.9)<br>6 mo: eSBI: 78 (24), control: 80 (24) |
| Hansen et al, 2012 [29] | Above recommended max drinking limit set by the Danish National Board of Health of 14 drinks/168 g ethanol for women or 21 drinks/252 g for men (standard drink=12 g ethanol) | PFI: fully automated, Internet-based single session of brief personalized and normative feedback; PBA: fully automated, Internet-based single session of brief personalized feedback and advice | Assessment only | 6 mo: eSBI PFI: 186 (39.0), eSBI PBA: 171 (38.0), control: 150 (33.0)<br>12 mo: eSBI PFI: 109 (22.9), eSBI PBA: 108 (24.0), control: 95 (20.9) |
| Hester et al, 2012 [30] | Met the National Institute for Alcohol and Alcohol Abuse (2004) criteria for heavy episodic drinking of ≥4 drinks per occasion (women) or ≥5 drinks per occasion (men) at least once in past 2 weeks and an estimated peak blood alcohol concentration of 80 mg% or more (standard drink=14 g ethanol) | Self-guided College Drinkers Check-up, delivered online, single session taking up to 35 min to complete; assessment, normative feedback, and advice | Assessment only | Exp 1 (1 mo): eSBI: 2 (3.1), control: 2.5)<br>Exp 1 (12 mo): eSBI: 6 (9.2), control: 8 (10.1)<br>Exp 2 (1 mo): eSBI: 0 (0.0), control: 1 (2.5) |

| Study ID | Screening cutoff[a] | eSBI details[a] | Control group | Dropouts at follow-up, n (%)[a] |
|---|---|---|---|---|
| Hester et al, 2005 [31] | Score ≥8 AUDIT (standard drink=14 g ethanol) | Computer-based DCU, assessment, feedback, and decision-making modules; single session can take up to 90 min to complete with the option of printing the feedback | Assessment only | 4 w: not reported |
| Kypri et al, 2009 [32] | Score ≥8 on AUDIT and exceeding the Australian National Health and Medical Research Councils guideline for acute risk (defined as 4 standard drinks for women or 6 for men in a single occasion in the last 4 weeks); standard drink=10 g ethanol | Single online session of personalized feedback | Assessment only | 1 mo: eSBI: 288 (23.0), control: 237 (20.0)<br>6 mo: eSBI: 442 (35.3), control: 420 (35.5) |
| Kypri et al, 2008 [33] | AUDIT score ≥8; standard drink=10 g ethanol | Single computer-delivered session of personalized and normative feedback taking a median 9.3 min to complete | Assessment and alcohol facts leaflet | 6 mo: eSBI: 22 (15.9), control: 22 (15.1)<br>12 mo: eSBI: 25 (18.1), control: 20 (13.7) |
| Kypri et al, 2013 [34] | Score ≥4 on AUDIT; standard drink=10 g ethanol | Single online session of personalized and normative feedback taking a median 4.3 min to complete | Assessment only | 5 mo: eSBI: 207 (22.0), control: 170 (20.0) |
| Kypri et al, 2004 [35] | Score ≥8 on AUDIT and consuming >4 standard drinks for men or >6 for women on ≥1 occasion in past 4 weeks (standard drink=10 g ethanol) | Computer-delivered single session of personalized feedback | Assessment and alcohol facts leaflet | 6 w: eSBI: 9 (17.6), control: 12 (22.6)<br>6 mo: eSBI: 4 (7.8), control: 6 (11.3) |
| Lewis et al, 2007 [36] | ≥1 heavy episode (≥4 standard drinks in 1 sitting for women and ≥5 standard drinks in 1 sitting for men) in the previous month; standard drink=14 g ethanol | eSBI specific: gender-specific Web-based personalized normative feedback; eSBI neutral: gender-neutral Web-based personalized normative feedback; feedback was read on screen and participants were given printout to take home | Assessment only | 5 mo: eSBI specific: 11 (14.7), eSBI neutral: 15 (18.3), control: 10 (11.4) |
| Murphy et al, 2010 [37] | ≥2 heavy drinking episodes in the past month (described as ≥4 standard drinks on 1 occasion for women and ≥5 standard drinks for men) or ≥1 heavy drinking episodes for minority students; standard drink=14 g ethanol | Interactive, Web-based intervention, E-CHUG (Electronic Check-up and Go), assessment and personalized feedback in a single session lasting up to 45 min with a brief comprehension test on completion | Assessment only | 1 mo: eSBI: 7 (15.6), control: 3 (7.1) |
| Neighbors et al, 2004 [38] | ≥1 heavy drinking episode in the previous month (defined as 4 standard drinks in 1 sitting for women and 5 standard drinks for men); standard drink=14 g ethanol | Single computer-delivered session of personalized normative feedback presented on screen for 1 min plus a printout | Assessment only | 3 mo: whole sample: 53 (21.0)<br>6 mo: whole sample: 45 (17.9) |
| Neighbors et al, 2010 [39] | ≥5 drinks for men and ≥4 drinks for women on ≥1 occasions in the past month; standard drink=14 g ethanol | eSBI GSF: single session delivered online giving personalized gender-specific feedback; eSBI GNSF: single session delivered online giving personalized gender-nonspecific feedback | Assessment and an attention test (facts about the university students were presented in the same format as the intervention) | 6 mo: eSBI GSF: 10 (6.1), eSBI GNSF: 16 (9.8), control: 13 (8.0)<br>24 mo: eSBI GSF: 33 (20.2), eSBI GNSF: 25 (15.2), control: 31 (19.0) |
| Neumann et al, 2006 [40] | AUDIT score ≥5 | Single session of computer-generated feedback and a printout to take home | Assessment only | 6 mo: eSBI:=213 (37.9), control: 207 (36.0)<br>12 mo: eSBI: 252 (44.9), control: 224 (39.0) |

| Study ID | Screening cutoff[a] | eSBI details[a] | Control group | Dropouts at follow-up, n (%)[a] |
|---|---|---|---|---|
| Palfai et al, 2011 [41] | Hazardous drinkers who either (1) consumed alcohol in the past month and scored ≥8 on AUDIT or (2) reported ≥2 heavy drinking episodes (defined as ≥5 drinks for men or ≥4 drinks for women in the past month; standard drink=14 g ethanol) | Single computer-delivered session of personalized, normative, and gender-specific feedback | Assessment and health guidelines for sleep and consumption of fruit and vegetables | 1 mo: whole sample: 0 (0.0) |
| Spijkerman et al, 2010 [42] | Age 15-16 y: engage in binge drinking at least once a month; age 17-20 y: engaged in binge drinking ≥1/week; binge drinking defined as drinking ≥4 alcoholic drinks for women or ≥6 for men on 1 occasion; standard drink=10 g ethanol | eSBI NNF: single online session of personalized feedback tailored to age and gender, took ~15 min to complete; eSBI NF: single online session of personalized normative gender- and age-specific feedback, took ~15 min to complete | Assessment only | 1 mo: eSBI NNF: 92 (47.9), eSBI NF: 93 (48.2), control: 68 (35.8))<br>3 mo: eSBI NNF: 106 (55.2), eSBI NF: 104 (53.9), control: 87 (45.8) |
| Wagener et al, 2012 [43] | ≥1 heavy drinking session (≥5 drinks on 1 occasion for men or ≥4 for women), drinking ≥20 drinks/month on average and experiencing negative consequences of that use in the last month (standard drink=14 g ethanol) | Single session using of computer-delivered assessment personalized feedback using an interactive program (DRAFT-CS), took ~45 min to complete; participants were given printout of their feedback | Assessment only | 10 w: eSBI: 2 (5.1), control: 3 (8.1) |
| Walters et al, 2009 [44] | Reported ≥1 heavy drinking session in the past 2 weeks defined as ≥5 standard drinks for men and ≥4 standard drinks for women (standard drink=14 g ethanol) | eSBI: single session of personalized feedback delivered through the online Check-Up to Go | Assessment only | 3 mo: eSBI: 9 (13.4), control: 6 (8.7)<br>6 mo: eSBI: 13 (19.4), control: 8 (11.6) |

[a] eSBI: electronic screening and brief intervention, AUDIT: Alcohol Use Disorders Identification Test, PFI: brief personalized feedback intervention, PBA: personalized brief advice intervention, DCU: Drinkers Check Up, GSF: gender-specific, GNSF: gender-nonspecific, NNF: intervention without normative feedback, NF: intervention with normative feedback, FBO: feedback only, DRAFT-CS: Drinking Assessment and Feedback Tool for College Students.

**Figure 1.** Flow diagram of study selection and inclusion.




## Grams of Ethanol per Week

Nine studies included data for a follow-up period of up to 3 months (mean 1.06 months, SD 0.18), 6 studies with a follow-up period between 3 and less than 6 months (mean 3.86 months, SD 1.07), 8 studies with a follow-up period between 6 and less than 12 months (all included studies had a follow-up period of 6 months ), and 5 studies included data for a follow-up period greater than 12 months (mean 16 months, SD 6.20) (Figure 2). There was a statistically significant difference in pooled mean difference in grams of ethanol per week consumed between those who received the eSBI and controls for follow-up period subgroups up to 3 months, between 3 and less than 6 months, and between 6 and less than 12 months (Table 4). This difference represents a significantly lower mean number of grams of ethanol consumed per week at follow-up by those in the eSBI group compared to controls. There was no statistically significant difference between groups in pooled mean difference in grams of ethanol per week for long-term follow-up. The greatest difference was found at less than 3 months follow-up, which decreased with length of follow-up (Figure 3).

There was statistically significant and moderate heterogeneity between studies included at less than 3 months follow-up. Heterogeneity was not statistically significant for any of the other follow-up groups. Egger's test was not statistically significant for all follow-up periods, indicating an absence of publication bias.

**Table 4.** Results of meta-analysis including significance test and heterogeneity statistics.

| Follow-up period | Sample size, n | | Mean difference significance test | | Heterogeneity statistic | | | |
|---|---|---|---|---|---|---|---|---|
| | Experimental | Control | *z* | *P* | *Q* | *df* | *P* | $I^2$ |
| <3 months | 1305 | 1307 | 2.67 | .01 | 17.19 | 8 | .03 | 53.5% |
| 3-6 months | 1211 | 811 | 2.34 | .02 | 8.62 | 6 | .20 | 30.4% |
| 6-12 months | 1921 | 1751 | 2.74 | .01 | 10.91 | 8 | .21 | 26.7% |
| ≥12 months | 899 | 816 | 0.82 | .41 | 8.49 | 5 | .13 | 41.1% |

**Figure 2.** Forest plot for weighted mean difference (WMD) in grams of ethanol per week at follow-up between those in the eSBI group and controls.

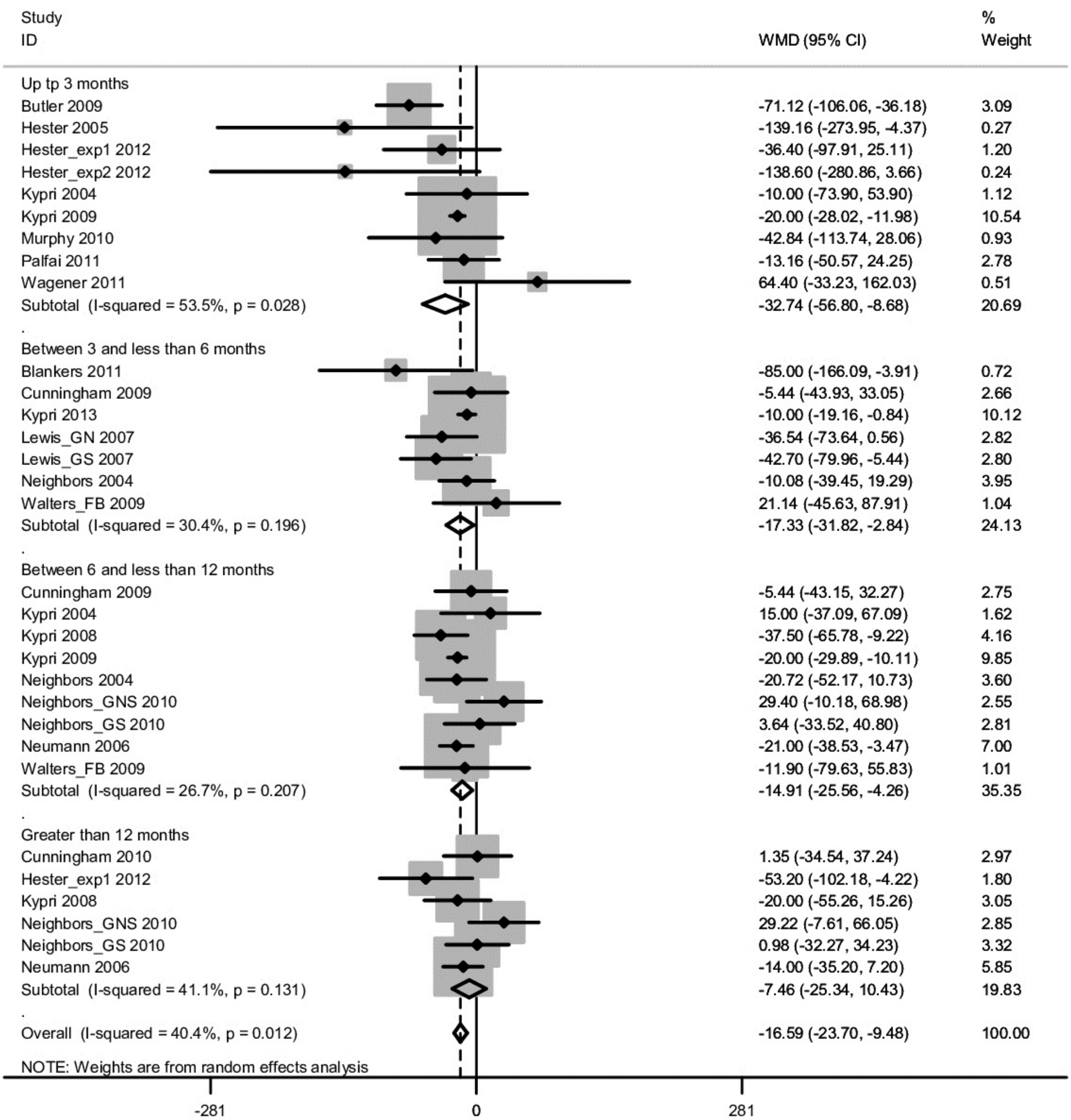
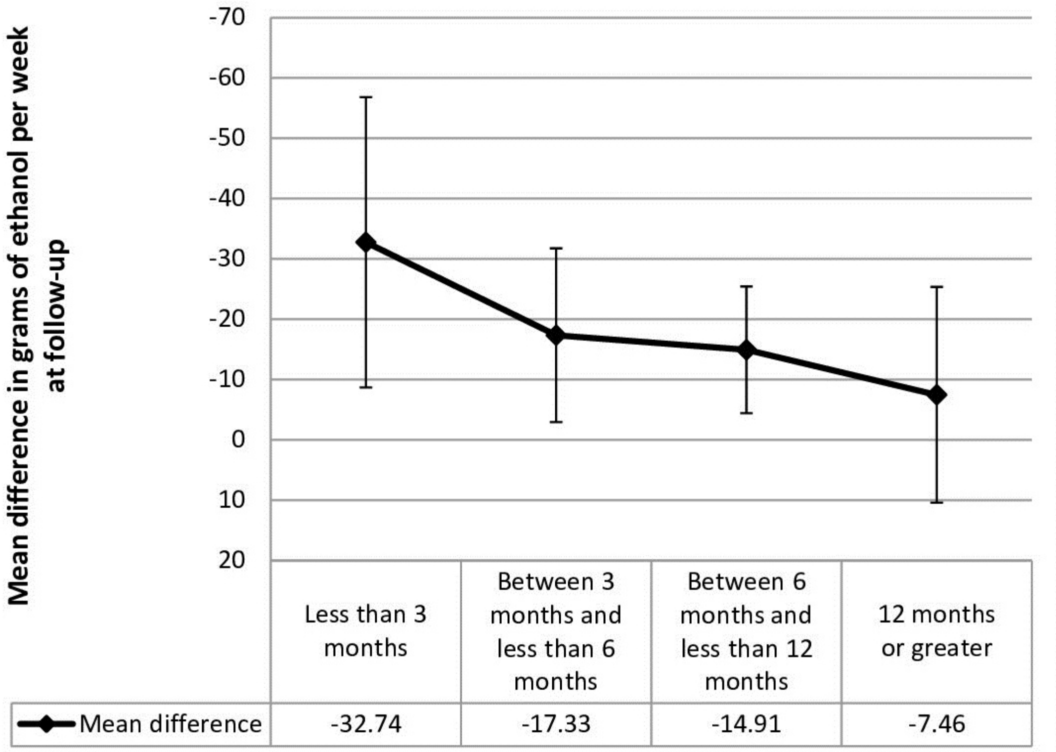


**Figure 3.** Mean difference in grams of ethanol per week at follow-up postintervention with 95% confidence intervals.




### Sensitivity Analysis

Participants in the intervention arm of the study conducted by Blankers et al [34] had access to the online self-help intervention at any time, but it was suggested that they access it daily during a 4-week period. This methodology is different from other studies included in this review in that the other studies allowed participants access to the electronic intervention for a single session. Therefore, sensitivity analysis was conducted to assess the impact of this study on the overall mean difference in consumption of alcohol between 3 and less than 6 months. Removal of the Blankers et al [34] study from the meta-analysis had little effect on the mean difference in grams of alcohol consumed per week for those in the intervention groups compared to controls (mean difference -13.40, 95% CI -23.94 to 2.85).

The length of the intervention in the study conducted by Hester et al [31] was on average 90 minutes; this is longer than the definition of brief intervention for eligibility of inclusion in this systematic review and meta-analysis. However, because the intervention was completed in 1 session it was decided that a sensitivity analysis would be conducted to explore the impact of this study on the pooled mean difference in alcohol consumption at up to 3 months. Removal of the study conducted by Hester et al [31] had minimal impact on the pooled mean difference in grams of alcohol consumed per week for those in the intervention group compared to controls (mean difference -29.53, 95% CI -52.50 to 6.56).

### Risk of Bias

The quality of the evidence reviewed was considered to be acceptable with most studies included in this review assessed as being adequate in terms of their methodological quality. Three studies were considered to be of high methodological quality [24,32,34]. The addition of future research may have an impact on the conclusions of the review and meta-analysis.

## Discussion

The results of this systematic review and meta-analysis suggest that eSBI is effective in reducing alcohol consumption in the follow-up postintervention period of less than 3 months, between 3 months and less than 6 months, and between 6 months and less than 12 months, but not in the longer term follow-up period of 12 months or longer. The overall mean difference in grams of ethanol per week consumed between those in the intervention and controls groups was 16.59 (Figure 2), which is equivalent to 2 standard drinks in the United Kingdom (1 standard drink=8 g ethanol). This difference is somewhat smaller compared to a previous review, which found an overall mean difference of 25.88 g of ethanol per week [14]. The current review did not include studies of treatment seeking populations or those in which individuals were randomized regardless of their drinking status at baseline; this may account for some of the variation in mean difference in alcohol consumption. Furthermore, there may have been a variation in the length of follow-up for studies included in the current research and Khadjesari et al’s [14] meta-analysis. The inclusion of more studies with a shorter follow-up length may have resulted in an inflated overall mean difference in alcohol consumption between controls and those who received the intervention.

The pattern of results found here are in-line with the results of Cunningham et al [16,17]. They reported significantly lower levels of weekly alcohol consumption in those who received a Web-based brief intervention compared to controls at 3 and 6 months, but not at 12-month follow-up. Cunningham et al

[16,17] is the only eSBI study included in this systematic review and meta-analysis to follow up participants over the 3 time points: 3-, 6-, and 12-month follow-ups. Meta-analysis allowed for replication of their results with a much larger sample size. The magnitude of the effect in this study reduced with increasing length of the follow-up period, from nearly 4 standard drinks at a follow-up point of less than 3 months to less than 1 standard drink at a longer duration of follow-up of 12 months or greater, indicating a decline in the effectiveness of eSBI to significantly reduce alcohol consumption. All the data included in this review were from studies using a single eSBI session, although the option of returning to the eSBI was available for one study [23] and a printout of personalized feedback was generally offered (see Table 3). Neighbors et al [39] found no compelling evidence to suggest that multiple doses of electronic personalized brief advice, administered every 6 months for 2 years, was more effective than a single one-off intervention.

There was a variation in the extent of eSBI delivered between studies included in this review with some interventions taking substantially longer to complete and one study encouraged daily use of their online self-help program [24]. It is possible that more extensive interventions will have a greater impact on alcohol consumption. However, a recent large cluster randomized controlled study of face-to-face SBI in primary care found no difference in effectiveness between an information leaflet, 5 minutes of structured brief advice, or 20 minutes of brief lifestyle counseling on proportion of individuals with a negative AUDIT score (<8) at 6- and 12-month follow-ups [5]. Furthermore, a meta-analysis of face-to-face SBI found that although the reduction in alcohol consumption (grams of ethanol per week) was greater for more substantial interventions (including those that were longer in duration and administered in more than one session) compared to less intensive interventions, the difference was not statistically significant [4]. To date there has been no comparable studies for eSBI.

A large attrition rate (up to 55%) has been noted in some of the eSBI studies included in this review. High attrition rates are common in electronic interventions for nontreatment-seeking individuals and reasons for this are likely to be complex and varied [45]. Attrition will have an obvious impact on the validity of results obtained and introduce bias, for example, those more committed to reducing their alcohol intake may remain in the trial and inflate positive alcohol outcomes. This has led to research into ways of reducing attrition using incentives. Khadjesari et al [46] investigated whether attrition could be improved in their study of a Web-based intervention (Down Your Drink) for reducing alcohol consumption by incentivizing study completion. Participants were randomized to receive no incentive, a £5 Amazon voucher, £5 donation to Cancer Research, or entry into a £250 prize draw. There was no significant difference in response rate between any of the study arms. A second study by Khadjesari et al [46] randomized participants to receive a higher value incentive of £10 Amazon voucher or no incentive. This resulted in a 9% difference in response rate between the 2 groups, suggesting that appropriate incentivization can reduce participant attrition. However, some caution is required when considering the use of incentives to reduce attrition in online interventions. In the previous study, incentives were given on completion of the intervention and follow-up, rather than on sign-up to the intervention; this prevented individuals signing up who were only doing so for the incentive not the potential benefits of the research. Further exploration of the mechanism of action of incentives is required in eSBI, socioeconomic status, cultural factors, and reasons for attrition may all influence how effective incentives are at improving attrition in research [45].

Seventeen studies were included in the meta-analysis and most of these took place in the United States and with student populations. Binge drinking among young adult and student populations continues to be a concern. In the United Kingdom, 45% of males and 46% of females aged 16-24 years drink more than twice the recommended amount of alcohol (3-4 units for males and 2-3 units for females) in a single session in the previous week [47]. Binge drinking can increase the risk of behaviors that are illegal, violent, or risky (eg, unprotected sex) [48,30,48]. Binge drinking at university may also lead to long-term problems with physical and mental health [48]. This may help to explain why the majority of studies included in this systematic review and meta-analysis were conducted with student populations. Furthermore, the population of a university is generally large with up-to-date information technology facilities, which would be ideal for the implementation of an eSBI. A culture of binge drinking is evident among student populations; the pattern of drinking is likely to be somewhat different to the general population. Because of the limited number of relevant eSBI trials available, further analysis to investigate the impact of population on the effectiveness of eSBI is needed. Therefore, the generalizability of the current findings for the general population is not known.

The studies included in this meta-analysis also varied in the length, content, and theoretical basis of the intervention. Although almost all the included studies incorporated an element of personalized feedback as part of the intervention, there remains variation in both the mechanism and the context of how this was delivered. Further investigation into the effective components of these interventions was not possible and this should form an area for future research.

A comprehensive search strategy was used to identify relevant published randomized controlled trials for inclusion in this review and meta-analysis. However, it is possible that some trials may have been missed because unpublished research was not sought although an Egger's test suggested that no publication bias was present.

The results of this systematic review and meta-analysis demonstrate significant reductions in weekly alcohol consumption between intervention and control conditions at a follow-up point of less than 3 months, between 3 and 6 months, and between 6 and 12 months; as such, eSBI should be judged an effective intervention, a recent review of effective interventions targeting adolescent populations adds further support for the use of Web-/smartphone-based technology [49]. Advantages inherent to eSBI, such as reduced cost of implementation and wider accessibility compared to conventional face-to-face SBI, should also be considered. However, because of a lack of consistency in reporting of alcohol consumption outcome measures, this review could only report on grams of ethanol consumed per week. A greater consensus in the reporting of outcome measures and more uniform reporting of the content and theoretical basis of eSBI would result in the ability to make more robust conclusions regarding the effectiveness of eSBI in reducing alcohol consumption and alcohol-related harms in the longer term.

## Acknowledgments

This study presents independent research funded by the National Institute for Health Research (NIHR) Programme Grants for Applied Research (RP-PG-0609-10162). Colin Drummond is partly funded by the NIHR Biomedical Research Centre for Mental Health at South London and Maudsley NHS Foundation Trust and King's College London and partly funded by the NIHR Collaborations for Leadership in Applied Health Research and Care South London at King's College Hospital NHS Foundation Trust. Thomas Phillips is funded by a NIHR Clinical Doctoral Research Fellowship. The views expressed are those of the author(s) and not necessarily those of the NHS, the NIHR, or the Department of Health.

## Conflicts of Interest

None declared.

## References

1. Rehm J, Mathers C, Popova S, Thavorncharoensap M, Teerawattananon Y, Patra J. Global burden of disease and injury and economic cost attributable to alcohol use and alcohol-use disorders. Lancet 2009 Jun 27;373(9682):2223-2233. [doi: 10.1016/S0140-6736(09)60746-7] [Medline: 19560604]
2. Cunningham JA, Breslin FC. Only one in three people with alcohol abuse or dependence ever seek treatment. Addict Behav 2004 Jan;29(1):221-223. [Medline: 14667433]
3. Drummond C, Oyefeso A, Phillips T, Cheeta S, Deluca P, Perryman K, et al. Alcohol needs assessment research project (ANARP): the 2004 national alcohol needs assessment for England. London: Department of Health; 2005. URL: http://www.alcohollearningcentre.org.uk/_library/Resources/ALC/OtherOrganisation/Alcohol_needs_assessment_research_project.pdf [accessed 2013-12-08] [WebCite Cache ID 6LifhxBwW]
4. Kaner EF, Beyer F, Dickinson HO, Pienaar E, Campbell F, Schlesinger C, et al. Effectiveness of brief alcohol interventions in primary care populations. Cochrane Database Syst Rev 2007(2):CD004148 [FREE Full text] [doi: 10.1002/14651858.CD004148.pub3] [Medline: 17443541]
5. Kaner E, Bland M, Cassidy P, Coulton S, Dale V, Deluca P, et al. Effectiveness of screening and brief alcohol intervention in primary care (SIPS trial): pragmatic cluster randomised controlled trial. BMJ 2013;346:e8501 [FREE Full text] [Medline: 23303891]
6. Crawford MJ, Patton R, Touquet R, Drummond C, Byford S, Barrett B, et al. Screening and referral for brief intervention of alcohol-misusing patients in an emergency department: a pragmatic randomised controlled trial. Lancet 2004;364(9442):1334-1339. [doi: 10.1016/S0140-6736(04)17190-0] [Medline: 15474136]
7. D'Onofrio G, Degutis LC. Preventive care in the emergency department: screening and brief intervention for alcohol problems in the emergency department: a systematic review. Acad Emerg Med 2002 Jun;9(6):627-638. [Medline: 12045080]
8. Nilsen P. Brief alcohol intervention--where to from here? Challenges remain for research and practice. Addiction 2010 Jun;105(6):954-959. [doi: 10.1111/j.1360-0443.2009.02779.x] [Medline: 20121717]
9. Wilson GB, Lock CA, Heather N, Cassidy P, Christie MM, Kaner EF. Intervention against excessive alcohol consumption in primary health care: a survey of GPs' attitudes and practices in England 10 years on. Alcohol Alcohol 2011;46(5):570-577 [FREE Full text] [doi: 10.1093/alcalc/agr067] [Medline: 21690169]
10. Bewick BM, Trusler K, Barkham M, Hill AJ, Cahill J, Mulhern B. The effectiveness of web-based interventions designed to decrease alcohol consumption--a systematic review. Prev Med 2008 Jul;47(1):17-26. [doi: 10.1016/j.ypmed.2008.01.005] [Medline: 18302970]
11. Champion KE, Newton NC, Barrett EL, Teesson M. A systematic review of school-based alcohol and other drug prevention programs facilitated by computers or the internet. Drug Alcohol Rev 2013 Mar;32(2):115-123. [doi: 10.1111/j.1465-3362.2012.00517.x] [Medline: 23039085]
12. Newton AS, Dong K, Mabood N, Ata N, Ali S, Gokiert R, et al. Brief emergency department interventions for youth who use alcohol and other drugs: a systematic review. Pediatr Emerg Care 2013 May;29(5):673-684. [doi: 10.1097/PEC.0b013e31828ed325] [Medline: 23640153]
13. Linke S, Murray E, Butler C, Wallace P. Internet-based interactive health intervention for the promotion of sensible drinking: patterns of use and potential impact on members of the general public. J Med Internet Res 2007;9(2):e10 [FREE Full text] [doi: 10.2196/jmir.9.2.e10] [Medline: 17513281]
14. Khadjesari Z, Murray E, Hewitt C, Hartley S, Godfrey C. Can stand-alone computer-based interventions reduce alcohol consumption? A systematic review. Addiction 2011 Feb;106(2):267-282. [doi: 10.1111/j.1360-0443.2010.03214.x] [Medline: 21083832]

15. Rooke S, Thorsteinsson E, Karpin A, Copeland J, Allsop D. Computer-delivered interventions for alcohol and tobacco use: a meta-analysis. Addiction 2010 Aug;105(8):1381-1390. [doi: 10.1111/j.1360-0443.2010.02975.x] [Medline: 20528806]
16. Cunningham JA, Wild TC, Cordingley J, van Mierlo T, Humphreys K. A randomized controlled trial of an internet-based intervention for alcohol abusers. Addiction 2009 Dec;104(12):2023-2032 [FREE Full text] [doi: 10.1111/j.1360-0443.2009.02726.x] [Medline: 19922569]
17. Cunningham JA, Wild TC, Cordingley J, Van Mierlo T, Humphreys K. Twelve-month follow-up results from a randomized controlled trial of a brief personalized feedback intervention for problem drinkers. Alcohol Alcohol 2010;45(3):258-262 [FREE Full text] [doi: 10.1093/alcalc/agq009] [Medline: 20150170]
18. National Collaborating Centre for Mental Health. Alcohol Use Disorders: The NICE Guideline on the Diagnosis, Assessment and Management of Harmful Drinking and Alcohol Dependence (NICE Clinical Guidelines). Leicester and London: The British Psychological Society and the Royal College of Psychiatrists; 2011.
19. SIGN. Critical appraisal: notes and checklists URL: http://www.sign.ac.uk/methodology/checklists.html [accessed 2013-12-09] [WebCite Cache ID 6LjcEfhx8]
20. Hozo SP, Djulbegovic B, Hozo I. Estimating the mean and variance from the median, range, and the size of a sample. BMC Med Res Methodol 2005;5:13 [FREE Full text] [doi: 10.1186/1471-2288-5-13] [Medline: 15840177]
21. International Center for Alcohol Policies. Standard drinks URL: http://www.icap.org/policyissues/drinkingguidelines/standarddrinks/tabid/126/default.aspx [accessed 2013-12-08] [WebCite Cache ID 6Lii3IZo5]
22. Higgins J, Green S. The Cochrane Collaboration.: The Cochrane Collaboration; 2011. Cochrane handbook for systematic reviews of interventions 5.1.0 URL: http://handbook.cochrane.org/ [accessed 2014-05-20] [WebCite Cache ID 6PiBcKDDk]
23. Araki I, Hashimoto H, Kono K, Matsuki H, Yano E. Controlled trial of worksite health education through face-to-face counseling vs. e-mail on drinking behavior modification. J Occup Health 2006 Jul;48(4):239-245 [FREE Full text] [Medline: 16902267]
24. Blankers M, Koeter MW, Schippers GM. Internet therapy versus internet self-help versus no treatment for problematic alcohol use: A randomized controlled trial. J Consult Clin Psychol 2011 Jun;79(3):330-341. [doi: 10.1037/a0023498] [Medline: 21534652]
25. Boon B, Risselada A, Huiberts A, Riper H, Smit F. Curbing alcohol use in male adults through computer generated personalized advice: randomized controlled trial. J Med Internet Res 2011;13(2):e43 [FREE Full text] [doi: 10.2196/jmir.1695] [Medline: 21719412]
26. Butler LH, Correia CJ. Brief alcohol intervention with college student drinkers: face-to-face versus computerized feedback. Psychol Addict Behav 2009 Mar;23(1):163-167. [doi: 10.1037/a0014892] [Medline: 19290702]
27. Cunningham JA, Hendershot CS, Murphy M, Neighbors C. Pragmatic randomized controlled trial of providing access to a brief personalized alcohol feedback intervention in university students. Addict Sci Clin Pract 2012;7(1):21 [FREE Full text] [doi: 10.1186/1940-0640-7-21] [Medline: 23185985]
28. Ekman DS, Andersson A, Nilsen P, Ståhlbrandt H, Johansson AL, Bendtsen P. Electronic screening and brief intervention for risky drinking in Swedish university students--a randomized controlled trial. Addict Behav 2011 Jun;36(6):654-659. [doi: 10.1016/j.addbeh.2011.01.015] [Medline: 21316157]
29. Hansen AB, Becker U, Nielsen AS, Grønbæk M, Tolstrup JS, Thygesen LC. Internet-based brief personalized feedback intervention in a non-treatment-seeking population of adult heavy drinkers: a randomized controlled trial. J Med Internet Res 2012;14(4):e98 [FREE Full text] [doi: 10.2196/jmir.1883] [Medline: 22846542]
30. Hester RK, Delaney HD, Campbell W. The college drinker's check-up: outcomes of two randomized clinical trials of a computer-delivered intervention. Psychol Addict Behav 2012 Mar;26(1):1-12 [FREE Full text] [doi: 10.1037/a0024753] [Medline: 21823769]
31. Hester RK, Squires DD, Delaney HD. The Drinker's Check-up: 12-month outcomes of a controlled clinical trial of a stand-alone software program for problem drinkers. J Subst Abuse Treat 2005 Mar;28(2):159-169. [doi: 10.1016/j.jsat.2004.12.002] [Medline: 15780546]
32. Kypri K, Hallett J, Howat P, McManus A, Maycock B, Bowe S, et al. Randomized controlled trial of proactive web-based alcohol screening and brief intervention for university students. Arch Intern Med 2009 Sep 14;169(16):1508-1514. [doi: 10.1001/archinternmed.2009.249] [Medline: 19752409]
33. Kypri K, Langley JD, Saunders JB, Cashell-Smith ML, Herbison P. Randomized controlled trial of web-based alcohol screening and brief intervention in primary care. Arch Intern Med 2008 Mar 10;168(5):530-536. [doi: 10.1001/archinternmed.2007.109] [Medline: 18332300]
34. Kypri K, McCambridge J, Vater T, Bowe SJ, Saunders JB, Cunningham JA, et al. Web-based alcohol intervention for Māori university students: double-blind, multi-site randomized controlled trial. Addiction 2013 Feb;108(2):331-338 [FREE Full text] [doi: 10.1111/j.1360-0443.2012.04067.x] [Medline: 22925046]
35. Kypri K, Saunders JB, Williams SM, McGee RO, Langley JD, Cashell-Smith ML, et al. Web-based screening and brief intervention for hazardous drinking: a double-blind randomized controlled trial. Addiction 2004 Nov;99(11):1410-1417. [doi: 10.1111/j.1360-0443.2004.00847.x] [Medline: 15500594]

36. Lewis MA, Neighbors C, Oster-Aaland L, Kirkeby BS, Larimer ME. Indicated prevention for incoming freshmen: personalized normative feedback and high-risk drinking. Addict Behav 2007 Nov;32(11):2495-2508 [FREE Full text] [doi: 10.1016/j.addbeh.2007.06.019] [Medline: 17658695]
37. Murphy JG, Dennhardt AA, Skidmore JR, Martens MP, McDevitt-Murphy ME. Computerized versus motivational interviewing alcohol interventions: impact on discrepancy, motivation, and drinking. Psychol Addict Behav 2010 Dec;24(4):628-639. [doi: 10.1037/a0021347] [Medline: 21198224]
38. Neighbors C, Larimer ME, Lewis MA. Targeting misperceptions of descriptive drinking norms: efficacy of a computer-delivered personalized normative feedback intervention. J Consult Clin Psychol 2004 Jun;72(3):434-447. [doi: 10.1037/0022-006X.72.3.434] [Medline: 15279527]
39. Neighbors C, Lewis MA, Atkins DC, Jensen MM, Walter T, Fossos N, et al. Efficacy of web-based personalized normative feedback: a two-year randomized controlled trial. J Consult Clin Psychol 2010 Dec;78(6):898-911. [doi: 10.1037/a0020766] [Medline: 20873892]
40. Neumann T, Neuner B, Weiss-Gerlach E, Tønnesen H, Gentilello LM, Wernecke KD, et al. The effect of computerized tailored brief advice on at-risk drinking in subcritically injured trauma patients. J Trauma 2006 Oct;61(4):805-814. [doi: 10.1097/01.ta.0000196399.29893.52] [Medline: 17033544]
41. Palfai TP, Zisserson R, Saitz R. Using personalized feedback to reduce alcohol use among hazardous drinking college students: the moderating effect of alcohol-related negative consequences. Addict Behav 2011 May;36(5):539-542. [doi: 10.1016/j.addbeh.2011.01.005] [Medline: 21295919]
42. Spijkerman R, Roek MA, Vermulst A, Lemmers L, Huiberts A, Engels RC. Effectiveness of a web-based brief alcohol intervention and added value of normative feedback in reducing underage drinking: a randomized controlled trial. J Med Internet Res 2010;12(5):e65 [FREE Full text] [doi: 10.2196/jmir.1465] [Medline: 21169172]
43. Wagener TL, Leffingwell TR, Mignogna J, Mignogna MR, Weaver CC, Cooney NJ, et al. Randomized trial comparing computer-delivered and face-to-face personalized feedback interventions for high-risk drinking among college students. J Subst Abuse Treat 2012 Sep;43(2):260-267. [doi: 10.1016/j.jsat.2011.11.001] [Medline: 22197301]
44. Walters ST, Vader AM, Harris TR, Field CA, Jouriles EN. Dismantling motivational interviewing and feedback for college drinkers: a randomized clinical trial. J Consult Clin Psychol 2009 Feb;77(1):64-73 [FREE Full text] [doi: 10.1037/a0014472] [Medline: 19170454]
45. Linke S, Brown A, Wallace P. Down your drink: a web-based intervention for people with excessive alcohol consumption. Alcohol Alcohol 2004;39(1):29-32 [FREE Full text] [Medline: 14691071]
46. Khadjesari Z, Murray E, Kalaitzaki E, White IR, McCambridge J, Thompson SG, et al. Impact and costs of incentives to reduce attrition in online trials: two randomized controlled trials. J Med Internet Res 2011;13(1):e26 [FREE Full text] [doi: 10.2196/jmir.1523] [Medline: 21371988]
47. Health and Social care Information Centre. Statistics on Alcohol: England 2013 URL: http://www.hscic.gov.uk/catalogue/PUB10932/alc-eng-2013-rep.pdf [accessed 2014-05-20]
48. Bewick BM, West R, Gill J, O'May F, Mulhern B, Barkham M, et al. Providing web-based feedback and social norms information to reduce student alcohol intake: a multisite investigation. J Med Internet Res 2010;12(5):e59 [FREE Full text] [doi: 10.2196/jmir.1461] [Medline: 21169171]
49. Patton R, Deluca P, Kaner E, Newbury-Birch D, Phillips T, Drummond C. Alcohol screening and brief intervention for adolescents: the how, what and where of reducing alcohol consumption and related harm among young people. Alcohol Alcohol 2014;49(2):207-212 [FREE Full text] [doi: 10.1093/alcalc/agt165] [Medline: 24232178]

## Abbreviations

**AUDIT:** Alcohol Use Disorders Identification Test
**eSBI:** electronic screening and brief intervention
**MCV:** mean corpuscular volume
**NIHR:** National Institute for Health Research
**SBI:** screening and brief intervention
**SIGN:** Scottish Intercollegiate Guidelines Network

*Edited by G Eysenbach; submitted 19.12.13; peer-reviewed by P Wallace, P Bendtsen; comments to author 11.02.14; revised version received 26.03.14; accepted 28.04.14; published 02.06.14.*

*Please cite as:*
*Donoghue K, Patton R, Phillips T, Deluca P, Drummond C*
*The Effectiveness of Electronic Screening and Brief Intervention for Reducing Levels of Alcohol Consumption: A Systematic Review and Meta-Analysis*
*J Med Internet Res 2014;16(6):e142*
*URL: http://www.jmir.org/2014/6/e142/*
*doi:10.2196/jmir.3193*
*PMID:24892426*

Original Paper

# Feasibility and Effectiveness of a Web-Based Positive Psychology Program for Youth Mental Health: Randomized Controlled Trial

Vijaya Manicavasagar[1], PhD; Deserae Horswood[1], BA; Rowan Burckhardt[1], MPsych(Clinical); Alistair Lum[1], BPsych (Hons); Dusan Hadzi-Pavlovic[2], MPsych(Clinical); Gordon Parker[2], MB, BS, MD, PhD, DSc, FRANZCP

[1]Black Dog Institute, School of Psychiatry, UNSW Australia, Randwick, Australia

[2]School of Psychiatry, UNSW Australia, Randwick, Australia

**Corresponding Author:**
Vijaya Manicavasagar, PhD
Black Dog Institute
School of Psychiatry
UNSW Australia
Hospital Rd
Randwick, 2031
Australia
Phone: 61 2 9382 4320
Fax: 61 2 9382 82 07
Email: v.manicavasagar@unsw.edu.au

## Abstract

**Background:** Youth mental health is a significant public health concern due to the high prevalence of mental health problems in this population and the low rate of those affected seeking help. While it is increasingly recognized that prevention is better than cure, most youth prevention programs have utilized interventions based on clinical treatments (eg, cognitive behavioral therapy) with inconsistent results.

**Objective:** This study explores the feasibility of the online delivery of a youth positive psychology program, Bite Back, to improve the well-being and mental health outcomes of Australian youth. Further aims were to examine rates of adherence and attrition, and to investigate the program's acceptability.

**Methods:** Participants (N=235) aged 12-18 years were randomly assigned to either of two conditions: Bite Back (n=120) or control websites (n=115). The Bite Back website comprised interactive exercises and information across a variety of positive psychology domains; the control condition was assigned to neutral entertainment-based websites that contained no psychology information. Participants in both groups were instructed to use their allocated website for 6 consecutive weeks. Participants were assessed pre- and postintervention on the Depression Anxiety Stress Scale-Short form (DASS-21) and the Short Warwick-Edinburgh Mental Well-Being Scale (SWEMWBS).

**Results:** Of the 235 randomized participants, 154 (65.5%) completed baseline and post measures after 6 weeks. Completers and dropouts were equivalent in demographics, the SWEMWBS, and the depression and anxiety subscales of the DASS-21, but dropouts reported significantly higher levels of stress than completers. There were no differences between the Bite Back and control conditions at baseline on demographic variables, DASS-21, or SWEMWBS scores. Qualitative data indicated that 49 of 61 Bite Back users (79%) reported positive experiences using the website and 55 (89%) agreed they would continue to use it after study completion. Compared to the control condition, participants in the Bite Back condition with high levels of adherence (usage of the website for 30 minutes or more per week) reported significant decreases in depression and stress and improvements in well-being. Bite Back users who visited the site more frequently (≥3 times per week) reported significant decreases in depression and anxiety and improvements in well-being. No significant improvements were found among Bite Back users who demonstrated low levels of adherence or who used the website less frequently.

**Conclusions:** Results suggest that using an online positive psychology program can decrease symptoms of psychopathology and increase well-being in young people, especially for those who use the website for 30 minutes or longer per week or more frequently (≥3 times per week). Acceptability of the Bite Back website was high. These findings are encouraging and suggest that the online delivery of positive psychology programs may be an alternate way to address mental health issues and improve youth well-being nationally.

**Trial Registration:** Australian New Zealand Clinical Trials Registry: ACTRN1261200057831; https://www.anzctr.org.au/Trial/Registration/TrialReview.aspx?id=362489 (Archived by Webcite at http://www.webcitation.org/6NXmjwfAy).

***(J Med Internet Res 2014;16(6):e140)*** doi:10.2196/jmir.3176

**KEYWORDS**

adolescent; resilience; psychological; mental health; Internet; early medical intervention

## Introduction

### Background

Addressing mental health problems in young people is a major public health concern [1]. Estimates suggest that 1 in 4 young people between the ages of 16 to 24 years have experienced at least 1 mental disorder in the preceding year [2]. Suicide, typically associated with severe distress and mental health issues, remains one of the leading causes of death among young people [3-5]. Such concerns are further exacerbated by low levels of youth help-seeking behavior for mental health issues [6,7]. Concerns about stigma and confidentiality, shame or embarrassment in discussing personal issues, financial costs, and/or limited access to services are among the many barriers to accessing help in this group [8].

In addressing the burgeoning issue of youth mental health problems, researchers and clinicians have focused on childhood and adolescence as a particularly fruitful area for targeting preventative interventions [9]. Subclinical symptoms, dysfunctional cognitive styles, and problematic behaviors which increase vulnerability to later mental health problems usually develop during this period, making childhood and adolescence an ideal time to direct prevention and early intervention programs [10-12].

To date, prevention programs for young people have tended to yield inconsistent results because of a number of factors, including the application of techniques originally developed for the treatment of clinical conditions, poor methodology, difficulties in measuring change in "normal populations," and/or lack of relevance to some subgroups within that population [13,14]. Furthermore, programs that have been successful in reducing psychopathology in adolescents have incurred high financial costs and relied on scarce resources, such as teachers' classroom time or researchers for program delivery [15]. A paradigm shift in mental health prevention programs is therefore required to ensure more effective and widespread delivery, improved levels of overall well-being, and high acceptability by young people.

### Positive Psychology

Positive psychology is the study of well-being, engagement, and optimal functioning and differs from clinical psychology in that it conceptualizes mental health as more than just the absence of mental illness. Positive psychology fits well with the World Health Organization's (WHO) definition of mental health: "a state of well-being in which the individual is able to realize their potential, cope with normal life stresses, and is able to work and contribute in the community" [16]. Positive psychology is best understood as a group of mental health domains that contribute to an individual's well-being. Although researchers debate the validity and relative importance of the various domains, a number have repeatedly been found to correspond with optimal mental health, including gratitude, mindfulness, positive social relationships, meaning, flow, optimism, hope, character strengths, and a healthy lifestyle [17]. Attempts have been made to refine these domains, such as the PERMA model proposed by Seligman [17], which stipulates that happiness is made up of 5 key components: positive emotions, engagement (similar to the concept of mindfulness), positive relationships, meaning, and accomplishment.

Evidence has accrued that addressing specific skills in these domains can promote overall well-being [18,19]. For example, interventions that increase hope have been shown to predict lower illicit substance use; lower levels of depression, anxiety, and hostility; less behavioral problems; and higher academic performance in adolescents [20,21]. Research has also linked increases in gratitude—the state of positive reflection and appreciation—to improved positive affect, life satisfaction, improved social relationships, as well as lower suicidal ideation and suicide attempts [22,23]. Longitudinal research has found that, for students faced with the challenges of entering university, higher optimism was predictive of higher well-being, better physical health, better adjustment, fewer symptoms of depression and stress, better social supports, higher levels of academic achievement, and lower dropout rates [24-27]. Optimism in adolescence has also been found to be the best predictor of life satisfaction in adulthood [28]. A meta-analysis that reviewed 51 positive psychology interventions across a spectrum of domains, found that positive psychology programs significantly increased well-being (mean $r$=.29) [29] and led to significant reductions in depressive symptoms (mean $r$=.31). These findings suggest that positive psychology may lend itself to early intervention programs targeting "normal" populations of young people.

### Online Delivery

Both eHealth and online programs provide a mode of delivery which is acceptable to youth and are financially sustainable [7,30,31]. Furthermore, users can maintain anonymity and confidentiality, determine their own rate of progression through a program, and use an online interactive format that is appealing and engaging [7]. Most young people in Australia have access to online facilities [32] as computers and Internet access are available in most schools and libraries. Other information communication technology, such as smartphones and tablets, are also becoming increasingly affordable [7]. Young people typically use online resources for dealing with distress, with a report by Mission Australia [33] quantifying that 1 in 5 young Australians (ages 11-24 years) ranked the Internet as an important source of information and support for sensitive personal issues. Similarly, ReachOut, a national youth mental health website, found that online avenues assist those who might not seek help in more traditional forms. Based on the ReachOut National Survey [34], up to 75% of young people experienced high to very high levels of psychological distress at the time of visiting the website and almost two-thirds of the sample had never accessed face-to-face mental health services.

From the perspective of service delivery, using an online format for a positive psychology program allows wider dissemination, reduces costs that would be associated with clinicians, and allows greater treatment fidelity [31,35]. Additionally, user progress can be easily monitored and the data collection process can be automated. At present, only online programs targeting single positive psychology domains have been evaluated as isolated exercises and there are no online multicomponent positive psychology programs for young people.

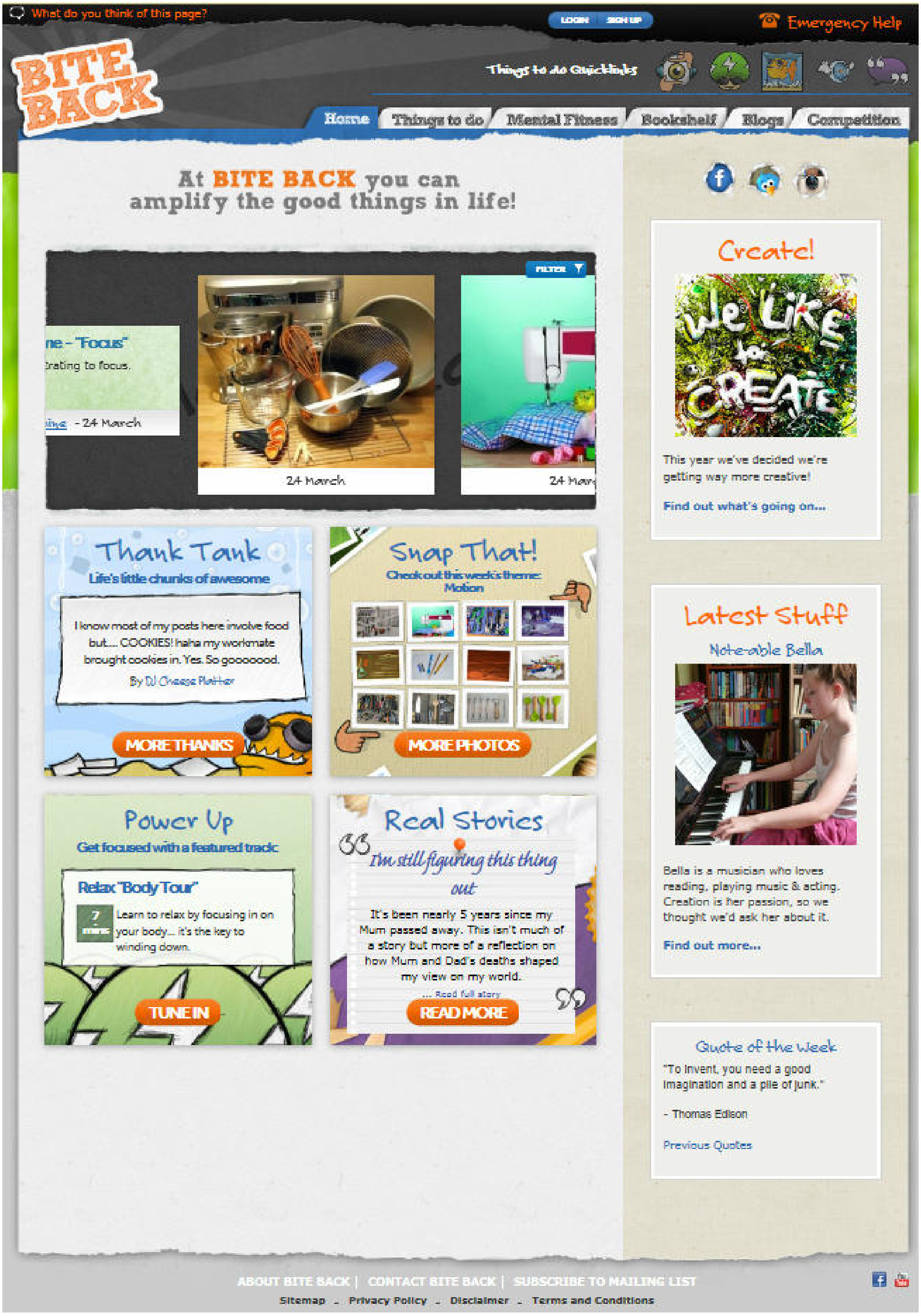
### The Current Study

This study aims to investigate the feasibility of implementing an online multicomponent positive psychology program, Bite Back (see Figure 1) developed by the Black Dog Institute, as a well-being program for young people [36].

The specific aims of this study were:

1. To examine the feasibility of an online positive psychology program for young people to improve the well-being and address mental health problems of Australian youth;
2. To investigate rates of adherence and attrition among young people who use this online positive psychology program; and
3. To investigate the acceptability/appeal of this program with young people.

**Figure 1.** Screenshot of the Bite Back website.



## Methods

### Participants/Recruitment

Participants were recruited through schools and youth organizations across Australia. Promotional information packs advertising the How Do You View the World Study were disseminated via mail and email and included a letter to the organization, principal, and/or school counselor that detailed the rationale, requirements, and participation incentives of the study, and a series of flyers promoting the study to young people. Organizations were asked to distribute the flyers or directly promote the study to young people (aged 12-18 years) in any manner they deemed appropriate (eg, notices in newsletters, on websites, and announcements). Recruitment was conducted from November 2011 to June 2012 when it was ceased because of funding constraints. This study was approved by the University of New South Wales Human Research Ethics Advisory Panel.

Inclusion criteria were: (1) 12-18 years of age, (2) currently living in Australia, (3) having a valid email address, (4) having access to a computer with an Internet connection, and (5) providing a signed parental consent form to researchers if under 16 years of age. No exclusion criteria were applied. Researchers had no face-to-face contact with any of the participants in this study. In cases in which duplicate email addresses or participant names were found during the sign-up stage, the first application was retained and duplicates discarded.

### Study Design

#### *Overview*

A 2-group pretest/posttest design was used with 2 independent variables: time (baseline and postprogram) and group (Bite Back and control conditions). Dependent variables were psychological symptoms (depression, anxiety, and stress) as well as a measure of well-being. Additionally, at postintervention, usage data and qualitative feedback about the websites were collected.

#### *Positive Psychology (Bite Back) Condition*

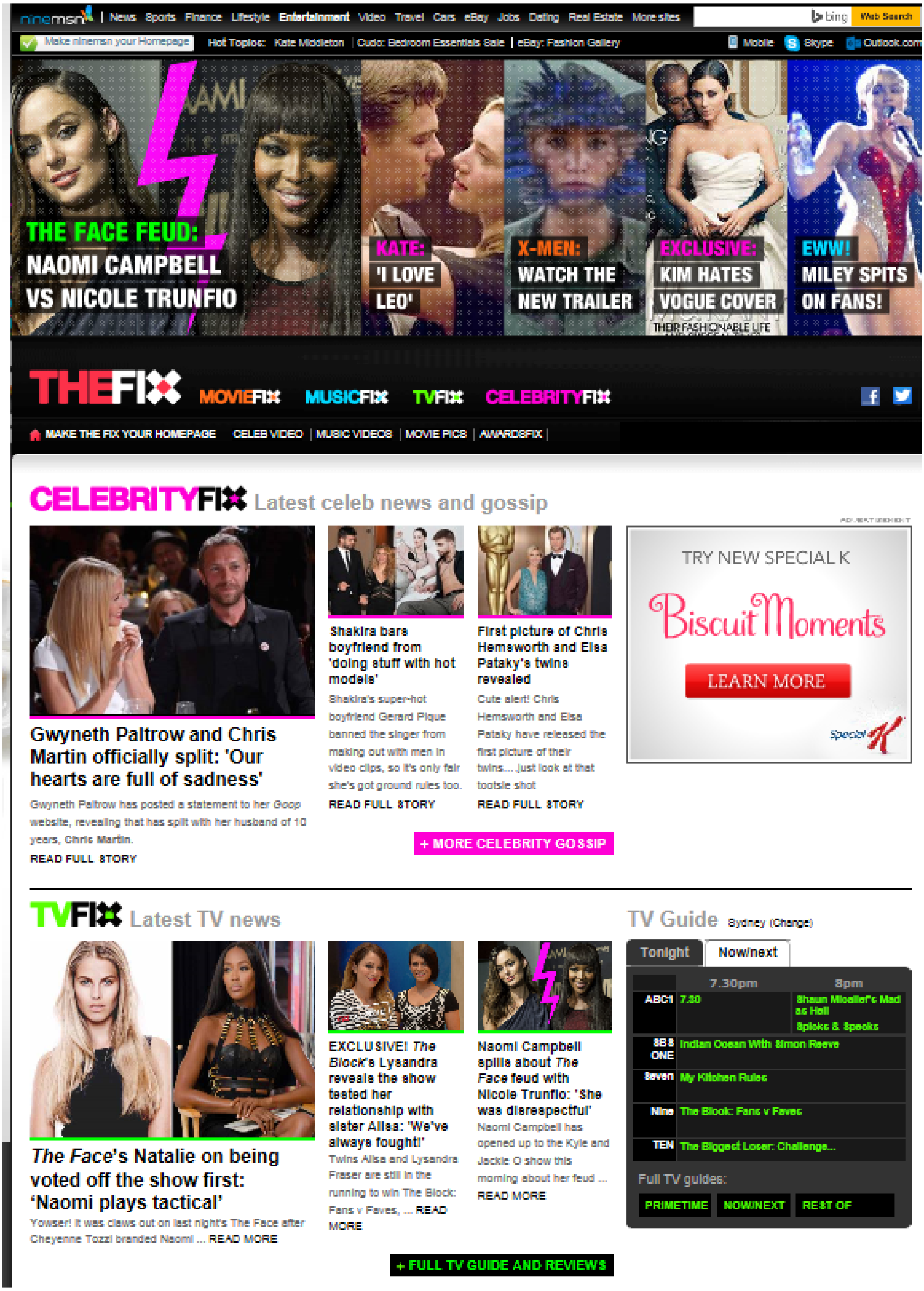
Bite Back is an online positive psychology website for adolescents and uses a combination of interactive exercises and information across 9 positive psychology domains: gratitude, optimism, flow, meaning, hope, mindfulness, character strengths, healthy lifestyle, and positive relationships. Furthermore, the website provides information about the benefits of increasing well-being, methods to develop skills in each of the positive psychology domains, provides links to other relevant resources, and allows for comments and online discussions. The website is aimed at adolescents aged 13 to 17 years and is premoderated with each comment and upload being monitored and approved before becoming available for public viewing.

#### *The Control Condition*

The two control condition websites that were chosen, Australian Broadcasting Corporation digital channel website, ABC3 (see Figure 2), and Nine MSN’s entertainment website, The Fix (see Figure 3), included features that would engage young people and were similar to the Bite Back website (ie, games and/or activities). ABC3 introduces young viewers to news, comedy, drama, music, sports, and nature [37]. The Fix engages youth in popular media news, music, and videos [38]. Similar to Bite Back, both control websites are multicomponent, self-guided, youth-oriented, and Australian-based, and each has the option of contributing personal pieces of work, opinions, and stories to the website. Neither of the control websites delivers positive psychology or information about well-being.

**Figure 2.** Screenshot of the ABC3 website.

**Figure 3.** Screenshot of The Fix website.




## Study Procedures

The study was advertised as the "How Do You View the World Study: an investigation into how websites impact on the way young people think, react, and interact with the world." It was important to conceal the clinical focus of this study and participants' allocated condition for 2 reasons: (1) to ensure that control participants did not use the Bite Back website, and (2) to minimize any expectancy effects. Participants were also offered an AU $20 voucher for their participation in this study.

Interested young people provided their email address, name, date of birth, sex, postcode, and a parental contact email if they were younger than 16 years of age. If eligible, participants were emailed a link to the battery of baseline questionnaires. Participants who completed the baseline questionnaires were randomly allocated to one of two conditions through a block randomization method. An independent researcher not associated with this study used a random number generator in Excel to allocate blocks of 10 participants to one of two conditions:

1. Bite Back Condition: participants were instructed to create a log-in and to use Bite Back over 6 consecutive weeks.
2. Control Condition: participants were instructed to select and use either of 2 youth websites over 6 consecutive weeks, ABC3 or The Fix.

Following baseline assessment, an email was sent to participants that included a link to their allocated website and instructions on how to use it however and whenever they wanted over the next 6 weeks, but "for at least an hour a week." Participants could access their allocated website from any Internet-enabled device and from any location. Given that all websites were open-access, it was not necessary to use the link to access the website. Both Bite Back and control participants received reminder emails once a week to encourage ongoing use and engagement with the websites. Six weeks from their date of commencement, participants were emailed the postintervention questionnaire battery and told that they no longer needed to access the website each week. Those who completed these questionnaires were emailed an AU $20 voucher from a digital media outlet.

## Measures

### Overview

Participants completed online questionnaires before and after the 6-week intervention period. Demographic information was collected at baseline to assess eligibility and participant characteristics.

### Adherence

Participant intervention adherence was measured by duration of exposure to the program during the course of the trial [39]. Participant's adherence was assessed by the question "How much time did you spend actually using the website each week?" In answering this question, participants had to nominate 1 of the following categories: 0-10 minutes per week, 10-20 minutes per week, 20-30 minutes per week, 30-40 minutes per week, 40-50 minutes per week, 50-60 minutes per week, or more than 1 hour per week. Those who reported usage duration of less than 1 hour per week for their allocated website were provided a supplementary open-ended question: "If you didn't use the website for an hour a week, was there a reason why?"

Self-reported frequency of site visits per week was also included as a measure of adherence. Participants reported their frequency of site visits by responding to the question "How many times a week did you use the site, on average?" Response options ranged from zero to more than 5 times per week.

### Acceptability of Exercises

To determine the appeal and usability of the positive psychology program, Bite Back, participants were required to respond on a Likert scale (from 1 to 7 where 1=strongly agree and 7=strongly disagree) to 3 statements about the website: (1) "The website was fun," (2) "The activities are interesting," and (3) "The website was easy to use." Intention to return to the Bite Back website after the completion of the study was also assessed.

### Efficacy of the Program

Efficacy of the program was assessed by self-report questionnaires at baseline and at 6-weeks via:

1. The Depression, Anxiety, and Stress Scale—Short form (DASS-21) [40] comprises 3 symptom-based subscales. Each subscale has 7 items which participants respond to on a 4-point Likert scale (0=not at all to 3=most of the time). Summed scores for each scale range from 0-42 following conversion of scores to match the DASS-42; more severe symptoms are indicated by higher scores. The DASS-21 has been used with adolescent samples and is reported to have a Cronbach alpha of .87 for depression, .79 for anxiety, and .83 for the stress subscales [41]. The DASS has also been demonstrated to correlate closely with the *Diagnostic and Statistical Manual of Mental Disorders* (*DSM*) diagnoses of panic disorder, generalized anxiety disorder, social phobia, simple phobia, and major depressive disorder [42,43]. The DASS-21 was modified slightly to aid comprehension of the wording for adolescents. These changes were approved by the authors and the original meaning of the items remained unchanged.
2. The Short Warwick-Edinburgh Mental Well-Being Scale (SWEMWBS) [44] is a 7-item measure that assesses participants' experiences of subjective positive mental health (well-being) over the past 2 weeks on a 5-point scale (1=none of the time to 5=all the time). Psychometric data of the measure on the original WEMWBS for adolescents has indicated satisfactory to high internal consistency ($r$=.87) and the short version has acceptable test-retest reliability ($r$=.66, 95% CI 0.59-0.72) [44,45]. In an adolescent population, the SWEMWBS has been demonstrated to be negatively correlated with the Strength's and Difficulties Questionnaire, a measure of adolescent psychopathology ($r$=–0.44, 95% CI –0.49 to –0.40), negatively correlated with the 12-item General Health Questionnaire ($r$=–.45, 95% CI –0.49 to –0.40), and positively correlated with both the WHO-Five Well-being Index ($r$=.57, 95% CI 0.53-0.61) [44].

# Results

## Attrition and Sample Characteristics

Of the 695 participants who expressed interest in the study, 235 met the inclusion criteria. The 235 participants who met the inclusion criteria were allocated to either the Bite Back or control condition and completed baseline questionnaires. After the 6-week trial period, 167 participants remained in the study and completed the follow-up questionnaires. A further 13 participants in the intervention condition were deemed to be noncompliant because they reported using the incorrect website (see Figure 4) as per protocol [46,47]. Noncompliant participants and noncompleters were excluded from the analysis. The researchers who conducted the analyses were not blinded to the allocated condition of participants. Figure 4 displays the consolidated standards of reporting trials (CONSORT) diagram for progression of participants at each stage of the evaluation.

There were no significant age or gender differences between completers and dropouts. Furthermore, completers and dropouts were equivalent on baseline scores for DASS-21 depression (mean 9.0, SD 8.5 vs mean 10.3, SD 9.0), anxiety (mean 6.4, SD 7.0 vs mean 7.5, SD 7.7), and the SWEMWBS (mean 24.8, SD 5.0 vs mean 23.8, SD 5.1). A significant difference ($F_{1,211}$=4.22, $P$=.04), between completers and dropouts was found on baseline stress scores (mean 10.7, SD 7.9 vs mean 13.2, SD 8.7).

The final sample of 154 participants was comprised of 104 (67.5%) females with a mean age of 15.4 (SD 1.7) years. At baseline, both Bite Back and control condition participants were equivalent in mean age, gender distribution, and mean scores on the DASS-21 depression, anxiety, and stress subscales and on the SWEMWBS (see Table 1).

Participants were divided into 2 groups based on the frequency of visits to their allocated website: low frequency (less than 3 site visits per week) and high frequency (3 or more site visits per week). There were no significant baseline differences in DASS-21 subscales or SWEMWBS scores across conditions for frequency of site visits. Participants were also divided into 2 groups based on the amount of time they spent on their assigned website: low (30 minutes or less per week) and high (30 minutes or more per week). There were no significant baseline differences in DASS-21 subscales or SWEMWBS scores across conditions for duration of site visits.

**Figure 4.** CONSORT diagram of participants.

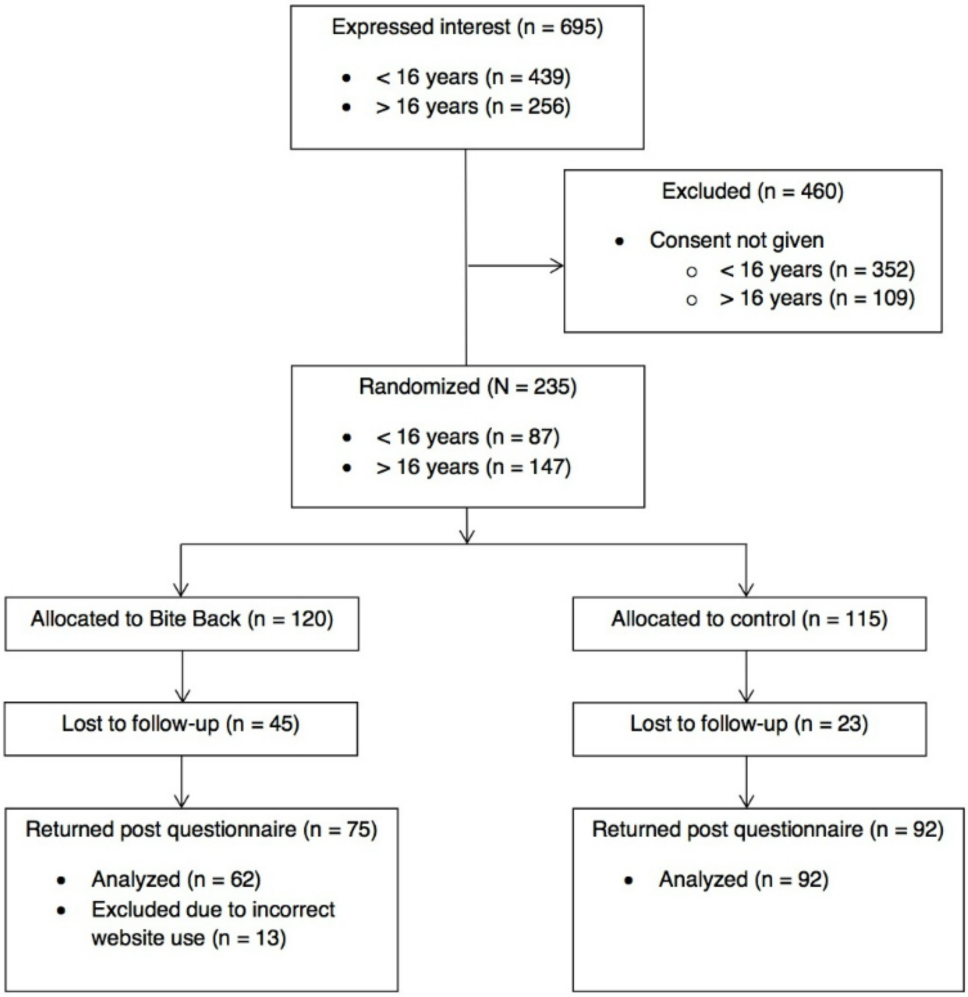


**Table 1.** Characteristics of the final sample (those who completed baseline and postintervention measures) for each condition.

| Characteristic | Bite Back, n=62 | Control, n=92 | Total, n=154 |
|---|---|---|---|
| Age (years), mean (SD) | 15.5 (1.6) | 15.3 (1.7) | 15.4 (1.7) |
| Female, n (%) | 40 (64.5) | 64 (69.6) | 104 (67.5) |
| **Baseline DASS depression, n** | 59 | 80 | 139 |
| Mean (SD) | 9.4 (8.3) | 8.6 (8.7) | 8.9 (8.5) |
| **Baseline DASS anxiety, n** | 53 | 86 | 139 |
| Mean (SD) | 7.2 (6.9) | 6.0 (7.3) | 6.4 (7.2) |
| **Baseline DASS stress, n** | 53 | 86 | 139 |
| Mean (SD) | 11.7 (7.3) | 9.9 (8.7) | 10.6 (7.9) |
| **Baseline SWEMWBS, n** | 58 | 87 | 145 |
| Mean (SD) | 24.1 (5.2) | 25.7 (5.4) | 24.8 (5.0) |

## Adherence

There were no significant differences between the reported duration spent using the websites each week between those allocated to the intervention and control conditions. In the intervention condition, 14 of the 61 participants (23%) reported using the website for between 50-60 minutes, 6 (10%) participants reported usage of between 40-50 minutes per week, and 37 (61%) participants reported usage less than 40 minutes per week. In the control condition, 26 of the 90 participants (29%) reported using their website for between 50-60 minutes, 14 (16%) participants reported usage between 40-50 minutes per week, and 46 (51%) of control participants reported usage at a rate less than two-thirds of the recommended duration.

Participants in the Bite Back condition who reported using the website for less than an hour a week were asked to provide a reason for their underusage. In all, 36 participants responded to the question “If you didn’t use the website for an hour a week, was there a reason why?” Responses were analyzed to extract key themes and coded to capture primary thematic components. Four main themes emerged: time constraints, technical issues, relevance, and website content.

Of the 36 participants who responded, 21 (58%) cited that the reason for their underusage was time constraints. This related to demands on time such as schoolwork, extracurricular activities, hobbies, family commitments, and going away on holidays. Technical issues accounted for 5 participants’ (14%) underusage, predominantly issues with Internet access:

> *It was hard to complete certain tasks and areas of the website as my data had run out on my Internet.* [participant 444, male, age 16 years]

Four participants (11%) reported that Bite Back did not seem relevant for them:

> *Sorry I lost interest, because although I thought it was a great site I didn’t think it was relevant for me.* [participant 352, female, age 17 years]

> *The site’s design was not appealing to me, it looked directed at 10-13 year olds.* [participant 115, female, age 17 year]

Furthermore, 6 participants (17%) stated that the content of the website was not sufficient to sustain their interest for an hour a week:

> *Honestly the first week, the website was pretty new to you, so to get around you had to learn your way, therefore it was pretty cool yeah? But then afterwards it was all too repetitive and much too the same, things I knew already there.* [participant 161, female, age 16 years]

> *The website was very similar each time I visited it and thus lost the initial flair it once had.* [participant 609, male, age 14 years]

### Acceptability of Exercises

Participants in the Bite Back condition were also asked to provide feedback on the appeal and usability of the positive psychology program. Of the 62 participants who used the program for 6 weeks, 49 reported that Bite Back was fun (79% rated mildly agree to strongly agree), with 52 agreeing that the activities were interesting (84% rated mildly agree to strongly agree), and 56 reporting that the site was easy to use (90% rated mildly agree to strongly agree).

Of the 62 participants in the Bite Back condition, 35 participants (57%) responded yes and 19 participants (31%) responded maybe. Only 7 participants (11%) responded that they would not revisit Bite Back in the future (1 participant gave no response).

### Efficacy of the Program

To analyze the efficacy of the program, a series of 2-tailed Wilcoxon signed rank tests were conducted to measure differences in psychopathology and well-being scores before and after the intervention. Nonparametric tests were employed because of violations of the normality assumption for almost all group cells (condition; condition × frequency of site visits; condition × length of site visits). Only the postintervention scores on the SWEMWBS did not demonstrate violations of normality. All violations were because of skew in the data that would be expected in a nonclinical population (ie, low scores on the DASS-21 and high scores on the SWEMWBS).

Participants in the Bite Back condition returned significantly lower DASS-21 depression ($z$=–2.44, $P$=.02, $r$=–.22) and stress scores ($z$=–2.14, $P$=.03, $r$=–.21) at 6 weeks postintervention. In addition, they returned significantly higher scores on the SWEMWBS ($z$=2.07, $P$=.04, $r$=.19). No significant differences in DASS-21 subscales or SWEMWBS scores were found in the control condition from preassessment to postassessment (see Table 2).

Samples for each condition were dichotomized (high and low) based on frequency of site visits and time spent on the site each week to derive approximately equal numbers in each subgroup. Two further Wilcoxon signed rank tests were conducted to determine if frequency of use or length of time of use affected postintervention levels of symptoms and well-being.

Participants who visited their corresponding site 2 times per week or less were classified as having low frequency of use, whereas those visiting their allocated website 3 or more times per week were classified as high frequency of use. Participants in the Bite Back condition who visited the site with high frequency reported significant reductions in depression ($z$=–2.39, $P$=.02, $r$=–.34) and anxiety ($z$=–1.98, $P$=.05, $r$=–.29) scores, as well as significant increases in well-being scores ($z$=2.28, $P$=.02, $r$=.34) from preintervention to postintervention. Participants in this group also reported a reduction in stress symptoms that approached significance ($z$=–1.80, $P$=.07, $r$=–.28) (see Table 3). No such differences were found in the control condition.

Participants who visited their allocated website for 30 minutes or less per week were classified as low duration of use, whereas those who used their website for 30 minutes or more per week were classified as high duration of use. Participants in the Bite Back group who visited the site for 30 minutes or more per week (ie, in the high duration group) reported significant reductions in depression ($z$=–2.57, $P$=.01, $r$=–.33) and stress ($z$=–2.74, $P$=.006, $r$=–.37) scores at postintervention. This group also reported a trend for lower anxiety ($z$=–1.92, $P$=.06, $r$=–.26) and increased well-being scores ($z$=1.89, $P$=.06, $r$=.24), but these differences failed to reach significance (see Table 4). A significant increase in anxiety scores at postintervention ($z$=2.95, $P$=.003, $r$=.35) was found in control condition participants who reported low levels of time spent on their assigned websites. A significant increase in well-being scores at postintervention, ($z$=2.00, $P$=.05, $r$=.20) was found in control condition participants who reported high levels of time spent on their assigned websites.

**Table 2.** Preprogram and postprogram DASS-21 and SWEMWBS scores for each condition.

| Variable and condition | Baseline | | Post | | *P* |
|---|---|---|---|---|---|
| | Mean (SD) | n | Mean (SD) | n | |
| **Depression** | | | | | |
| Bite Back | 9.39 (8.26) | 59 | 6.68 (7.72) | 59 | .02 |
| Control | 8.60 (8.73) | 80 | 8.28 (8.48) | 80 | .83 |
| **Anxiety** | | | | | |
| Bite Back | 7.17 (6.91) | 53 | 6.38 (7.26) | 53 | .27 |
| Control | 5.98 (7.31) | 86 | 6.86 (8.61) | 86 | .09 |
| **Stress** | | | | | |
| Bite Back | 11.66 (7.35) | 53 | 10.08 (8.10) | 53 | .03 |
| Control | 9.88 (8.17) | 86 | 9.35 (8.69) | 86 | .42 |
| **Well-being** | | | | | |
| Bite Back | 24.12 (5.16) | 58 | 25.78 (5.35) | 58 | .04 |
| Control | 25.17 (4.87) | 87 | 25.75 (5.43) | 87 | .23 |

**Table 3.** Preprogram and postprogram DASS-21 and SWEMWBS scores by frequency of site visits for each condition.

| Variable, condition, and frequency | Baseline | | Post | | *P* |
|---|---|---|---|---|---|
| | Mean (SD) | n | Mean (SD) | n | |
| **Depression** | | | | | |
| **Bite Back** | | | | | |
| Low | 7.82 (6.31) | 33 | 7.09 (7.65) | 33 | .30 |
| High | 11.84 (9.91) | 25 | 6.40 (7.98) | 25 | .02 |
| **Control** | | | | | |
| Low | 8.24 (9.36) | 34 | 7.18 (7.96) | 34 | .69 |
| High | 8.36 (7.64) | 45 | 8.80 (8.72) | 45 | .73 |
| **Anxiety** | | | | | |
| **Bite Back** | | | | | |
| Low | 6.69 (6.57) | 29 | 7.17 (8.53) | 29 | .71 |
| High | 8.09 (7.37) | 23 | 5.65 (5.38) | 23 | .05 |
| **Control** | | | | | |
| Low | 4.67 (6.40) | 36 | 5.33 (6.56) | 36 | .21 |
| High | 6.86 (7.91) | 49 | 7.88 (9.84) | 49 | .24 |
| **Stress** | | | | | |
| **Bite Back** | | | | | |
| Low | 12.654 (7.82) | 31 | 12.00 (8.75) | 31 | .18 |
| High | 10.76 (6.28) | 21 | 7.62 (6.38) | 21 | .07 |
| **Control** | | | | | |
| Low | 9.46 (9.28) | 37 | 8.81 (8.27) | 37 | .81 |
| High | 10.13 (7.36) | 48 | 9.58 (9.07) | 48 | .36 |
| **Well-being** | | | | | |
| **Bite Back** | | | | | |
| Low | 24.65 (4.10) | 34 | 25.24 (5.09) | 34 | .50 |
| High | 23.04 (6.33) | 23 | 26.30 (5.74) | 23 | .02 |
| **Control** | | | | | |
| Low | 24.81 (5.43) | 37 | 25.59 (5.07) | 37 | .32 |
| High | 25.44 (4.45) | 50 | 25.86 (5.73) | 50 | .45 |

**Table 4.** Preprogram and postprogram DASS-21 and SWEMWBS scores by duration of use for each condition.

| Variable, condition, and length of visit | Baseline | | Post | | *P* |
|---|---|---|---|---|---|
| | Mean (SD) | n | Mean (SD) | n | |
| **Depression** | | | | | |
| **Bite Back** | | | | | |
| Low | 8.22 (7.77) | 27 | 7.78 (9.37) | 27 | .52 |
| High | 10.71 (8.57) | 31 | 5.94 (5.99) | 31 | .01 |
| **Control** | | | | | |
| Low | 9.26 (8.42) | 35 | 9.49 (9.42) | 35 | .69 |
| High | 8.18 (9.11) | 44 | 7.18 (7.66) | 44 | .34 |
| **Anxiety** | | | | | |
| **Bite Back** | | | | | |
| Low | 7.04 (7.77) | 25 | 7.68 (9.07) | 25 | .72 |
| High | 7.56 (6.14) | 27 | 5.41 (5.05) | 27 | .06 |
| **Control** | | | | | |
| Low | 7.11 (8.40) | 36 | 9.22 (10.74) | 36 | .003 |
| High | 5.22 (6.44) | 49 | 4.90 (6.06) | 49 | .53 |
| **Stress** | | | | | |
| **Bite Back** | | | | | |
| Low | 10.83 (7.62) | 24 | 11.67 (9.99) | 24 | .95 |
| High | 12.79 (6.89) | 28 | 9.00 (5.98) | 28 | .006 |
| **Control** | | | | | |
| Low | 11.29 (8.68) | 34 | 11.35 (9.51) | 34 | .75 |
| High | 9.04 (7.92) | 50 | 7.84 (7.80) | 50 | .09 |
| **Well-being** | | | | | |
| **Bite Back** | | | | | |
| Low | 24.40 (5.38) | 25 | 25.12 (5.75) | 25 | .36 |
| High | 23.69 (4.99) | 32 | 26.09 (5.04) | 32 | .06 |
| **Control** | | | | | |
| Low | 24.14 (5.37) | 36 | 24.19 (5.65) | 36 | .87 |
| High | 25.88 (4.47) | 49 | 26.88 (5.13) | 49 | .05 |

## Discussion

### Principal Findings

This study examined the feasibility and challenges of an online, open-access, positive psychology program (Bite Back) to increase well-being and reduce mental health symptoms in young people. Despite difficulties maintaining high levels of adherence and low levels of attrition, positive qualitative feedback from participants indicated that adolescents enjoyed Bite Back and found it interesting and easy to use. In addition, significant improvements in symptoms of depression, stress, and well-being scores were observed for the Bite Back condition.

Further investigation also suggested that those who visited the Bite Back website more frequently during the intervention period and for greater amounts of time each week gained the most benefit. Participants in at least one of these high-adherence groups reported lower depression, anxiety, and stress scores, and higher well-being scores at postintervention. The beneficial outcomes at 6 weeks are particularly noteworthy given the short-term and entirely self-directed nature of this intervention.

However, the most beneficial outcomes were present among participants who visited the website for 30 minutes or more during each week of the intervention period or 3 or more times during each week of the intervention. No significant changes were found among Bite Back users who did not meet these levels of adherence indicating that the program requires a certain level of usage for a positive effect. Overall, these positive findings suggest that further research into Bite Back's effectiveness is warranted, particularly if adolescents' engagement with the site can be improved.

Retention rates for the Bite Back condition were moderate. A total of 167 of 235 participants who completed the battery of questionnaires at baseline also completed the battery after the 6-week trial period: retention rates across time periods were 71% for the total sample and 58% for the Bite Back condition alone (although only 66% of the total sample and 52% of the Bite Back condition were used in the analysis because of the exclusion of the noncompliant participants). A systematic review of attrition rates from Internet-based treatment programs where therapist contact was minimal found an average dropout rate of 35%, with a range of 2% to 83% [46]. Although that review was based on psychological treatment programs for adults, it suggests that the current trial returned an acceptable attrition rate in the context of eHealth programs. One unexpected finding was that the large discrepancy between the attrition and noncompliance rates for the Bite Back condition compared to the control condition. The only factor examined that differed significantly between completers and dropouts were baseline stress scores, with the attrition group reporting significantly higher stress at the start of the program. Although the baseline stress scores did not differ significantly between the Bite Back and control conditions, the Bite Back condition reported higher baseline stress scores. It is possible to speculate, therefore, that the stress they were experiencing interfered with their ability to stay engaged with the program.

Approximately half the participants' self-reported usage was below the prescribed 1 hour per week over the 6-week trial period. However, these rates of usage were equivalent across both the intervention and control websites. Therefore, it is likely that these low levels of adherence are reflective of the more general methodological challenges associated with open-access trials [39], as opposed to a particular failing of Bite Back to sustain participants' attention.

This interpretation is further supported by qualitative reports from Bite Back participants. Primary reasons cited for underusage were time constraints (related to school, extracurricular, and family commitments) and technical issues, such as problems in accessing the Internet. In addition, acceptability ratings of Bite Back were favorable: 79% agreed the program was fun, 84% agreed that it was interesting, and 90% agreed that it was easy to use. Most users stated an intention to return to Bite Back after the completion of the study. Users who were disappointed (11%) with Bite Back cited content relevance and lack of age appropriateness. Thus, it seems evident that although logistical issues were primarily related to low adherence rates, website content also affected users' continued engagement.

Bite Back users who reported using the website for 30 minutes or less per week or fewer than 3 times per week were predominantly older than 16 years of age and stated that the content had little relevance or was not sufficiently interesting to sustain their attention. These findings suggest that Bite Back may have more appeal for those 16 years of age or younger. Developmentally, adolescence is a time of rapid change, particularly emotional and intellectual. As such, there is considerable heterogeneity across the age 12 to 18 years group that makes it difficult to pitch activities and conceptual explanations that are universally appropriate. Further data are needed to assess whether age is a specific factor for content relevance, which age groups most strongly identified with the site, and which positive psychology domains or site activities were effective at maintaining engagement for older adolescents.

### Limitations of the Study

Despite the encouraging results from this pilot study, methodological limitations preclude us from drawing definitive conclusions. Our study may have been affected by measurement sensitivity (ie, the psychopathology measure selected was designed for a clinical population and so floor effects could have impacted on our results). This problem may have been exacerbated by the small sample sizes in each condition making it less likely to obtain significant differences.

Furthermore, our usage data heavily relied on participants' self-report which could have been affected by memory and reporting biases [48]. In addition, adolescent samples may be likely to underreport mental health symptoms [48,49], although the anonymous nature of this study may have lessened this likelihood. Utilizing corroborative evidence from teachers and parents may have improved the accuracy of our measurements of change in symptom alleviation and well-being and should be considered for further studies in this area.

The study gathered limited information about participants' use of Bite Back, such as content accessed, uploads to interactive activities, and time spent on the various activities. Because the website was comprised of multiple components, including videos, psychoeducational information, interactive exercises, and community noticeboards, it is difficult to ascertain which parts of the website were instrumental to the changes observed. Information on usage patterns would have provided interesting insights of how young people navigate the website and a better understanding of the differential impact of its various components. Further research into this area would shed light on the way in which young people relate to specific online positive psychology interventions.

The age distribution of our population was also an important factor in considering the results of this study. Although a larger percentage of those younger than 16 year expressed interest in participating, fewer of the participants younger than 16 years progressed through to actually participate in the study because of the need for them to obtain parental permission. Given that our qualitative responses suggested that Bite Back may be more acceptable to the younger age group, this barrier to participation by younger users may have excluded an important segment of our target population in this trial.

Although Bite Back was developed as a preventative program for youth, this feasibility study was primarily concerned with obtaining feedback on users' enjoyment and willingness to engage in the site's activities. As such, the preliminary pilot data from this study is insufficient to demonstrate preventative effects. Further studies utilizing a longer-term follow-up are necessary to examine this important aspect of preventative health in youth.

## Conclusions

This study explored the feasibility of an online, open-access, multicomponent, positive psychology program for adolescents. The findings from this study demonstrate that an online positive psychology program (Bite Back) has the potential to reduce symptoms of psychopathology and promote mental well-being. However, issues of adherence and age appropriateness need to be addressed for optimal outcomes. Nevertheless, the positive findings from this study suggest that online positive psychology programs may have a major impact on the emerging field of adolescent-focused eHealth for improving well-being and resilience.

## Acknowledgments

This study was conducted with the support of a research grant from the Australian Department of Health and Ageing. This work was completed at the Black Dog Institute at the University of New South Wales. We are also grateful to Professor Felicia Huppert for advice on the methodology to this study and to Jacqui Wallace and Nic Newling for technical assistance in running this trial.

## Multimedia Appendix 1

CONSORT-EHEALTH checklist V1.6.2 [50].

[PDF File (Adobe PDF File), 998KB - jmir_v16i6e140_app1.pdf ]

## References

1. Patel V, Flisher AJ, Hetrick S, McGorry P. Mental health of young people: a global public-health challenge. Lancet 2007 Apr 14;369(9569):1302-1313. [doi: 10.1016/S0140-6736(07)60368-7] [Medline: 17434406]
2. Australian Institute of Health and Welfare. Young Australians: their health and wellbeing 2011. Canberra: Australian Institute of Health and Welfare; 2011. URL: http://www.aihw.gov.au/WorkArea/DownloadAsset.aspx?id=10737419259 [accessed 2014-05-15] [WebCite Cache ID 6PZljTuFs]
3. Australian Bureau of Statistics. Causes of Death, Australia, cat.no.3303.0. 2011. URL: http://www.abs.gov.au/AUSSTATS/abs@.nsf/Lookup/3303.0Main+Features12011?OpenDocument [accessed 2013-12-03] [WebCite Cache ID 6La8t1o04]
4. Burns JM, Patton GC. Preventive interventions for youth suicide: a risk factor-based approach. Aust NZ J Psychiat 2000 Jun;34(3):388-407. [Medline: 10881963]
5. Harrison J, Moller J, Bordeaux S. Australian Institute of Health and Welfare. 1997. Youth suicide and self-injury in Australia URL: http://www.nisu.flinders.edu.au/pubs/bulletin15/bulletin15sup.html/ [accessed 2013-09-18] [WebCite Cache ID 6JiFupoTB]
6. Slade T, Johnston A, Teesson M, Whiteford H, Burgess P, Pirkis J, et al. The Mental Health of Australians 2: report on the 2007 National Survey of Mental Health & Wellbeing. 2009. URL: http://www.health.gov.au/internet/main/publishing.nsf/Content/46AB7A3FEF9664E4CA2575D2000A6D09/$File/mhaust2.pdf [accessed 2013-09-18] [WebCite Cache ID 6JiGy899V]
7. Campbell AJ, Robards F. Young and Well Cooperative Research Centre. 2013. Using technologies safely and effectively to promote young people's wellbeing: a better practice guide for services URL: http://www.youngandwellcrc.org.au/knowledge-hub/publications/using-technologies-safely-effectively-promote-young-peoples-wellbeing/ [accessed 2013-09-18] [WebCite Cache ID 6JiGYTzNK]
8. Booth M, Bernard D, Quine S, Kang M, Beasley L, Usherwood T, NSW Centre for the Advancement of Adolescent Health, Westmead. Access study phase I - access to health care among NSW adolescents. 2002. URL: http://www.caah.chw.edu.au/resources/access_phase_1_report_final.pdf [accessed 2013-09-18] [WebCite Cache ID 6JiGq1UhR]
9. Kessler RC, Berglund P, Demler O, Jin R, Merikangas KR, Walters EE. Lifetime prevalence and age-of-onset distributions of DSM-IV disorders in the National Comorbidity Survey Replication. Arch Gen Psychiatry 2005 Jun;62(6):593-602. [doi: 10.1001/archpsyc.62.6.593] [Medline: 15939837]
10. Eckersley R. National Centre for Epidemiology. Canberra: Population Health, ANU; 2008. Never better – or getting worse? The health and wellbeing of young Australians URL: http://www.australia21.org.au/product/never-better-or-getting-worse/ [WebCite Cache ID 6JiHjWTAY]
11. Kirby M. Mental Health Commission of Canada: out of the shadows forever. Can Med Assoc J 2008;178(10):1320-1322. [doi: 10.1503/cmaj.071897]
12. Rickwood DJ, Deane FP, Wilson CJ. When and how do young people seek professional help for mental health problems? Med J Aust 2007 Oct 1;187(7):S35-S39. [Medline: 17908023]
13. Sheffield JK, Spence SH, Rapee RM, Kowalenko N, Wignall A, Davis A, et al. Evaluation of universal, indicated, and combined cognitive-behavioral approaches to the prevention of depression among adolescents. J Consult Clin Psychol 2006 Feb;74(1):66-79. [doi: 10.1037/0022-006X.74.1.66] [Medline: 16551144]
14. Mitchell J, Stanimirovic R, Klein B, Vella-Brodrick D. A randomised controlled trial of a self-guided internet intervention promoting well-being. Comput Hum Behav 2009 May;25(3):749-760. [doi: 10.1016/j.chb.2009.02.003]

15. Merry S, McDowell H, Wild CJ, Bir J, Cunliffe R. A randomized placebo-controlled trial of a school-based depression prevention program. J Am Acad Child Adolesc Psychiatry 2004 May;43(5):538-547. [doi: 10.1097/00004583-200405000-00007] [Medline: 15100560]
16. World Health Organization. 2011. Mental health: a state of wellbeing URL: http://www.who.int/features/factfiles/mental_health/en/ [accessed 2013-09-18] [WebCite Cache ID 6JiII89oM]
17. Seligman MEP. Flourish: A Visionary New Understanding of Happiness and Well-Being. New York: Free Press; 2011.
18. Lyubomirsky S, King L, Diener E. The benefits of frequent positive affect: does happiness lead to success? Psychol Bull 2005 Nov;131(6):803-855. [doi: 10.1037/0033-2909.131.6.803] [Medline: 16351326]
19. Norrish J, Vella-Brodrick D. Positive psychology and adolescents: where are we now? Where to from here? Aus. Psychologist 2009 Dec 1;44(4):270-278. [doi: 10.1080/00050060902914103]
20. Carvajal SC, Clair SD, Nash SG, Evans RI. Relating optimism, hope, and self-esteem to social influences in deterring substance use in adolescents. J Soc Clin Psychol 1998 Dec;17(4):443-465. [doi: 10.1521/jscp.1998.17.4.443]
21. Ciarrochi J, Heaven PC, Davies F. The impact of hope, self-esteem, and attributional style on adolescents' school grades and emotional well-being: a longitudinal study. J Res Pers 2007 Dec;41(6):1161-1178. [doi: 10.1016/j.jrp.2007.02.001]
22. Li D, Zhang W, Li X, Li N, Ye B. Gratitude and suicidal ideation and suicide attempts among Chinese adolescents: direct, mediated, and moderated effects. J Adolesc 2012 Feb;35(1):55-66. [doi: 10.1016/j.adolescence.2011.06.005] [Medline: 21774977]
23. Froh JJ, Yurkewicz C, Kashdan TB. Gratitude and subjective well-being in early adolescence: examining gender differences. J Adolesc 2009 Jun;32(3):633-650. [doi: 10.1016/j.adolescence.2008.06.006] [Medline: 18760465]
24. Chemers MM, Hu L, Garcia BF. Academic self-efficacy and first year college student performance and adjustment. J Educ Psychol 2001;93(1):55-64. [doi: 10.1037/0022-0663.93.1.55]
25. Nes LS, Evans DR, Segerstrom SC. Optimism and college retention: mediation by motivation, performance, and adjustment. J Appl Soc Psychol 2009 Aug;39(8):1887-1912. [doi: 10.1111/j.1559-1816.2009.00508.x]
26. Ruthig JC, Haynes TL, Stupnisky RH, Perry RP. Perceived Academic Control: mediating the effects of optimism and social support on college students' psychological health. Soc Psychol Educ 2008 Nov 13;12(2):233-249. [doi: 10.1007/s11218-008-9079-6]
27. Aspinwall LG, Taylor SE. Modeling cognitive adaptation: a longitudinal investigation of the impact of individual differences and coping on college adjustment and performance. J Pers Soc Psychol 1992 Dec;63(6):989-1003. [Medline: 1460565]
28. Daukantaitė D, Zukauskiene R. Optimism and subjective well-being: affectivity plays a secondary role in the relationship between optimism and global life satisfaction in the middle-aged women. Longitudinal and cross-cultural findings. J Happiness Stud 2011 Jan 21;13(1):1-16. [doi: 10.1007/s10902-010-9246-2]
29. Sin NL, Lyubomirsky S. Enhancing well-being and alleviating depressive symptoms with positive psychology interventions: a practice-friendly meta-analysis. J Clin Psychol 2009 May;65(5):467-487. [doi: 10.1002/jclp.20593] [Medline: 19301241]
30. Seligman MEP, Ernst RM, Gillham J, Reivich K, Linkins M. Positive education: positive psychology and classroom interventions. Oxford Rev Educ 2009 Jun;35(3):293-311. [doi: 10.1080/03054980902934563]
31. McCrone P, Knapp M, Proudfoot J, Ryden C, Cavanagh K, Shapiro DA, et al. Cost-effectiveness of computerised cognitive-behavioural therapy for anxiety and depression in primary care: randomised controlled trial. Br J Psychiat 2004 Jul;185:55-62 [FREE Full text] [Medline: 15231556]
32. Australian Communications and Media Authority. Internet use and social networking by young people. Report 1: Media and communications in Australian families series. 2008. URL: http://www.acma.gov.au/webwr/_assets/main/lib310665/no1_internet_use_social_networking_young_people.pdf [accessed 2013-09-18] [WebCite Cache ID 6JiIsDVxD]
33. National survey of young Australians 2011: key and emerging issues. Sydney: Mission Australia; 2011. URL: https://www.missionaustralia.com.au/2020-strategy-page/doc_download/65-national-survey-of-young-australians-2011 [accessed 2013-09-18] [WebCite Cache ID 6JiId8PV8]
34. Metcalf A, Kauer S. National survey 2012. Camperdown, Australia: Inspire Foundation; 2013. URL: http://www.academia.edu/3550210/Metcalf_A_Kauer_S_2012_ReachOut.com_National_Survey_2012_Inspire_Foundation [accessed 2013-09-18] [WebCite Cache ID 6JiIkJlzw]
35. Khanna M, Aschenbrand SG, Kendall PC. New frontiers: computer technology in the treatment of anxious youth. Behav Therapist 2007 Jan;30:22-25.
36. Bite Back. URL: http://www.biteback.org.au/ [accessed 2014-02-21] [WebCite Cache ID 6NXtFqiDS]
37. ABC3. URL: http://www.abc.net.au/abc3/ [accessed 2014-02-21] [WebCite Cache ID 6NXtKaGrg]
38. The Fix. URL: http://thefix.ninemsn.com.au/ [accessed 2014-02-21] [WebCite Cache ID 6NXtM7JrH]
39. Christensen H, Griffiths KM, Farrer L. Adherence in internet interventions for anxiety and depression. J Med Internet Res 2009 Apr;11(2):e13 [FREE Full text] [doi: 10.2196/jmir.1194] [Medline: 19403466]
40. Szabó M. The short version of the Depression Anxiety Stress Scales (DASS-21): factor structure in a young adolescent sample. J Adolesc 2010 Feb;33(1):1-8. [doi: 10.1016/j.adolescence.2009.05.014] [Medline: 19560196]
41. Antony MM, Bieling PJ, Cox BJ, Enns MW, Swinson RP. Psychometric properties of the 42-item and 21-item versions of the Depression Anxiety Stress Scales in clinical groups and a community sample. Psychol Assessment 1998;10(2):176-181. [doi: 10.1037/1040-3590.10.2.176]

42. Brown TA, Chorpita BF, Korotitsch W, Barlow DH. Psychometric properties of the Depression Anxiety Stress Scales (DASS) in clinical samples. Behav Res Ther 1997 Jan;35(1):79-89. [Medline: 9009048]
43. Lovibond PF, Lovibond SH. The structure of negative emotional states: comparison of the Depression Anxiety Stress Scales (DASS) with the Beck Depression and Anxiety Inventories. Behav Res Ther 1995 Mar;33(3):335-343. [Medline: 7726811]
44. Stewart-Brown S, Tennant A, Tennant R, Platt S, Parkinson J, Weich S. Internal construct validity of the Warwick-Edinburgh Mental Well-being Scale (WEMWBS): a Rasch analysis using data from the Scottish Health Education Population Survey. Health Qual Life Outcomes 2009 Feb;7:15 [FREE Full text] [doi: 10.1186/1477-7525-7-15] [Medline: 19228398]
45. Clarke A, Friede T, Putz R, Ashdown J, Martin S, Blake A, et al. Warwick-Edinburgh Mental Well-being Scale (WEMWBS): validated for teenage school students in England and Scotland. A mixed methods assessment. BMC Public Health 2011;11:487 [FREE Full text] [doi: 10.1186/1471-2458-11-487] [Medline: 21693055]
46. Melville KM, Casey LM, Kavanagh DJ. Dropout from internet-based treatment for psychological disorders. Br J Clin Psychol 2010 Nov;49(Pt 4):455-471. [doi: 10.1348/014466509X472138] [Medline: 19799804]
47. Armijo-Olivo S, Warren S, Magee D. Intention to treat analysis, compliance, drop-outs and how to deal with missing data in clinical research: a review. Phys Ther Rev 2009 Feb 01;14(1):36-49. [doi: 10.1179/174328809X405928]
48. Sawyer MG, Baghurst P, Clark J. Differences between reports from children, parents and teachers: implications for epidemiological studies. Aust NZ J Psychiat 1992 Jan;26(4):652-660. [doi: 10.3109/00048679209072102]
49. Nisbett RE, Wilson TD. Telling more than we can know: verbal reports on mental processes. Psychol Rev 1977;84(3):231-259. [doi: 10.1037/0033-295X.84.3.231]
50. Eysenbach G, CONSORT-EHEALTH Group. CONSORT-EHEALTH: improving and standardizing evaluation reports of Web-based and mobile health interventions. J Med Internet Res 2011;13(4):e126 [FREE Full text] [doi: 10.2196/jmir.1923] [Medline: 22209829]

## Abbreviations

**ABC:** Australian Broadcasting Corporation
**CONSORT:** Consolidated Standards of Reporting Trials
**DASS-21:** Depression, Anxiety, Stress Scale—short form
**SWEMWBS:** Short Warwick-Edinburgh Mental Well-Being Scale

*Edited by G Eysenbach; submitted 15.12.13; peer-reviewed by D Vella-Brodrick, J Grohol; comments to author 12.02.14; revised version received 11.03.14; accepted 13.04.14; published 04.06.14.*

*Please cite as:*
*Manicavasagar V, Horswood D, Burckhardt R, Lum A, Hadzi-Pavlovic D, Parker G*
*Feasibility and Effectiveness of a Web-Based Positive Psychology Program for Youth Mental Health: Randomized Controlled Trial*
*J Med Internet Res 2014;16(6):e140*
*URL: http://www.jmir.org/2014/6/e140/*
*doi:10.2196/jmir.3176*
*PMID:24901900*

Original Paper

# Effectiveness of a Web- and Mobile Phone-Based Intervention to Promote Physical Activity and Healthy Eating in Middle-Aged Males: Randomized Controlled Trial of the ManUp Study

Mitch Duncan[1], PhD; Corneel Vandelanotte[2], PhD; Gregory S Kolt[3], PhD; Richard R Rosenkranz[4], PhD; Cristina M Caperchione[5]; Emma S George[3], BHlthSc (Hons); Hang Ding[6]; Cindy Hooker[2], BSc; Mohan Karunanithi[6], PhD; Anthony J Maeder[7], PhD; Manny Noakes[8], PhD; Rhys Tague[7]; Pennie Taylor[8]; Pierre Viljoen[9], PhD; W Kerry Mummery[10], PhD

[1]School of Medicine & Public Health, Priority Research Centre in Physical Activity and Nutrition, Faculty of Health and Medicine, University of Newcastle, Newcastle, Australia

[2]Institute for Health and Social Science Research, Centre for Physical Activity Studies, Central Queensland University, Rockhampton, Australia

[3]School of Science and Health, Unviersity of Western Sydney, Sydney, Australia

[4]Department of Human Nutrition, Kansas State University, Manhattan, KS, United States

[5]School of Health and Exercise Sciences, University of British Columbia, Kelowna, BC, Canada

[6]The Australian eHealth Research Centre, CSIRO, Brisbane, Australia

[7]School of Computing, Engineering and Mathematics, University of Western Sydney, Sydney, Australia

[8]Animal, Food and Health Sciences, CSIRO, Adelaide, Australia

[9]Central Queensland University, Mackay, Australia

[10]Faculty of Physical Education, University of Alberta, Edmonton, AB, Canada

**Corresponding Author:**
Mitch Duncan, PhD
School of Medicine & Public Health, Priority Research Centre in Physical Activity and Nutrition
Faculty of Health and Medicine
University of Newcastle
ATC Building, University Drive, University of Newcastle
Newcastle, 2300
Australia
Phone: 61 0249215215
Fax: 61 0249212084
Email: Mitch.Duncan@newcastle.edu.au

## Abstract

**Background:** The high number of adult males engaging in low levels of physical activity and poor dietary practices, and the health risks posed by these behaviors, necessitate broad-reaching intervention strategies. Information technology (IT)-based (Web and mobile phone) interventions can be accessed by large numbers of people, yet there are few reported IT-based interventions targeting males' physical activity and dietary practices.

**Objective:** This study examines the effectiveness of a 9-month IT-based intervention (ManUp) to improve the physical activity, dietary behaviors, and health literacy in middle-aged males compared to a print-based intervention.

**Methods:** Participants, recruited offline (eg, newspaper ads), were randomized into either an IT-based or print-based intervention arm on a 2:1 basis in favor of the fully automated IT-based arm. Participants were adult males aged 35-54 years living in 2 regional cities in Queensland, Australia, who could access the Internet, owned a mobile phone, and were able to increase their activity level. The intervention, ManUp, was based on social cognitive and self-regulation theories and specifically designed to target males. Educational materials were provided and self-monitoring of physical activity and nutrition behaviors was promoted. Intervention content was the same in both intervention arms; only the delivery mode differed. Content could be accessed throughout the 9-month study period. Participants' physical activity, dietary behaviors, and health literacy were measured using online surveys at baseline, 3 months, and 9 months.

**Results:** A total of 301 participants completed baseline assessments, 205 in the IT-based arm and 96 in the print-based arm. A total of 124 participants completed all 3 assessments. There were no significant between-group differences in physical activity and dietary behaviors ($P \geq .05$). Participants reported an increased number of minutes and sessions of physical activity at 3 months (exp(β)=1.45, 95% CI 1.09-1.95; exp(β)=1.61, 95% CI 1.17-2.22) and 9 months (exp(β)=1.55, 95% CI 1.14-2.10; exp(β)=1.51, 95% CI 1.15-2.00). Overall dietary behaviors improved at 3 months (exp(β)=1.07, 95% CI 1.03-1.11) and 9 months (exp(β)=1.10, 95% CI 1.05-1.13). The proportion of participants in both groups eating higher-fiber bread and low-fat milk increased at 3 months (exp(β)=2.25, 95% CI 1.29-3.92; exp(β)=1.65, 95% CI 1.07-2.55). Participants in the IT-based arm were less likely to report that 30 minutes of physical activity per day improves health (exp(β)=0.48, 95% CI 0.26-0.90) and more likely to report that vigorous intensity physical activity 3 times per week is essential (exp(β)=1.70, 95% CI 1.02-2.82). The average number of log-ins to the IT platform at 3 and 9 months was 6.99 (SE 0.86) and 9.22 (SE 1.47), respectively. The average number of self-monitoring entries at 3 and 9 months was 16.69 (SE 2.38) and 22.51 (SE 3.79), respectively.

**Conclusions:** The ManUp intervention was effective in improving physical activity and dietary behaviors in middle-aged males with no significant differences between IT- and print-based delivery modes.

**Trial Registration:** Australian New Zealand Clinical Trials Registry: ACTRN12611000081910; https://www.anzctr.org.au/Trial/Registration/TrialReview.aspx?ACTRN=12611000081910 (Archived by WebCite at http://www.webcitation.org/6QHIWad63).

***(J Med Internet Res 2014;16(6):e136)*** doi:10.2196/jmir.3107

**KEYWORDS**

physical activity; diet; mobile phone; Web-based; randomized controlled trial

## Introduction

Regular physical activity and healthy eating are key health behaviors that contribute to reducing the risk of chronic disease [1,2]. These behaviors and their impact on health are particularly relevant for Australian males because the majority of Australian males are physically inactive and have poor dietary behaviors [3]. For example, approximately 48% of males are not sufficiently physically active and most males do not meet the recommended intake levels of fruit (54%), vegetables (85%), low-fat dairy (63%), or foods containing high levels of saturated fat and sugar (70%) [3-5]. Males are also less likely to participate in behavioral and information technology (IT)-based interventions compared to females [6-8]. In addition, many males have low levels of health literacy, which is the ability to understand and process health information and use this to assist in changing behaviors [9-11]. Health literacy is an important determinant of health; higher levels of health literacy are associated with engagement in various health-promoting behaviors including physical activity and fruit and vegetable consumption [12]. Improving health literacy has been recognized as key to assisting in improving the overall health of Australian males [13]. The high prevalence of poor health behaviors and low levels of health literacy in males combined with the low levels of engagement by males in many behavioral interventions, particularly IT-based interventions, highlights the need for broad-reaching effective interventions specifically developed for this population.

It is widely acknowledged that Web-based- and/or mobile phone-based interventions (IT-based) provide a delivery method that can be conveniently accessed by a large number of individuals thereby increasing the potential reach relative to other commonly used intervention modes, such as print-based materials [14-16]. IT-based interventions have been used to effectively change physical activity and healthy eating behaviors and are viewed positively by males as an intervention delivery mode [7,17-19]. A broad range of features and components can be implemented in these interventions, including education materials, social interaction/support tools, self-monitoring, and goal-setting features, all of which have been associated with increased behavior change [16,20]. Increased participant use of and engagement with the intervention platform is also associated with greater behavior change [21-24]. Mobile phones and smartphones offer participants greater convenience to access intervention materials, and intervention delivery via smartphone and a website is associated with greater levels of self-monitoring and behavior change when compared to self-monitoring via website only [23]. Therefore, delivery of IT-based interventions using a combination of website and mobile devices may be an effective way to increase participant engagement with the intervention and promote greater behavior change. Despite the potential of IT-based interventions to change physical activity and dietary behaviors, there have been few IT-based interventions that have been specifically developed for and targeted toward males [7,8]. Therefore, the purpose of this study is to examine the effectiveness of a 9-month Web- and mobile phone-based (IT-based) intervention to improve the physical activity and dietary behaviors compared to a print-based intervention [25]. A secondary objective is to compare changes in health literacy between the IT- and print-based intervention groups. It was hypothesized that the IT-based intervention would be more effective in improving outcomes compared to the print-based intervention.

## Methods

### Design

The rationale, design, and methods for the ManUp study, including an outline of the intervention, are described in detail elsewhere [25] and only summarized in brief here. The ManUp study was a 2-arm randomized controlled trial (RCT) with participants randomly allocated to either the IT-based (website and mobile device) intervention arm or a print-based intervention arm. A print-based intervention was selected as the comparison group because they are effective in improving health behaviors [26,27]. All participants received written and verbal explanation of the project requirements before providing consent and provided informed consent before participation in the study. The Central Queensland University (H10/07-131) and the University of Western Sydney Human Research Ethics Committee approved the study (H8605). The study was registered with the Australian New Zealand Clinical Trials Registry (ACTRN12611000081910).

## Participants

Males aged 35 to 54 years who (1) owned a mobile telephone, (2) had access to the Internet, (3) did not have a mobility impairment, (4) resided in the cities of Gladstone or Rockhampton (Queensland, Australia), and (5) were classified as low risk to increase physical activity according to established guidelines were eligible to participate in the study [28]. A combination of online forms and phone contact was used to screen participants for eligibility criteria. To recruit participants, advertisements in local newspapers, trading magazines, face-to-face information sessions with local businesses, and distribution of leaflets and posters to local businesses, medical clinics, and offices of allied health professionals were used. No participant incentives were provided in the study. Participants (N=317) were recruited from October 2010 to September 2011, and following initial screening for inclusion criteria, participants were randomly allocated to 1 of the 2 intervention arms. Because IT-based interventions are less frequently examined in male populations [7,8], the number of participants allocated to the intervention arm was maximized in a 2:1 ratio in favor of the IT-based intervention arm. Randomization lists were generated by one of the authors (MJD) using freely available software [29]. Participants were advised of their group allocation via phone. Participants in the IT-based intervention were emailed details to access the intervention platform, including website uniform resource locator (URL), username, and password; participants in the print-based group provided their mailing address to receive the print-based intervention materials. Participants were blinded to group allocation until after baseline assessments were completed. Given that participants completed the assessment of outcome measures via online survey, nonblinding of researchers to participant group allocation was unlikely to bias outcomes.

## ManUp Intervention

The ManUp study was informed by our reviews of published physical activity and dietary interventions for males, our formative research concerning barriers to physical activity and healthy eating behaviors, and our research regarding males' preferences for IT-based interventions [7,8,17,18]. Both intervention arms provided participants with the same intervention materials and capacity to self-monitor physical activity and dietary behaviors. The IT-based intervention, however, provided participants with the additional ability to receive automated feedback on their progress toward completing their physical activity and dietary behavior goals (ManUp challenge), as well as the ability to interact with other participants on the website [25]. Additionally, specific components of the IT-based intervention (My Profiles, My Mates, My Groups) were intended to foster social support between participants via commenting on and viewing the progress of others in-line with social cognitive theory. There was little to no interaction between project staff and participants in either intervention arm.

Both interventions arms were provided with educational materials that were specifically designed to present information on the benefits of physical activity and healthy eating and on the volume and type of activity needed to achieve health benefits. Materials provided to participants allowed daily self-monitoring of physical activity and dietary behaviors and highlighted the importance of self-monitoring as a way to change behavior and keep track of the changes made. Participants could record physical activity and dietary behaviors using any metric specified in Table 1. Informed by social cognitive theory and self-regulation theory. ManUp "challenges" were developed to change target behaviors by providing a goal for behavior change, having participants engage in goal setting and self-monitoring behaviors, and also build confidence to make positive changes to behaviors [25,30,31]. An overview of these theories and the role of self-monitoring in changing behavior can be found elsewhere [30-32].

**Table 1.** Description of the ManUp physical activity and healthy eating challenges.

| Activity | Light strength (3 weeks) | Mid strength (6 weeks) | Full strength (12 weeks) |
|---|---|---|---|
| Walking | 1.5 hours/week or 7500 steps/day | 2.5 hours/week or 10000 steps/day | 3.5 hours/week or 12000 steps/day |
| Cycling | 1 hours/week or 25 km/week | 2 hours/week or 50 km/week | 4 hours/week or 100 km/week |
| Swimming | 0.5 hours/week or 1 km/week | 1 hours/week or 2 km/week | 1.5 hours/week or 3 km/week |
| Running | 0.5 hours/week or 5 km/week | 1 hours/week or 10 km/week | 2.0 hours/week or 20 km/week |
| Sport and recreation | 0.5 hours/week | 1 hours/week | 1.5 hours/week |
| Strengthening | Set 8 exercises 1× set (8-10 reps) 2×/week | Set 8 exercises 2× set (8-10 reps) 2×/week | Set 8 exercises 3× set (8-10 reps) 2×/week |
| Healthy eating[a] | ≥3 healthy eating goals/day | ≥5 healthy eating goals/day | ≥7 healthy eating goals/day |

[a]The ManUp healthy eating goals were: (1) eat 2 servings of fruit, (2) eat 5 servings of vegetables, (3) eat 1 serving of fish, (4) choose whole-grain bread instead of white bread, (5) choose low-fat dairy products, (6) have a soft drink- (soda-) free day, (7) have an alcohol-free day, (8) have an red meat–free day, (9) have an unhealthy snack-free day, and (10) have a fast food–free day.

## ManUp Challenges

The ManUp challenges consisted of 6 physical activity and a multicomponent healthy eating challenge. Each challenge had 3 different "strengths" (light, mid, full), which varied the duration and the amount of activity or healthy eating that males were asked to achieve to complete the challenge. To complete a challenge, participants had to record the required number of minutes/distance/steps for activities or the number of healthy eating goals before the end of the challenge period; failure to do this meant the challenge was not completed. The variation between challenge strengths was intended to provide participants with an appropriate target relative to their current level of physical activity or healthy eating, or to provide a progression toward engaging in higher levels of physical activity or healthy eating. The challenges could be completed in any order preferred by participants and there was no requirement to complete all the different strength challenges or different physical activity challenges. The different activities selected for inclusion were based on those activities frequently performed by Australian males [33]. The ManUp healthy eating challenges were based on achieving a maximum of 10 daily healthy eating goals. These goals were informed by the dietary guidelines for Australian adults that promote dietary diversity and encourage the reduction of the intake of saturated fat, salt, alcohol, and foods that contain added sugars [34]. Although the challenges were informed by the sorts of physical activities frequently participated in by males and the need to promote dietary diversity, they were not intended to promote adherence to public health guidelines for either physical activity or dietary behaviors. Rather, they were designed to increase overall engagement in physical activity and healthy eating. Further details on the types of different physical activities and dietary behaviors targeted, the requirements for each challenge, and supporting educational materials are provided in Table 1 and elsewhere [25].

## Intervention Arms

### *Information Technology–Based Intervention Arm*

Upon completing the baseline assessment participants in the IT-based intervention arm received access to the password-protected ManUp website, which had 6 main sections [25]. The 6 sections were:

1. My Profile where participants could review their current challenges, record their progress toward any current challenges, post personal updates to their profile, schedule future activities, and view information on the groups they were a member of and the list of their mates (online friends on the website).
2. My Progress where participants could review their progress toward their current challenges.
3. My Mates where participants could search for online friends and view their mates' progress. Online friends were limited only to participants allocated to the IT-based intervention; participants could not view an online list of other participants nor were they informed by project staff who else was enrolled in the study because of privacy concerns, but participants could search for other users by entering a name or part of a name into the search tool provided on the website.
4. My Groups where participants could create a group and view the progress of groups they were part of.
5. My Weight, which provided participants with information on the benefits of achieving a healthy weight, and allowed them to record their height, weight, and waist circumference. This section did not allow participants to track these metrics over time; rather, it provided immediate feedback on what category, such as body mass index (BMI) category or waist circumference category, the respective measure was classified as in comparison to established categories for BMI and waist circumference [35].
6. Information Center, which provided educational materials related to physical activity and healthy eating, and the challenges [25].

As a form of online social support, participants could comment on their mates' My Profile page. In addition, participants could also challenge their mates to complete a physical activity or healthy eating challenge either in a one-on-one basis, or as part of a larger group. A mobile phone Web application was developed as an additional tool to facilitate quick and convenient recording of progress toward the ManUp challenges. The mobile phone Web application only allowed users to self-monitor behavior and body weight, and to review progress toward challenge completion. Any participant in the IT-based intervention arm who owned a mobile phone capable of accessing the Internet had access to the mobile phone Web application. Figure 1 shows the My Profile section of the website and Figures 2 and 3 display the app data entry screen for healthy eating, the screen showing feedback information on the level of activity needed to complete a particular challenge. Graphical- and text-based feedback of progress toward the completion of a challenge was automatically provided by both the website and app, and was updated based on participant's self-monitoring entries of physical activity and health eating. Participants were not provided with any detailed instruction on how to use the IT platform or the frequency that it should be used. The initial email providing log-in details suggested they should visit the intervention platform and initiate a ManUp challenge. A short video presenting the main features and functionality of the website was available for viewing on the front page of the website without having to log in to the website. This video was viewed 243 times in total throughout the intervention period.

**Figure 1.** Screenshot of the My Profile section of the ManUp website.

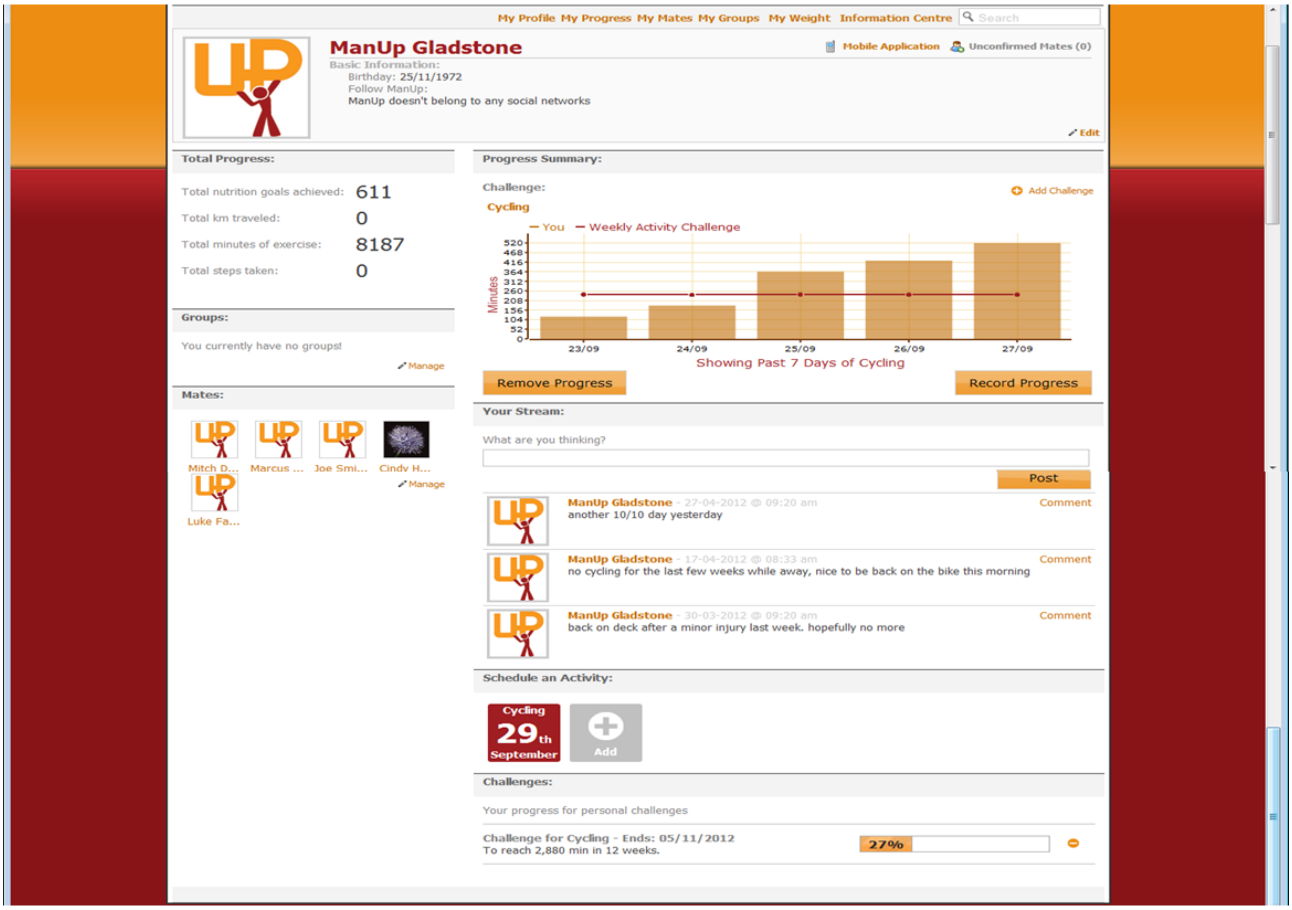
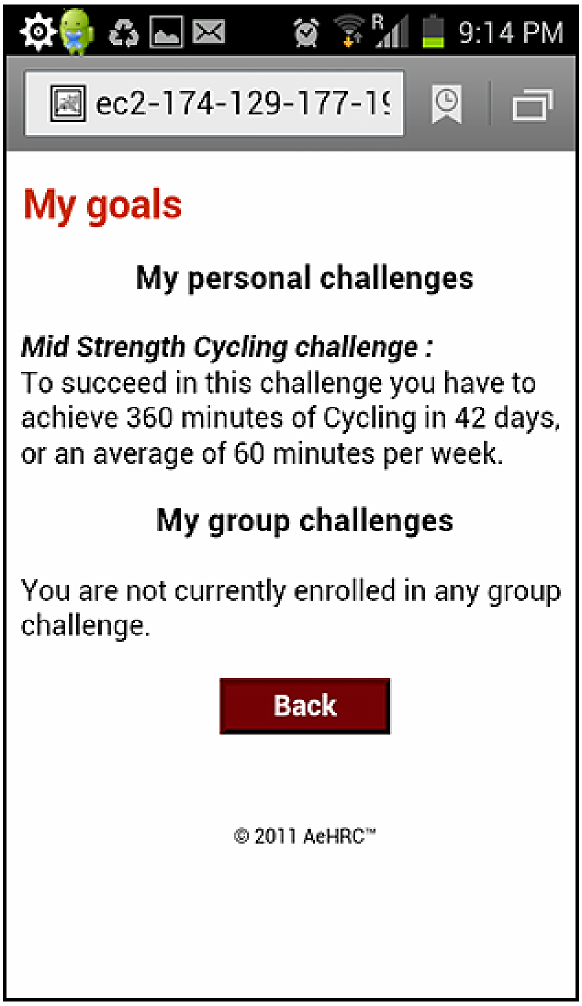



**Figure 2.** Screenshot of the healthy eating data entry screen of the ManUp app.

**Figure 3.** Screenshot of the challenge progress feedback screen of the ManUp app.




### *Print-Based Intervention Arm*

Participants in the print-based group received a hard-copy booklet that provided the same educational materials (including content from the My Weight section) and ManUp challenges as those provided to participants in the IT-based intervention. Participants in the print-based group were provided with information about using the provided log sheets and could self-monitor progress and/or successful completion of the ManUp physical activity or healthy eating challenges using the log sheets. Participants in the print-based group were not provided with information regarding their peers who were also part of this group. The hard-copy booklet was not collected from participants and no information about the challenges completed or self-monitoring was obtained. Hard-copy booklets were not collected because of logistical reasons and to allow participants to keep a record of their progress to assist in behavior change.

## Outcome Measures

### *Overview*

Participants completed online surveys at baseline (0 months), 3 months, and 9 months to assess sociodemographic, behavioral, and health literacy outcomes. Measures of satisfaction with the intervention were also obtained at the 9-month assessment point. All participants received up to 3 phone calls or emails at each assessment point to remind them to complete their assessments.

### *Physical Activity*

Physical activity was assessed using the Active Australia Questionnaire, a valid and reliable instrument that is also sensitive to change in physical activity [36-39]. This questionnaire asks participants to report the duration of recreational and transport walking, moderate and vigorous intensity physical activity in the previous week, and the number of times (sessions) they engaged in these activities. Standard scoring protocols were applied to provide 2 outcomes: total minutes of physical activity and the total number of sessions of physical activity [36].

### *Dietary Behaviors*

Dietary behaviors were assessed using 19 items adapted from existing instruments used to monitor dietary habits of the Australian population [40,41]. These items have sound psychometric properties [40]. Two separate items assessed the daily number of servings of fruit and vegetables consumed in the past week, response options ranged from zero servings (don't eat this food) to 10 or more servings. The frequency that red meat, fish, meat products (sausages, salami, meat pies, etc), cooked cereals, soft drinks, chips, takeaway foods, and sweet or savory foods were consumed in the past week were assessed using response options from rarely/never (don't eat this food) to more than 10 times. The type of milk (whole milk or full cream, reduced fat, soymilk, condensed milk, don't drink milk) and bread (white, wholemeal, multigrain, rye, sour dough, other, don't eat bread) usually consumed were also assessed. Three dietary outcomes were created: type of milk consumed (reduced fat vs whole milk), type of bread consumed (higher-fiber wholemeal, multigrain, white with high fiber, sour dough, rye vs white) and an overall index of other dietary behaviors (the dietary score). The dietary score was created by summing the number of servings and number of times the following foods were consumed: fruit, vegetables, red meat, fish, meat products, soft drinks, chips, takeaway (take-out) foods, and sweet and savory foods. Several items were reversed-scored so that higher dietary scores (a better diet) reflected more frequent consumption of healthy food and less frequent consumption of less healthy foods. The dietary score reflected the fact that the ManUp healthy eating challenge focused on maximizing consumption of healthy foods and minimizing consumption of less healthy foods.

### *Health Literacy*

Health literacy in relation to physical activity was assessed using the 5 awareness items from the Active Australia Questionnaire [36]. Using a 5-point Likert-type scale from strongly agree to strongly disagree, the items assess awareness of the benefits associated with physical activity participation, and the intensity and duration required to receive health benefits. Dietary behavior literacy was assessed using the Nutritional Literacy Survey, a valid and reliable 28-item instrument that assesses participants' understanding of the type of foods that promote heart health, and the fat and cholesterol content of different foods and portion sizes [42].

### *Satisfaction*

Participant satisfaction with the intervention platform and challenge concept was assessed using 4 items. Using a 5-point scale ranging from strongly agree to strongly disagree, participants indicated if they would like to continue to use the IT- or print-based materials, if the materials (print booklet or IT-based platform) were easy to use, and if they liked the overall concept of the physical activity and healthy eating challenges.

### *Information Technology Platform Usage*

Usage of the IT-based platform was measured using in-built tracking software measuring the number of times a participant logged into the Web- and mobile-based platform, made a self-monitoring entry, and the type and number of challenges they initiated and completed.

### Sample Size

Using established methods to estimate sample size [43], the study was powered to detect a 60-minute change in moderate-to-vigorous intensity physical activity per week from baseline to 9 months using an alpha level of .05 and a power level of 90%. Based on this calculation, it was estimated that 197 participants would be required. However, this number was increased to account for the 2:1 allocation of participants in favor of the IT-based intervention arm and the expected dropout rate of participants (45%) [21,44]. A higher dropout rate was used in the current study given the acknowledged difficulty in engaging and retaining males in interventions [7,8]. As a result, the estimated total sample size was 321: 107 allocated to the print-based group and 214 allocated to the IT-based group [25].

### Analysis

Comparisons between groups at baseline were conducted using generalized linear models and chi-square tests. Comparisons between those participants completing all 3 assessment points (completers) and those completing less than 3 assessment points (noncompleters) were made on age, education, physical activity, dietary behaviors, and health literacy using *t* tests (where parametric assumptions were met) or Mann-Whitney *U* for continuous variables, and chi-square tests for categorical variables. Generalized linear mixed models use all available data at each time point allowing participants with missing data at follow-up time points to be retained in the analysis. Therefore, generalized linear mixed models with an unstructured covariance matrix were used to examine change over time and differences between intervention arms in physical activity, dietary behaviors, and health literacy outcomes. All analyses were adjusted for baseline age, occupation, and education because these variables likely impact upon the physical activity and dietary behaviors of males [45]. Outcomes of the generalized linear mixed model analyses are reported as exponentiated coefficients (exp(β)). To explore the impact of missing data, a sensitivity analysis using baseline observation carried forward (BOCF) for participants with missing data at follow-up time points was performed for physical activity, dietary behaviors, and health literacy outcomes; this analysis also adjusted for baseline age, occupation, and education. Comparison of change in physical activity, dietary behaviors, and health literacy with and without BOCF revealed only small differences in the magnitude of these outcomes with the exception of consumption of higher-fiber bread and low-fat milk consumption. For both of these outcomes, the significant time effects present at 3 months in the analysis without BOCF were in the same direction, although not statistically significant in the analysis with BOCF. Given these minor differences, only the results from the analyses without BOCF are reported.

Analyses examining the relationship between usage of the IT platform and change in behavior within the IT-based intervention arm were conducted using generalized linear models adjusted for age, occupation, education, and the baseline level of the outcome examined. The specific model type, link function used for analyses, and the total number of observations included are listed in the footnotes of the relevant tables. All analyses were conducted with SPSS version 20 (IBM Corp, Armonk, NY, USA), followed intention-to-treat principles, and used an alpha level of .05.

## Results

### Participants

The flow of participants through the study, including the number of participants completing each assessment, is provided in Figure 4. A total of 327 males expressed an interest in participating in the study: 10 males were excluded because they did not satisfy eligibility criteria or were no longer interested in participating, 317 males were randomized to an intervention arm of which 16 withdrew from the study before completing a baseline assessment (Figure 4). A total of 301 participants completed the baseline assessment, 159 completed the 3-month assessment, 148 completed the 9-month assessment, and 125 completed all 3 assessment points. No significant differences were observed between those who completed 3 assessment points (completers) compared to those completing less than 3 assessment points (noncompleters) on baseline minutes and sessions of physical activity, dietary score, and type of bread consumed (data not shown). Completers were significantly different from noncompleters in terms of age (mean 45.11, SE 0.51 vs mean 43.32, SE 0.44; *P*=.01), the proportion working in professional level occupations (66.4% vs 49.4%; *P*=.03), the proportion reporting a university-level education (62.6% vs 41.5%; *P*=.002), the proportion reporting to consume low-fat milk (66.4% vs 49.7%; *P*=.01), the proportion reporting that at least 20 minutes of vigorous intensity physical activity 3 times per week is essential to improve health (35.8% vs 64.2%; *P*=.01), and nutritional literacy (mean 25.53, SE 0.16 vs mean 24.98, SE 0.16; *P*=.02).

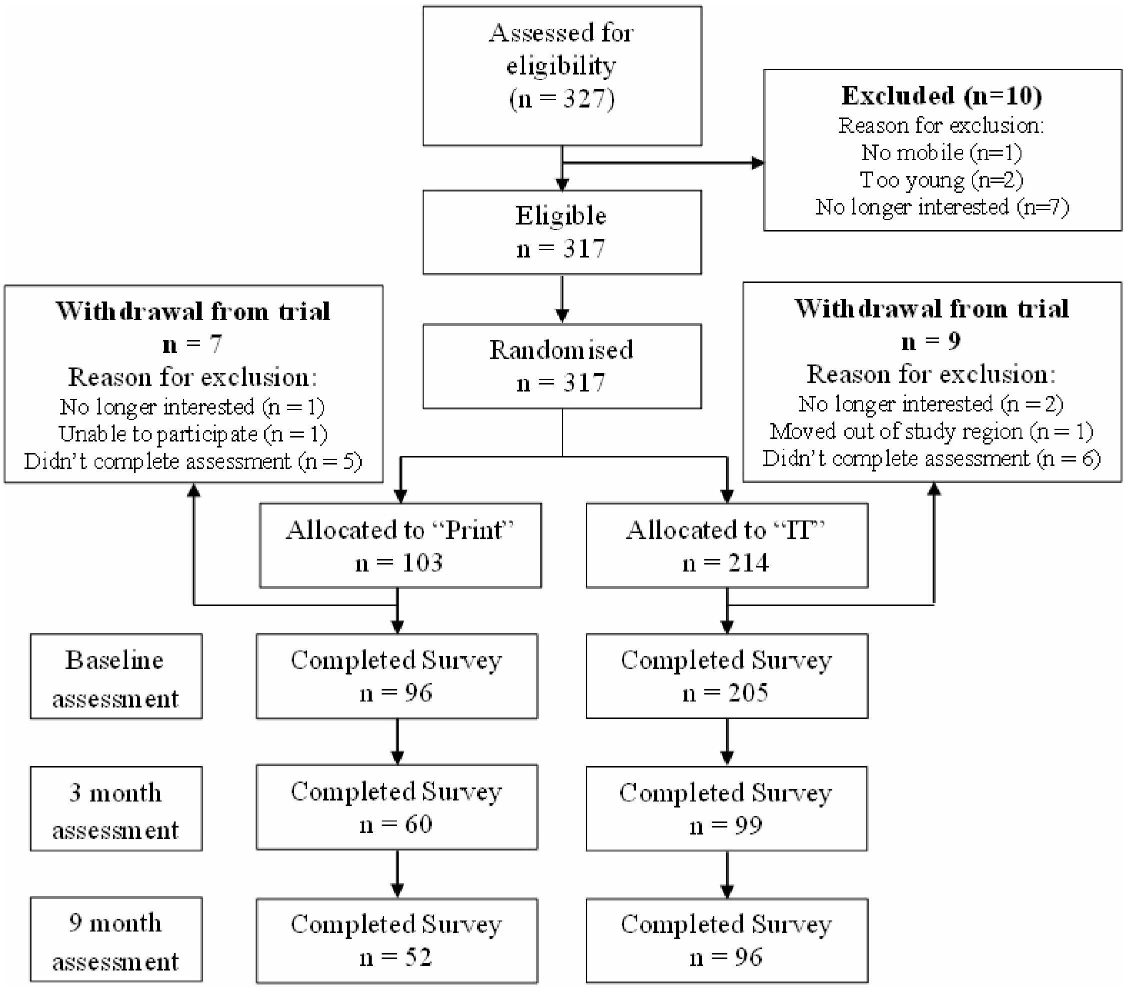
There were no significant baseline differences between the print-based arm and the IT-based arm for any demographic behavioral and health literacy variable, with the exception that there were fewer participants who agreed that 30 minutes of physical activity is enough to improve health in the IT-based arm compared to the print-based arm (Table 2). In-line with the eligibility criteria, all participants owned a mobile phone and 151 (73.2%) of the IT-based intervention owned a phone that could access the Internet.

**Table 2.** Sociodemographic, anthropometric, and behavioral characteristics of participants at baseline.

| Participant characteristic | Print-based n=96 | IT-based n=205 | *P* |
|---|---|---|---|
| Age (years), mean (SE) | 43.84 (0.59) | 44.17 (0.41) | .66 |
| **Occupation, n (%)** | | | .64 |
| Professional | 52 (54.2) | 118 (57.6) | |
| White collar | 8 (8.3) | 16 (7.8) | |
| Blue collar | 23 (24.0) | 37 (18.0) | |
| Other | 13 (13.5) | 34 (16.6) | |
| **Education level, n (%)** | | | .72 |
| Secondary school or less | 20 (20.8) | 45 (22.0) | |
| TAFE[a] | 25 (26.0) | 61 (29.8) | |
| University | 51 (53.1) | 99 (48.3) | |
| **Self-reported BMI, n (%)** | | | .46 |
| Healthy weight | 13 (13.5) | 19 (9.3) | |
| Overweight | 41 (42.7) | 85 (41.5) | |
| Obese | 42 (43.8) | 101 (49.3) | |
| Self-reported minutes of physical activity/week, mean (SE) | 277.94 (29.15) | 286.12 (24.72) | .83 |
| Self-reported sessions of physical activity/week, mean (SE) | 4.0 (1.0, 8.0) | 4.0 (1.0, 7.0) | .95 |
| Dietary score, median (IQR) | 52.0 (46.0, 56.75) | 52.0 (47.0, 57.0) | .33 |
| Higher-fiber bread, n (%) | 93 (57.0) | 195 (68.2) | .06 |
| Low-fat milk, n (%) | 87 (57.5) | 182 (56.0) | .83 |
| **Physical activity literacy (% agree), n (%)** | | | |
| ≥30 min/day improves health | 79 (82.3%) | 144 (70.2%) | .03 |
| 30 min brisk walking improves health | 79 (82.3%) | 153 (74.6%) | .14 |
| 20 min of vigorous activity 3 times/week is essential | 54 (56.3%) | 139 (67.8%) | .05 |
| 10-min blocks of activity are okay | 52 (54.2%) | 106 (51.7%) | .69 |
| Moderate activity can improve health | 87 (90.6%) | 177 (86.3%) | .29 |
| Nutritional literacy, median (IQR) | 25 (24, 26) | 26 (24, 27) | .66 |

[a]Technical and further education (TAFE) is a provider of vocational nonbachelor education up to level of advanced diploma.

**Figure 4.** Flow of participants through the study.




## Change in Physical Activity and Dietary Behaviors

There were no significant between-group differences or group×time interaction effects in any of the physical activity and dietary behaviors examined; however, significant main effects for time were observed (Table 3). Self-reported minutes (3 months: exp(β)=1.45, 95% CI 1.09-1.95; 9 months: exp(β)=1.55, 95% CI 1.14-2.10) and sessions of physical activity (3 months: exp(β)=1.61, 95% CI 1.17-2.22; 9 months: exp(β)=1.51, 95% CI 1.15-2.00) were significantly higher at 3 and 9 months compared to baseline in both groups. Dietary scores were significantly higher (improved) at both 3 and 9 months compared to baseline (3 months: exp(β)=1.07, 95% CI 1.03-1.11; 9 months: exp(β)=1.10, 95% CI 1.05-1.13) in both groups. A significantly higher proportion of participants reported consuming higher-fiber bread (exp(β)=2.25, 95% CI 1.29-3.92) and low-fat milk (exp(β)=1.65, 95% CI 1.07-2.55) at 3 months compared to baseline in both groups; consumption of higher-fiber bread and low-fat milk were not significantly higher at 9 months compared to baseline in both groups.

**Table 3.** Comparison of self-reported measured health behaviors between intervention groups over the intervention period.

| Health behavior | exp(β) (95% CI) | Model effects, *P* | | |
|---|---|---|---|---|
| | | Group | Time | Group×time |
| **Self-report minutes of physical activity per week** [a] | | .60 | <.001 | .66 |
| IT-based vs print-based[b] | 1.03 (0.78-1.36) | | | |
| 3 vs 0 months[b] | 1.45 (1.09-1.95) | | | |
| 9 vs 0 months[b] | 1.55 (1.14-2.10) | | | |
| **Self-report sessions of physical activity per week** [a] | | .32 | <.001 | .55 |
| IT-based vs print-based[b] | 0.97 (0.75-1.25) | | | |
| 3 vs 0 months[b] | 1.61 (1.17-2.22) | | | |
| 9 vs 0 months[b] | 1.51 (1.15-2.00) | | | |
| **Dietary score** [c] | | .68 | <.001 | .09 |
| IT-based vs print-based[b] | 1.02 (0.98-1.06) | | | |
| 3 vs 0 months[b] | 1.07 (1.03-1.11) | | | |
| 9 vs 0 months[b] | 1.10 (1.05-1.13) | | | |
| **Higher-fiber bread** [d] | | .05 | <.001 | .92 |
| IT-based vs print-based[b] | 1.60 (0.94-2.71) | | | |
| 3 vs 0 months[b] | 2.25 (1.29-3.92) | | | |
| 9 vs 0 months[b] | 1.89 (0.99-3.60) | | | |
| **Low-fat milk** [e] | | .54 | .002 | .90 |
| IT-based vs print-based[b] | 0.88 (0.52-1.49) | | | |
| 3 vs 0 months[b] | 1.65 (1.07-2.55) | | | |
| 9 vs 0 months[b] | 1.41 (0.92-2.17) | | | |

[a]Model (negative binomial with log link) included age, education level, and occupational classification as covariates. Number of observations=616.

[b]Reference category for comparison.

[c]Model (negative binomial with log link) included age, education level, and occupational classification as covariates. Number of observations=608. This outcome was examined as the change in the total number of times the food was consumed and the servings of a food.

[d]Model (binomial with logit link) included age, education level, and occupational classification as covariates. Number of observations=587. This outcome was examined as the change in the proportion of participants consuming higher-fiber bread.

[e]Model (binomial with logit link) included age, education level, and occupational classification as covariates. Number of observations=542. This outcome was examined as the change in the proportion of participants consuming low-fat milk.

## Change in Health Literacy

A significantly lower proportion of participants in the IT-based intervention arm reported agreeing that 30 minutes of physical activity per day improves health compared to the print-based arm (exp(β)=0.48, 95% CI 0.26-0.90); there were no significant time or group×time interaction effects for this outcome (Table 4). A significantly higher proportion of participants in the IT-based intervention arm reported agreeing that 20 minutes of vigorous intensity physical activity performed 3 times per week is essential to improve health (exp(β)=1.70, 95% CI 1.02-2.82). There were no significant group or group×time interaction effects for the proportion of participants reporting that blocks of a minimum of 10 minutes physical activity are acceptable to acquire health benefits; however, a significantly higher proportion of participants reported agreeing with this statement at 9 months compared to baseline in both groups (exp(β)=2.52, 95% CI 1.28-4.94). No other statistically significant differences were observed in physical activity and nutrition literacy (Table 4).

**Table 4.** Comparison of health literacy outcomes between intervention groups over the intervention period.[a]

| Health literacy outcome | exp(β) (95% CI) | Model effects, *P* | | |
|---|---|---|---|---|
| | | Group | Time | Group×time |
| **≥30 minutes/day improves health**[b] | | .17 | .11 | .28 |
| IT-based vs print-based[c] | 0.48 (0.26-0.90) | | | |
| 3 vs 0 months[c] | 1.02 (0.50-2.09) | | | |
| 9 vs 0 months[c] | 1.37 (0.65-2.89) | | | |
| **30 minutes brisk walking improves health** [b] | | .91 | .01 | .13 |
| IT-based vs print-based[c] | 0.63 (0.34-1.16) | | | |
| 3 vs 0 months[c] | 1.33 (0.58-3.06) | | | |
| 9 vs 0 months[c] | 1.51 (0.60-3.81) | | | |
| **20 minutes of vigorous activity 3 times/week is essential** [b] | | .01 | .99 | .88 |
| IT-based vs print-based[c] | 1.70 (1.02-2.82) | | | |
| 3 vs 0 months[c] | 0.96 (0.49-1.87) | | | |
| 9 vs 0 months[c] | 1.08 (0.57-2.04) | | | |
| **10-minute blocks of activity are okay** [b] | | .33 | .001 | .58 |
| IT-based vs print-based[c] | 0.89 (0.54-1.45) | | | |
| 3 vs 0 months[c] | 1.51 (0.83-2.72) | | | |
| 9 vs 0 months[c] | 2.52 (1.28-4.94) | | | |
| **Nutrition literacy** [d] | | .78 | .44 | .51 |
| IT-based vs print-based[c] | 1.01 (0.99-1.03) | | | |
| 3 vs 0 months[c] | 1.01 (0.99-1.03) | | | |
| 9 vs 0 months[c] | 1.01 (0.97-1.05) | | | |

[a]Analysis of change in the physical activity literacy outcome of "moderate physical can improve health" is not reported as there was insufficient variation in the outcome to allow the model to be accurately estimated. The proportion of participants agreeing with this statement at each time point in each group is: Baseline: IT-based=86.3%, print-based=90.6%; 3 months: IT-based=88.9%, print-based=86.7%; 9 months: IT-based=100.0%, print-based=95.8%.

[b]Model (binomial with logit link) included age, educational level, and occupational classification as covariates. Number of observations=608.

[c]Reference category for comparison.

[d]Model (negative binomial with log link) included age, educational level, and occupational classification as covariates. Number of observations=608.

### ManUp Challenges

Because of the difficulty in obtaining records in logbook usage and challenge completion in the print-based intervention arm, data on the usage of ManUp challenges is only reported for the IT-based intervention arm. Figure 5 demonstrates the number of participants in the IT-based intervention arm who started and completed light-, mid-, or full-strength physical activity and healthy eating challenges over the 9-month intervention period. A higher number of participants initiated physical activity challenges compared to the healthy eating challenges, and no participants completed a healthy eating challenge—this was because of participants not completing the required number of healthy eating goals in the specified time period (3-, 6-, or 12-week challenge duration depending on challenge strength selected); thus, they did not complete the challenge. When examining the number of challenges initiated and completed over the 9-month period by all IT-group participants, light-strength physical activity challenges were the most frequently selected (n=147) and completed (n=137), followed by mid-strength physical activity challenges (initiated: n=80; completed: n=68), and full-strength physical activity challenges (initiated: n=69; completed: n=53). Healthy eating challenges were initiated at a lower frequency compared to physical activity challenges but followed a similar pattern; light-strength healthy eating challenges were the most frequently selected (initiated: n=60; completed: n=0), followed by mid-strength healthy eating challenges (initiated: n=28; completed: n=0), and full-strength healthy eating challenges (initiated: n=14; completed: n=0).

Information on the type of physical activity challenges selected by participants is provided in Figure 6. Walking was the most frequently selected challenge type, followed by cycling and strengthening activities. Figure 7 shows the number of different health eating goals selected; fast food–, soft drink–, and alcohol-free days and eating 2 pieces of fruit were the most frequently selected goals across all challenges.

**Figure 5.** Number of participants in the IT-based intervention who started and completed ManUp challenges.

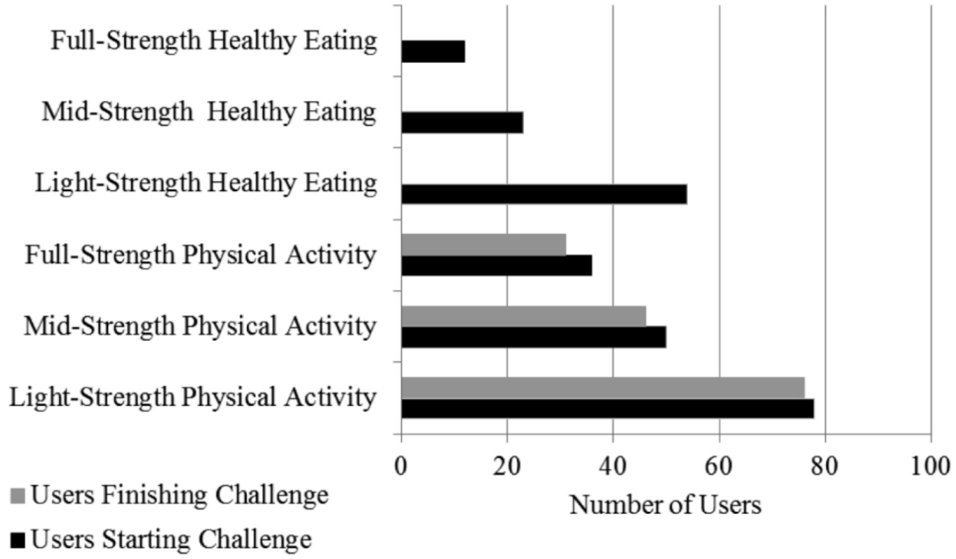



**Figure 6.** Number of physical activity challenge types completed by challenge strength.

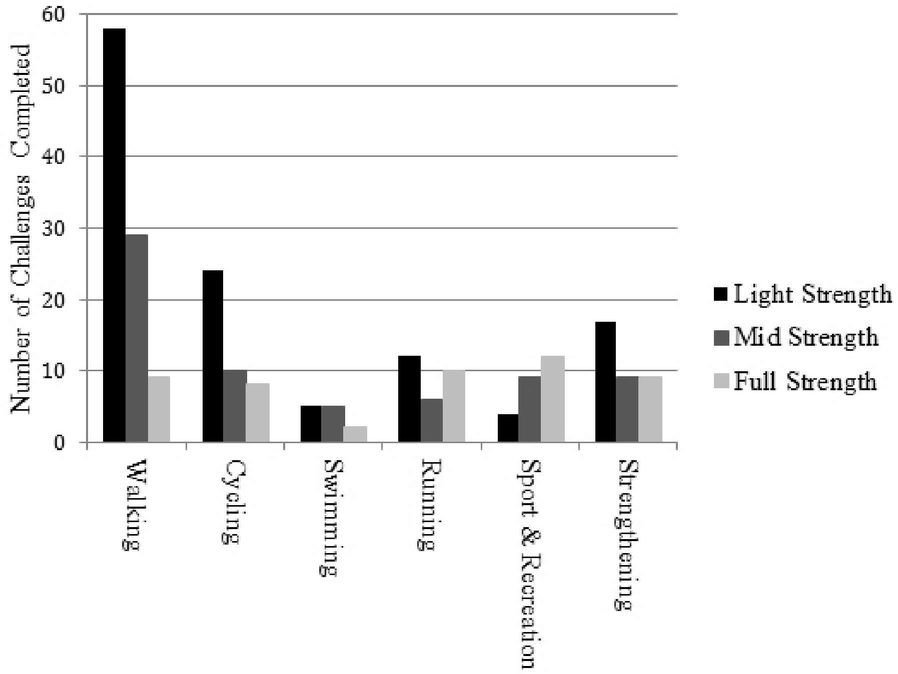
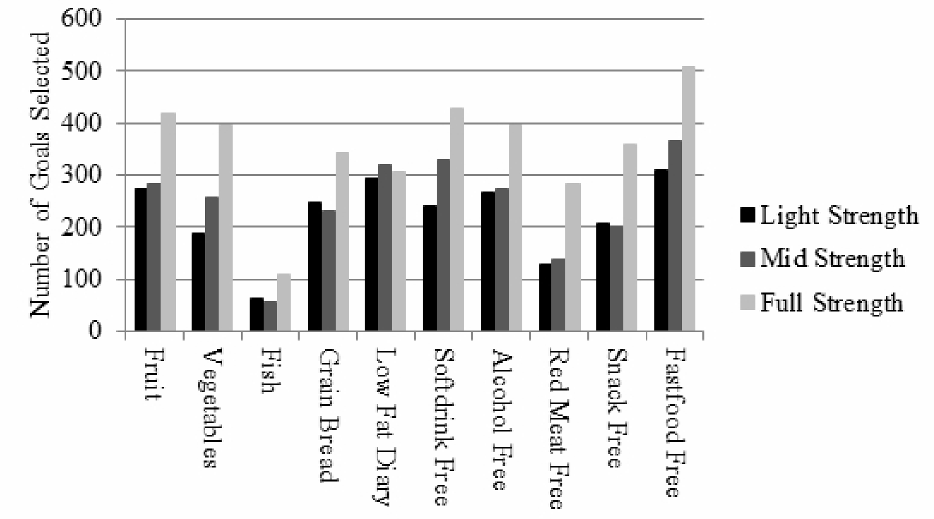


**Figure 7.** Number of healthy eating goals selected by challenge strength (based on goals logged via the website only).




### Information Technology Platform Usage

The median number of log-ins to the IT platform per week at 3 months and 9 months was 2.00 (IQR 6.00) and 2.00 (IQR 6.50), respectively; the average number of log-ins to the IT platform at these same time periods was 6.99 (SE 0.86) and 9.22 (SE 1.47). Median number of self-monitoring entries per week at 3 months and 9 months was 1.00 (IQR 20.0) and 1.00 (IQR 21.5), respectively; the average number of self-monitoring entries at 3 months and 9 months was 16.69 (SE 2.38) and 22.51 (SE 3.79), respectively. Participants who logged in 2 or more times in the first 3 months of the intervention made significantly more self-monitoring entries (median 18.00, IQR 38.00) compared to participants logging in less than 2 times (median 0.00, IQR 0.00; $U$=1195.50, $P$<.001). Figure 8 shows the number of users logging in at least once and making at least 1 self-monitoring entry each week over the intervention period. Following the initial reduction in usage between week 1 and week 3, usage continued to decline throughout the intervention period. No measure of usage of the IT-based platform was associated with any of the physical activity or dietary behaviors examined (Table 5). Use of the Mate feature and posts to update their progress was low; 21 participants used the Mate feature and no participants using this feature had more than 1 mate on the platform; 36 participants used the post feature (minimum=1 post, maximum=26 posts). Minimal reports of bugs or errors (<10) on the IT-based platform were received during the intervention period via the "report a bug" feature. Of the 33 participants who completed survey items regarding satisfaction of the print materials, 33.3% (11/33) agreed or strongly agreed that they would like to continue to use the ManUp booklet in the future, and 75.8% (25/33) agreed or strongly agreed that it was easy to use. Of the 60 participants who completed survey items regarding satisfaction of the website, 25.0% (15/60) of participants agreed or strongly agreed that they would like to continue to use the website and 85.0% (51/60) reported it was easy to use. Of the 139 participants who completed items regarding satisfaction with the concept of the physical activity and healthy eating challenges, 60.4% (29/48) and 52.7% of participants (48/91) in the print and IT-based groups, respectively, reported satisfaction with the physical activity challenge with no significant differences between groups ($\chi^2_1$=0.7, $P$=.34). There were no differences in the proportion of participants in the print (60.4%, 29/48) and IT-based groups (48.4%, 44/91) who reported being satisfied with the healthy eating challenge ($\chi^2_1$=1.8, $P$=.18)

**Table 5.** Associations between IT-platform usage and self-reported physical activity and dietary behaviors.

| Health behavior | Number of log-ins, exp(β) (95% CI) | Number of self-monitoring entries, exp(β) (95% CI) | Model effects, *P* | |
|---|---|---|---|---|
| | | | Number of log-ins | Number of self-monitoring entries |
| **Self-report minutes of physical activity per week** [a] | | | | |
| 3 months | 1.00 (0.98-1.01) | 1.00 (0.997-1.01) | .43 | .38 |
| 9 months | 1.00 (0.99-1.00) | 1.00 (1.00-1.01) | .25 | .10 |
| **Self-report sessions of physical activity per week** [b] | | | | |
| 3 months | 0.99 (0.98-1.01) | 1.01 (1.00-1.01) | .19 | .05 |
| 9 months | 1.00 (0.99-1.00) | 1.00 (1.00-1.01) | .41 | .16 |
| **Dietary score** [c] | | | | |
| 3 months | 1.00 (1.00-1.00) | 1.00 (0.99-1.00) | .65 | .76 |
| 9 months | 1.00 (1.00-1.00) | 1.00 (1.00-1.00) | .11 | .63 |
| **Higher-fiber bread** | | | | |
| 3 months[d] | 1.03 (0.93-1.13) | 1.02 (0.99-1.05) | .59 | .25 |
| 9 months[e] | — | — | — | — |
| **Low-fat milk** [f] | | | | |
| 3 months | 0.97 (0.90-1.04) | 1.01 (0.98-1.04) | .33 | .71 |
| 9 months | 1.00 (0.98-1.03) | 1.00 (0.99-1.01) | .71 | .54 |

[a]Model (Tweedie with log link) included age, educational level, occupational classification, access to the mobile platform, and baseline minutes of physical activity as covariates. 3 months: n=101; 9 months: n=100.

[b]Model (negative binomial with log link) included age, educational level, occupational classification, access to the mobile platform, and baseline sessions of physical activity as covariates. 3 months: n=101; 9 months: n=100.

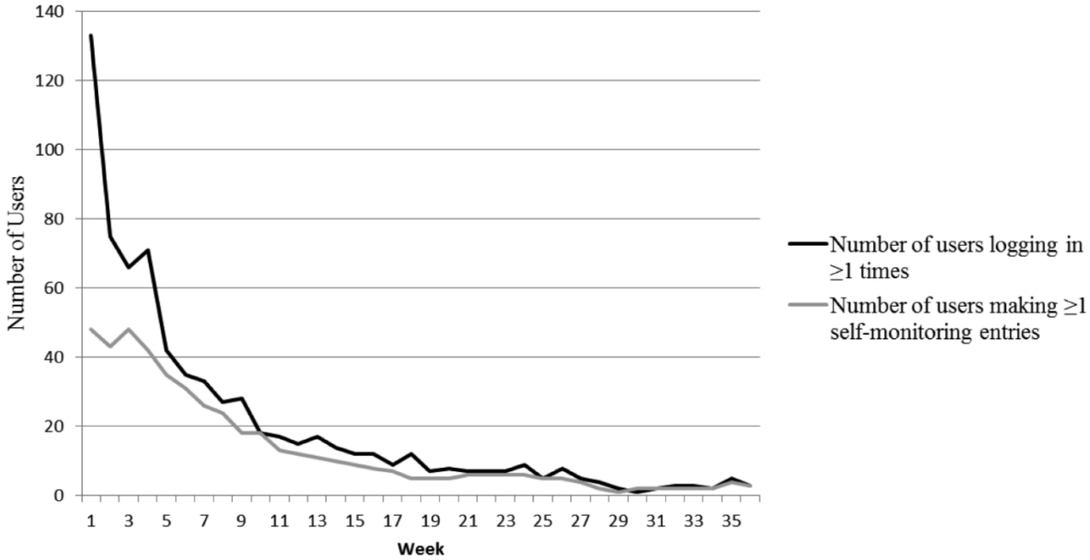
[c]Model (Tweedie with log link) included age, educational level, occupational classification, access to the mobile platform, and baseline dietary score as covariates. 3 months: n=99; 9 months: n=96.

[d]Model (binomial with logit link) included age, educational level, occupational classification, access to the mobile platform, and baseline bread consumption as covariates. Number of participants=93.

[e]Results are not reported for this time point as the model had partial or complete separation and parameters could not be reliably estimated.

[f]Model (binomial with logit link) included age, educational level, occupational classification, access to the mobile platform, and baseline milk consumption as covariates. 3 months: n=82; 9 months: n=80.

**Figure 8.** Participant usage of the IT-based intervention platform each week over the intervention period.



## Discussion

This study examined the relative effectiveness of the ManUp intervention materials delivered by an IT-based intervention platform compared to a print-based intervention to improve middle-aged males' physical activity and dietary behaviors, and health literacy of these behaviors. Analyses revealed significant improvements over time in self-reported minutes and sessions of physical activity and self-reported overall dietary behaviors in both groups. These changes did not significantly differ between participants receiving access to the IT- or print-based intervention materials. Three components of physical activity literacy changed during the intervention period. First, a lower proportion of participants in the IT-based intervention arm reported agreeing that 30 minutes of physical activity per day is enough to improve health. Second, a higher proportion of participants in the IT-based intervention arm reported agreeing that 20 minutes of vigorous intensity physical activity 3 times per week is necessary to improve health. Finally, a higher proportion of participants from both intervention arms reported agreeing that accumulating physical activity in blocks of a minimum 10 minutes are acceptable to improve health at the 9-month assessment point compared to baseline. Nutrition literacy did not change over time or between intervention arms.

Print- and IT-based interventions have been shown to be effective in improving physical activity, dietary behaviors, or both behaviors in male populations in earlier research [19,46-49]. These studies demonstrated positive intervention effects on target behaviors for time periods ranging between 14 weeks and 12 months [19,48]. Consistent with this literature, the current study demonstrated positive changes in both physical activity and dietary behaviors over a 9-month period. Notwithstanding the limitations of the self-report data in the current study, the sustained nature of the changes is encouraging given that poor physical activity and dietary behaviors are prevalent and significant contributors to chronic disease risk in male populations [3-5,13]. Most previous research has targeted only 1 of these behaviors and comparatively fewer interventions aimed at males have targeted both behaviors simultaneously [7,8]. As such, outcomes of the ManUp study contribute to the evidence that it is feasible to target and significantly improve multiple health behaviors simultaneously in various populations [50-52]. The ability of the intervention platform to improve physical activity and dietary behaviors and the lack of differences between the delivery modes suggests that IT-based approaches are useful to improve males' engagement in these behaviors. This observation is useful given the large number of males engaging in poor levels of physical activity and dietary behaviors and the potential reach of IT-based interventions relative to other delivery modes. However, as others have noted, the challenge lies in attracting and engaging individuals to the platform [15,53], particularly males who are an acknowledged difficult group to engage in these types of interventions [7,8].

An advantage of IT-based platforms is that participant engagement and usage can be monitored throughout the intervention period. Figure 8 shows a modest level of engagement and usage in the initial weeks of the intervention period followed by a steady decline over time. The modest level of initial usage may be related to the minimal instruction provided to participants on usage of the platform; however, this was intended to reflect the level of instruction provided in other publicly available websites. Platform usage rates may also be related to the levels of participant satisfaction reported which were not as high as expected given the materials and intervention platform were developed specifically for this population. However, given the limited number of participants who completed participant satisfaction survey items these results should be interpreted cautiously. Analysis of the frequency of user log-in and self-monitoring entries revealed no statistically significant association with behavior at either the 3- or 9-month assessment points. Although the pattern of declining participant usage over time is similar to that of previous studies [45,54], the absence of an association with behavior change is not [22-24,45,55]. The lack of association could be because of a lack of statistical power or the measures of engagement and usage applied in the current study failed to capture real participant engagement with the platform. Donkin et al [24] suggested that more in-depth analysis of participant engagement and platform usage is required to understand the relationship between engagement and behavior change; the findings of this study support the assertion that simplistic measures of usage may not be the strongest predictors of behavior change. Alternatively, it may be that participants received an adequate exposure to intervention materials to promote behavior change during their initial use of the platform. The suggestion that an individual's behavior can be changed following a single exposure to an intervention is supported by previous studies [50,56,57]. Several interventions now seek to maintain and increase greater engagement through various IT-based strategies to foster greater or more sustained behavior change, and evaluation of these strategies to prolong user engagement are in their infancy [45,58]. Given the consistently reported declines in platform usage and engagement over time [15,45], and evidence of effectiveness of repeated interventions delivered in a booster style [59,60], comparing the effectiveness of these 2 intervention approaches to change behavior may contribute to understanding the most effective way to change behavior.

Potential reasons for low engagement, usage, and satisfaction could be a mismatch between participants' expectations of the intervention and intervention reality. For example, process evaluation of participants in this trial revealed that many wanted prescriptive and personalized information and feedback on their progress [61]. Participants also expressed a desire to transfer the print-based intervention to online platforms to increase accessibility, and for the ManUp app to be usable without requiring an Internet connection [61]. As such, it appears that participants desired an increased accessibility to content above that provided by the current intervention platform. These issues may have adversely impacted engagement and satisfaction. Managing the user expectations by providing a flexible intervention platform that is highly accessible may improve platform usage above that observed in the current trial [61].

One strategy intended to promote prolonged engagement is social interaction among participants [58]. In the current study, 10% of participants had an online friend or mate, and website statistics showed that all these participants had no more than 1 mate. The number of participants with online friends is slightly higher than that reported in a subsample of users of the 10,000 Steps website (4.3%), yet use of online friends appears to be low by participants of health behavior change interventions [22]. Low use of this feature in the current study could be due to several factors, including a lack of awareness of this feature on the intervention platform, the fact the platform required users to search by name for a mate without knowing who else was on the platform, a reluctance to befriend individuals online when they are not "real-life" friends, and the limited number of participants on the website (n=205) compared to other online social networking sites (eg, Twitter, Facebook). The study did not assess if participants knew the identity of other participants also enrolled in the study. These issues should be considered in the design of future interventions seeking to implement a social support/interaction feature. Some of these restrictions were imposed to preserve the integrity of the RCT design, which poses interesting design issues for future studies seeking to evaluate the effectiveness of social interaction within RCT designs. These issues include how to foster online social interaction between individuals who do not know one another in real life, or allowing study participant's real-life friends to use the platform and maintain the integrity of the trial.

The ManUp challenges allowed participants to select from a range of different challenges that varied in the length of challenge and the amount of the behavior to be performed, and analysis of the challenges selected by participants revealed some interesting results. Figure 5 shows that light-strength challenges were the most frequently initiated challenges for both physical activity and dietary behaviors. This may be a function of participants seeking to try a new activity or dietary change to build confidence in their ability to change before committing to longer-term change [25]. This aligns with behavior change theory, which indicates that successfully completing a task is useful in building confidence to complete subsequent tasks [30]. For the physical activity challenges, participant data indicated that some users selected a variety of different challenge activities, which may be one way users sought to introduce variety to their physical activity regime to maintain interest over a longer time period. The most frequently completed challenge was walking; this is interesting because it has been suggested that walking does not appeal to males in this age range [62]. Yet this does not seem to be the case in the current study, nor does it appear to be mirror broader data for Australian males that indicate walking is the most popular recreational activity engaged in [33]. Figure 7 shows the number of each healthy eating goal completed by challenge strength. The higher number of full-strength goals completed reflects the longer duration and higher number of goals required for this challenge strength. Fast food-, alcohol-, and soft drink-free days and consuming 2 pieces of fruit were the 4 most frequently completed goals overall, which partly aligns with the objective of the healthy eating challenges to incorporate positive changes to dietary habits to improve overall dietary quality. That no healthy eating challenges were completed indicates either poor compliance with implementing changes or that the way in which a challenge needed to be completed (specific number of goals over a specified time period) could be improved. ManUp challenges were designed to provide ready-made targets for males, yet some males expressed a desire to have greater flexibility in setting their own goals and recording progress in their preferred metric [61]. Adopting this approach may have increased the completion rate of the challenges.

Approximately three-quarters of participants in the IT-based arm owned a mobile phone that allowed them to access the Internet and, therefore, the mobile component of the intervention. This is higher than previous reports in Australia, and is likely to continue to increase as ownership of Internet-capable mobile devices continues to increase [63]. Yet only 21.8% of participants in the IT-based intervention who had access actually logged in to the mobile phone platform. The low-level usage of the mobile phone component may be related to its limited functionality. Limiting functionality was a conscious design decision to maximize potential use across a wide variety of mobile phones, including some older mobile phones that did not allow the navigation and functionality of newer smartphone devices. Interviews with intervention participants indicated that needing to be connected to the Internet to use the mobile app was a limiting factor for some users and this may have also contributed to the low usage [61]. Recent growth in and expected growth of smartphone sales and ownership, self-monitoring devices (ie, Fitbit, Jawbone), and willingness of some males to use smartphone technology [17,63,64] will allow future interventions to take advantage of the greater functionality offered by these devices including the ability to perform self-monitoring via installed apps without the device/app requiring an Internet connection.

Health literacy allows individuals to use and apply knowledge to process information and inform decisions concerning their health and is identified as a priority for males [13]. ManUp educational materials were designed to provide clear and concise information on the rationale for changing physical activity and dietary behaviors and how to achieve these changes consistent with formative research and behavior change theory [18,25,30]. Study outcomes show mixed support for the effectiveness of the materials to improve physical activity and nutritional literacy. Nutrition literacy remained unchanged throughout the study and may have been impacted by the moderately high level of nutritional literacy at baseline [42]. Dietary educational materials provided information on the amount and frequency that particular food groups should be eaten consistent with national guidelines and the benefits of consuming the particular food group and an overall healthy diet [25,34]. Although the nutritional literacy scale assessed some components addressed by educational materials (eg, required servings of fruit and vegetables, high-sugar foods contain a high number of kilojoules), other components were much broader (eg, how to prevent food poisoning from eggs, cost and weed control methods of organic farms). As such, the discrepancy between the educational materials provided in the intervention and the instrument used to assess nutritional literacy may have limited the ability to detect change in this construct. Alternatively, participants may not have read these educational materials or preferred a more prescriptive approach to the dietary information provided [61]. Baseline physical activity literacy was lower than previously reported, particularly regarding knowledge that blocks of a minimum of 10 minutes of activity are acceptable to improve health [65]. This was the only measure to significantly change over time with a significantly higher number of participants agreeing with this at 9 months (68.9%) compared to baseline (52.5%). Changes in the proportion of participants agreeing that moderate intensity physical activity can improve health were not statistically examined because more than 95% participants agreed with this statement at 9 months, which resulted in insufficient variability for the analysis to take place (Table 4). Although not statistically examined, this may be viewed as an improvement in one component of physical activity literacy. The significant between-group differences in the proportion of participants agreeing that vigorous intensity physical activity performed 3 times per week is essential for health and that 30 minutes of moderate intensity physical activity per day can improve health are likely because of differing levels between groups at baseline. The reasons for the baseline differences between intervention groups on the proportion who agreed that 30 minutes of moderate intensity physical activity per day can improve health are unknown, particularly because qualitative research indicates that males have a good knowledge of the volumes and frequencies of physical activity needed to improve health [18,66]. Based on these observations, the ManUp education materials may have been more effective at improving physical activity literacy of participants compared to nutritional literacy.

Males are acknowledged as a hard-to-reach population in the health behavior intervention literature and this is reflected in the low recruitment rate in this study (approximately 27 participants per month of recruitment). IT-based interventions frequently report low participant retention rates, and in this study the overall retention rate at 9 months was 49.2% with a lower retention rate in the IT-based group (46.8%) compared to the print-based group (54.2%, *P*=.24). Low retention rates in IT-based studies are an acknowledged issue and the level of retention in this study is comparable to previous intervention studies [67-70]; as such, the low retention rate may not be an issue specific to the target population. The low retention rate limited the number of observations available for analysis over time; however, analytic methods using all available data were employed to minimize the impact of this potential limitation. Consistent with study objectives to improve regular engagement in physical activity and healthy eating, the ManUp study did not focus on weight loss during recruitment which previous studies have promoted in their recruitment [47,48]. This may have contributed to lower than expected recruitment rates given the prevalence of overweight and obesity in males.

Because of logistical constraints, it was not possible to assess usage of the print-based materials and self-monitoring behavior of participants in this intervention arm. The lack of this usage data prohibits between-group comparisons of usage and behavior change, which may contribute to better understanding the relationship between platform usage and behavior change; this is a limitation of the study. Other limitations of the study include a reliance on self-report measures. Although a subsample of participants (n=91) were provided with accelerometers to objectively measure physical activity [25], poor participant compliance with measurement protocols resulted in too few participants providing valid data for meaningful analysis and these data are not reported in this paper. The usage rate of the mobile component and use and functionality aspects of the Mate feature are also limitations of the current study.

This study evaluated the effectiveness of an intervention delivered by IT- and print-based materials to promote self-monitoring of physical activity and dietary behaviors and health literacy of these behaviors. Although study outcomes show mixed support for the intervention to change health literacy, IT- and print-based modes were effective in improving physical activity and dietary behaviors in middle-aged males with no differences between delivery modes. This suggests both may be useful intervention delivery modes.

## Acknowledgments

Queensland Health provided funding to conduct this project and to develop all intervention materials. This manuscript was partially supported by the CQ University Health CRN.

## Conflicts of Interest

None declared.

## Multimedia Appendix 1

CONSORT-EHEALTH checklist V1.6.2 [71].

[PDF File (Adobe PDF File), 997KB - jmir_v16i6e136_app1.pdf ]

## References

1. Artinian NT, Fletcher GF, Mozaffarian D, Kris-Etherton P, Van Horn L, Lichtenstein AH, American Heart Association Prevention Committee of the Council on Cardiovascular Nursing. Interventions to promote physical activity and dietary lifestyle changes for cardiovascular risk factor reduction in adults: a scientific statement from the American Heart Association. Circulation 2010 Jul 27;122(4):406-441 [FREE Full text] [doi: 10.1161/CIR.0b013e3181e8edf1] [Medline: 20625115]
2. Australian Institute of Health and Welfare. Cardiovascular disease: Australian facts 2011. In: Cardiovascular Disease Series. Canberra: Australian Institute of Health and Welfare; 2011.

3. Australian Bureau of Statistics. 4364.0.55.001 - Australian Health Survey: First Results, 2011-12. Canberra: Australian Bureau of Statistics; 2012.
4. Vandelanotte C, Duncan MJ, Caperchione C, Hanley C, Mummery WK. Physical activity trends in Queensland (2002 to 2008): are women becoming more active than men? Aust N Z J Public Health 2010 Jun;34(3):248-254. [doi: 10.1111/j.1753-6405.2010.00521.x] [Medline: 20618264]
5. McNaughton SA, Ball K, Crawford D, Mishra GD. An index of diet and eating patterns is a valid measure of diet quality in an Australian population. J Nutr 2008 Jan;138(1):86-93 [FREE Full text] [Medline: 18156409]
6. Waters LA, Galichet B, Owen N, Eakin E. Who participates in physical activity intervention trials? J Phys Act Health 2011 Jan;8(1):85-103. [Medline: 21297189]
7. George ES, Kolt GS, Duncan MJ, Caperchione CM, Mummery WK, Vandelanotte C, et al. A review of the effectiveness of physical activity interventions for adult males. Sports Med 2012 Apr 1;42(4):281-300. [doi: 10.2165/11597220-000000000-00000] [Medline: 22350570]
8. Taylor PJ, Kolt GS, Vandelanotte C, Caperchione CM, Mummery WK, George ES, et al. A review of the nature and effectiveness of nutrition interventions in adult males--a guide for intervention strategies. Int J Behav Nutr Phys Act 2013;10:13 [FREE Full text] [doi: 10.1186/1479-5868-10-13] [Medline: 23360498]
9. Marmot M, Commission on Social Determinants of Health. Achieving health equity: from root causes to fair outcomes. Lancet 2007 Sep 29;370(9593):1153-1163. [doi: 10.1016/S0140-6736(07)61385-3] [Medline: 17905168]
10. Nutbeam D. The evolving concept of health literacy. Soc Sci Med 2008 Dec;67(12):2072-2078. [doi: 10.1016/j.socscimed.2008.09.050] [Medline: 18952344]
11. Australian Bureau of Statistics. Health Literacy, Australia. 4233.0. Canberra: Australian Bureau of Statistics; 2006.
12. Adams R, Piantadosi C, Ettridge K, Miller C, Wilson C, Tucker G, et al. Functional health literacy mediates the relationship between socio-economic status, perceptions and lifestyle behaviors related to cancer risk in an Australian population. Patient Educ Couns 2013 May;91(2):206-212. [doi: 10.1016/j.pec.2012.12.001] [Medline: 23276386]
13. Australian Government. National Male Health Policy: Building on the stengths of Australian males - healthy routines. Canberra: Department of Health and Aging; 2010.
14. Norman GJ, Zabinski MF, Adams MA, Rosenberg DE, Yaroch AL, Atienza AA. A review of eHealth interventions for physical activity and dietary behavior change. Am J Prev Med 2007 Oct;33(4):336-345 [FREE Full text] [doi: 10.1016/j.amepre.2007.05.007] [Medline: 17888860]
15. Vandelanotte C, Spathonis KM, Eakin EG, Owen N. Website-delivered physical activity interventions a review of the literature. Am J Prev Med 2007 Jul;33(1):54-64. [doi: 10.1016/j.amepre.2007.02.041] [Medline: 17572313]
16. Kohl LF, Crutzen R, de Vries NK. Online prevention aimed at lifestyle behaviors: a systematic review of reviews. J Med Internet Res 2013;15(7):e146 [FREE Full text] [doi: 10.2196/jmir.2665] [Medline: 23859884]
17. Vandelanotte C, Caperchione CM, Ellison M, George ES, Maeder A, Kolt GS, et al. What kinds of website and mobile phone-delivered physical activity and nutrition interventions do middle-aged men want? J Health Commun 2013;18(9):1070-1083. [doi: 10.1080/10810730.2013.768731] [Medline: 23647448]
18. Caperchione CM, Vandelanotte C, Kolt GS, Duncan M, Ellison M, George E, et al. What a man wants: understanding the challenges and motivations to physical activity participation and healthy eating in middle-aged Australian men. Am J Mens Health 2012 Nov;6(6):453-461. [doi: 10.1177/1557988312444718] [Medline: 22516565]
19. Morgan PJ, Lubans DR, Collins CE, Warren JM, Callister R. 12-month outcomes and process evaluation of the SHED-IT RCT: an internet-based weight loss program targeting men. Obesity (Silver Spring) 2011 Jan;19(1):142-151. [doi: 10.1038/oby.2010.119] [Medline: 20523304]
20. Webb TL, Joseph J, Yardley L, Michie S. Using the internet to promote health behavior change: a systematic review and meta-analysis of the impact of theoretical basis, use of behavior change techniques, and mode of delivery on efficacy. J Med Internet Res 2010;12(1):e4 [FREE Full text] [doi: 10.2196/jmir.1376] [Medline: 20164043]
21. Neve M, Morgan PJ, Jones PR, Collins CE. Effectiveness of web-based interventions in achieving weight loss and weight loss maintenance in overweight and obese adults: a systematic review with meta-analysis. Obes Rev 2010 Apr;11(4):306-321. [doi: 10.1111/j.1467-789X.2009.00646.x] [Medline: 19754633]
22. Davies C, Corry K, Van Itallie A, Vandelanotte C, Caperchione C, Mummery WK. Prospective associations between intervention components and website engagement in a publicly available physical activity website: the case of 10,000 Steps Australia. J Med Internet Res 2012;14(1):e4 [FREE Full text] [doi: 10.2196/jmir.1792] [Medline: 22260810]
23. Kirwan M, Duncan MJ, Vandelanotte C, Mummery WK. Using smartphone technology to monitor physical activity in the 10,000 Steps program: a matched case-control trial. J Med Internet Res 2012;14(2):e55 [FREE Full text] [doi: 10.2196/jmir.1950] [Medline: 22522112]
24. Donkin L, Hickie IB, Christensen H, Naismith SL, Neal B, Cockayne NL, et al. Rethinking the dose-response relationship between usage and outcome in an online intervention for depression: randomized controlled trial. J Med Internet Res 2013;15(10):e231 [FREE Full text] [doi: 10.2196/jmir.2771] [Medline: 24135213]
25. Duncan MJ, Vandelanotte C, Rosenkranz RR, Caperchione CM, Ding H, Ellison M, et al. Effectiveness of a website and mobile phone based physical activity and nutrition intervention for middle-aged males: trial protocol and baseline findings

of the ManUp Study. BMC Public Health 2012;12:656 [FREE Full text] [doi: 10.1186/1471-2458-12-656] [Medline: 22894747]

26. Marcus BH, Lewis BA, Williams DM, Dunsiger S, Jakicic JM, Whiteley JA, et al. A comparison of Internet and print-based physical activity interventions. Arch Intern Med 2007 May 14;167(9):944-949. [doi: 10.1001/archinte.167.9.944] [Medline: 17502536]
27. Short CE, James EL, Plotnikoff RC, Girgis A. Efficacy of tailored-print interventions to promote physical activity: a systematic review of randomised trials. Int J Behav Nutr Phys Act 2011;8:113 [FREE Full text] [doi: 10.1186/1479-5868-8-113] [Medline: 21999329]
28. Australian Government Department of Health and Ageing. Sports Medicine Australia pre-exercise screening system. 2009. URL: http://sma.org.au/wp-content/uploads/2009/05/new_pre_screening.pdf [accessed 2014-05-19] [WebCite Cache ID 6PgERyLFY]
29. Randomization.com. URL: http://www.randomization.com/ [accessed 2014-04-29] [WebCite Cache ID 6PCw090cd]
30. Bandura A. Social cognitive theory of self-regulation. Organizational Behavior and Human Decision Processes 1991 Dec;50(2):248-287. [doi: 10.1016/0749-5978(91)90022-L]
31. Maes S, Karoly P. Self-regulation assessment and intervention in physical health and illness: A review. Applied Psychology 2005 Apr;54(2):267-299. [doi: 10.1111/j.1464-0597.2005.00210.x]
32. Bandura A. The primacy of self-regulation in health promotion. Applied Psychology 2005 Apr;54(2):245-254. [doi: 10.1111/j.1464-0597.2005.00208.x]
33. Australian Bureau of Statistics. Participation in Sport and Physical Recreation: 4177.0. Canberra: Australian Bureau of Statistics; 2010.
34. National Health & Medical Research Council. Dietary Guidelines for Australian Adults. Canberra: National Health & Medical Research Council; 2003.
35. WHO Consultation on Obesity. Obesity: preventing and managing the global epidemic. Report of a WHO consultation. World Health Organ Tech Rep Ser 2000;894:i-xii, 1. [Medline: 11234459]
36. Australian Institute of Health and Welfare (AIHW). The Active Australia Survey: A Guide and Manual for Implementation, Analysis and Reporting. Canberra: Australian Institute of Health and Welfare; 2003.
37. Brown W, Bauman A, Chey T, Trost S, Mummery K. Comparison of surveys used to measure physical activity. Aust N Z J Public Health 2004 Apr;28(2):128-134. [Medline: 15233351]
38. Brown WJ, Trost SG, Bauman A, Mummery K, Owen N. Test-retest reliability of four physical activity measures used in population surveys. J Sci Med Sport 2004 Jun;7(2):205-215. [Medline: 15362316]
39. Reeves MM, Marshall AL, Owen N, Winkler EA, Eakin EG. Measuring physical activity change in broad-reach intervention trials. J Phys Act Health 2010 Mar;7(2):194-202. [Medline: 20484758]
40. Marks G, Webb K, Rutishauser IHE, Riley M. Monitoring Food Habits in the Australian Population Using Short Questions. Canberra: Ausinfo; 2001.
41. Australian Bureau of Statistics. National Health Survey Questionnaire. Canberra: Australian Bureau of Statistics; 2005.
42. Diamond JJ. Development of a reliable and construct valid measure of nutritional literacy in adults. Nutr J 2007;6:5 [FREE Full text] [doi: 10.1186/1475-2891-6-5] [Medline: 17300716]
43. Wittes J. Sample size calculations for randomized controlled trials. Epidemiol Rev 2002;24(1):39-53 [FREE Full text] [Medline: 12119854]
44. Eysenbach G. The law of attrition. J Med Internet Res 2005;7(1):e11 [FREE Full text] [doi: 10.2196/jmir.7.1.e11] [Medline: 15829473]
45. Brindal E, Freyne J, Saunders I, Berkovsky S, Smith G, Noakes M. Features predicting weight loss in overweight or obese participants in a web-based intervention: randomized trial. J Med Internet Res 2012;14(6):e173 [FREE Full text] [doi: 10.2196/jmir.2156] [Medline: 23234759]
46. Leahey TM, Crane MM, Pinto AM, Weinberg B, Kumar R, Wing RR. Effect of teammates on changes in physical activity in a statewide campaign. Prev Med 2010 Jul;51(1):45-49 [FREE Full text] [doi: 10.1016/j.ypmed.2010.04.004] [Medline: 20394768]
47. Morgan PJ, Lubans DR, Collins CE, Warren JM, Callister R. The SHED-IT randomized controlled trial: evaluation of an Internet-based weight-loss program for men. Obesity (Silver Spring) 2009 Nov;17(11):2025-2032. [doi: 10.1038/oby.2009.85] [Medline: 19343018]
48. Morgan PJ, Collins CE, Plotnikoff RC, Cook AT, Berthon B, Mitchell S, et al. Efficacy of a workplace-based weight loss program for overweight male shift workers: the Workplace POWER (Preventing Obesity Without Eating like a Rabbit) randomized controlled trial. Prev Med 2011 May;52(5):317-325. [doi: 10.1016/j.ypmed.2011.01.031] [Medline: 21300083]
49. Maruyama C, Kimura M, Okumura H, Hayashi K, Arao T. Effect of a worksite-based intervention program on metabolic parameters in middle-aged male white-collar workers: a randomized controlled trial. Prev Med 2010 Jul;51(1):11-17. [doi: 10.1016/j.ypmed.2010.04.008] [Medline: 20403374]
50. Parekh S, Vandelanotte C, King D, Boyle FM. Improving diet, physical activity and other lifestyle behaviours using computer-tailored advice in general practice: a randomised controlled trial. Int J Behav Nutr Phys Act 2012;9:108 [FREE Full text] [doi: 10.1186/1479-5868-9-108] [Medline: 22963354]

51. King AC, Castro CM, Buman MP, Hekler EB, Urizar GG, Ahn DK. Behavioral impacts of sequentially versus simultaneously delivered dietary plus physical activity interventions: the CALM trial. Ann Behav Med 2013 Oct;46(2):157-168. [doi: 10.1007/s12160-013-9501-y] [Medline: 23609341]
52. Hyman DJ, Pavlik VN, Taylor WC, Goodrick GK, Moye L. Simultaneous vs sequential counseling for multiple behavior change. Arch Intern Med 2007 Jun 11;167(11):1152-1158. [doi: 10.1001/archinte.167.11.1152] [Medline: 17563023]
53. Davies CA, Spence JC, Vandelanotte C, Caperchione CM, Mummery WK. Meta-analysis of internet-delivered interventions to increase physical activity levels. Int J Behav Nutr Phys Act 2012;9:52 [FREE Full text] [doi: 10.1186/1479-5868-9-52] [Medline: 22546283]
54. Glasgow R, Christiansen SM, Kurz D, King DK, Woolley T, Faber AJ, et al. Engagement in a diabetes self-management website: usage patterns and generalizability of program use. J Med Internet Res 2011;13(1):e9 [FREE Full text] [doi: 10.2196/jmir.1391] [Medline: 21371992]
55. Funk KL, Stevens VJ, Appel LJ, Bauck A, Brantley PJ, Champagne CM, et al. Associations of internet website use with weight change in a long-term weight loss maintenance program. J Med Internet Res 2010;12(3):e29 [FREE Full text] [doi: 10.2196/jmir.1504] [Medline: 20663751]
56. Vandelanotte C, De Bourdeaudhuij I, Brug J. Two-year follow-up of sequential and simultaneous interactive computer-tailored interventions for increasing physical activity and decreasing fat intake. Ann Behav Med 2007 Apr;33(2):213-219. [doi: 10.1080/08836610701310086] [Medline: 17447874]
57. Spittaels H, De Bourdeaudhuij I, Vandelanotte C. Evaluation of a website-delivered computer-tailored intervention for increasing physical activity in the general population. Prev Med 2007 Mar;44(3):209-217. [doi: 10.1016/j.ypmed.2006.11.010] [Medline: 17197015]
58. Kolt G, Rosenkranz RR, Savage TN, Maeder AJ, Vandelanotte C, Duncan MJ, et al. WALK 2.0 - using Web 2.0 applications to promote health-related physical activity: a randomised controlled trial protocol. BMC Public Health 2013;13:436 [FREE Full text] [doi: 10.1186/1471-2458-13-436] [Medline: 23642010]
59. Grandes G, Sanchez A, Montoya I, Ortega Sanchez-Pinilla R, Torcal J, PEPAF Group. Two-year longitudinal analysis of a cluster randomized trial of physical activity promotion by general practitioners. PLoS One 2011;6(3):e18363 [FREE Full text] [doi: 10.1371/journal.pone.0018363] [Medline: 21479243]
60. Scholz U, Ochsner S, Luszczynska A. Comparing different boosters of planning interventions on changes in fat consumption in overweight and obese individuals: a randomized controlled trial. Int J Psychol 2013;48(4):604-615. [doi: 10.1080/00207594.2012.661061] [Medline: 22519565]
61. Short CE, Vandelanotte C, Dixon MW, Rosenkranz R, Caperchione C, Hooker C, et al. Examining participant engagement in an information technology-based physical activity and nutrition intervention for men: the manup randomized controlled trial. JMIR Res Protoc 2014;3(1):e2 [FREE Full text] [doi: 10.2196/resprot.2776] [Medline: 24389361]
62. Burton NW, Walsh A, Brown WJ. It just doesn't speak to me: mid-aged men's reactions to '10,000 Steps a Day'. Health Promot J Austr 2008 Apr;19(1):52-59. [Medline: 18481933]
63. Australian Communications Media Authority. Report 3-Smartphones and tablets: Take-up and use in Australia. Canberra: Australian Communications and Media Authority; 2013.
64. Walker S. IHS Electronics & Media. In: Wearable Technology - World - 2013. United States: IHS Electronics & Media; 2013.
65. Armstrong T, Bauman A, Davies J. Physical activity patterns of Australian adults: Results of the 1999 National Physical Activity Survey. Canberra: Australian Institute of Health and Welfare; 2000.
66. George E, Kolt GS, Rosenkranz RR, Guagliano JM. Physical activity and sedentary time: male perceptions in a university work environment. Am J Mens Health 2014 Mar;8(2):148-158. [doi: 10.1177/1557988313497217] [Medline: 23966228]
67. Buis LR, Poulton TA, Holleman RG, Sen A, Resnick PJ, Goodrich DE, et al. Evaluating Active U: an Internet-mediated physical activity program. BMC Public Health 2009;9:331 [FREE Full text] [doi: 10.1186/1471-2458-9-331] [Medline: 19744311]
68. Kosma M, Cardinal BJ, McCubbin JA. A pilot study of a web-based physical activity motivational program for adults with physical disabilities. Disabil Rehabil 2005 Dec 15;27(23):1435-1442. [doi: 10.1080/09638280500242713] [Medline: 16418058]
69. Carr LJ, Bartee RT, Dorozynski C, Broomfield JF, Smith ML, Smith DT. Internet-delivered behavior change program increases physical activity and improves cardiometabolic disease risk factors in sedentary adults: results of a randomized controlled trial. Prev Med 2008 May;46(5):431-438. [doi: 10.1016/j.ypmed.2007.12.005] [Medline: 18207228]
70. McConnon A, Kirk SF, Cockroft JE, Harvey EL, Greenwood DC, Thomas JD, et al. The Internet for weight control in an obese sample: results of a randomised controlled trial. BMC Health Serv Res 2007;7:206 [FREE Full text] [doi: 10.1186/1472-6963-7-206] [Medline: 18093289]
71. Eysenbach G, CONSORT-EHEALTH Group. CONSORT-EHEALTH: improving and standardizing evaluation reports of Web-based and mobile health interventions. J Med Internet Res 2011;13(4):e126 [FREE Full text] [doi: 10.2196/jmir.1923] [Medline: 22209829]

## Abbreviations

**BMI:** body mass index
**BOCF:** baseline observation carried forward
**exp(β):** exponentiated coefficient
**IT:** information technology
**RCT:** randomized controlled trial
**URL:** uniform resource locator
**TAFE:** Technical and further education

*Edited by G Eysenbach; submitted 20.11.13; peer-reviewed by J Kolodziejczyk, D Schoffman, T Myllymaki, E Stolte; comments to author 16.12.13; revised version received 10.02.14; accepted 09.04.14; published 12.06.14.*

*Please cite as:*
*Duncan M, Vandelanotte C, Kolt GS, Rosenkranz RR, Caperchione CM, George ES, Ding H, Hooker C, Karunanithi M, Maeder AJ, Noakes M, Tague R, Taylor P, Viljoen P, Mummery WK*
*Effectiveness of a Web- and Mobile Phone-Based Intervention to Promote Physical Activity and Healthy Eating in Middle-Aged Males: Randomized Controlled Trial of the ManUp Study*
*J Med Internet Res 2014;16(6):e136*
*URL: http://www.jmir.org/2014/6/e136/*
*doi:10.2196/jmir.3107*
*PMID:24927299*

Review

# Online Social Networks That Connect Users to Physical Activity Partners: A Review and Descriptive Analysis

Atul Nakhasi[1*], BA; Album Xiaotian Shen[2*], BS; Ralph Joseph Passarella[1], BS; Lawrence J Appel[1], MD, MPH; Cheryl AM Anderson[3], MPH, MS, PhD

[1]School of Medicine, Johns Hopkins University, Baltimore, MD, United States

[2]Johns Hopkins University, Baltimore, MD, United States

[3]School of Medicine, Department of Family and Preventive Medicine, University of California, San Diego, La Jolla, CA, United States

[*]these authors contributed equally

**Corresponding Author:**
Cheryl AM Anderson, MPH, MS, PhD
School of Medicine
Department of Family and Preventive Medicine
University of California, San Diego
9500 Gilman Drive
MC-0725
La Jolla, CA, 92093
United States
Phone: 1 8585344456
Fax: 1 8585344456
Email: c1anderson@ucsd.edu

## Abstract

**Background:** The US Centers for Disease Control and Prevention have identified a lack of encouragement, support, or companionship from family and friends as a major barrier to physical activity. To overcome this barrier, online social networks are now actively leveraging principles of companion social support in novel ways.

**Objective:** The aim was to evaluate the functionality, features, and usability of existing online social networks which seek to increase physical activity and fitness among users by connecting them to physical activity partners, not just online, but also face-to-face.

**Methods:** In September 2012, we used 3 major databases to identify the website addresses for relevant online social networks. We conducted a Google search using 8 unique keyword combinations: the common keyword "find" coupled with 1 of 4 prefix terms "health," "fitness," "workout," or "physical" coupled with 1 of 2 stem terms "activity partners" or "activity buddies." We also searched 2 prominent technology start-up news sites, TechCrunch and Y Combinator, using 2 unique keyword combinations: the common keyword "find" coupled with 1 of 2 stem terms "activity partners" and "activity buddies." Sites were defined as online social health activity networks if they had the ability to (1) actively find physical activity partners or activities for the user, (2) offer dynamic, real-time tracking or sharing of social activities, and (3) provide virtual profiles to users. We excluded from our analysis sites that were not Web-based, publicly available, in English, or free.

**Results:** Of the 360 initial search results, we identified 13 websites that met our complete criteria of an online social health activity network. Features such as physical activity creation (13/13, 100%) and private messaging (12/13, 92%) appeared almost universally among these websites. However, integration with Web 2.0 technologies such as Facebook and Twitter (9/13, 69%) and the option of direct event joining (8/13, 62%) were not as universally present. Largely absent were more sophisticated features that would enable greater usability, such as interactive engagement prompts (3/13, 23%) and system-created best fit activities (3/13, 23%).

**Conclusions:** Several major online social networks that connect users to physical activity partners currently exist and use standardized features to achieve their goals. Future research is needed to better understand how users utilize these features and how helpful they truly are.

***(J Med Internet Res 2014;16(6):e153)*** doi:10.2196/jmir.2674

**KEYWORDS**

behavior; behavior control; behavioral research; exercise; health; health behavior; information services; Internet; intervention studies; online systems; physical fitness; social media; social medicine; social networking; social support; telemedicine; Web

## Introduction

In 2006, it was estimated that direct medical costs in the United States because of a lack of physical activity totaled more than $188 billion annually [1]. The US Centers for Disease Control and Prevention (CDC) have identified a lack of encouragement, support, or companionship from family and friends as a major barrier to physical activity [2]. Online social networks are now actively leveraging principles of companion social support in novel ways to overcome this barrier. For example, services that facilitate step-count sharing between friends and allow users to engage in fitness challenges with one another by sharing workout routines have recently emerged [3]. Users have embraced physical activity social networks, such as Fitocracy, Spark People, and Run Keeper, which currently have an estimated 1 million, 15 million, and 23 million users, respectively [4-6].

With the boom of online social networks focused on physical activity, new sites that directly connect individuals to physical activity partners have emerged. The social support provided through the discussion forums of these networks and the ability to connect with users online likely increases physical activity; the existing literature supports that having one friend to exercise with increases the likelihood of doing so by 45% [7]. As the industry for online physical activity social networks grows, it would be helpful to characterize existing networks and examine approaches taken by sites to leverage social support to increase physical activity engagement.

As a first step toward understanding the potential that online social networks have to increase physical activity and in an effort to inform the development of future networks, we aim to (1) describe established and emerging social networks that connect users to physical activity partners face-to-face, and (2) describe the functionality, features, and usability of these networks.

## Methods

### Identification of Established and Emerging Social Health Activity Networks

To identify the established and emerging social health activity networks, we searched 3 major databases: the Google search engine and 2 start-up news sites, TechCrunch [8] and Y Combinator [9]. TechCrunch and Y Combinator comprehensively cover online social networks, and these 3 sites were selected with the expectation that they covered social networks with sufficient popularity and exposure. Initially, we identified established networks using a Google search for the top 30 results from use of the common keyword “find” coupled with 1 of 4 different prefix terms “health,” “fitness,” “workout,” or “physical” coupled with 1 of 2 different stem terms “activity partners” or “activity buddies” (ie, “find health activity partners”). This produced 8 key phrase permutations with 30 results for each to give a total of 240 results.

Next, we identified emerging networks by searching TechCrunch and Y Combinator for the top 30 results from use of the common keyword “find” with the 2 stem terms “activity partners” and “activity buddies.” Prefix terms were excluded from the search to create a broader key phrase terminology with increased sensitivity to capturing emerging sites on TechCrunch and Y Combinator. This gave 2 key phrase permutations with 30 results for each of 2 start-up sites for a total 120 results. Together the searches produced a final list of 360 sites. Searches were conducted in September 2012.

For our review, we defined a “physical activity partner” as an individual who engages in physical activities offline with another user. Sites were defined as physical activity partner social networks if they had the ability to (1) actively find physical activity partners or activities for the user, (2) offer dynamic, real-time tracking or sharing of social activities, and (3) provide virtual profiles to users. We excluded from our analysis sites that were not Web-based, publicly available, in English, or free. Additionally, sites or applications that were mobile only or lacked a social network facet were excluded. The searches and determination of eligibility were conducted by 3 individuals (authors AN, AS, and RP) by using personal computers. Any discrepancies or conflicting opinions were brought before the group to reach a consensus.

### Analysis

We accessed and used each physical activity partner network to analyze site functionality and usability. A total of 12 key features (see Table 1 for descriptions of each feature) were assessed using a binomial scale (1=site has feature; 0=site does not have feature) for each site. Because there was sparse existing literature on which specific social network features would have an impact on physical activity, we looked to the existing sites themselves to determine which features were being used, developed, and incorporated into these sites with the goal of connecting physical activity partners to determine which features were important to analyze and characterize. Assessed features were placed into 1 of 3 categories: communication, activity optimization, and sophistication. Categories were picked to represent domains that would influence change in physical activity behaviors. The communication category broadly represented networks with features such as messaging, chat, or user updates. More specifically, this category included (1) ability to input or update status, (2) group creation, (3) private messaging, and (4) real-time messaging. The activity optimization category broadly represented networks with features allowing for tailoring of variables important in doing physical activity. This category included (1) ability to create activities, (2) activity creation customization, and (3) ability to directly confirm or join activities. The sophistication category broadly represented networks with advanced features that enhance user experience, interactivity, and value. This category included (1) exclusivity to physical activity, (2) filtering preferences, (3) interactive engagement prompts, (4) site-suggested recommendations for best fit activities, and (5) Web 2.0 technology integration (ie, with sites such as Facebook and Twitter).

**Table 1.** Description of key features and categories.

| Category/feature name | Description |
|---|---|
| **Activity optimization** | Features that focus on the specifications of physical activity events that users can create or participate in |
| Ability to create event | The website enables users to post or generate a new physical activity event |
| Activity creation customization | Meets at least 5 of 9 predetermined variables relating to the user's ability to customize activity creation: (1) the ability to customize according to specific activity type (eg, basketball), (2) time or day of event, (3) location, (4) event privatization, (5) invitation of individual participants, (6) invitation of groups, (7) skill level of participants, (8) maximum number of participants, and (9) the provision of a free response text box for further event information |
| Direct ability to join event | Users may view physical activity events and have the option of selecting which events they intend on participating |
| **Communication** | Features that promote interactions between users |
| Ability to input/update status | Users can submit text or media-based entries to describe their recent progress or activities |
| Group creation | Users are able to create groups of common interest and have interactions within the group visible to all members of the group |
| Private messaging of users | The website provides direct one-on-one messaging of users visible only to the users involved |
| Real-time messaging (chat) of users | The website provides instant messaging for users to communicate directly with one another |
| **Sophistication** | Advanced features that support functionality of the site and are in place to lessen user burden connecting to the site and the physical activities offered |
| Exclusivity to physical activity | The website has a singular focus on physical activities and does not specialize in connecting users based on nonphysical activities |
| Filtering preferences | Meets at least 3 of 5 predetermined variables relating to the user's ability to filter activities: (1) specific activity type, (2) user availability, (3) location, (4) user skill level, and (5) keyword |
| Interactive engagement prompts | The website interacts with users through prompts such as questions about their physical activity interests or availability with the goal of connecting them to new activities |
| Site-suggested best fit activities | The website offers activity recommendations for users based on previous site activity and collected user data |
| Web 2.0 technology integration | The website has some connectivity involved with other social media sites, such as Facebook and Twitter |

Of the 12 features, 3 were placed in the communication category, 4 were placed in the activity optimization category, and 5 were placed in the sophistication category. Of note, for the "activity creation customization" feature, a score of 1 was given if the site included at least 5 of 9 predetermined variables relating to the user's ability to customize activity creation. The 9 predetermined variables were (1) the ability to customize according to specific activity type (eg basketball), (2) time or day of event, (3) location, (4) event privatization, (5) invitation of individual participants, (6) invitation of groups, (7) skill level of participants, (8) maximum number of participants, and (9) the provision of a free response text box for further event information. Additionally, for the "filtering preferences" feature, a score of 1 was given if the site included at least 3 of 5 predetermined variables relating to the user's ability to filter activities. The 5 predetermined variables were (1) specific activity type, (2) user availability, (3) location, (4) user skill, and (5) keyword. The features were reviewed by 3 individuals (coauthors AN, AS, and RP) using individual personal computers. Each reviewer created an online account on each site and searched the site for the features of interest. All discrepancies among the reviewers were discussed until consensus was reached.

Examples for some websites meeting the requirements for such features are represented in figures as follows. Sponduu meets the criteria for the ability to create event as well as activity creation customization by allowing users to create events and customize them with parameters that include activity type, skill level, title, free response text for description, date and time, location, event privatization, and invitation of individual participants (Figure 1). FitTogether offers group creation by allowing users to create groups that share photo albums, videos, events, and discussion visible to its users (Figure 2). CribSocial meets the filtering preferences criteria by allowing users to search for activities and filter by keyword, activity type, location, and number of participants (Figure 3). RunKeeper exhibits Web 2.0 technology integration by allowing users to sign up and sign in using their Facebook or Google accounts (Figure 4). Fitocracy offers interactive engagement prompts by asking the user for information regarding their interests in fitness, and recommends friends, groups, and activities that are relevant to their selected interests (Figure 5).

**Figure 1.** Sponduu: Ability to create event and activity creation customization.

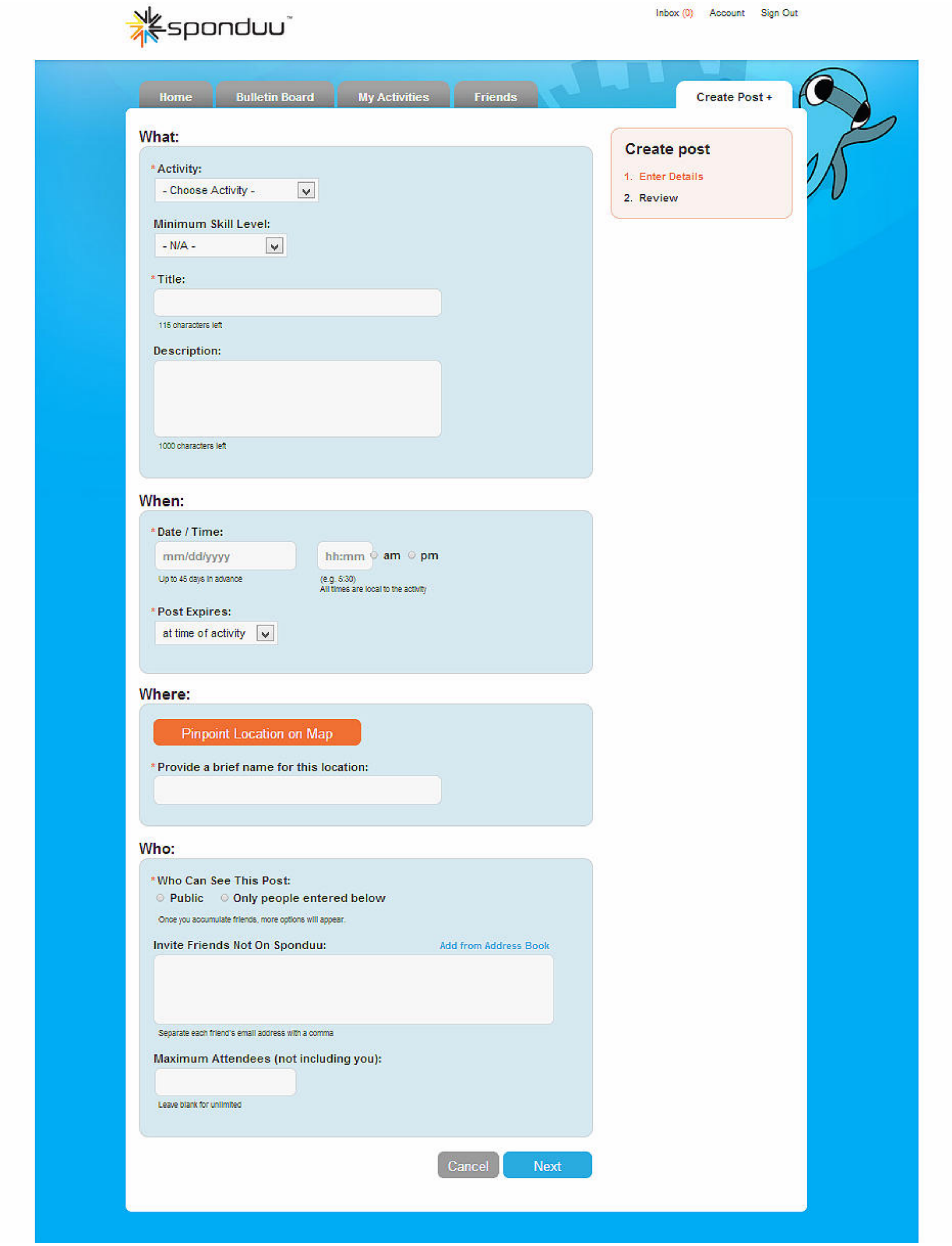


**Figure 2.** FitTogether: Group creation.

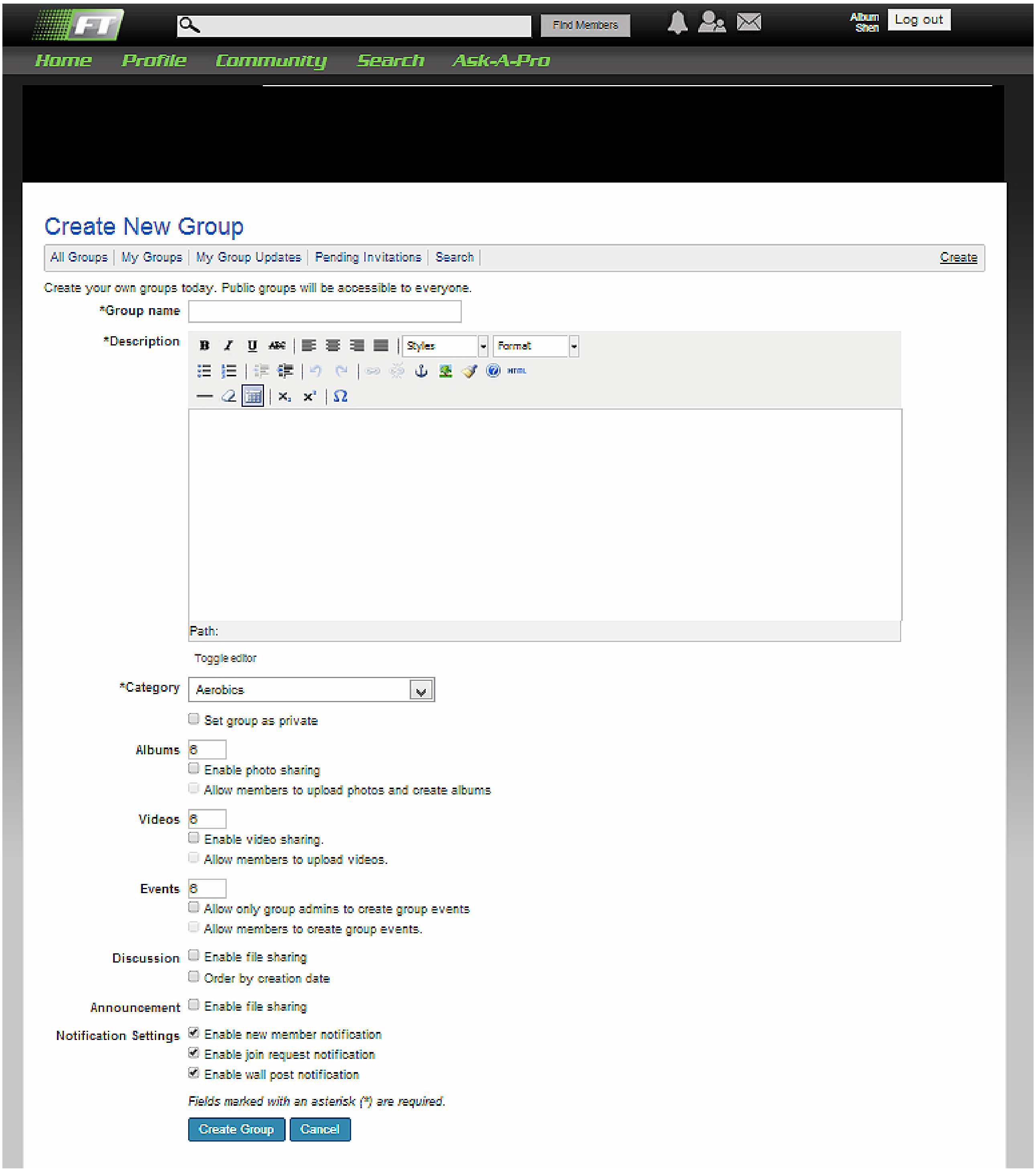


**Figure 3.** CribSocial: Filtering preferences.

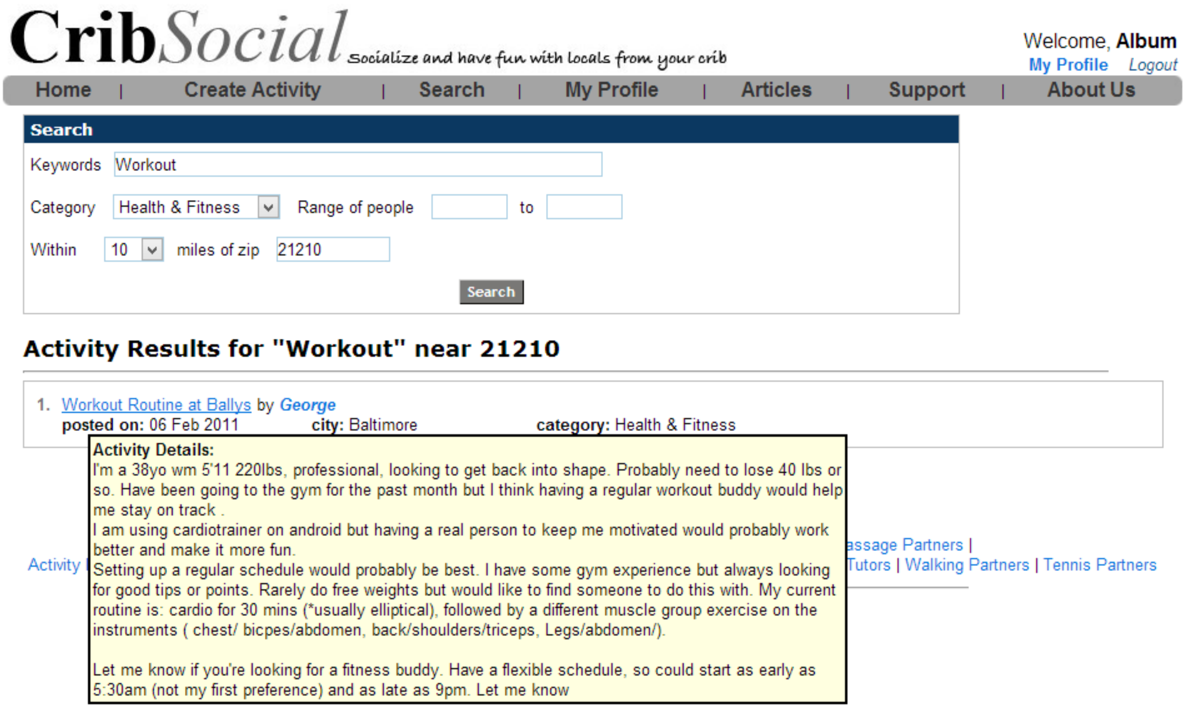
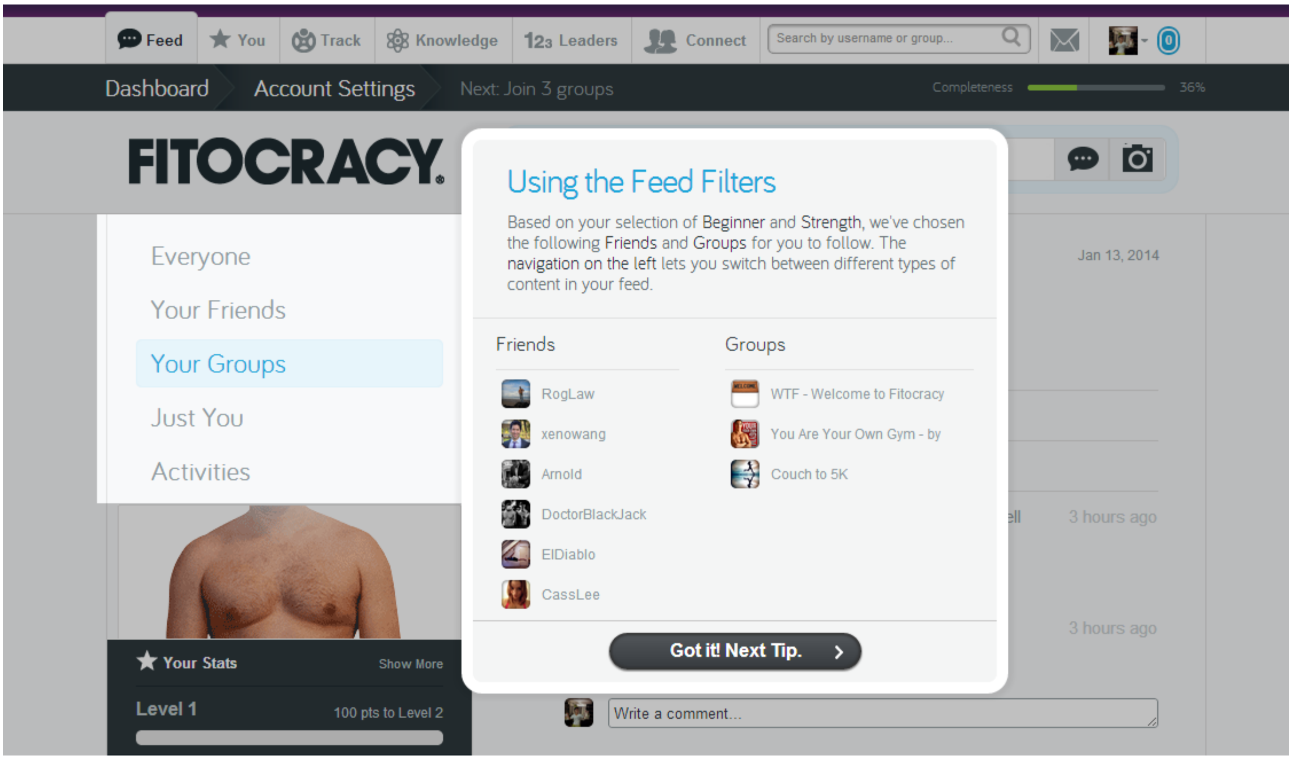


**Figure 4.** RunKeeper: Web 2.0 technology integration.


**Figure 5.** Fitocracy: Interactive engagement prompts.



## Results

### Web Ranking

Of the 360 initial search results, we identified 13 established or emerging online social networks focused on physical activity. We arrived at these 13 sites after narrowing the search results by excluding results that were not social networks, that were repetitive or overlapping, or that were social networks but did not meet the criteria defined in our methods. The main characteristics of these websites are shown in Table 2, including the website name, worldwide website rank according to Alexa [10], and whether the site is established or emerging. The Web ranking measures a site's popularity based on website traffic data; the lower the number, the higher the Web ranking and popularity. In 2012, the networks with the highest Web rankings were SparkPeople (2420), RunKeeper (5493), and Fitocracy (26,490).

**Table 2.** Description of websites for online social networks that connect users to physical activity partners.

| Website name | 2012 Web rank | Web presence |
|---|---|---|
| activity8 [11] | n/a | Emerging (beta) |
| BuddyUp [12] | 3,138,866 | Established |
| CribSocial [13] | 1,246,680 | Established |
| ExerciseFriends [14] | 1,040,377 | Established |
| Fitocracy [15] | 26,490 | Established |
| FitTogether [16] | 358,988 | Established |
| Friendeavor [17] | 13,324,867 | Established |
| Meet in Real Life [18] | 5,556,996 | Established |
| RunKeeper [19] | 5493 | Established |
| SparkPeople [5] | 2420 | Established |
| Sponduu [20] | 12,274,504 | Established |
| The Activity Partner [21] | 15,847,153 | Established |
| ZoomPal [22] | 2,258,515 | Emerging (beta) |

### Distribution and Frequency of Features

Table 3 shows the frequencies of 12 key features across the networks, by whether they were prevalent (80%-100%), common (50%-79%), or rare (0-49%). These features are placed into 3 categories: communication, activity optimization, and sophistication. Features that appeared almost universally among these sites included the ability to create events (13/13, 100%), and private messaging (12/13, 92%). Common features among the sites were integration with Web 2.0 technologies, such as Facebook and Twitter (9/13, 69%), direct joining of activities (8/13, 62%), and group creation (8/13, 62%). Finally, highly sophisticated features were generally rare and often lacking on sites, such as filtering preferences (2/13, 15%), site-suggested best fit activities (3/13, 23%), and interactive engagement prompts that solicit user interaction (3/13, 23%).

Tables 4 and 5 display each of the 12 features (rows) for the 13 websites (columns) surveyed, along with the percent of features included in each website overall. The percentage of features that each website offered ranged from 25% to 75%. On average, the 13 social networks had 6.08 (SD 2.00) or 47% of 12 features assessed. The 2 social networks with the greatest percentage of the listed features were FitTogether and Fitocracy, each with 75% (9/12 features). Two other social networks, Sponduu and SparkPeople, had 58% or 7 of 12 features.

Among all sites, the activity optimization features category was best represented. On average, the sites included 67% (2/3) of the activity optimization category features, followed by 44% (1.77/4) of communication category features, and 37% (1.85/5) of sophistication category features.

**Table 3.** Features of online social networks categorized according to frequency (prevalent, common, or rare; N=13).

| Frequency | Category | Frequency of feature among sites, n (%) |
|---|---|---|
| **Prevalent (80%-100%)** | | |
| Ability to create event | Activity optimization | 13 (100) |
| Private messaging of users | Communication | 12 (92) |
| **Common (50%-79%)** | | |
| Web 2.0 technology integration | Sophistication | 9 (69 |
| Direct ability to join event | Activity optimization | 8 (62) |
| Exclusivity to physical activity | Sophistication | 7 (54) |
| **Rare (0-49%)** | | |
| Group creation | Communication | 6 (46) |
| Activity creation customization | Activity optimization | 5 (38) |
| Ability to input/update status | Communication | 4 (31) |
| Interactive engagement prompts | Sophistication | 3 (23) |
| Site-suggested best fit activities | Sophistication | 3 (23) |
| Filtering preferences | Sophistication | 2 (15) |
| Real-time messaging (chat) of users | Communication | 1 (8) |

**Table 4.** Features of online social networks that connect users to physical activity partners (A-F).

| Feature | activity8 | BuddyUp | CribSocial | Exercise Friends | Fitocracy | Fit Together | Friendeavor |
|---|---|---|---|---|---|---|---|
| **Activity optimization** | | | | | | | |
| Ability to create event | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Activity creation customization | No | No | Yes | No | Yes | Yes | No |
| Direct ability to join event | No | Yes | Yes | No | Yes | Yes | Yes |
| **Communication** | | | | | | | |
| Ability to input/update status | Yes | No | No | No | Yes | No | Yes |
| Group creation | No | Yes | No | Yes | Yes | No | Yes |
| Private messaging of users | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Real-time messaging (chat) of users | No | No | No | No | Yes | No | No |
| **Sophistication** | | | | | | | |
| Exclusivity to physical activity | Yes | Yes | No | Yes | Yes | No | Yes |
| Filtering preferences | No | No | Yes | No | No | No | No |
| Interactive engagement prompts | No | No | No | No | No | No | Yes |
| Site-suggested best fit activities | No | No | No | No | No | No | Yes |
| Web 2.0 technology integration | Yes | No | Yes | No | Yes | No | Yes |
| % of Features | 41% | 41% | 50% | 33% | 75% | 33% | 75% |

**Table 5.** Features of online social networks that connect users to physical activity partners (M-Z).

| Feature | MIRL | RunKeeper | SparkPeople | Sponduu | TheActivity Partner | ZoomPal |
|---|---|---|---|---|---|---|
| **Activity optimization** | | | | | | |
| Ability to create event | Yes | Yes | Yes | Yes | Yes | Yes |
| Activity creation customization | No | No | Yes | No | No | Yes |
| Direct ability to join event | No | Yes | Yes | No | No | Yes |
| **Communication** | | | | | | |
| Ability to input/update status | Yes | No | No | No | No | No |
| Group creation | No | No | Yes | Yes | No | No |
| Private messaging of users | Yes | Yes | Yes | Yes | Yes | No |
| Real-time messaging (chat) of users | No | No | No | No | No | No |
| **Sophistication** | | | | | | |
| Exclusivity to physical activity | No | Yes | No | No | No | Yes |
| Filtering preferences | No | No | Yes | No | No | No |
| Interactive engagement prompts | No | Yes | No | No | No | Yes |
| Site-suggested best fit activities | No | Yes | No | No | Yes | No |
| Web 2.0 technology integration | Yes | Yes | Yes | No | Yes | Yes |
| % of Features | 33% | 58% | 58% | 25% | 33% | 50% |

## Discussion

### Principal Findings

In our investigation of 13 online physical activity social networks that connect users both online and face-to-face, we found that only half of these social networks contained more than 6 (50%) of the 12 distinct features we evaluated. Features related to activity optimization and communication were the most common among the social networks, whereas features related to sophistication were less common.

Today, more than ever, individuals are looking for easily accessible, low-cost, online technologies to address their health needs [23]. Currently, no particular website offers strong capabilities across the board in the areas of communication, activity optimization, and sophistication. This limits the extent to which these technologies may be successful in engaging individuals and, just as importantly, in fostering their behavior change.

Depending on the needs of individuals, particular sites may be of greater utility. SparkPeople and Fitocracy were the most sophisticated options and would suit individuals with low motivation levels who require a reduced-burden site and a more user-friendly experience. Although motivation and user-friendliness were not quantified in this analysis, the increased interactivity of these services might reflect users' perceived effectiveness and value of the service [24]. A recent study tracked 1258 users of SparkPeople and found that those who were more active on the site (ie, by posting comments and messages to other users) saw the most significant weight loss outcomes [25]. For individuals with very specific activity needs, Sponduu offers the most tailored ability to optimize physical activity preferences by allowing users to create activities and customize them by using inputs such as activity type, time, location, skill level, privacy settings, maximum attendees, and a description text box. Additionally, its search feature allows users to filter results by using 149 physical or volunteering activities, location, and activity creator (friends, public, volunteer organization). The main advantage of such customization depth is that it takes into account user preferences, which include how rigorous the desired activities may be, and with whom the user would like to engage in the activity. Thus, such optimization reflects user needs, offering enhanced ability to interact with ideal target physical activity partners [26]. For individuals in need of communicative social support, MatchMySport and FitTogether provide an array of tools in the form of messaging, chat, and sharing of life updates. In addition to these features, certain websites, such as SparkPeople, also offered additional benefits such as calorie counting and diet tracking (ie, nutritional content beyond calories) features for users who are also interested in diet monitoring.

Out of the 13 websites evaluated in our research, FitTogether and Fitocracy had the highest percentage of the features at 75.0% or 9 of 12 features. However, FitTogether was particularly weak in the sophistication category, lacking 3 of 5 features (filtering preferences, interactive engagement prompts, site-suggested best fit activities). By lacking sophistication, user burden may be elevated to the point that engagement with the service is inconvenient and decreases over time. This is withstanding the notion that some simplistic platforms may provide lesser cognitive load and user burden. Here, we suggest that there is the possibility of further reducing user burden through use of more sophisticated software that aids in the automation of how social networks are used. This type of technological sophistication may operate on the backend such that users would only perceive the benefits of these algorithms or features without viewing added complexity to the interface [27]. Fitocracy may appear to have a more balanced collection of features than the other social networks by lacking just 1 item from each of the 3 categories (activity creation customization, real-time messaging, and filtering preferences), but among these missing features is the ability to create events that engage and connect people in their physical community. Fitocracy may not be able to sustain user commitment to regular physical activity as effectively without this option. Although it may not be impossible for users to meet with one another offline, it would be much more difficult for them to do so through the site.

Existing research has demonstrated both modest and significant gains in physical activity and health through the use of physical activity social network interventions [25,28-31]. Our study addresses the larger movement of catalyzing behavior change through online technologies and the need for scientific evidence. Although there exists no one-size-fits-all solution to combating physical inactivity today, the possibility of creating a scalable, low-cost, and universally accessible intervention now exists. Online social networks have already demonstrated effective behavior change in the areas of smoking cessation and safe sex practices [32]. Studies have shown that participants with access to an interactive computer program were likely to achieve higher smoking cessation rates [32]. Furthermore, study participants who used the program accompanied by a stop smoking forum were even more likely to retain progress than those with a less complete program [32]. An additional feasibility study has indicated that minimal contact/self-help interventions have yielded a 20.7% rate in 7-day cessation, and a 75% increase in participants' reported intention to quit smoking [33]. What once required resource-intensive clinical management or elaborate public health strategy now may be possible with more simple technological aids.

### Strengths and Limitations

There are limitations to this work that are worth noting. First, we only evaluated websites that aimed to connect its users both online and face-to-face. We acknowledge that there are many ways to increase social support for physical activity without having to connect face-to-face, but these sites were not the focus of this descriptive work. Additionally, given our exclusion of certain networks from this analysis, we are limited in our ability to describe features for mobile apps that are not Web-based (eg, LoseIt!) or are sensor-driven networks (eg, Fitbit). Lastly, because of the descriptive nature of this work we are able to comment on the characteristics of sites, but are unable to comment on which of these characteristics actually engage users in physical activity. In principle, we analyzed features of websites rather than the effects of these sites on health. There are also several strengths of this work. First, these results may help guide health professionals faced with patients looking for online social support for their physical activity efforts. Additionally, it provides a snapshot of existing features of sites that aim to connect individuals both online and face-to-face for physical activity. Lastly, we generate hypotheses about what features of the online social networks reviewed might be helpful in initiation and maintenance of physical activity.

### Clinical Implications

Previous studies suggest that online social networks are good platforms for intervention delivery especially among young adults [34,35]. There is evidence that features such as tailored content and goal setting assists in promoting the effectiveness of physical activity interventions [36]. Further, it has been hypothesized that interventions may yield more favorable outcomes with the use of advanced features, such as automated dialog and more personalized forms of communicating information [37]. Participant dropout from physical activity intervention programs has been a notable problem in this area of research [38]. Certain features, such as email reminders, supervision and contact through texting, and regularly updated content, might be harnessed to help with adherence [39].

A major concern in this quickly growing area of research is the extent to which technological creation is quickly outpacing scientific evidence. Online services are adopted at a blazing pace. For example, SparkPeople and RunKeeper were used by over 15 million and 23 million users, respectively [5,6].

### Moving Forward

The objective of this descriptive analysis was to characterize the existing features of sites in play that connect users with physical activity partners both online and face-to-face. In principle, this analysis allows us to generate hypotheses about why certain sites may help individuals initiate or maintain physical activity behaviors, but it does not provide information on the effect of these sites on physical activity or health. Moving forward, research is needed to evaluate the impact of these features on physical activity given the need for empirical foundations for the continued use or elimination of features. Currently, viral word-of-mouth and popularity impacts adoption [40,41], whereas ideally this would be driven by data. The use of a site's popularity to increase user adoption is a precarious path for those looking for genuine evidence-based health care interventions because popular programs (eg, video games) have been shown to be ineffective in promoting physical activity [42].

We found that the distribution of features on each site varied widely, with no single site including 100% of the features we reviewed. Although it is not necessary to include every feature to be effective in promoting physical activity, as a next step, it is worth generating evidence about which features are most important to users and which features are most effective in promoting physical activity. It has been suggested that online social networks makes forming groups easier than it has even been, that there can be either positive or negative effects of the easy collaborative nature of online social networks, and that a that a critical mass of individuals is required for social networks to be useful [43-45]. Moving forward, we suggest additional research to explore several hypotheses. For example, we would hypothesize that features such as communication, activity optimization, and sophistication might be key contributors to behavior change. We would also hypothesize that if sites had more engaging user interfaces, including easier navigation, simpler layouts, and refined esthetics, there would be greater initiation of use and physical activity. Lastly, we would hypothesize that the features we identified could potentially be used to overcome the challenge of requiring a critical mass of individuals for social network sites to be useful. Although it is promising to see the development and availability of public physical activity social networks, research is needed that includes other networks, such as those that are Web-based or sensor-driven, as well as research that discerns which tools can offer meaningful behavioral impact and guide effective public health policy and clinical counseling. Many questions remain around how users utilize these services and how helpful they truly are.

## Authors' Contributions

Atul Nakhasi authored the primary manuscript draft and all major revisions, led design of the statistical plan and conducted all statistical analyses, interpretation of data and analysis of results, critically reviewed and edited manuscript, and approved the final version. Album Xiaotian Shen interpreted data and analysis of results and created all tables/figures, critically reviewed and edited manuscript, and approved the final version. Ralph Passarella helped refine study protocol and design, interpretation of data and analysis of results, critically reviewed and edited manuscript, and approved the final version. Lawrence Appel critically reviewed and edited the manuscript and approved the final version. Cheryl Anderson performed or directly oversaw all aspects of the study from conception through completion, critically reviewed and edited manuscript, and approved the final version. She had full access to all the data in the study and had final responsibility for the decision to submit for publication.

## Conflicts of Interest

None declared.

## References

1. National Coalition for Supporting Physical Activity. 2013 Jan 23. NCPPA endorses Sen Tom Harkin's "HeLP America" Act URL: http://www.ncppa.org/home/news/75/ [accessed 2013-06-29] [WebCite Cache ID 6HkU2dCSj]
2. Centers for Disease Control and Prevention. 2012 Jan 09. Overcoming barriers to physical activity URL: http://www.cdc.gov/physicalactivity/everyone/getactive/barriers.html [accessed 2012-01-09] [WebCite Cache ID 64ZuUMZvf]
3. Borriello G, Brunette W, Lester J, Powledge P, Rea A. An ecosystem of platforms to support sensors for personal fitness. International Workshop on Wearable and Implantable Body Sensor Networks 2006:175-178. [doi: 10.1109/BSN.2006.8]
4. Crook J. Tech Crunch. 2013 Mar 26. Fitocracy's 1M users, including Arnold Schwarzenegger, are more engaged than any other social network besides Facebook URL: http://techcrunch.com/2013/03/26/fitocracys-1m-users-including-arnold-schwarzenegger-are-more-engaged-than-any-other-social-network-besides-facebook/ [accessed 2013-06-28] [WebCite Cache ID 6His0q3oa]
5. SparkPeople. URL: http://www.sparkpeople.com/ [accessed 2013-06-28] [WebCite Cache ID 6HisFiTQw]
6. Shontell A. Business Insider. 2013 Jun 25. RunKeeper, a Boston startup with 23 Million users that wowed Mark Zuckerberg, now tracks calories as well as miles URL: http://www.businessinsider.com/runkeeper-partners-with-myfitnesspal-2013-6 [accessed 2013-06-28] [WebCite Cache ID 6HirhNXif]
7. Brownson RC, Baker EA, Housemann RA, Brennan LK, Bacak SJ. Environmental and policy determinants of physical activity in the United States. Am J Public Health 2001 Dec;91(12):1995-2003. [Medline: 11726382]
8. TechCrunch. URL: http://techcrunch.com/ [accessed 2014-03-26] [WebCite Cache ID 6OMhCx0sg]
9. Y Combinator. URL: https://news.ycombinator.com/ [accessed 2014-03-26] [WebCite Cache ID 6OMhMv2SP]
10. Alexa. URL: http://www.alexa.com/ [accessed 2014-03-30] [WebCite Cache ID 6OT9BN1Mu]
11. activity8. URL: http://activity8.com/Account/SignIn [accessed 2014-03-26] [WebCite Cache ID 6OMheqfzQ]
12. BuddyUp. URL: http://buddyup.com/default.asp [accessed 2014-03-26] [WebCite Cache ID 6OMhwXc96]
13. CribSocial. URL: http://www.cribsocial.com/ [accessed 2014-03-26] [WebCite Cache ID 6OMi1uMOu]
14. ExerciseFriends. URL: http://exercisefriends.com/ [accessed 2014-03-26] [WebCite Cache ID 6OMiW3Zp7]
15. Fitocracy. URL: https://www.fitocracy.com/ [accessed 2014-03-26] [WebCite Cache ID 6OMifc6z1]
16. FitTogether. URL: http://fittogether.com/ [accessed 2014-03-26] [WebCite Cache ID 6OMikvvZV]
17. Friendeavor. URL: http://friendeavor.com/ [accessed 2014-03-26] [WebCite Cache ID 6OMisSLMI]
18. Meet in Real Life. URL: http://www.MIRL.com [accessed 2014-03-26] [WebCite Cache ID 6OMj8f1Dc]
19. RunKeeper. URL: http://runkeeper.com/ [accessed 2014-03-26] [WebCite Cache ID 6OMjBp3Pw]
20. Sponduu. URL: http://www.sponduu.com/ [accessed 2014-03-26] [WebCite Cache ID 6OMjLlz5w]
21. The Activity Partner. URL: http://www.theactivitypartner.com/index.php [accessed 2014-03-26] [WebCite Cache ID 6OMjYgvC8]
22. ZoomPal. URL: http://zoompal.com/ [accessed 2014-03-26] [WebCite Cache ID 6OMjgRcf1]
23. Fallows D. How somen and men use the Internet. Washington, DC: Pew Internet & American Life Project; 2005 Dec 28. URL: http://www.pewinternet.org/pdfs/PIP_Women_and_Men_online.pdf [accessed 2007-04-27] [WebCite Cache ID 5OQ8tt5Kb]
24. Hock-Hai T, Lih-Bin O, Chunhui L, Kwok-Kee W. An empirical study of the effects of interactivity on web user attitude. International Journal of Human-Computer Studies 2003;58(3):281-305. [doi: 10.1016/S1071-5819(03)00008-9]

25. Hwang KO, Ning J, Trickey AW, Sciamanna CN. Website usage and weight loss in a free commercial online weight loss program: retrospective cohort study. J Med Internet Res 2013;15(1):e11 [FREE Full text] [doi: 10.2196/jmir.2195] [Medline: 23322819]
26. Abbattista F, Degemmis M, Licchelli O, Lops P, Semeraro G, Zambetta F. Improving the usability of an e-commerce web site through personalization. In: Recommendation and Personalization in eCommerce. Malaga, Spain: Universidad de Málaga; 2002:20-29.
27. Hansen AW, Grønbæk M, Helge JW, Severin M, Curtis T, Tolstrup JS. Effect of a Web-based intervention to promote physical activity and improve health among physically inactive adults: a population-based randomized controlled trial. J Med Internet Res 2012 Oct;14(5):e145 [FREE Full text] [doi: 10.2196/jmir.2109] [Medline: 23111127]
28. Davies CA, Spence JC, Vandelanotte C, Caperchione CM, Mummery WK. Meta-analysis of internet-delivered interventions to increase physical activity levels. Int J Behav Nutr Phys Act 2012;9:52 [FREE Full text] [doi: 10.1186/1479-5868-9-52] [Medline: 22546283]
29. Napolitano MA, Fotheringham M, Tate D, Sciamanna C, Leslie E, Owen N, et al. Evaluation of an internet-based physical activity intervention: A preliminary investigation. ann. behav. med 2003 Apr;25(2):92-99. [doi: 10.1207/S15324796ABM2502_04]
30. Richardson CR, Buis LR, Janney AW, Goodrich DE, Sen A, Hess ML, et al. An online community improves adherence in an internet-mediated walking program. Part 1: results of a randomized controlled trial. J Med Internet Res 2010;12(4):e71 [FREE Full text] [doi: 10.2196/jmir.1338] [Medline: 21169160]
31. Watson A, Bickmore T, Cange A, Kulshreshtha A, Kvedar J. An internet-based virtual coach to promote physical activity adherence in overweight adults: randomized controlled trial. J Med Internet Res 2012 Jan;14(1):e1 [FREE Full text] [doi: 10.2196/jmir.1629] [Medline: 22281837]
32. Schneider SJ, Walter R, O'Donnell R. Computerized communication as a medium for behavioral smoking cessation treatment: Controlled evaluation. Computers in Human Behavior 1990 Jan;6(2):141-151. [doi: 10.1016/0747-5632(90)90002-X]
33. Stoddard J, Delucchi K, Muñoz R, Collins N, Stable EP, Augustson E, et al. Smoking cessation research via the internet: a feasibility study. J Health Commun 2005 Feb;10(1):27-41. [doi: 10.1080/10810730590904562] [Medline: 15764442]
34. Cavallo DN, Tate DF, Ries AV, Brown JD, DeVellis RF, Ammerman AS. A social media-based physical activity intervention: a randomized controlled trial. Am J Prev Med 2012 Nov;43(5):527-532. [doi: 10.1016/j.amepre.2012.07.019] [Medline: 23079176]
35. Irvine AB, Gelatt VA, Seeley JR, Macfarlane P, Gau JM. Web-based intervention to promote physical activity by sedentary older adults: randomized controlled trial. J Med Internet Res 2013 Feb;15(2):e19 [FREE Full text] [doi: 10.2196/jmir.2158] [Medline: 23470322]
36. Vandelanotte C, Spathonis KM, Eakin EG, Owen N. Website-delivered physical activity interventions a review of the literature. Am J Prev Med 2007 Jul;33(1):54-64. [doi: 10.1016/j.amepre.2007.02.041] [Medline: 17572313]
37. Morrison LG, Yardley L, Powell J, Michie S. What design features are used in effective e-health interventions? A review using techniques from Critical Interpretive Synthesis. Telemed J E Health 2012 Mar;18(2):137-144. [doi: 10.1089/tmj.2011.0062] [Medline: 22381060]
38. Kelders SM, Van Gemert-Pijnen JE, Werkman A, Nijland N, Seydel ER. Effectiveness of a Web-based intervention aimed at healthy dietary and physical activity behavior: a randomized controlled trial about users and usage. J Med Internet Res 2011 Apr;13(2):e32 [FREE Full text] [doi: 10.2196/jmir.1624] [Medline: 21493191]
39. Brouwer W, Kroeze W, Crutzen R, de Nooijer J, de Vries NK, Brug J, et al. Which intervention characteristics are related to more exposure to internet-delivered healthy lifestyle promotion interventions? A systematic review. J Med Internet Res 2011;13(1):e2 [FREE Full text] [doi: 10.2196/jmir.1639] [Medline: 21212045]
40. Crutzen R, de Nooijer J, Brouwer W, Oenema A, Brug J, de Vries N. Effectiveness of online word of mouth on exposure to an Internet-delivered intervention. Psychol Health 2009 Jul;24(6):651-661. [doi: 10.1080/08870440802521094] [Medline: 20205018]
41. Crutzen R, de Nooijer J, Brouwer W, Oenema A, Brug J, de Vries NK. Internet-delivered interventions aimed at adolescents: a Delphi study on dissemination and exposure. Health Educ Res 2008 Jun;23(3):427-439 [FREE Full text] [doi: 10.1093/her/cym094] [Medline: 18209115]
42. Baranowski T, Baranowski J, Thompson D, Buday R, Jago R, Griffith MJ, et al. Video game play, child diet, and physical activity behavior change a randomized clinical trial. Am J Prev Med 2011 Jan;40(1):33-38 [FREE Full text] [doi: 10.1016/j.amepre.2010.09.029] [Medline: 21146765]
43. Shirky C. Here Comes Everybody: How Change Happens when People Come Together. New York: Penguin Press; 2008:1-352.
44. Shirky C. Here Comes Everybody: The Power of Organizing Without Organizations. New York: Penguin Press; 2008:1-352.
45. Shirky C. Here Comes Everybody: How Digital Networks Transform Our Ability to Gather and Cooperate. New York: Penguin Press; 2008.

## Abbreviations

**URL:** uniform resource locator

*Edited by G Eysenbach; submitted 18.04.13; peer-reviewed by B Turner-McGrievy, E Hekler; comments to author 21.05.13; revised version received 03.07.13; accepted 20.01.14; published 16.06.14.*

*Please cite as:*
*Nakhasi A, Shen AX, Passarella RJ, Appel LJ, Anderson CAM*
*Online Social Networks That Connect Users to Physical Activity Partners: A Review and Descriptive Analysis*
*J Med Internet Res 2014;16(6):e153*
*URL: http://www.jmir.org/2014/6/e153/*
*doi:10.2196/jmir.2674*
*PMID:24936569*

Original Paper

# Pretreatment Attrition and Formal Withdrawal During Treatment and Their Predictors: An Exploratory Study of the Anxiety Online Data

Ali M AL-Asadi[1,2], MA, MSc; Britt Klein[3,4,5], DPsych (Clinical); Denny Meyer[1], DBL

[1]School of Health Sciences, Swinburne University of Technology, Hawthorn, Australia

[2]Department of Arts and Education, Grande Prairie Regional College, Grande Prairie, AB, Canada

[3]DVC-Research & Innovation Portfolio and the School of Health Sciences & the Collaborative Research Network, Federation University, Ballarat, Australia

[4]Centre for Mental Health Research, The Australian National University, Canberra, Australia

[5]National eTherapy Centre, School of Health Sciences, Swinburne University of Technology, Hawthorn, Australia

**Corresponding Author:**
Ali M AL-Asadi, MA, MSc
Department of Arts and Education
Grande Prairie Regional College
10726 - 106 Ave
Grande Prairie, AB, T8V 4C4
Canada
Phone: 1 780 539 2061
Fax: 1 780 538 0960
Email: aalasadi@gprc.ab.ca

## Abstract

**Background:** Although in its infancy, the field of e-mental health interventions has been gaining popularity and afforded considerable research attention. However, there are many gaps in the research. One such gap is in the area of attrition predictors at various stages of assessment and treatment delivery.

**Objective:** This exploratory study applied univariate and multivariate analysis to a large dataset provided by the Anxiety Online (now called Mental Health Online) system to identify predictors of attrition in treatment commencers and in those who formally withdrew during treatment based on 24 pretreatment demographic and personal variables and one clinical measure.

**Methods:** Participants were assessed using a complex online algorithm that resulted in primary and secondary diagnoses in accordance with the Diagnostic and Statistical Manual of Mental Disorders, Fourth Edition, Text Revision (DSM-IV-TR). Those who received a primary or secondary diagnosis of 1 of 5 anxiety disorders (generalized anxiety disorder, social anxiety disorder, obsessive-compulsive disorder, posttraumatic stress disorder, and panic disorder) were offered an online 12-week disorder-specific treatment program.

**Results:** Of 9394 potential participants, a total of 3880 clients enrolled and 5514 did not enroll in one of the treatment programs following the completion of pretreatment assessment measures (pretreatment attrition rate: 58.70%). A total of 3199 individuals did not formally withdraw from the 12-week treatment cycle, whereas 142 individuals formally dropped out (formal withdrawal during treatment dropout rate of 4.25%). The treatment commencers differed significantly ($P$<.001-.03) from the noncommencers on several variables (reason for registering, mental health concerns, postsecondary education, where first heard about Anxiety Online, Kessler-6 score, stage of change, quality of life, relationship status, preferred method of learning, and smoking status). Those who formally withdrew during treatment differed significantly ($P$=.002-.03) from those who did not formally withdraw in that they were less likely to express concerns about anxiety, stress, and depression; to rate their quality of life as very poor, poor, or good; to report adequate level of social support; and to report readiness to make or were in the process of making changes.

**Conclusions:** This exploratory study identified predictors of pretreatment attrition and formal withdrawal during treatment dropouts for the Anxiety Online program.

**Trial Registration:** Australian and New Zealand Clinical Trials Registry ACTRN121611000704998; http://www.anzctr.org.au/trial_view.aspx?ID=336143 (Archived by WebCite at http://www.webcitation.org/618r3wvOG).

*(J Med Internet Res 2014;16(6):e152)* doi:10.2196/jmir.2989

**KEYWORDS**

pretreatment attrition; treatment withdrawal dropouts; predictors, anxiety disorders; eTherapy; e-mental health; Internet interventions

## Introduction

Although e-mental health interventions for the treatment of anxiety disorders have been shown to be effective [1-6] and increasing in popularity [7,8], research tends to be limited by high rates of attrition [8-10] and small to moderate sample sizes reported by most trials (see [11]). In addition, there appears to be little consensus regarding how attrition is defined in the literature. This lack of consensus is largely a result of each program offering different numbers of treatment modules and each study setting a different minimum number of treatment modules (or sessions) before a participant is considered a completer of a treatment program. Despite high rates of attrition, the majority of research published to date includes little or no analysis of relationships between demographic variables and attrition.

Attrition rates for e-mental health programs vary according to definition and treatment variables. Researchers report attrition rates for e-mental health treatment programs for anxiety or depression ranging from as high as 99% to as low as 1% [10-14] with the majority reporting attrition rates ranging between 20% and 40%. In a review of the effectiveness of e-mental health treatment programs for panic disorder, attrition rates for online therapy ranged between 4% and 36% [15]. Along similar lines, a recent examination of the efficacy of e-mental health programs for major depression, panic disorder, social phobia, and generalized anxiety disorder using a meta-analysis of 22 studies, revealed a range of 48% to 100% with a median of 80% of participants who began computerized cognitive behavioral therapy (CBT) completed all stages of their program [12].

Attrition appears to be greater in studies of Internet-based treatment that are open to the general public [16] and online therapy in which there is no therapist involvement [17,18] than in studies dealing with in-clinic samples and online samples in which assessors and therapists are involved. For instance, a study examining the usage and effectiveness of freely available, nontherapist-assisted, Internet-based CBT for panic disorder reported a very high attrition rate, with only 12 of 1161 registered users completing the 12-week therapy program [10]. In a study examining symptom change in people with anxiety and depression, the general public users completed significantly fewer symptom assessments than trial participants; out of 19,607 general public users, 12,141 (61.9%) completed at least 1 symptom assessment and 3055 (15.6%) completed 2 or more symptom assessments, whereas 157 of 182 (86.3%) trial participants completed at least 1 symptom assessment and 121 (66.5%) completed 2 or more symptom assessments [9]. Although demographic variables were collected, not many of these studies examined these variables in relation to attrition.

In clinical practice, attrition rates for the treatment of anxiety disorders vary by treatment setting and definition with a range from 10% to 60% [19-21]. Although females and older people are linked to greater participation [22], patients with milder anxiety disorder-specific symptoms, patients with higher levels of physical disability, women [23], and patients with a comorbid diagnosis [24], greater age and lower income [25], and lower level of education [26] have been linked to greater dropout rates. However, other researchers have reported no significant effect for all or some of these aforementioned variables [23,27-29]. Pretreatment attrition in clinic-based samples is typically higher than during treatment attrition [22,30], with more severe comorbid depressive symptoms and the presence of at least 1 or more children shown to be significant predictors of pretreatment attrition [23]. On the other hand, years of education, race, age, and employment status were significant predictors of attendance at the initial interview for treatment [31].

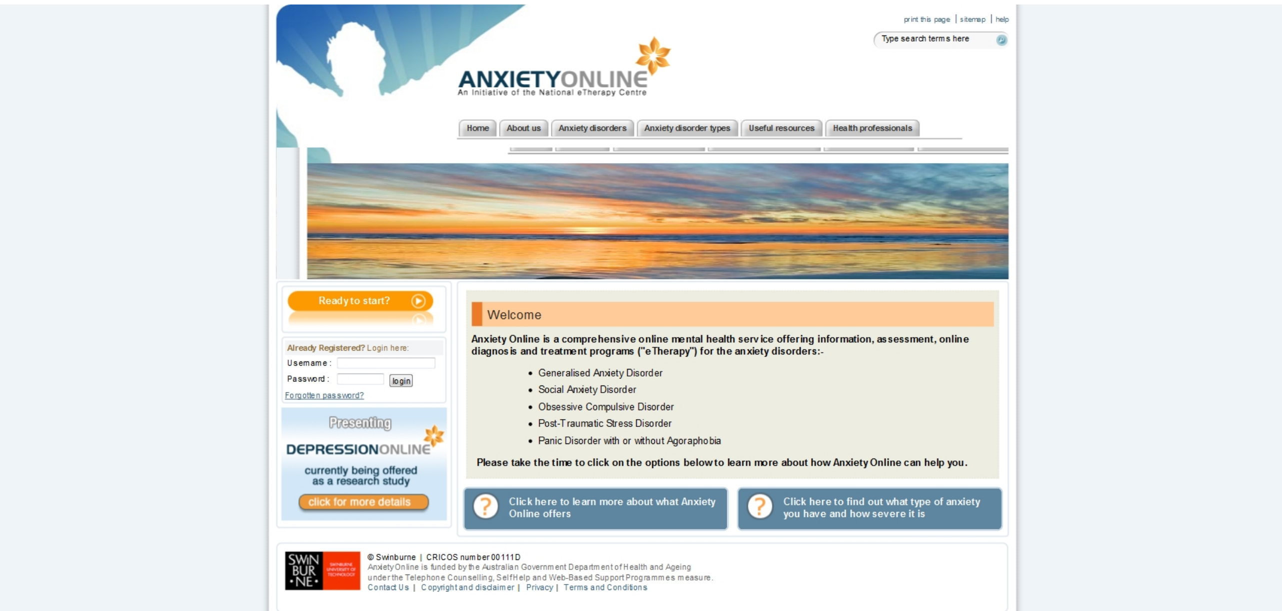
In summary, attrition rates have been reported for a large variety of treatment programs. It appears that attrition rates in both online and clinic-based samples are affected by treatment and demographic variables and tend to vary considerably depending on how attrition is defined. Although data on attrition rates for online and clinic-based treatment are widely available, research regarding the relationship between demographic variables and attrition for individuals participating in e-mental health treatment programs is inconclusive. Although more data are available regarding the demographic variables associated with attrition in clinic-based samples, the research that is available is inconclusive.

In this exploratory study, pretreatment attrition and formal withdrawal during treatment and their predictors are examined using data from the Anxiety Online platform. Because we have the number of participants who formally withdrew during treatment only and do not have data on how many modules each participant completed, this necessitated a different approach from the one outlined in the literature. To avoid any confusion, we elected to use the terms "formal withdrawal during treatment" rather than attrition and "no formal withdrawal during treatment" rather than completion.

Anxiety Online is funded by the Australian Federal Government and is operated through the National eTherapy Centre at Swinburne University of Technology. This open access online service provides online assessment, including diagnosis of 21 mental health disorders in accordance with the *Diagnostic and Statistical Manual of Mental Disorders, Fourth Edition, Text Revision* (*DSM-IV-TR*), and self-guided and therapist-assisted treatment programs for the 5 anxiety disorders ([32]; Figure 1). It should be noted that the Anxiety Online platform was upgraded in September 2013 and now uses the name Mental Health Online [32].

This paper reports on one clinical measure and 24 demographic variables that are potentially associated with pretreatment attrition and formal withdrawal during treatment, in an effort to identify individuals who are likely to refuse treatment and individuals who formally withdraw from treatment prematurely. This is rather useful because identifying the characteristics that are more likely to lead to attrition and formally dropping out of treatment would make it possible to change aspects of the program to make it more engaging for these particular subgroups via tailoring and personalizing. In the absence of clear indicators as to the direction of associations between pretreatment attrition and formal withdrawal during treatment and demographic variables, the null hypothesis for all associations shall be assumed.

**Figure 1.** Homepage of Anxiety Online.




## Methods

### Procedure

The Anxiety Online (now called Mental Health Online) platform consists of 4 centers: psychoeducational, assessment, treatment, and training. The psychoeducational center is a website that provides psychoeducational information about prevalence, symptoms, and treatments of anxiety disorders as well as links to useful resources. The assessment center contains the electronic psychological assessment screening system (e-PASS). The treatment center provides and manages the 5 anxiety treatment programs. The training center provides the eTherapist training programs and a health care practitioner portal. The online psychological assessment and referral program, e-PASS, includes a variety of demographic and personal questions, including the Kessler-6 measure of psychological distress, as well as the online diagnostic program. Individuals can access the Anxiety Online service from anywhere in the world provided they have an Internet connection. People complete the e-PASS if they want a psychological assessment and/or if they are interested in online treatment. Based on an individual's response to some of the e-PASS questions, a person may be given a primary diagnosis and/or multiple secondary diagnoses. Those adults (18 years old or older) diagnosed with panic disorder, social anxiety disorder, generalized anxiety disorder, posttraumatic stress disorder, or obsessive-compulsive disorder are offered a 12-week self-guided or therapist-assisted treatment program (the therapist-assisted program is only available to Australian residents). To accommodate a formal withdrawal during treatment, an opt-out button within each account is provided. When this button is pressed, participants are asked whether they would like to complete the exit survey (8 questions about why they are withdrawing). Following the 12-week treatment cycle, patients are asked to complete e-PASS again. The posttreatment questions are essentially the same as the pretreatment questions. Patients are also encouraged to complete e-PASS at yearly intervals for 5 years following treatment program cycle completion (see [14] for more details). Those who wanted to undertake the e-PASS were first required to register and consent to the Anxiety Online terms and conditions [32]. The procedures for collecting and reporting of the Anxiety Online data were approved by the Swinburne University Human Research Ethics Committee. From the time of its launch to the public in October 2009 until January 2012, the e-PASS program had been accessed by 10,745 people.

### Online Questions/Questionnaire: Self-Report

As shown in Multimedia Appendix 1, a total of 24 demographic and personal questions and 2 items that screen for suicide risk and psychosis made up the questionnaire that preceded the online diagnostic program. After completing the questionnaire, the person then completed the online diagnostic program, which consisted of many questions and measures, including the commonly used Kessler-6 [33] for clinical assessment of mental health.

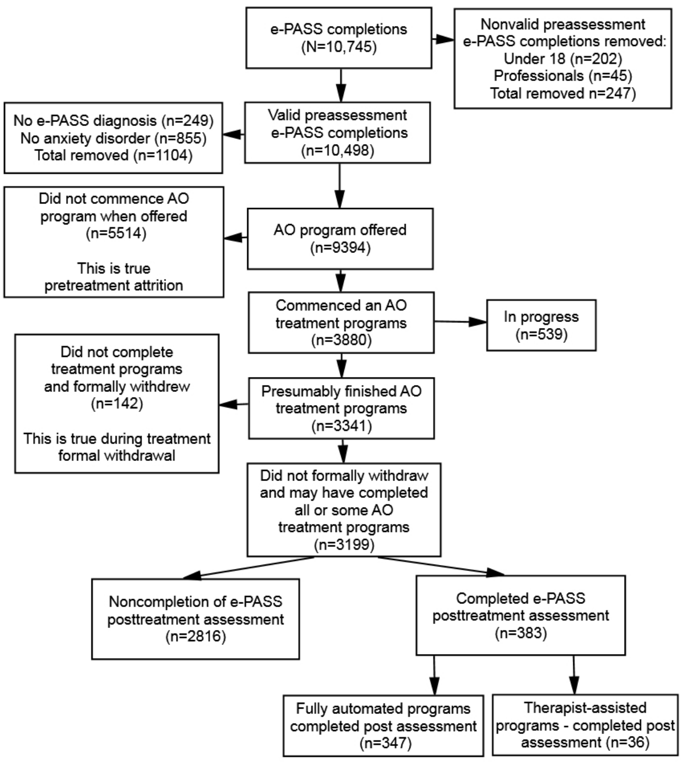
The Kessler-6 consists of 6 items measured on a 5-point Likert scale, measuring nonspecific psychological distress over the past 30 days. Normative data indicate that 71.7% of the population report low distress scores of 6-11, 16.6% of the population report moderate distress scores of 12-15, 7.16% of the population report high distress scores of 16-19, whereas 2.5% of the population report very high distress scores of 20-30 [33,34].

## Participants

As shown in Figure 2, a total of 10,745 individuals completed the pretreatment assessment phase between October 2009 and January 2012. Some of those individuals were younger than 18 years (n=202) and some were professionals (n=45) who were exploring the assessment instrument. These 247 individuals were removed from the data leaving 10,498 valid completers of the e-PASS program. In addition, 249 individuals did not receive an e-PASS diagnosis and another 855 individuals who did not receive a diagnosis of any anxiety disorders were also removed from the dataset. This left 4771 (50.79%) with a primary diagnosis and 4623 (49.21%) with a secondary diagnosis of at least one of the anxiety disorders, for a total of 9394 e-PASS completers. All 9394 were offered a treatment program, although it was recommended that those with a primary diagnosis other than anxiety should seek help elsewhere. A total of 3880 (41.30%) individuals accepted and commenced a 12-week online treatment cycle, including 105 patients who selected the therapist-assisted path; 5514 individuals did not accept the offer of an anxiety treatment program. Of those who commenced treatment, 2321 (59.82%) had one of the anxiety disorders as their primary diagnosis, whereas 1559 (40.18%) had at least one anxiety disorder as their secondary diagnosis. Of those who did not commence treatment, 2450 (44.43%) had one of the anxiety disorders as their primary diagnosis, whereas 3064 (55.57%) had at least one anxiety disorder as their secondary diagnosis. The first part of the analysis in this study investigates the differences between the treatment commencers and those who choose not to start 1 of the 5 anxiety disorder treatment programs in terms of the pretreatment assessment variables described in Multimedia Appendix 1.

We considered treatment nonacceptance as pretreatment attrition in this study. At the time of analysis, there were 539 individuals still undergoing treatment; therefore, 3341 individuals either had or had not formally withdrawn from the 12-week treatment cycle. A total of 3199 individuals did not formally withdraw from their treatment program cycle, whereas 142 individuals formally withdrew during their treatment program cycle. Those who did not formally withdraw from the treatment cycle consisted of 1005 (31.42%) males aged between 18 and 78 years with a mean age of 38.43 (SD 12.23) years, and 2194 (68.58%) females aged between 18 and 81 years with a mean age of 35.81 (SD 11.87) years. The second part of the analysis investigates the differences between those who did not formally withdraw during treatment in comparison to those who did formally withdraw on the basis of pretreatment assessment measures. We defined the formal withdrawal during treatment rate as the proportion of individuals who formally withdrew from their treatment cycle relative to the total number of individuals who commenced the treatment program cycle.

**Figure 2.** Recruitment and enrollment rate of participants to Anxiety Online (AO) website.




## Analysis

The same method of analysis was used for analyzing pretreatment attrition and formal withdrawal during treatment. The initial univariate analyses used chi-square tests of association to determine which of the previously described variables have a significant relationship with attrition. A multivariate analysis was used to confirm the univariate results. Multivariate binary logistic regression analyses were performed with a forward selection approach used to identify the most important predictor variables. The final model, using only the most important predictor variables, was evaluated using a

Hosmer-Lemeshow test. All analyses were conducted using SPSS version 20 (IBM Corp, Armonk, NY, USA).

## Results

### Pretreatment Attrition (Profile of Treatment Commencers)

In this study, there were 9394 individuals with a valid pretreatment e-PASS assessment who were offered a 12-week Anxiety Online treatment program. Only 3880 of these individuals actually commenced a treatment cycle, whereas 5514 individuals chose not to participate in any of the 5 Anxiety Online treatment programs, yielding a pretreatment attrition rate of 58.70% and a commencement rate of 41.30%.

As shown in Table 1, the chi-square tests of association showed 22 e-PASS pretreatment assessment variables were significantly associated with program commencement. Those who accepted and commenced treatment tended to differ from those who did not accept to enroll in the treatment program in several ways. On average, it was more likely that the treatment commencers had heard about the program through traditional media rather than the Internet; were seeking online assistance with the primary goal of finding a self-help program; were willing to provide consumer feedback; were married; were living in metropolitan areas; were employed full-time; had completed grade 12 schooling; were postgraduates; were nonsmokers; thought that they had adequate social support; rated their self-confidence as good; rated their quality of life as good; were prepared to take action or were in the process of making changes to deal with their mental health issues; said that they learn by reading; had lower pretreatment Kessler-6 scores; were slightly older; and had expressed concerns about their anxiety symptoms, but not about depression, eating disorders, or alcohol and substance abuse. This last characteristic is to be expected because individuals with a primary diagnosis other than anxiety were advised to seek treatment elsewhere.

**Table 1.** Predictor analysis for attrition categories for those who commenced treatment vs those who did not commence treatment (N=9394).

| Variables | Attrition categories | | Test of association | | |
|---|---|---|---|---|---|
| | Did not commence treatment (n=5514) | Commenced treatment (n=3880) | $\chi^2$ (*df*) | $F_{1,9392}$ | *P* |
| **How did you hear about us?, n (%)** | | | 134.4 (4) | | .001 |
| Internet | 2712 (49.18) | 1694 (43.66) | | | |
| Health professional | 781 (14.16) | 573 (14.77) | | | |
| Friend/family | 530 (9.61) | 272 (7.01) | | | |
| Media | 768 (13.93) | 878 (22.63) | | | |
| Other | 723 (13.11) | 463 (11.93) | | | |
| **Reason for seeking online assistance, n (%)** | | | 657.8 (1) | | .001 |
| To complete one of the self-help programs | 1694 (30.72) | 2220 (57.22) | | | |
| Join research registry (yes), n (%) | 1686 (30.58) | 1270 (32.73) | 4.1 (1) | | .04 |
| Provide consumer feedback (yes), n (%) | 2444 (44.32) | 1932 (49.79) | 22.8 (1) | | .001 |
| **Gender, n (%)** | | | 13.8 (1) | | .001 |
| Male | 1555 (28.20) | 1232 (31.75) | | | |
| Female | 3959 (71.80) | 2648 (68.25) | | | |
| **Relationship status, n (%)** | | | 62.6 (6) | | .001 |
| Married | 1599 (29.00) | 1389 (35.80) | | | |
| Single | 1693 (30.70) | 1114 (28.71) | | | |
| Cohabiting | 1073 (19.46) | 716 (18.45) | | | |
| Not living together | 669 (12.13) | 375 (9.66) | | | |
| Separated/divorced | 351 (6.37) | 217 (5.59) | | | |
| Widowed | 21 (0.38) | 23 (0.59) | | | |
| Other | 108 (1.96) | 46 (1.19) | | | |
| **Setting, n (%)** | | | 28.3 (3) | | .001 |
| Metropolitan | 3335 (60.48) | 2553 (65.80) | | | |
| Regional | 1485 (26.93) | 895 (23.07) | | | |
| Rural | 630 (11.43) | 398 (10.26) | | | |
| Remote | 64 (1.16) | 34 (0.88) | | | |
| **Employment status, n (%)** | | | 19.4 (6) | | .004 |
| Employed full-time | 2121 (38.47) | 1611 (41.52) | | | |
| Employed part-time | 1359 (24.65) | 930 (23.97) | | | |
| Home duties | 430 (7.80) | 280 (7.22) | | | |
| Disability support | 223 (4.04) | 142 (3.66) | | | |
| Unemployed | 664 (12.04) | 396 (10.21) | | | |
| Retired | 106 (1.92) | 101 (2.60) | | | |
| Other | 611 (11.08) | 420 (10.82) | | | |
| **Highest level of schooling, n (%)** | | | 32.8 (5) | | .001 |
| None | 66 (1.20) | 37 (0.95) | | | |
| Primary school | 53 (0.96) | 24 (0.62) | | | |
| Secondary (grade 9) | 157 (2.85) | 98 (2.53) | | | |
| Secondary (grade 10) | 534 (9.68) | 343 (8.84) | | | |
| Secondary (grade 11) | 490 (8.89) | 243 (6.26) | | | |

| Variables | Attrition categories | | Test of association | | |
|---|---|---|---|---|---|
| | Did not commence treatment (n=5514) | Commenced treatment (n=3880) | $\chi^2$ (*df*) | $F_{1,9392}$ | *P* |
| Secondary (grade 12) | 4214 (76.42) | 3135 (80.80) | | | |
| **Postsecondary, n (%)** | | | 144.0 (6) | | .001 |
| None | 855 (15.51) | 492 (12.68) | | | |
| Apprenticeship/trade | 278 (5.04) | 155 (3.99) | | | |
| Certificate | 754 (13.67) | 387 (9.97) | | | |
| Diploma | 633 (11.48) | 395 (10.18) | | | |
| Undergraduate | 869 (15.76) | 492 (12.68) | | | |
| Postgraduate | 826 (14.98) | 840 (21.65) | | | |
| Other | 1299 (23.56) | 1119 (28.84) | | | |
| **Mental health concern, n (%)** | | | 314.2 (6) | | .001 |
| None | 73 (1.32) | 33 (0.85) | | | |
| Anxiety | 3445 (62.48) | 3040 (78.35) | | | |
| Stress | 465 (8.43) | 246 (6.34) | | | |
| Depression | 885 (16.05) | 362 (9.33) | | | |
| Substance abuse/alcohol | 74 (1.34) | 19 (0.49) | | | |
| Eating | 378 (6.86) | 75 (1.93) | | | |
| Other | 194 (3.52) | 105 (2.71) | | | |
| Currently receiving mental health assistance (yes), n (%) | 2121 (38.47) | 1415 (36.47) | 3.9 (1) | | .05 |
| **Number of doctor visits, n (%)** | | | 12.5 (2) | | .002 |
| None | 2310 (41.89) | 1690 (43.56) | | | |
| 1-2 visits | 2416 (43.82) | 1732 (44.64) | | | |
| 3 or more | 788 (14.29) | 458 (11.80) | | | |
| Do you smoke? (yes), n (%) | 1300 (23.58) | 632 (16.29) | 74.0 (1) | | .001 |
| Social support (yes), n (%) | 2312 (41.93) | 1775 (45.75) | 13.5 (1) | | .001 |
| **Self-confidence, n (%)** | | | 37.6 (4) | | .001 |
| Very poor | 511 (9.27) | 264 (6.80) | | | |
| Poor | 1577 (28.60) | 997 (25.70) | | | |
| Neither | 1990 (36.09) | 1460 (37.63) | | | |
| Good | 1239 (22.47) | 1008 (25.98) | | | |
| Very good | 197 (3.57) | 151 (3.89) | | | |
| **Quality of life, n (%)** | | | 28.7 (4) | | .001 |
| Very poor | 215 (3.90) | 126 (3.25) | | | |
| Poor | 1019 (18.48) | 592 (15.26) | | | |
| Neither | 1653 (29.98) | 1123 (28.94) | | | |
| Good | 2213 (40.13) | 1705 (43.94) | | | |
| Very good | 414 (7.51) | 334 (8.61) | | | |
| **Making changes, n (%)** | | | 84.9 (4) | | .001 |
| Not interested | 79 (1.43) | 23 (0.59) | | | |
| Neither | 533 (9.67) | 199 (5.13) | | | |
| Prepared to take action | 2808 (50.92) | 2089 (53.84) | | | |

| Variables | Attrition categories | | Test of association | | |
|---|---|---|---|---|---|
| | Did not commence treatment (n=5514) | Commenced treatment (n=3880) | $\chi^2$ (*df*) | $F_{1,9392}$ | *P* |
| In process of making changes | 1440 (26.12) | 1118 (28.81) | | | |
| Relapse | 654 (11.86) | 451 (11.62) | | | |
| **How do you best learn?, n (%)** | | | 31.1 (3) | | .001 |
| Hearing | 361 (6.55) | 222 (5.72) | | | |
| Reading | 1371 (24.86) | 1164 (30.00) | | | |
| Looking | 1065 (19.31) | 707 (18.22) | | | |
| Doing | 2717 (49.27) | 1787 (46.06) | | | |
| Pre-Kessler-6 (total score), mean (SD) | 18.35 (4.73) | 16.89 (4.84) | | 212.86 | .001 |
| Age (years), mean (SD) | 34.23 (11.90) | 36.43 (12.07) | | 77.30 | .001 |

As shown in Table 2, the final binary logistic regression with forward selection of predictors for pretreatment attrition contained 10 significant predictors. The Hosmer-Lemeshow goodness-of-fit test indicated an adequate model fit. When statistically controlling for the other variables in the model, we found significant odds ratios for the predictors reason, mental health concerns, postsecondary education, where first heard about Anxiety Online, pre-Kessler-6 score, stage of change, quality of life, relationship status, preferred method of learning, and smoking. We should note here that the same 10 predictors were also found to be significantly associated with pretreatment attrition using chi-square tests as shown in Table 1.

The odds ratios for enrolling in an Anxiety Online treatment program cycle in order of significance were: 2.9 times higher for individuals who gave “seeking to use one of the online self-help programs” as a reason for joining the program relative to all other reasons; 0.7 times as great for those who expressed concerns about eating and weight issues as for those who reported “none” for concerns; 1.29 times higher for those who completed undergraduate degrees and 0.81 times as great for those who hold other certificates as for those who reported having no postsecondary education; 1.35 times higher for those who heard about Anxiety Online from the traditional media relative to all other sources that are not listed in Table 3; 3% reduction in likelihood for each additional point an individual scored on the Kessler-6 total score; 2.16, 2.21, and 2.29 times higher for those who were prepared to make changes, reporting that they were already making changes, and who reported being in relapse and seeking further assistance, respectively, relative to those who were disinterested or indifferent; 1.92, 1.35, and 1.26 times higher for those who rated their quality of life as very poor, poor, and neither poor or good, respectively, relative to those who gave a rating of very good; 1.55 and 1.53 times higher for married and single individuals, respectively, relative to those reporting some other relationship status not listed in Table 3; 1.18 times higher for those indicating that they learn best by reading relative to those who said they learn best by doing; and finally, 1.19 times higher for those who identified themselves as nonsmokers relative to smokers.

**Table 2.** Binary logistic regression model for pretreatment attrition.

| Variables | Wald | *df* | *P* | OR | 95% CI |
|---|---|---|---|---|---|
| **Heard (reference group: other sources)** | 34.59 | 4 | .001 | | |
| Surfing the net | 0.07 | 1 | .79 | 0.98 | 0.85-1.13 |
| Health professional | 0.08 | 1 | .78 | 1.03 | 0.86-1.22 |
| Friend or family | 3.48 | 1 | .06 | 0.83 | 0.67-1.01 |
| Media | 12.65 | 1 | .001 | 1.35 | 1.14-1.59 |
| Reason (online self-help)(reference group: other reasons) | 514.46 | 1 | .001 | 2.90 | 2.65-3.18 |
| **Relationship status (reference group: other relationship status)** | 15.27 | 6 | .02 | | |
| Married | 4.94 | 1 | .03 | 1.55 | 1.05-2.27 |
| Single | 4.65 | 1 | .03 | 1.53 | 1.04-2.25 |
| Cohabiting | 3.13 | 1 | .08 | 1.42 | 0.96-2.10 |
| Not living together | 1.07 | 1 | .30 | 1.24 | 0.83-1.84 |
| Separated/divorce and not in relationship | 1.52 | 1 | .22 | 1.30 | 0.86-1.97 |
| Widowed and not in relationship | 3.00 | 1 | .08 | 1.91 | 0.92-3.95 |
| **Postsecondary education (reference group: none)** | 43.14 | 6 | .001 | | |
| Apprenticeship/trade certificate | 2.28 | 1 | .13 | 0.83 | 0.65-1.06 |
| Other certificates | 5.45 | 1 | .02 | 0.81 | 0.68-0.97 |
| Diploma | 0.39 | 1 | .53 | 0.94 | 0.79-1.13 |
| Current undergraduate | 0.28 | 1 | .60 | 0.96 | 0.80-1.13 |
| Completed undergraduate | 9.47 | 1 | .002 | 1.29 | 1.10-1.52 |
| Postgraduate degree | 3.74 | 1 | .05 | 1.16 | 1.00-1.348 |
| **Mental health concerns (reference group: none)** | 201.96 | 6 | .001 | | |
| Anxiety | 1.92 | 1 | .17 | 1.37 | 0.88-2.14 |
| Stress | 0.44 | 1 | .51 | 0.85 | 0.53-1.37 |
| Depression | 1.15 | 1 | .28 | 0.78 | 0.49-1.23 |
| Substance/alcohol abuse | 3.68 | 1 | .06 | 0.51 | 0.26-1.02 |
| Eating/weight issues | 21.30 | 1 | .001 | 0.30 | 0.18-0.50 |
| Other | 0.11 | 1 | .75 | 1.09 | 0.65-1.82 |
| Smoke (nonsmoking) (reference group: smoking) | 8.47 | 1 | .004 | 1.19 | 1.06-1.34 |
| **Quality of life (reference group: very good)** | 21.72 | 4 | .001 | | |
| Very poor | 16.64 | 1 | .001 | 1.92 | 1.40-2.63 |
| Poor | 7.47 | 1 | .006 | 1.35 | 1.09-1.67 |
| Neither poor or good | 5.83 | 1 | .02 | 1.26 | 1.05-1.52 |
| Good | 1.20 | 1 | .27 | 1.10 | 0.93-1.31 |
| **Making changes (reference group: disinterested or indifferent)** | 22.89 | 4 | .001 | | |
| Neither here nor there | 2.66 | 1 | .10 | 1.55 | 0.92-2.62 |
| Prepared to take action | 9.02 | 1 | .003 | 2.16 | 1.31-3.58 |
| Already in the process of making changes | 9.36 | 1 | .002 | 2.21 | 1.33-3.67 |
| Relapsed and looking for additional assistance | 9.79 | 1 | .002 | 2.29 | 1.36-3.85 |
| **Learning (reference group: doing)** | 10.35 | 3 | .02 | | |
| By hearing | 0.12 | 1 | .73 | 0.97 | 0.80-1.17 |
| By reading | 9.36 | 1 | .002 | 1.18 | 1.06-1.34 |
| By looking/watching | 0.87 | 1 | .35 | 1.06 | 0.94-1.20 |

| Variables | Wald | *df* | *P* | OR | 95% CI |
|---|---|---|---|---|---|
| Pre-Kessler-6 | 30.01 | 1 | .001 | 0.97 | 0.95-0.98 |
| Constant | 10.35 | 1 | .001 | 0.29 | |

**Table 3.** Predictor analysis for categories for formal treatment cycle withdrawal.

| Variables | Categories | | Test of association | | |
|---|---|---|---|---|---|
| | Not formally withdrawn from treatment (n=3199) | Formal treatment dropouts (n=142) | $\chi^2$ (*df*) | $F_{1,3339}$ | *P* |
| **How did you hear about us?, n (%)** | | | 9.4 (4) | | .05 |
| Internet | 1344 (42.01) | 71 (50.0) | | | |
| Heath professional | 475 (14.85) | 19 (13.4) | | | |
| Friend/family | 227 (7.10) | 15 (10.6) | | | |
| Media | 761 (23.79) | 28 (19.7) | | | |
| Other | 392 (12.25) | 9 (6.3) | | | |
| Reason for seeking online assistance | | | 1.8 (1) | | .19 |
| Join research registry | | | 0.0 (1) | | .91 |
| Provide consumer feedback | | | 0.9 (1) | | .63 |
| Gender | | | 0.1 (1) | | .78 |
| Relationship status | | | 0.7 (3) | | .87 |
| Setting | | | 5.1 (2) | | .08 |
| Employment status | | | 4.3 (3) | | .23 |
| Highest level of schooling | | | 0.5 (3) | | .91 |
| Postsecondary | | | 2.2 (6) | | .90 |
| **Mental health concern, n (%)** | | | 11.7 (3) | | .009 |
| Anxiety | 2510 (78.46) | 103 (72.5) | | | |
| Stress | 204 (6.38) | 8 (5.6) | | | |
| Depression | 302 (9.44) | 13 (9.2) | | | |
| Other | 183 (5.72) | 18 (12.7) | | | |
| Currently receiving mental health assistance | | | 0.1 (1) | | .82 |
| Have you accessed mental health in last 12 months | | | 0.3 (1) | | .61 |
| Have you ever accessed mental health | | | 0.0 (1) | | .85 |
| Any diagnosed physical health condition | | | 0.1 (1) | | .80 |
| Doctor visit | | | 0.2 (2) | | .89 |
| Do you smoke? | | | 0.1 (1) | | .79 |
| Do you drink alcohol? | | | 2.2 (1) | | .14 |
| Adequate social support (yes), n (%) | 1482 (46.33) | 54 (38.0) | 3.8 (1) | | .05 |
| Self-confidence | | | 2.2 (4) | | .71 |
| Quality of life | | | 4.5 (3) | | .22 |
| **Making changes (change), n (%)** | | | 8.9 (3) | | .03 |
| Not matter | 171 (5.35) | 15 (10.6) | | | |
| Prepared | 1722 (53.83) | 73 (51.4) | | | |
| Already | 936 (29.26) | 34 (23.9) | | | |
| relapse | 370 (11.57) | 20 (14.1) | | | |
| How do you best learn? | | | 1.3 (3) | | .73 |
| Age in years | | | | 0.04 | .84 |
| Kessler-6 (total scores) | | | | 0.01 | .92 |

### Formal Withdrawal During Treatment (Predictors of Formal Dropouts)

There were 3880 individuals who commenced a 12-week Anxiety Online treatment program cycle. The number of individuals still undergoing treatment at the time of this analysis was 539; therefore, 3341 individuals were included in the analysis. A total of 142 individuals formally withdrew from their Anxiety Online treatment program cycle; therefore, 3199 individuals did not formally withdraw and potentially completed some or all of a 12-week treatment program cycle. The formal withdrawal during treatment rate was defined as the number of individuals who formally withdrew from their treatment program cycle in relation to the total number of individuals who commenced treatment. The formal withdrawal during treatment rate was 4.25% (142/3341) with 95.75% (3199/3341) not formally withdrawing during treatment. It is important to note that this rate is an underestimate of the true attrition because it relies exclusively on those who formally withdrew from the treatment program.

As shown in Table 3, the chi-square tests of association showed 2 pretreatment variables, mental health concerns and stages of change, were significantly associated with those who formally dropped out of treatment. Those who formally withdrew from the Anxiety Online treatment program cycle were, on average, less likely to express concern about anxiety and were less prepared to make changes in their lives to deal with their conditions than those who did not formally withdraw from treatment.

To simplify the interpretation of the odds ratios, we have reported the odds for not formally withdrawing from the treatment program. As shown in Table 4, the final binary logistic regression with forward selection of predictors for not formally dropping out of the treatment program contained 4 significant predictors. When statistically controlling for the other variables in the model, we found significant odds ratios for the predictors mental health concerns, adequate social support, quality of life, and stages of change. The Hosmer-Lemeshow goodness-of-fit test indicated an adequate model fit.

The odds of not formally dropping out of the Anxiety Online treatment program cycle in order of significance were: 2.34, 2.59, and 2.30 times higher for those who expressed concerns over anxiety, stress, and depression, respectively, relative to those who expressed concerns over other mental health issues; 2.62, 2.13, and 1.87 times higher for those who rated their quality of life as very poor/poor, neither poor or good, and good relative to those who gave a rating of very good; 1.70 times higher for those who reported having adequate level of social support; and 1.96 and 2.32 times for those who were prepared to make changes and those reporting that they were already making changes, respectively, relative to those who were disinterested or indifferent. Conversely, these odds ratios suggest that in general the likelihood of formally withdrawing from the treatment programs decreased for those who expressed concerns over anxiety, stress, and depression; viewed their quality of life as very poor/poor, neither good or poor, and good; reported adequate level of social support; and were already making changes or prepared to make changes.

**Table 4.** Binary logistic regression model for formal treatment withdrawal.

| Variables | Wald | *df* | *P* | OR | 95% CI |
|---|---|---|---|---|---|
| **Mental health concern (reference group: other)** | 10.28 | 3 | .02 | | |
| Anxiety | 9.83 | 1 | .002 | 2.34 | 1.38-3.98 |
| Stress | 4.65 | 1 | .03 | 2.59 | 1.09-6.13 |
| Depression | 4.75 | 1 | .03 | 2.30 | 1.09-4.86 |
| Social support (adequate)(reference group: not adequate) | 7.38 | 1 | .007 | 1.70 | 1.16-2.49 |
| **Quality of life (reference group: very good)** | 8.38 | 3 | .04 | | |
| Very poor and poor | 7.74 | 1 | .005 | 2.62 | 1.33-5.15 |
| Neither poor or good | 6.02 | 1 | .01 | 2.13 | 1.16-3.89 |
| Good | 4.98 | 1 | .03 | 1.87 | 1.08-3.24 |
| **Making changes (reference group: disinterested or indifferent)** | 7.66 | 3 | .05 | | |
| Prepared to take action | 5.07 | 1 | .02 | 1.96 | 1.09-3.53 |
| Already making changes | 6.70 | 1 | .01 | 2.32 | 1.23-4.38 |
| Relapsed and looking for additional assistance | 1.33 | 1 | .25 | 1.51 | 0.75-3.05 |
| Constant | 3.58 | 1 | .06 | 2.28 | |

## Discussion

In this study, pretreatment attrition was defined as not accepting 1 of 5 Anxiety Online treatment programs, whereas formal withdrawal during treatment was defined simply as those who formally withdrew from their 12-week Anxiety Online treatment program cycle. The purpose of this study was to identify predictors of pretreatment attrition and predictors of those who formally withdrew or, conversely, those who did not formally withdraw from the treatment program cycle.

The results showed that the Anxiety Online program was found to have a pretreatment attrition rate of 58.7%. There are few studies that have reported pretreatment attrition for online or face-to-face treatment. Only 1 study reported a higher pretreatment attrition rate of 85% for individuals with social anxiety [31], whereas 2 studies reported approximately half the pretreatment attrition value of this study: Richards and Borglin [30] for a study on anxiety and depression reported a pretreatment attrition of 27% and Issakidis and Andrews [23] for a study on anxiety disorders reported a pretreatment attrition of 30.4%. Our higher pretreatment attrition may be because of the fact that Anxiety Online is an e-mental health service, whereas the other 2 studies were face-to-face clinic-based services. This is not surprising because public e-mental health treatment services tend to have higher treatment attrition rates [16-18].

The Anxiety Online treatment programs were found to have a during-treatment formal withdrawal rate of 4.3% (defined by those participants who formally dropped out of a program after commencement). This low rate could be related to our too-inclusive approach. The fact that we used those who did not formally withdraw during the 12-week treatment cycle may account for this low attrition rate. We do not have the data to show whether or not those who did not formally withdraw accessed all 12 modules, but we do know that they did not formally withdraw during the 12-week treatment cycle. It is possible that all patients who did not formally withdraw completed all 12 treatment modules, but it is equally possible that they did not work through all the modules. Therefore, further studies on the Anxiety Online data are required when module completion data becomes available. It should be emphasized that the diversity of attrition definitions in general and the approach we used in this work make any comparison of attrition rates problematic.

In this study, 24 demographic variables and one clinical measure of psychological distress were used to predict pretreatment attrition variables and formal withdrawal from treatment variables. Chi-square tests of association and binary logistic regression were used to relate these variables to pretreatment and during-treatment formal withdrawal. Results showed that the likelihood of enrolling in one of the Anxiety Online treatment programs increased for those who were seeking to use one of the self-help treatment programs; had an undergraduate degree; heard about the program via traditional media sources; were prepared to make changes, already making changes, or in relapse and looking for additional assistance; rated their quality of life as very poor, poor, or neutral rather than very good; married or single; reported learning best by reading; and those who identified themselves as nonsmokers. In general, these results should be expected. People who are seeking online self-help are likely to accept online treatment. If we extend the recent findings by Dahlstrom [35] and Edwards [36] that most undergraduates are comfortable with various communication technologies and favor the use of virtual communication in their education, then it is not surprising that the probability of enrolling in the online treatment program was greater for those who held undergraduate degrees; those who hold undergraduate degrees are likely to be more familiar and comfortable with the technology. It is not surprising that individuals who are prepared to or are making changes would enroll in treatment programs. The less people thought that their quality of life was good, the more likely they were to accept treatment. People who think they have a very good quality of life, regardless of mental health concerns, perhaps do not believe that treatment would further improve their lives. Because the Anxiety Online service is online and largely text-based, it is logical to find that the probability of enrolling in a treatment program increases for those who learn best by reading.

The odds of enrolling in the treatment program decreased for those who expressed concerns over eating and weight issues, probably because individuals with these problems presenting as their primary disorder were advised to find help elsewhere. Finally, those who reported greater psychological distress as measured by the Kessler-6 were less likely to accept the offer to enroll in the treatment program, probably because patients with higher scores may have felt too overwhelmed to commence treatment at this stage and may have opted for face-to-face treatment instead. Finally, it should be noted that some people who completed the e-PASS measures were not interested or ready to start treatment; rather, they just wanted an assessment.

On the other hand, results showed that the odds of formally withdrawing from treatment increased for those who did not express concerns about anxiety, stress, and depression; decreased for those who rated their quality of life as less than very good; decreased for those who reported having an adequate level of social support; and decreased for those who were prepared to make changes or were already making changes to improve their mental health. Participants who commenced the online anxiety treatment cycle would have received one of the anxiety disorder diagnoses as either a primary or secondary diagnosis. As such, it makes sense that those who expressed concerns about symptoms (anxiety, stress, and depression) that were congruent with their diagnoses would more likely not formally withdraw from the treatment cycle than those who expressed concerns about other issues that were not congruent with their diagnoses. That is, those who were less concerned about symptoms of anxiety, stress, and depression were more likely to formally drop out. Individuals who reported adequate social support were more likely not to formally withdraw from the program, perhaps because their social support resources provided a good safety net during times of stress. Moreover, such people may be more likely to have a positive outlook on life and perhaps greater potential for change.

As was the case in the pretreatment attrition predictors, individuals who perceived their quality of life as less than very good and who were willing or in the process of making changes were more likely not to formally withdraw from their treatment cycle. Individuals who reported a very good quality of life were more likely to formally withdraw from treatment. This is probably because participants who perceived their quality of life as very good were unlikely to think that treatment could further improve the quality of their lives. Finally, part of any treatment program is to make changes in one’s life; therefore, it is understandable why those who were not in the process of making or were unprepared to make changes were more likely to formally withdraw from their treatment program cycle.

Comparison of attrition rates between studies is problematic for 3 reasons. Firstly, definitions of attrition vary between studies. For example, the definition of treatment attrition in the literature varies from dropping out after one treatment session to dropping out after several treatment sessions or, as in this study, to those who formally withdraw during treatment. Although it seems logical to define attrition as simply noncompleters of a treatment program regardless of the number of treatment modules (or sessions in some studies) attended, it is often the case that only a few participants complete all treatment modules or drop out without formally withdrawing from treatment and, therefore, it becomes desirable to include individuals who attend at least most modules in the completers group. Moreover, some people may not need to complete all the modules to acquire what they need to improve [37,38]. Secondly, the studies being compared may involve very different treatments with very different durations of intervention. For these reasons, comparisons with existing studies should be approached with caution. The third problem with comparisons of attrition studies relates to the paucity of such studies that explain how attrition relates to demographic and treatment factors.

Comparing the predictor variables found in this study with previous findings is difficult because of the lack of studies on predictors of pretreatment and formal withdrawal, during treatment especially for online therapy, and the lack of consensus regarding predictors of attrition. However, in general our results are in agreement with Issakidid and Andrews [23] in finding significant relationships between pretreatment attrition and severity of symptoms. In relation to formal treatment withdrawal, sex, age, income, educational level, and comorbidity were not found to be significant predictors of formal withdrawal during treatment, which is contrary to the findings of several studies [22-26]. But these studies were conducted on clinical samples receiving clinic-based face-to-face treatment rather than e-mental health treatments and did not use our formal withdrawal from treatment approach. Also, perhaps our group of participants is more homogeneous in that the group is already biased by virtue of selecting to engage in online therapy and the group is likely to share the cluster of anxiety disorders. That is, a group of this kind has more characteristics in common. Consequently, formally dropping out of the treatment program cycle by such a group may depend largely on only transient and controllable attributes such as concern, or lack of concern, over anxiety and depression, perception of quality of life, and readiness, or lack of, to make changes, and characteristics of the surroundings such as the availability of adequate social support, rather than more permanent and less controllable attributes.

Future research should examine the difference between the characteristics of those who select online therapy and those who prefer the more traditional method of face-to-face treatment. It is likely that as a group, those who are more comfortable with the technology and seek to do things online differ from those who are less inclined to embrace technology on many attributes. Future research should also examine the demographic profiles of these 2 groups.

The lack of research and the inconsistent results on attrition predictor variables is primarily because of the recency of online therapy, the diversity of definitions of attrition, and the inclusion or exclusion of a large number of potential predictor variables. In the future and with the increase in e-mental health treatment, more research on attrition and predictors of attrition specific to online therapy is required.

## Acknowledgments

The authors would like to thank the Australian Government Department of Health and Ageing who provided the funding for the development of the Anxiety Online service and its ongoing maintenance. e-PASS and the Anxiety Online e-therapy treatment programs are available to the international public at no cost (fully automated self-help). The therapist-assisted version is open only to Australian residents at a minimal cost. The funders of Anxiety Online (Australian Government Department of Health and Ageing) had no other involvement in this study or report.

## Conflicts of Interest

None declared.

## Multimedia Appendix 1

Self-report online questionnaire.

[PDF File (Adobe PDF File), 27KB - jmir_v16i6e152_app1.pdf ]

## References

1. Berger T, Caspar F, Richardson R, Kneubühler B, Sutter D, Andersson G. Internet-based treatment of social phobia: a randomized controlled trial comparing unguided with two types of guided self-help. Behav Res Ther 2011 Mar;49(3):158-169. [doi: 10.1016/j.brat.2010.12.007] [Medline: 21255767]
2. Furmark T, Carlbring P, Hedman E, Sonnenstein A, Clevberger P, Bohman B, et al. Guided and unguided self-help for social anxiety disorder: randomised controlled trial. Br J Psychiatry 2009 Nov;195(5):440-447 [FREE Full text] [doi: 10.1192/bjp.bp.108.060996] [Medline: 19880935]

3. Kaltenthaler E, Parry G, Beverley C. Computerized cognitive behaviour therapy: a systematic review. Behav Cognit Psychother 1999;32(1):31-55. [doi: 10.1017/S135246580400102X]
4. Klein B, Mitchell J, Gilson K, Shandley K, Austin D, Kiropoulos L, et al. A therapist-assisted Internet-based CBT intervention for posttraumatic stress disorder: preliminary results. Cogn Behav Ther 2009;38(2):121-131. [doi: 10.1080/16506070902803483] [Medline: 20183691]
5. Klein B, Mitchell J, Abbott J, Shandley K, Austin D, Gilson K, et al. A therapist-assisted cognitive behavior therapy internet intervention for posttraumatic stress disorder: pre-, post- and 3-month follow-up results from an open trial. J Anxiety Disord 2010 Aug;24(6):635-644. [doi: 10.1016/j.janxdis.2010.04.005] [Medline: 20447802]
6. Przeworski A, Newman MG. Efficacy and utility of computer-assisted cognitive behavioural therapy for anxiety disorders. Clinical Psychologist 2006 Mar 02;10(2):43-53. [doi: 10.1080/13284200500378779]
7. Christensen H, Griffiths K, Groves C, Korten A. Free range users and one hit wonders: community users of an Internet-based cognitive behaviour therapy program. Aust N Z J Psychiatry 2006 Jan;40(1):59-62. [doi: 10.1111/j.1440-1614.2006.01743.x] [Medline: 16403040]
8. Donkin L, Christensen H, Naismith SL, Neal B, Hickie IB, Glozier N. A systematic review of the impact of adherence on the effectiveness of e-therapies. J Med Internet Res 2011;13(3):e52 [FREE Full text] [doi: 10.2196/jmir.1772] [Medline: 21821503]
9. Christensen H, Griffiths KM, Korten AE, Brittliffe K, Groves C. A comparison of changes in anxiety and depression symptoms of spontaneous users and trial participants of a cognitive behavior therapy website. J Med Internet Res 2004 Dec 22;6(4):e46 [FREE Full text] [doi: 10.2196/jmir.6.4.e46] [Medline: 15631970]
10. Farvolden P, Denisoff E, Selby P, Bagby RM, Rudy L. Usage and longitudinal effectiveness of a Web-based self-help cognitive behavioral therapy program for panic disorder. J Med Internet Res 2005;7(1):e7 [FREE Full text] [doi: 10.2196/jmir.7.1.e7] [Medline: 15829479]
11. Christensen H, Griffiths KM, Farrer L. Adherence in internet interventions for anxiety and depression. J Med Internet Res 2009;11(2):e13 [FREE Full text] [doi: 10.2196/jmir.1194] [Medline: 19403466]
12. Andrews G, Cuijpers P, Craske MG, McEvoy P, Titov N. Computer therapy for the anxiety and depressive disorders is effective, acceptable and practical health care: a meta-analysis. PLoS One 2010;5(10):e13196 [FREE Full text] [doi: 10.1371/journal.pone.0013196] [Medline: 20967242]
13. Carlbring P, Bohman S, Brunt S, Buhrman M, Westling BE, Ekselius L, et al. Remote treatment of panic disorder: a randomized trial of internet-based cognitive behavior therapy supplemented with telephone calls. Am J Psychiatry 2006 Dec;163(12):2119-2125. [doi: 10.1176/appi.ajp.163.12.2119] [Medline: 17151163]
14. Klein B, Meyer D, Austin DW, Kyrios M. Anxiety online: a virtual clinic: preliminary outcomes following completion of five fully automated treatment programs for anxiety disorders and symptoms. J Med Internet Res 2011;13(4):e89 [FREE Full text] [doi: 10.2196/jmir.1918] [Medline: 22057287]
15. Richards J, Klein B, Carlbring P. Internet-based treatment for panic disorder. Cogn Behav Ther 2003;32(3):125-135. [doi: 10.1080/16506070302318] [Medline: 16291544]
16. Titov N, Andrews G, Choi I, Schwencke G, Johnston L. Randomized controlled trial of web-based treatment of social phobia without clinician guidance. Aust NZ J Psychiatry 2009 Jan;43(10):913-919. [doi: 10.1080/00048670903179160]
17. Andersson G, Carlbring P, Grimlund A. Predicting treatment outcome in internet versus face to face treatment of panic disorder. Computers in Human Behavior 2008 Sep;24(5):1790-1801. [doi: 10.1016/j.chb.2008.02.003]
18. Ruwaard J, Broeksteeg J, Schrieken B, Emmelkamp P, Lange A. Web-based therapist-assisted cognitive behavioral treatment of panic symptoms: a randomized controlled trial with a three-year follow-up. J Anxiety Disord 2010 May;24(4):387-396. [doi: 10.1016/j.janxdis.2010.01.010] [Medline: 20227241]
19. Longo DA, Lent RW, Brown SD. Social cognitive variables in the prediction of client motivation and attrition. Journal of Counseling Psychology 1992;39(4):447-452. [doi: 10.1037/0022-0167.39.4.447]
20. Mitte K. Meta-analysis of cognitive-behavioral treatments for generalized anxiety disorder: a comparison with pharmacotherapy. Psychol Bull 2005 Sep;131(5):785-795. [doi: 10.1037/0033-2909.131.5.785] [Medline: 16187860]
21. Smits JA, Hofmann SG. A meta-analytic review of the effects of psychotherapy control conditions for anxiety disorders. Psychol Med 2009 Feb;39(2):229-239. [doi: 10.1017/S0033291708003498] [Medline: 18466666]
22. Van Der Veen WJ, Van Der Meer K, Penninx BW. Screening for depression and anxiety: correlates of non-response and cohort attrition in the Netherlands study of depression and anxiety (NESDA). Int J Methods Psychiatr Res 2009 Dec;18(4):229-239. [doi: 10.1002/mpr.297] [Medline: 20027601]
23. Issakidis C, Andrews G. Pretreatment attrition and dropout in an outpatient clinic for anxiety disorders. Acta Psychiatr Scand 2004 Jun;109(6):426-433. [doi: 10.1111/j.1600-0047.2004.00264.x] [Medline: 15117287]
24. Gonzalez A, Weersing VR, Warnick EM, Scahill LD, Woolston JL. Predictors of treatment attrition among an outpatient clinic sample of youths with clinically significant anxiety. Adm Policy Ment Health 2011 Sep;38(5):356-367 [FREE Full text] [doi: 10.1007/s10488-010-0323-y] [Medline: 20976618]
25. Grilo CM, Money R, Barlow DH, Goddard AW, Gorman JM, Hofmann SG, et al. Pretreatment patient factors predicting attrition from a multicenter randomized controlled treatment study for panic disorder. Compr Psychiatry 1998;39(6):323-332. [Medline: 9829138]

26. Keijsers GP, Kampman M, Hoogduin CA. Dropout prediction in cognitive behavior therapy for panic disorder. Behavior Therapy 2001 Sep;32(4):739-749. [doi: 10.1016/S0005-7894(01)80018-6]
27. Hofmann SG, Suvak M. Treatment attrition during group therapy for social phobia. J Anxiety Disord 2006;20(7):961-972. [doi: 10.1016/j.janxdis.2006.03.005] [Medline: 16621439]
28. Turner SM, Beidel DC, Wolff PL, Spaulding S, Jacob RG. Clinical features affecting treatment outcome in social phobia. Behav Res Ther 1996 Oct;34(10):795-804. [Medline: 8952122]
29. White KS, Allen LB, Barlow DH, Gorman JM, Shear MK, Woods SW. Attrition in a multicenter clinical trial for panic disorder. J Nerv Ment Dis 2010 Sep;198(9):665-671. [doi: 10.1097/NMD.0b013e3181ef3627] [Medline: 20823729]
30. Richards DA, Borglin G. Implementation of psychological therapies for anxiety and depression in routine practice: two year prospective cohort study. J Affect Disord 2011 Sep;133(1-2):51-60. [doi: 10.1016/j.jad.2011.03.024] [Medline: 21501876]
31. Coles ME, Turk CL, Jindra L, Heimberg RG. The path from initial inquiry to initiation of treatment for social anxiety disorder in an anxiety disorders specialty clinic. J Anxiety Disord 2004;18(3):371-383. [doi: 10.1016/S0887-6185(02)00259-1] [Medline: 15125983]
32. Mental Health Online. Victoria, Australia: Swinburne University of Technology URL: https://www.anxietyonline.org.au/default.aspx [accessed 2014-05-22] [WebCite Cache ID 6PlcUEtHy]
33. Kessler RC, Barker PR, Colpe LJ, Epstein JF, Gfroerer JC, Hiripi E, et al. Screening for serious mental illness in the general population. Arch Gen Psychiatry 2003 Feb;60(2):184-189. [Medline: 12578436]
34. Furukawa TA, Kessler RC, Slade T, Andrews G. The performance of the K6 and K10 screening scales for psychological distress in the Australian National Survey of Mental Health and Well-Being. Psychol Med 2003 Feb;33(2):357-362. [Medline: 12622315]
35. Dahlstrom E. ECAR study of undergraduate students and information technology (Research Report). Louisville, CO: EDUCAUSE Center for Applied Research; 2012. URL: http://net.educause.edu/ir/library/pdf/ERS1208/ERS1208.pdf [accessed 2014-05-22] [WebCite Cache ID 6PldJEYXL]
36. Edwards JT. Undergraduate millennial students' perceptions of virtual office hours. International Journal of Instructional Technology and Distance Learning 2009;6(4):45-54 [FREE Full text]
37. Martinez M. High attrition rates in e-learning: challenges, predictors, and solutions. The E-Learning Developers' Journal 2003 Jul 14:1-9 [FREE Full text]
38. Christensen H, Mackinnon A. The law of attrition revisited. J Med Internet Res 2006;8(3):20-20 [FREE Full text]

## Abbreviations

**CBT:** cognitive behavioral therapy
**DSM-IV-TR:** Diagnostic and Statistical Manual of Mental Disorders, 4th edition, text revision
**e-PASS:** electronic psychological assessment screening system

*Edited by G Eysenbach; submitted 29.09.13; peer-reviewed by L Palmili, F Lamers, A Geraghty; comments to author 23.10.13; revised version received 06.02.14; accepted 28.04.14; published 17.06.14.*

*Please cite as:*
*AL-Asadi AM, Klein B, Meyer D*
*Pretreatment Attrition and Formal Withdrawal During Treatment and Their Predictors: An Exploratory Study of the Anxiety Online Data*
*J Med Internet Res 2014;16(6):e152*
*URL: http://www.jmir.org/2014/6/e152/*
*doi:10.2196/jmir.2989*
*PMID:24938311*

Original Paper

# Evaluation of an eHealth Intervention in Chronic Care for Frail Older People: Why Adherence is the First Target

Peter Makai[1], MSc, PhD; Marieke Perry[1], MD, PhD; Sarah HM Robben[2], MD, PhD; Henk J Schers[3], MD, PhD; Maud M Heinen[4], RN, PhD; Marcel GM Olde Rikkert[1], MD, PhD; René F Melis[1], MD, PhD

[1]Radboud University Medical Center, Department of Geriatrics, Nijmegen, Netherlands
[2]Jeroen Bosch Hospital, Department of Internal Medicine, Hertogenbosch, Netherlands
[3]Radboud University Medical Center, Department of Primary and Community Care, Nijmegen, Netherlands
[4]Radboud Univesrity Medical Center, Scientific Institute for Quality in Healthcare, Nijmegen, Netherlands

**Corresponding Author:**
Peter Makai, MSc, PhD
Radboud University Medical Center
Department of Geriatrics
Renier Postlaan 4
Nijmegen, 6500 HB
Netherlands
Phone: 31 24 361 98 07
Fax: 31 24 361 74 08
Email: Peter.Makai@radboudumc.nl

## Abstract

**Background:** Older people suffering from frailty often receive fragmented chronic care from multiple professionals. According to the literature, there is an urgent need for coordination of care.

**Objective:** The objective of this study was to investigate the effectiveness of an online health community (OHC) intervention for older people with frailty aimed at facilitating multidisciplinary communication.

**Methods:** The design was a controlled before-after study with 12 months follow-up in 11 family practices in the eastern part of the Netherlands. Participants consisted of frail older people living in the community requiring multidisciplinary (long-term) care. The intervention used was the health and welfare portal (ZWIP): an OHC for frail elderly patients, their informal caregivers and professionals. ZWIP contains a secure messaging system supplemented by a shared electronic health record. Primary outcomes were scores on the Instrumental Activities of Daily Living scale (IADL), mental health, and social activity limitations.

**Results:** There were 290 patients in the intervention group and 392 in the control group. Of these, 76/290 (26.2%) in the intervention group actively used ZWIP. After 12 months follow-up, we observed no significant improvement on primary patient outcomes. ADL improved in the intervention group with a standardized score of 0.21 (*P*=.27); IADL improved with 0.50 points, *P*=.64.

**Conclusions:** Only a small percentage of frail elderly people in the study intensively used ZWIP, our newly developed and innovative eHealth tool. The use of this OHC did not significantly improve patient outcomes. This was most likely due to the limited use of the OHC, and a relatively short follow-up time. Increasing actual use of eHealth intervention seems a precondition for large-scale evaluation, and earlier adoption before frailty develops may improve later use and effectiveness of ZWIP.

***(J Med Internet Res 2014;16(6):e156)*** doi:10.2196/jmir.3057

**KEYWORDS**

eHealth; frail elderly; care coordination; chronic care

## Introduction

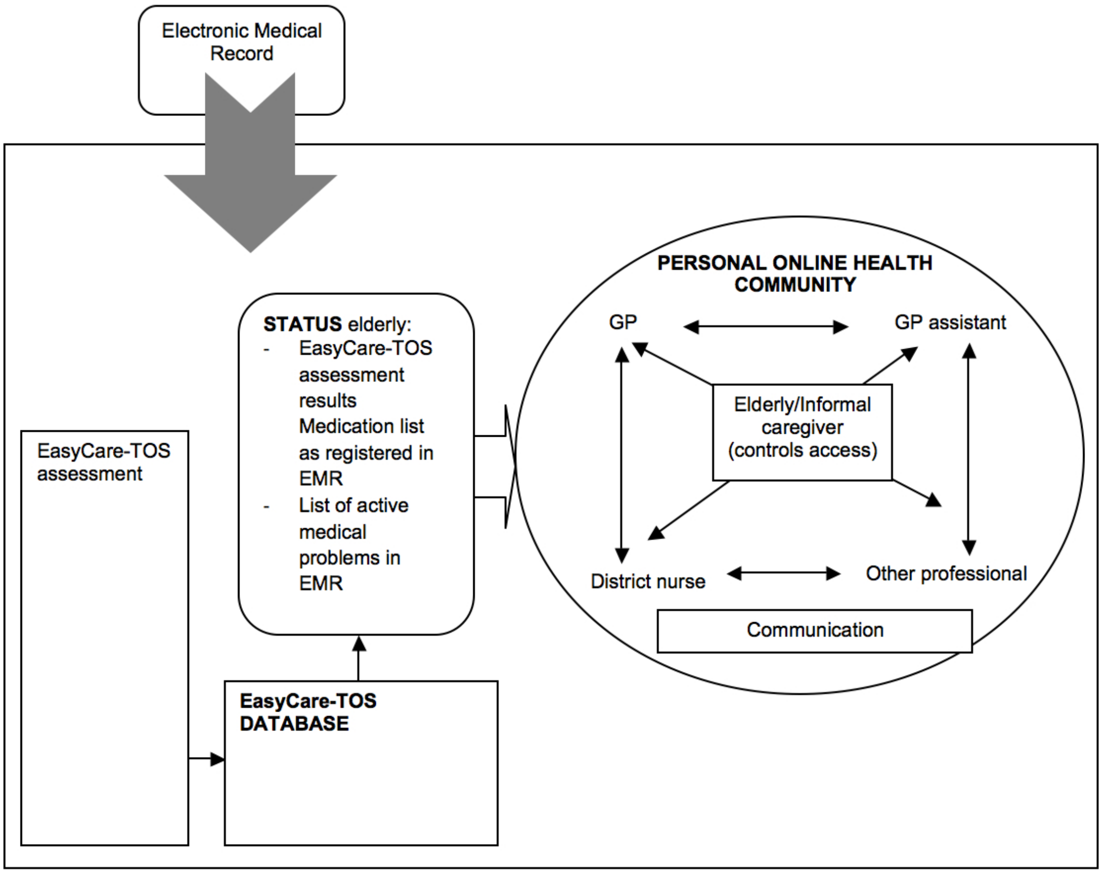
Chronic care for frail older people is fragmented, with involvement from a large and constantly changing group of professionals who are frequently unaware that they provide care to the same patient [1]. Such professionals include home care professionals, general practitioners (GPs), clinicians, physiotherapists, and case managers dedicated to long-term care of the patients in the community. Frail elderly often suffer from comorbidities, which results in care by multiple health care professionals [2]. Therefore lack of communication between professionals leads to a fragmented and ineffective health care delivery for frail elderly [3]. To reduce fragmentation and promote continuity of care, better coordination and communication between professionals and with patients is necessary. Online health communities (OHCs) have been recognized as an effective mechanism for supporting continuous care for frail older people [4], allowing better coordination and more efficient communication with patients and among professionals. OHCs consist of Internet-based platforms that unite groups of individuals with a shared goal or similar interest, including both professionals and patients [5]. The main strength of OHCs is that they allow communication between people who would not have met each other otherwise [5]. Thus, OHCs are particularly suited for improving the coordination of care for frail elderly who have multiple professional caregivers. For this purpose, we developed and evaluated the Health and Welfare Information Portal (Zorg en Welzijns Informatie Portaal, ZWIP, in Dutch) [1,6] on its effectiveness.

## Methods

### Intervention

ZWIP is an OHC [5] that aims to facilitate communication for patients, their informal caregivers, and their professionals. ZWIP contains a secure messaging system supplemented by a shared electronic health record. All messages shared in a patient's ZWIP are visible for all users, thus stimulating involvement of and discussion between patients and a team of health professionals. All informal caregivers and health care professionals have access to the electronic health record. To ensure confidentiality, professionals can participate in a patient's personal care network in ZWIP only at the invitation of the patient. Patients who were not able to manage their own ZWIP account could appoint an informal caregiver to act on their behalf. Figure 1 demonstrates the conceptual model underlying ZWIP, and the video in Multimedia Appendix 1 illustrates the use of ZWIP by a patient and an informal caregiver.

**Figure 1.** A conceptual model of the ZWIP.




### Development and Implementation

The development of ZWIP and the process of implementation have been described elsewhere [1,6]. In brief, ZWIP was developed using intervention mapping [7], a stepwise approach for the systematic development of interventions informed by both evidence and theory [1]. Main steps of intervention mapping for ZWIP were (1) needs assessment in frail elderly, (2) developing program objectives, (3) selecting theory informed intervention methods and strategies, (4) creating and pilot testing program components, (5) planning program adoption and implementation, and (6) planning for evaluation [1]. Theoretically, ZWIP was based on social cognitive theory [8], with special attention paid to improving self-efficacy, the belief people have in their ability to complete tasks and achieve specific goals [9]. Following the steps of intervention mapping and as suggested in the guideline on development and evaluation of complex interventions [8], the ZWIP was piloted by 2 frail elderly and 7 professionals, including one GP. Furthermore, newly developed elements of ZWIP were regularly piloted by similar user panels.

To enhance implementation of the ZWIP, we used several strategies for professionals such as a continuing medical education (CME) accredited education program based on active learning theory [10], direct experience, and modeling [1]. Additionally, drawing from organization theory, we installed a telephonic helpdesk and provided e-coaching and financial compensation to support the uptake of ZWIP by professionals [7,11]. To facilitate the use of ZWIP among elderly patients, a number of approaches were used: flyers were distributed in the primary care centers, a hard-copy version of ZWIP was provided in order for patients to familiarize themselves with ZWIP, coaching on the use of ZWIP was made available, involvement of informal caregivers was encouraged, and the GPs actively advocated the use of ZWIP, thus drawing on modeling, guided practice, and tailoring support for use of the intervention [1,6]. During the implementation phase, we designated one key person in each family practice who coordinated implementation activities and helped colleagues with questions [6].

### Inclusion and Design

Between July 2010 and July 2011, frail older patients were included in an observational, controlled before-after study with 12 months follow-up to investigate ZWIP's effects on patient outcomes. Participating primary care centers were recruited from the university primary care network around the city of Nijmegen, the Netherlands. These centers identified their frail older people using the EASYcare Two-step Older person Screening (TOS) instrument [12]. Therefore, both intervention and control practices had to implement an identification scheme and redesign care for their frail elderly. Interventions centers were selected based on willingness to participate in ZWIP, whereas control practices were selected from a separate project: the EASYcare-TOS validation study [13]{van Kempen, 2013 #7718}. Frail status as determined by the EASYcare-TOS was the only inclusion criterion for included patients. Patients in the intervention group patients needed to agree to the creation of a ZWIP account. No exclusion criteria were specified.

All measurements were performed by trained nurses in the patients' homes, using a face-to-face questionnaire at baseline and at follow-up. The study was exempt from ethics review by the local ethics committee because of its observational nature and nonintrusive data collection. Nevertheless, oral informed consent was obtained to analyze the data during data collection.

### Outcomes

Primary outcomes were Activities of Daily Living (ADL) as measured by the Katz index [14], combined ADL and Instrumental Activities of Daily Living (IADL) as measured by the Katz-15, a combined measure of the ADL and Lawton-index [14,15], SF-36 mental health and social activity limitation dimensions [16]. The Katz index consists of yes or no responses on ADL items such as bathing or dressing. ADL scores range from 0-6 with higher scores indicating higher dependency. The Katz-15 consists of yes or no responses on ADL and additional IADL items such as using the telephone and managing money [14]. The Katz-15 scores range from 0-15 with higher scores indicating more limitations. Both scales are established in the literature and have adequate reliability and validity [17]. The SF-36 mental health dimension, consisting of the following subscales: happy, calm, blue, down, nervous scoring from 0-5 with higher numbers indicating a higher score. The scores were summed into a summary score ranging from 0-100, with 100 indicating full mental health, and 0 low mental health [16]. To assess differences in social activity limitations, the social activity limitation item from the SF-36 was used [16]. This item measures the frequency in which respondents experienced social activity limitations due to health. The item used in this current study is scored from 0 (none of the time) to 5 (all of the time). The various SF-36 subscales have excellent reliability and validity [17]. Secondary outcomes were several self-developed scales of patient satisfaction and GPs' subjective experience with care coordination. Patient satisfaction items were scored on a 5-point Likert scale ranging from 1 (way too little or way too much) to 5 (optimal), similar to this article [18]. GP experience with coordination of care was scored between 1 (uncoordinated) to 10 (optimal coordination). Important covariates were measured including a frailty index based on the accumulation of deficits concept [19,20]. The frailty index is the number of deficits present divided by a total possible number of deficits [2]. As such, the frailty index can account for all kinds of health-related imbalances between the intervention and control group and provides an accurate measure of individuals' frailty.

### Analysis

For comparing baseline characteristics, chi-square tests were used to compare nominal variables, and *t* tests were used for normally distributed continuous variables. Effects were determined using linear mixed models within a highly efficient analysis of covariance (ANCOVA) framework [21] to allow for clustering within a primary care center. Adjustments were made for frailty status and centered baseline status of the outcome variable and additional covariates with baseline imbalance. All analyses were performed with SAS 9.2.

## Results

Overall, 290/622 (46.6%) of all frail persons identified within 11 practices participated in the intervention group. From 6 practices 392 frail older people participated in the control group. At 12-month follow-up, in the intervention group 179/290 (61.7% of original) patients provided data at follow-up, versus 270/392 (68.8% of original) patients in the control group. At baseline, participants in the intervention group were more likely to have completed primary education only, have more informal caregivers, and have higher complexity of care compared to the participants in the control group. Further, participants in the intervention groups also had a higher average frailty index score, and GPs had lower experience with coordination of care (Table 1).

One quarter 45/117 (25%) of all patients in the intervention group used ZWIP at least once a month during a period of 12 months. Controlling for frailty and other unbalanced baseline characteristics, we found no significant differences in primary patient outcomes (Table 2). Change in coordination of care as reported by GPs improved in the control group.

**Table 1.** Demographic and care-related characteristics in the intervention and control group.

| Demographic and care-related characteristics | Category | Total | Intervention ZWIP, n=179, n (%) | Control regular care, n=270, n (%) | *P* value[a] |
|---|---|---|---|---|---|
| Sex, n (%) | Female | 284 | 117 (65.4) | 167 (61.8) | .45 |
| Age, mean (SD) | | 449 | 81.69 (5.38) | 81.32 (5.72) | .49 |
| **Education, n (%)** | | | | | |
| | Primary or less than primary education | 67 | 30 (19.1) | 37 (14.8) | <.01 |
| | Secondary education | 339 | 123 (76.5) | 216 (82.1) | |
| | University/tertiary education | 15 | 7 (4.4) | 8 (3.1) | |
| **Marital status, n (%)** | | | | | |
| | Married | 196 | 80 (45.2) | 116 (44.3) | .43 |
| | Divorced | 28 | 7 (3.4) | 21 (7.4) | |
| | Widow/widower/partner deceased | 199 | 79 (44.3) | 120 (44.1) | |
| | Unmarried | 24 | 12 (6.7) | 12 (4.2) | |
| Informal caregiver, n (%) | Available | 253 | 147 (82.6) | 106 (39.7) | <.01[a] |
| Living independently, n (%) | Yes | 230 | 86 (50.3) | 144 (53.0) | .46 |
| **Complexity of care, n (%)** | | | | | |
| | One professional | 63 | 12 (6.8) | 51 (18.7) | <.01[a] |
| | 2 or 3 professionals | 311 | 128 (71.9) | 183 (67.4) | |
| | >3 professionals | 74 | 38 (21.3) | 36 (13.9) | |
| Frailty index, mean (SD) | | 447 | 0.29 (0.07) | 0.27 (0.07) | .02[a] |
| Multimorbidity, mean (SD) | | 447 | 1.70 (1.22) | 1.73 (1.35) | .78 |
| GP experience with coordination of care around the patient, mean (SD) | | 449 | 5.92 (2.36) | 6.76 (3.45) | <.01[a] |

[a]2-sided chi-square for discrete and *t* tests for continuous variables.

**Table 2.** Change in outcomes by 12 months application of the ZWIP Web-based tool for patient-professional and interprofessional communication.

| Variable | Total | Intervention ZWIP baseline | Intervention ZWIP follow-up | Control baseline | Control follow-up | Standardized difference between study groups | *P* value (mixed model) |
|---|---|---|---|---|---|---|---|
| | N | mean (95% CI) | mean (95% CI) | mean (95% CI) | mean (95% CI) | mean, (95% CI) | |
| Katz ADL | 442 | 1.09 (0.91-1.27) | 1.35 (1.14-1.56) | 0.85 (0.72-0.98) | 1.02 (0.86-1.18) | 0.21 (-0.17-0.59) | .27 |
| Katz-15 | 442 | 5.08 (4.73-5.44) | 5.76 (5.32-6.21) | 4.24 (3.92-4.57) | 4.93 (4.58-5.28) | 0.50 (-1.59-2.60) | .64 |
| SF-36 mental health | 440 | 76.30 (74.32-78.28) | 74.59 (72.83-76.36) | 76.27 (74.77-77.77) | 79.06 (77.36-80.75) | -8.34 (-17.02-0.34) | .06 |
| SF-36 social | 436 | 1.44 (1.23-1.64) | 1.20 (1.01-1.39) | 0.87 (0.73-1.01) | 0.93 (0.79-1.08) | 0.84 (-0.78-2.45) | .31 |
| Patient experience with coordination of care | 303 | 4.66 (4.50-4.83) | 4.78 (4.65-4.91) | 4.59 (4.44-4.75) | 4.77 (4.67-4.88) | -0.25 (-0.99-0.49) | .58 |
| Patient experience with co-decision making | 399 | 3.51 (3.41-3.61) | 4.86 (4.77-4.95) | 3.63 (3.54-3.72) | 4.73 (4.62-4.83) | 0.16 (-0.40-0.71) | .64 |
| Patient preferences for influence | 414 | 3.59 (3.42-3.75) | 3.59 (3.42-3.76) | 3.22 (3.08-3.36) | 3.33 (3.20-3.45) | 0.36 (-1.28-1.99) | .08 |
| Patient knowledge of providers (health and social) | 432 | 3.51 (3.41-3.61) | 3.57 (3.46-3.68) | 3.63 (3.54-3.72) | 3.68 (3.59-3.77) | -0.68 (-1.44-0.08) | .08 |
| Patient experience with self-management | 386 | 4.85 (4.76-4.93) | 4.87 (4.80-4.95) | 4.78 (4.67-4.88) | 4.72 (4.61-4.83) | 0.38 (-0.29-1.06) | .26 |
| GP experience with coordination of care around the patient | 432 | 5.92 (5.58-6.27) | 7.11 (6.81-7.42) | 6.76 (6.34-7.17) | 8.18 (7.94-8.42) | -5.28 (-10.64-0.07) | .04 |

## Discussion

### Summary of Results

There were 290 patients who participated in the intervention group and 392 in the control group. In the intervention group 76/290 (26.2%) of the patients actively used ZWIP. After a follow-up of 12 months, we observed no significant improvement on primary patient outcomes, ADL, IADL, and mental health.

### Strengths and Limitations

The online ZWIP platform was specifically developed for reducing fragmentation of care delivery in older people. Almost half of a frail elderly population without exclusion criteria could be included in the intervention group for using the online ZWIP tool [6]. This is modestly higher than what can be expected in the Dutch context, where 39% persons older than 75 years report having Internet access [22]. This study has two important limitations that can impact results. First, due to the observational nature of the study, comparability between the intervention and the control groups was limited. Despite adjusting for a range of covariates, there may be residual confounding.

Observational, controlled before-after designs are common for complex interventions, where randomized controlled trials (RCTs) are often not appropriate or feasible for evaluation [23]. In the case of ZWIP, contamination between patients would have made individual-level randomization inappropriate. Cluster randomization was not feasible because the level of commitment required from a number of local stakeholders could not be sustained in the control group.

A second limitation was the fact that actual usage of ZWIP was low, even though the implementation of ZWIP was prepared systematically during the development of ZWIP, as this is a structural part of intervention mapping [1,6,7,24,25]. Additionally, implementation strategies were added or adapted when needed during the actual implementation phase. A wide range of implementation strategies were used to encourage uptake; for example, a training program was developed for professionals and an active recruitment phase led to a high participation of older persons. Therefore, low levels of use were attained not because of the lack of, but despite using state of the art implementation techniques. Failure to integrate eHealth interventions in health care is widespread [26], and therefore the low levels of use of these frail older subjects is not surprising. This is especially true for sustained usage of an eHealth intervention [27]. As in other studies [26], further efforts should be focused on improving usability of the intervention, in terms of compatibility for frail older people in chronic disease trajectories [28].

### Future Directions

In addition to further refinement, it is essential to identify those who benefit most from ZWIP and eHealth applications in general. The use of eHealth applications in frail populations could be increased by first identifying frail people with a high likelihood of early adoption of the eHealth intervention, such as people with high computer literacy. Which frail elderly are likely adopters requires further research [26]. Therefore, we plan to perform a quantitative and qualitative evaluation of ZWIP usage as well, going beyond the scope of this paper. We must recognize that in the early stages of evaluation, we take more of an efficacy approach to the evaluation, rather than a pragmatic trial approach. Although the efficacy approach limits generalizability, it allows a thorough investigation of the intervention's working mechanisms under more controlled, laboratory-like conditions. Such work may also reveal ideal levels of use of ZWIP, as it is possible that communication was already adequate in the case of some patients, making ZWIP usage superfluous. Using both quantitative and qualitative methods in this development phase may elicit remaining barriers and reveal more effective implementation strategies. Only after adapting to this group and proven efficacy is large-scale implementation warranted. Successful wide-scale implementation is a precondition for investigating the effectiveness of eHealth interventions. Otherwise finding no differences between treatment arms cannot be interpreted as a lack of effectiveness. These arguments show that, sufficient time and resources are required to develop, test, and retest new eHealth interventions before finally evaluating their effectiveness in pragmatic trials [29,30].

### Conclusions

Overall, the study confirmed that introducing eHealth interventions in the elderly is a difficult task. Despite using a theory-driven intervention design and state of the art implementation techniques, usage remained low and effectiveness was not observed. Performing a thorough proof of principle study in early adopters may be crucial to improving the use of eHealth interventions in the elderly before evaluating effects on a larger scale.


## Acknowledgments

This study was supported by the Netherlands Organization for Health Service and Development (ZonMw) project #311050201. The funder had no role in conducting the study, analysis of the data, or publication of the manuscript.

We would like to thank Wilma Derksen-Driessen, Emile ter Horst Mark Kuster, Charlotte Neger, Jean Nielen, Joep Scheltinga, and Leontien van Nieuwenhuijzen for their assistance in the development and implementation of the program. We would also like to thank Jennifer Lutomski for English editing.


## Authors' Contributions

PM drafted the manuscript, conducted the analysis, and interpreted the data. MP, SHMR, and HJS contributed to the design, data collection, and revised the manuscript for important content. MMH and MGMOR contributed to the design and revised the manuscript for important intellectual content. RJFM contributed to the design, interpretation of the data, and revised the manuscript for important intellectual content. All authors approved the final manuscript.

## Conflicts of Interest

None declared.

## Multimedia Appendix 1

Short video of ZWIP in use.

[WMV File (Windows Media Video), 1MB - jmir_v16i6e156_app1.wmv ]

## References


1. Robben SH, Huisjes M, van Achterberg T, Zuidema SU, Olde Rikkert MG, Schers HJ, ZOWEL NN Study Group. Filling the Gaps in a Fragmented Health Care System: Development of the Health and Welfare Information Portal (ZWIP). JMIR Res Protoc 2012;1(2):e10 [FREE Full text] [doi: 10.2196/resprot.1945] [Medline: 23611877]
2. Mitnitski AB, Mogilner AJ, Rockwood K. Accumulation of deficits as a proxy measure of aging. ScientificWorldJournal 2001 Aug 8;1:323-336 [FREE Full text] [doi: 10.1100/tsw.2001.58] [Medline: 12806071]
3. Stange KC. The problem of fragmentation and the need for integrative solutions. Ann Fam Med 2009;7(2):100-103 [FREE Full text] [doi: 10.1370/afm.971] [Medline: 19273863]
4. Weiner M, Callahan CM, Tierney WM, Overhage JM, Mamlin B, Dexter PR, et al. Using information technology to improve the health care of older adults. Ann Intern Med 2003 Sep 2;139(5 Pt 2):430-436. [Medline: 12965971]
5. van der Eijk M, Faber MJ, Aarts JW, Kremer JA, Munneke M, Bloem BR. Using online health communities to deliver patient-centered care to people with chronic conditions. J Med Internet Res 2013;15(6):e115 [FREE Full text] [doi: 10.2196/jmir.2476] [Medline: 23803284]

6. Robben SH, Perry M, Huisjes M, van Nieuwenhuijzen L, Schers HJ, van Weel C, et al. Implementation of an innovative web-based conference table for community-dwelling frail older people, their informal caregivers and professionals: a process evaluation. BMC Health Serv Res 2012;12:251 [FREE Full text] [doi: 10.1186/1472-6963-12-251] [Medline: 22894654]
7. Bartholomew LK, Parcel GS, Kok G, Gottlieb NH, Fernandez ME. Planning health promotion programs: An intervention mapping approach. New York: John Wiley & Sons; Jan 25, 2011:-768.
8. Bandura A. Health promotion by social cognitive means. Health Educ Behav 2004 Apr;31(2):143-164. [doi: 10.1177/1090198104263660] [Medline: 15090118]
9. Bandura A. Self-efficacy. In: Ramachandran VS, editor. Encyclopedia of Human Behavior, Second Edition. CA: Academic Press; 2012.
10. Prince M. Does Active Learning Work? A Review of the Research. Journal of Engineering Education 2004 Jul;93(3):223-231. [doi: 10.1002/j.2168-9830.2004.tb00809.x]
11. Butterfoss F, Kegler M, Francisco V. Mobilizing organizations for health promotion: theories of organizational change. In: Glanz K , editor. Health behavior and health education: theory, research and practice. San Francisco, CA: Jossey-Bass; 2008:335-361.
12. van Kempen JA, Schers HJ, Jacobs A, Zuidema SU, Ruikes F, Robben SH, et al. Development of an instrument for the identification of frail older people as a target population for integrated care. Br J Gen Pract 2013 Mar;63(608):e225-e231 [FREE Full text] [doi: 10.3399/bjgp13X664289] [Medline: 23561790]
13. van Kempen JA, Schers HJ, Jacobs A, Zuidema SU, Ruikes F, Robben SH, et al. Development of an instrument for the identification of frail older people as a target population for integrated care. Br J Gen Pract 2013 Mar;63(608):e225-e231 [FREE Full text] [doi: 10.3399/bjgp13X664289] [Medline: 23561790]
14. Katz S. Assessing self-maintenance: activities of daily living, mobility, and instrumental activities of daily living. J Am Geriatr Soc 1983 Dec;31(12):721-727. [Medline: 6418786]
15. Weinberger M, Samsa GP, Schmader K, Greenberg SM, Carr DB, Wildman DS. Comparing proxy and patients' perceptions of patients' functional status: results from an outpatient geriatric clinic. J Am Geriatr Soc 1992 Jun;40(6):585-588. [Medline: 1587975]
16. Ware JE, Sherbourne CD. The MOS 36-item short-form health survey (SF-36). I. Conceptual framework and item selection. Med Care 1992 Jun;30(6):473-483. [Medline: 1593914]
17. McDowell I, Newell C. Measuring health: a guide to rating scales and questionnaires. New York: Oxford University Press; 2006:-748.
18. Goldberg SE, Bradshaw LE, Kearney FC, Russell C, Whittamore KH, Foster PE, Medical Crises in Older People Study Group. Care in specialist medical and mental health unit compared with standard care for older people with cognitive impairment admitted to general hospital: randomised controlled trial (NIHR TEAM trial). BMJ 2013;347:f4132 [FREE Full text] [Medline: 23819964]
19. Lutomski JE, Baars MA, van Kempen JA, Buurman BM, den Elzen WP, Jansen AP, et al. Validation of a frailty index from the older persons and informal caregivers survey minimum data set. J Am Geriatr Soc 2013 Sep;61(9):1625-1627. [doi: 10.1111/jgs.12430] [Medline: 24028364]
20. Rockwood K, Mitnitski A. Frailty in relation to the accumulation of deficits. J Gerontol A Biol Sci Med Sci 2007 Jul;62(7):722-727. [Medline: 17634318]
21. Teerenstra S, Eldridge S, Graff M, de Hoop E, Borm GF. A simple sample size formula for analysis of covariance in cluster randomized trials. Stat Med 2012 Sep 10;31(20):2169-2178. [doi: 10.1002/sim.5352] [Medline: 22495809]
22. Statistics Netherlands. Web Magazine. 2013. Rapid increase internet usage among older people URL: http://www.cbs.nl/en-GB/menu/themas/vrije-tijd-cultuur/publicaties/artikelen/archief/2013/2013-4005-wm.htm?Languageswitch=on [accessed 2014-06-10] [WebCite Cache ID 6QE0xa1Q7]
23. Craig P, Dieppe P, Macintyre S, Michie S, Nazareth I, Petticrew M, Medical Research Council Guidance. Developing and evaluating complex interventions: the new Medical Research Council guidance. BMJ 2008;337:a1655 [FREE Full text] [Medline: 18824488]
24. Brendryen H, Johansen A, Nesvåg S, Kok G, Duckert F. Constructing a Theory- and Evidence-Based Treatment Rationale for Complex eHealth Interventions: Development of an Online Alcohol Intervention Using an Intervention Mapping Approach. JMIR Res Protoc 2013;2(1):e6 [FREE Full text] [doi: 10.2196/resprot.2371] [Medline: 23612478]
25. Vonk Noordegraaf A, Huirne JA, Pittens CA, van Mechelen W, Broerse JE, Brölmann HA, et al. eHealth program to empower patients in returning to normal activities and work after gynecological surgery: intervention mapping as a useful method for development. J Med Internet Res 2012;14(5):e124 [FREE Full text] [doi: 10.2196/jmir.1915] [Medline: 23086834]
26. Vedel I, Akhlaghpour S, Vaghefi I, Bergman H, Lapointe L. Health information technologies in geriatrics and gerontology: a mixed systematic review. J Am Med Inform Assoc 2013;20(6):1109-1119. [doi: 10.1136/amiajnl-2013-001705] [Medline: 23666776]
27. Eysenbach G. The law of attrition. J Med Internet Res 2005;7(1):e11 [FREE Full text] [doi: 10.2196/jmir.7.1.e11] [Medline: 15829473]

28. Scandurra I, Sjölinder M. Participatory Design With Seniors: Design of Future Services and Iterative Refinements of Interactive eHealth Services for Old Citizens. Med 2.0 2013 Oct 08;2(2):e12 [FREE Full text] [doi: 10.2196/med20.2729]
29. van Gemert-Pijnen JE, Nijland N, van Limburg M, Ossebaard HC, Kelders SM, Eysenbach G, et al. A holistic framework to improve the uptake and impact of eHealth technologies. J Med Internet Res 2011;13(4):e111 [FREE Full text] [doi: 10.2196/jmir.1672] [Medline: 22155738]
30. Makai P, Melis RJ, Olde-Rikkert MG. Technical difficulties and evaluating e-health interventions. JAMA Intern Med 2014 Feb 1;174(2):304-305. [doi: 10.1001/jamainternmed.2013.12753] [Medline: 24493611]

## Abbreviations

**ADL:** Activities of Daily Living
**ANCOVA:** analysis of covariance
**EASYcare-TOS:** EASYcare Two-step Older person Screening
**GP:** general practitioner
**IADL:** Instrumental Activities of Daily Living
**OHC:** Online Health Community
**ZWIP:** Health and Welfare portal

*Edited by G Eysenbach; submitted 29.10.13; peer-reviewed by M Wise, S Langrial; comments to author 09.01.14; revised version received 10.02.14; accepted 31.05.14; published 23.06.14.*

*Please cite as:*
*Makai P, Perry M, Robben SHM, Schers HJ, Heinen MM, Olde Rikkert MGM, Melis RF*
*Evaluation of an eHealth Intervention in Chronic Care for Frail Older People: Why Adherence is the First Target*
*J Med Internet Res 2014;16(6):e156*
*URL: http://www.jmir.org/2014/6/e156/*
*doi:10.2196/jmir.3057*
*PMID:24966146*

Original Paper

# Tablet-Based Strength-Balance Training to Motivate and Improve Adherence to Exercise in Independently Living Older People: Part 2 of a Phase II Preclinical Exploratory Trial

Eva van het Reve[1*], MSc; Patrícia Silveira[2*], PhD; Florian Daniel[2*], PhD; Fabio Casati[2*], PhD; Eling D de Bruin[1,3,4*], PhD

[1]Institute of Human Movement Sciences and Sport, Department of Health Sciences and Technology, ETH Zurich, Zurich, Switzerland

[2]University of Trento, Department of Information Engineering and Computer Science, University of Trento, Trento, Italy

[3]CAPHRI School for Public Health and Primary Care, Department of Epidemiology, Maastricht University, Maastricht, Netherlands

[4]Centre for Evidence Based Physiotherapy, Maastricht University, Maastricht, Netherlands

[*]all authors contributed equally

**Corresponding Author:**
Eva van het Reve, MSc
Institute of Human Movement Sciences and Sport
Department of Health Sciences and Technology
ETH Zurich
HIT J31.2
Wolfgang-Pauli-Strasse 27
Zurich, 8093
Switzerland
Phone: 41 44 632 4018
Fax: 41 44 632 1142
Email: eva.vanhetreve@hest.ethz.ch

## Abstract

**Background:** Home-based exercise programs can improve physical functioning and health status of elderly people. Successful implementation of exercise interventions for older people presents major challenges and supporting elderly people properly while doing their home-based exercises is essential for training success. We developed a tablet-based system—ActiveLifestyle—that offers older adults a home-based strength-balance training program with incorporated motivation strategies and support features.

**Objective:** The goal was to compare 3 different home-based training programs with respect to their effect on measures of gait quality and physical performance through planned comparisons between (1) tablet-based and brochure-based interventions, (2) individual and social motivation strategies, and (3) active and inactive participants.

**Methods:** A total of 44 autonomous-living elderly people (mean 75, SD 6 years) were assigned to 3 training groups: social (tablet guided, n=14), individual (tablet guided, n=13), and brochure (brochure guided, n=17). All groups joined a 12-week progressive home-based strength-balance training program. Outcome measures were gait performance under single and dual task conditions, dual task costs of walking, falls efficacy, and physical performance as measured by the Short Physical Performance Battery (SPPB). Furthermore, active (≥75% program compliance) and inactive (<75% program compliance) individuals were compared based on their characteristics and outcome measures.

**Results:** The tablet groups showed significant improvements in single and dual task walking, whereas there were no significant changes observable in the brochure group. Between-groups comparisons revealed significant differences for gait velocity ($U$=138.5; $P$=.03, $r$=.33) and cadence ($U$=138.5, $P$=.03 $r$=.34) during dual task walking at preferred speed in favor of the tablet groups. The brochure group had more inactive participants, but this did not reach statistical significance ($U$=167, $P$=.06, $r$=.29). The active participants outperformed the inactive participants in single and dual task walking, dual task costs of walking, and SPPB scores. Significant between-groups differences were seen between the tablet groups and the brochure group, in favor of the tablet groups.

**Conclusions:** A tablet-based strength-balance training program that allows monitoring and assisting autonomous-living older adults while training at home was more effective in improving gait and physical performance when compared to a brochure-based program. Social or individual motivation strategies were equally effective. The most prominent differences were observed between active and inactive participants. These findings suggest that in older adults a tablet-based intervention enhances training compliance; hence, it is an effective way to improve gait.

***(J Med Internet Res 2014;16(6):e159)*** doi:10.2196/jmir.3055

**KEYWORDS**

gait; aging; exercise therapy; tablet; delivery of health care

## Introduction

One of the major opportunities to extend years of active independent life and to promote an independent lifestyle is to be physically active on a regular basis [1-3]. Physical activity can prevent several diseases (eg, cancer and type II diabetes mellitus) and has the potential to enhance both physical and cognitive functioning and cardiovascular and psychological health [4-8]. For older adults, structured exercise training is recommended to postpone frailty and vulnerability [9,10] and to minimize several chronic degenerative diseases that result from an inactive lifestyle [11,12]. The evidence that sedentary people lose a relatively large fraction of their muscle mass in the aging process [1] confirms that avoiding physical inactivity is an obvious aim for interventions [12]. In past research, the effect of physical activity has also been linked to an increase in life expectancy [13], diminishing probability of a fall [14-16], and in preventing sarcopenia [1,17]. Accordingly, keeping older adults physically active is a crucial step toward prevention of several diseases.

Walking requires efficient circulatory, heart, lung, nervous, and musculoskeletal systems [18]. In combination with deficits in these systems, walking ability in old age often deteriorates. Gait quality assessment with dedicated gait analysis systems [19], expressed through measures of variability [20], showed that both stride time and stride length variability are associated with the control of the rhythmic stepping mechanism [21]. Errors in foot placement control and/or displacement of the center of mass may result in higher variability [21,22], which in turn leads to falls in older adults [23,24]. Furthermore, gait speed is one of the factors reflecting functional ability and independence [25]. Slowed walking may reflect damaged organ systems [18,26]. Relationships between faster gait speed and reduced mortality [18,27], and shorter length of stay in geriatric hospitals [28,29] have been demonstrated. In contrast, reduced gait speed can be associated with falls and a decline in cognitive factors [30], such as attention and psychomotor speed [31]. This reduction in gait speed in older people has been shown to be a result of shorter step lengths [32,33] and increased double support time [33,34], which are changes in gait that relate to falls in elderly [35]. Another important determinant of gait function in both healthy and unhealthy elderly is lower extremity muscle function [36]. To summarize, a decrease in walking ability and abnormal walking frequently results in disability and falls, which can lead to a loss of independence in activities of daily living [37], institutionalization, and death [38,39]. Furthermore, a lack in gait quality can lead to a fear of falling [37].

When strength training is complemented with balance exercises, a transfer to functional tasks of daily living may be expected [40]. Therefore, to optimize walking quality, strength and balance training, previously showed to be effective [41-43], should be applied and adhered to.

Home-based exercise programs—provided that they are performed correctly—can be effective in improving physical functioning [15] and health status of elderly people [1]. Especially for older adults without access to exercise facilities (eg, because they live in rural or remote areas), an effective home-based intervention at regular intervals potentially offers great benefits. Large travel distances and deteriorations in locomotion could potentially limit the ability of these people to visit a training center [44,45]. However, despite the fact that exercise has been widely accepted as beneficial for health, successful implementation of exercise interventions presents a major challenge for many older people [46].

The importance of monitoring and supporting elderly people while doing their home-based exercises should not be neglected. Providing feedback, social support, motivation, and encouragement seem to be essential factors in enhancing adherence [47-49]. Although older adults often express the desire for training support at home [50], these factors are difficult to implement in home-based exercise programs. Remote feedback strategies may have the potential to replace live supervision while exercising at home [51]. For an overview about related work on this topic, we refer to our previous studies describing our phase II study [52] with the tablet-based app ActiveLifestyle [53]. This part of our study compares 3 different home-based training programs and their effect on measures of gait quality while considering adherence to the training program. We hypothesized differing results for (1) tablet-based groups when compared to a brochure group, (2) a tablet group with social motivation strategies when compared to a tablet group with individual motivation strategies, and (3) active participants when compared to inactive participants.

## Methods

### The ActiveLifestyle App

ActiveLifestyle offers autonomous-living older adults tablet-based software that supports them doing their physical exercises. The app assists, monitors, and motivates this group of people while doing their exercise program at home. The program consists of a strength and balance training plan. Exercises are shown with videos and explained with written and oral instructions. Details of the exercises are given in the Intervention Program section. The ActiveLifestyle app comes in 2 different versions: the individual version contains individual motivation strategies and the social version consists of individual and social motivation strategies. Social and individual motivation strategies were included to help participants comply with the training plan. A summary description of these motivation strategies is provided here because a detailed description has been published elsewhere [53]. The intention of the integrated individual motivation strategies (ie, conditioning through positive and negative reinforcement, goal setting, self-monitoring, awareness) is to convince the person about the expected gain for himself/herself (eg, enhance awareness of health benefits by doing strength and balance exercises). Social motivation strategies (ie, comparison, external monitoring, emotional support, collaboration) aim at supporting individuals (eg, through a social network consisting of training partners and caregivers). ActiveLifestyle supports 6 main features accessible through its menu:

1. The What's Next? option invites the users to start the performance of due workout sessions.
2. The Weekly Exercises option shows the scheduled strength-balance sessions organized per week.
3. The Progress option shows the user's progress through the conditioning, goal setting, and self-monitoring strategies previously mentioned in both versions. The social version, in addition to these strategies, also supports the collaboration strategy through a collaborative game.
4. The Bulletin Board allows the users to receive written messages, which may include links to websites and YouTube videos. Three types of messages are supported: (1) workout session completed messages to inform the participant(s) about the conclusion of a scheduled session of exercises, (2) ActiveLifestyle tips messages to support the awareness motivation strategy, and (3) public messages written by the training members. It is important to note that only the social version supports the third type of messages and can send messages to the whole training plan community.
5. The Friends option lists the members of the training plan community (ie, older users and experts). Only the social version supports this feature.
6. The inBox option allows users of the social version to exchange private text messages with their list of friends.

To minimize failure to follow the program because of a memory lapse, an alarm clock helps to remind participants about their training thrice daily. The application has previously shown to be feasible for older adults [54].

## Participants

A sample of 44 autonomously living older adults was selected according to the following inclusion criteria: older than 65 years, able to walk 20 meters with or without aids, and free of rapidly progressive illness, acute illness, or unstable chronic illness. Ethical approval for the study was obtained from the ETH Ethics Committee (EK 2011-N-64). All participants provided written consent before they participated in the study.

Participants were recruited by convenience sampling from 2 institutions for older people and 1 organization responsible for coordinating and providing at-home nursing care for seniors. The Senioren Begegnungszentrum Baumgärtlihof, a day center dedicated to deliver services and information related to the older population (Horgen, Switzerland), advised potential participants through its mailing list and by notes in the local newspaper. The Alterswohnungen Turm-Matt, a cooperative offering housing and daily living facilities to older people (Wollerau, Switzerland), informed and advised potential participants in person or by phone and distributed flyers to advertise the study. The Fachstelle für präventive Beratung Spitex-Zürich, a home-care nursing organization (Spitex-Zürich), promoted the study sending letters and specifically inviting patients in need of better physical performance. Spitex nurses selected potential participants based on the eligibility criteria.

Participants who fulfilled the inclusion criteria were assigned to either the brochure group (n=17), the social group (n=13), or the individual group (n=14). The social and individual groups received a tablet with the ActiveLifestyle app. Both the social and individual group versions of the app consisted of individual motivation strategies, whereas social motivation strategies were added only for the social group. Participants in the brochure group did their exercises using a training plan on paper sheets.

Participants who stopped doing their exercises during the 12 weeks of the program were defined as dropouts.

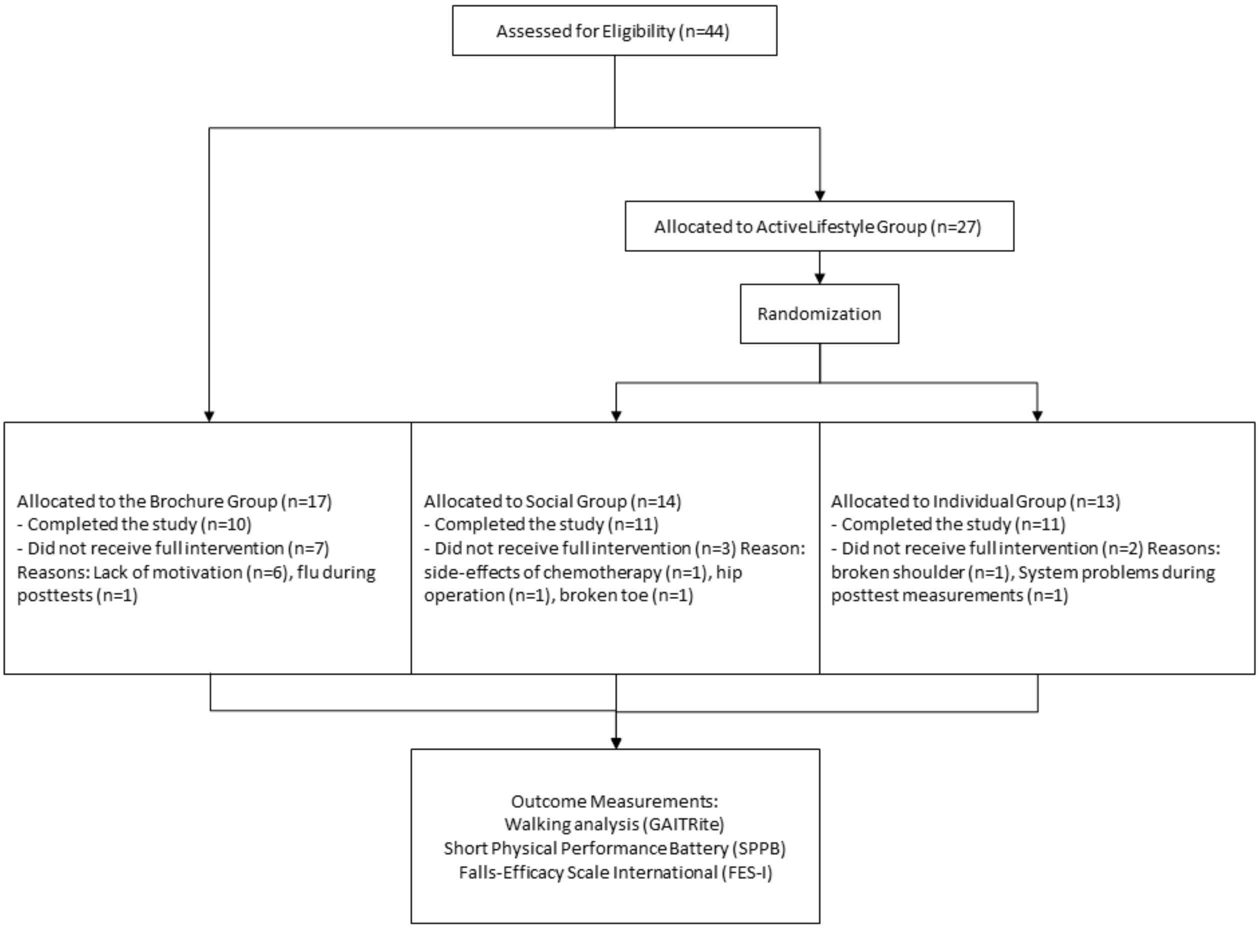
## Design

### *Overview*

This study was designed as a phase II preclinical exploratory trial. The outcome variables were measured at baseline (T0) and after 3 months of the intervention. Pre and post measurements took place in suitable locations at the participating institutions. Individuals from the tablet groups visited 1 class to learn how to use the tablet and the included ActiveLifestyle app. A second class was held for all 3 groups to give instructions on how to do the exercises. The training exercise program was to be conducted at home. A flowchart of participants is presented in Figure 1.

At entry to the study, a medical history through self-report was taken for demographic and health-related information.

**Figure 1.** The study flowchart.




### *Motor Intervention Program*

Interventions that aim to improve walking function and prevent falls should include both strengthening and balance exercises [55]. Therefore, we developed a program with the help of guidelines and recommendations from previous studies [12,56-58]. Participants from all groups performed the same strength and balance exercises. Detailed information about the physical exercises is shown in Table 1 and an exercise example is given in Figure 2.

The intervention consisted of twice-weekly progressive resistance training for 12 weeks. Training devices used were resistance bands and soft balls. Exercises with resistance bands showed to be efficient in enhancing physical functioning in autonomously living older adults [59]. Before the strength exercises, participants conducted a warm up. Flexibility exercises followed the program to maintain or improve range of motion necessary for daily activities. Additionally, all participants performed 3 balance exercises 5 times a week. Frequency, intensity, and duration of the exercises were based on published recommendations [12,56,58,60].

To ensure exercise progression during the whole program, the intervention was divided into 3 levels (Figure 3). From week 1 to week 4, participants trained at the beginner level; from week 5 to week 8, they trained at the intermediate level; and from week 9 to week 12, they trained at the expert level. The 3 training levels differed in exercise execution, number of sets, and training additives (eg, ankle weights for strength exercises, towels for balance exercises).

Following performance of each strength and balance exercise, participants registered their performed sets, repetitions, and perceived exertion on Borg's scale of perceived exertion [61]. The social and individual groups were automatically asked to provide feedback of their exercise experience in the app. Without this feedback, the program would not continue. The brochure group received a paper form to provide this feedback information with a pencil. This information was expected following each strength and balance exercise.

**Table 1.** Exercises of the intervention program.

| Exercises | Beginner | Intermediate | Expert |
|---|---|---|---|
| Warm up; 2 times/week | 1 set, 10 repetitions | 1 set, 10 repetitions | 1 set, 10 repetitions |
| | Shoulder rotation | Standing shoulder rotation | Standing shoulder rotation |
| | Arms circles | Standing arms circles | Standing arms circles |
| | Leg raises | March | March |
| | Pointed foot to heel | Standing foot to heel point | Standing foot to heel point |
| | Hip abduction and adduction | Standing side tap | Standing side tap |
| | Rest head left and right | Rest head left and right | Rest head left and right |
| Strength training; 2 times/week | 2 sets, 12 repetitions | 3 sets, 12 repetitions | 3 sets, 12 repetitions |
| | Chair stand | Chair stand, arms stretched out | Fast chair stand |
| | Seated hip flexion | Standing hip flexion | Standing hip flexion without placing foot on the floor |
| | Seated hip adduction | Seated hip adduction | Standing hip adduction |
| | Seated hip abduction | Standing hip abduction[a] | Standing hip abduction without placing foot on floor[a] |
| | Seated leg extension | Seated leg extension[a] | Standing leg extension[a] |
| | Standing leg curl | Standing leg curl a | Standing leg curl a, without placing foot on floor |
| | Standing heel lift | Standing heel lift[a] | One-leg heel lift[a] |
| | Seated sit-ups | Seated sit-ups, arms behind head | Seated sit-ups, straight arms overhead |
| | Seated side arm raise with resistance band | Standing side arm raise with resistance band | Side arm raise with resistance band, fast movement |
| | Seated toe lift | Seated toe lift[a] | Standing toe lift[a] |
| Stretching; 2 times/week | 3 sets, 15 seconds | 3 sets, 15 seconds | 3 sets, 15 seconds |
| | Seated leg stretch | Seated leg stretch | Seated leg stretch |
| | Seated hip stretch | Seated hip stretch | Seated hip stretch |
| Balance; 5 times/week | 3 sets, 15 seconds | 3 sets, 15 seconds | 3 sets, 15 seconds |
| | One-leg stand | One-leg stand on a towel | One-leg stand, eyes closed |
| | Full tandem stand | Full tandem stand on a towel | Full tandem stand, eyes closed |
| | Heel-to-toe walk | Heel-to-toe walk, forward and backward | Heel-to-toe walk, eyes closed |

[a]With ankle weights (0.5-2 kg per leg).

**Figure 2.** Example of an exercise instruction: intermediate seated leg extension with weights.

| | |
|---|---|
| **Strength training** | 1. Tie the weight cuff around your ankle. |
| **Exercise 5** | 2. Breathe in slowly |
| Seated leg extension | 3. While exhaling, straighten the leg |
| **3 x 12** | 4. While inhaling you lower the heel |
| | Knees should always remain at the same height, body is straight. |

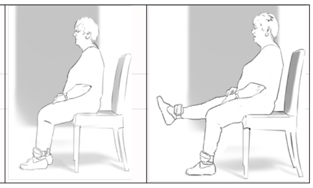
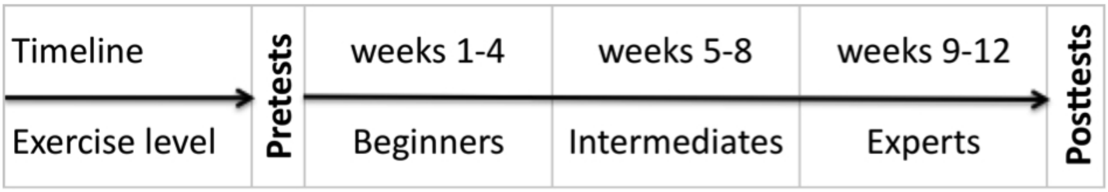


**Figure 3.** Timeline and exercise levels.




## Test Procedures and Outcome Measures

### *Program Adherence*

The criteria for success of our pilot study [62] were based on feasibility objectives and focused on compliance with the training plan (eg, the attendance rate of participants). For adherence to the intervention, the compliance of the participants with all trainings was recorded. A compliance rate of 75% was deemed acceptable [63]. Participants were defined as active participants when 75% or more of all planned exercises were performed or as inactive with an attendance less than 75% [64]. Compliance within the exercise program for the groups using tablets was assessed with an automatic registration after completing the exercises, whereas participants of the brochure group had to fill in a training plan diary.

### *Gait Analysis*

Gait was measured with the portable electronic GAITRite walkway with Platinum Version 4.0 software (CIR Systems, Sparta, NJ, USA). Sampling rate was 60 Hz [65,66]. This system is a valid and reliable tool for measuring spatial and temporal parameters of gait [67]. Participants were instructed to walk under 4 conditions for 2 or 3 trials each, depending on their physical condition: (1) at their self-selected speed (preferred walking), (2) at their fastest speed (fast walking), (3) at their self-selected speed while concurrently performing a cognitive task (dual task preferred walking), and (4) at their fastest speed while concurrently performing a cognitive task (dual task fast walking). For the cognitive task, participants were asked to continuously subtract 7 or 3 from a given number while walking. If they were not able to perform the cognitive task, the arithmetical task was modified to a verbal fluency task. The verbal fluency task consisted of enumerating animals or flowers. Participants were asked not to give priority to one task over the other in the dual task test condition, but to try to perform both (walking and calculating) equally well at the same time.

The following temporal-spatial parameters were taken for analysis: velocity (cm/s), cadence (steps/min), step time (s), step length (cm), double support time (s), and variability of step time and length. Variability was expressed as standard deviation of step time (SD step time) and standard deviation of step length (SD step length) over the measured number of gait cycles while walking on the GAITRite walkway.

To quantify participants' ability to execute 2 tasks simultaneously, we calculated the relative dual task costs (DTC) of walking according the following formula [68,69]: DTC (%)=100 * (single task score-dual task score) / single task score.

### *Physical Performance and Fear of Falling*

Lower extremity functioning was assessed with the Short Physical Performance Battery (SPPB). This test battery consists of a balance test, a 3-meter gait test, and a 5 chair-rises test. The sum of the 3 components comprises the final SPPB score with a possible range from 0 to 12 (12 indicating the highest degree of lower extremity functioning). The SPPB is a valid and reliable measure of mobility in older adults [70] and can predict future disability [71].

The Falls Efficacy Scale International (FES-I) questionnaire was used as a measure of concern about falling to determine the transfer effects of training. This scale assesses both easy and difficult physical activities and social activities (scale: 1=not at all concerned, 2=somewhat concerned, 3=fairly concerned, 4=very concerned). The FES-I has excellent internal and test-retest reliability [72].

## Statistical Analysis

All statistical procedures were conducted with SPSS version 21.00 (SPSS Inc. Chicago, IL, USA). All available data were analyzed by initial group assignment and were performed with an intention-to-treat approach [73]. All participants were included in the analysis regardless of their adherence rate. We assumed that all missing responses were constant and replaced the missing values with mean values of the group to which participants were originally allocated [74]. Because of the nonnormality of the data, baseline comparison and interaction effects of groups (between-groups differences) were undertaken using a Mann-Whitney $U$ test. The effects size, $r$, was calculated as $r=z/\sqrt{N}$ (where $z$ is the approximation of the observed difference in terms of the standard normal distribution and N is the total sample number). To identify differences between pretests and posttests (within-group differences) a Wilcoxon signed rank test was conducted. We identified differences between (1) the brochure group and the tablet groups (brochure group vs social and individual groups), (2) between the 2 tablet groups: (social group vs individual group), and (3) between active and inactive participants using planned comparisons.

Suggested norms for interpreting $r$ are .10=small effect, .30=moderate effect, and .50=large effect. A probability level of $P<.05$ was considered to be statistically significant.

# Results

## Overview

Participants' demographics and baseline characteristics are summarized in Table 2. Results are based on a self-report health questionnaire. In general, there were no significant between-groups differences of baseline demographics for most parameters using planned comparisons: (1) brochure group vs social group and individual groups and (2) social group vs individual group. We detected significant differences between (1) brochure group vs social and individual groups in joint diseases, practiced some sport in the past, and 3 or more medications daily. The brochure group reported less joint diseases (*U*=139, *P*=.01, *r*=.38), practiced less sport in the past (*U*=144, *P*=.02, *r*=.36), and took less medication (*U*=166.5, *P*=.04, *r*=.32).

**Table 2.** Participants' demographics and baseline characteristics (N=44).

| Characteristic | Group | | | Activity level | |
|---|---|---|---|---|---|
| | Brochure n=17 | Social n=13 | Individual n=14 | Active n=26 | Inactive n=18 |
| Age, mean (SD) | 76 (15) | 74 (5) | 75 (6) | 75 (5) | 76 (7) |
| **Sex, n (%)** | | | | | |
| Female | 10 | 8 (62) | 10 (71) | 15 (58) | 13 (72) |
| Male | 7 | 5 (38) | 4 (29) | 11 (42) | 5 (28) |
| **Fall risk factors, n (%)** | | | | | |
| Slow walking speed (<1.22 m/s) | 10 (59) | 9 (69) | 7 (50) | 14 (54) | 12 (67) |
| Fell in the last 6 months[a] | 4 (24) | 5 (38) | 2 (14) | 5 (19) | 6 (33) |
| 3 or more prescription medications | 1 (6) | 4 (31) | 5 (36) | 8 (30) | 2 (11) |
| Physical functioning; SPPB (points) | 9.8 | 9.7 | 9.9 | 10.1 | 9.4 |
| Fear of falling; FES-I (points) | 17.9 | 20.0 | 18.5 | 18.9 | 18.9 |
| **Education/profession, n (%)** | | | | | |
| University/college | 1 (6) | 2 (15) | 3 (21) | 3 (12) | 3 (17) |
| Vocational education | 10 (59) | 7 (54) | 7 (50) | 18 (69) | 8 (44) |
| No educated profession | 6 (35) | 4 (31) | 4 (29) | 5 (19) | 7 (39) |
| In a sitting position past profession | 6 (35) | 6 (46) | 7 (50) | 13 (50) | 8 (44) |
| **Health questions, n (%)** | | | | | |
| **Number of self-reported chronic diseases** | | | | | |
| Joint diseases | 4 (24) | 7 (54) | 9 (64) | 13 (50) | 8 (44) |
| Hypertension | 5 (29) | 4 (31) | 3 (21) | 8 (31) | 4 (22) |
| Cardiac problems | 3 (18) | 4 (31) | 4 (29) | 6 (23) | 5 (28) |
| Osteoporosis | 3 (18) | 2 (15) | 2 (14) | 3 (12) | 4 (22) |
| Type II diabetes mellitus | 1 (6) | 1 (8) | 3 (21) | 1 (4) | 5 (28) |
| **Self-reported walking problems** | 5 (29) | 6 (46) | 3 (21) | 8 (31) | 6 (33) |
| Need walking aid | 1 (6) | 2 (15) | 1 (7) | 3 (12) | 1 (6) |
| Hearing problems | 6 (35) | 5 (38) | 4 (29) | 8 (31) | 7 (39) |
| Vision problems | 8 (47) | 6 (46) | 4 (29) | 11 (42) | 7 (39) |
| Dizziness | 3 (18) | 5 (38) | 2 (14) | 6 (23) | 4 (22) |
| **Estimated good health** | 8 (47) | 8 (62) | 5 (36) | 17 (65) | 9 (50) |
| Estimated better health compared with contemporary | 8 (47) | 3 (23) | 5 (36) | 11 (42) | 5 (28) |
| Estimated good balance | 5 (29) | 3 (23) | 4 (29) | 7 (27) | 5 (28) |
| Feel pain daily | 4 (24) | 2 (15) | 3 (21) | 5 (19) | 4 (22) |
| **Physical activity questions, n (%)** | | | | | |
| Practice some physical activity | 7 (41) | 6 (46) | 3 (21) | 11 (42) | 5 (28) |
| Practiced some sport in the past | 10 (59) | 8 (62) | 10 (71) | 14 (54) | 9 (50) |
| Practiced strength exercises in the past | 3 (18) | 6 (46) | 3 (21) | 6 (23) | 6 (33) |

[a]A fall was defined as an event, which resulted in a person coming to rest on the ground or other lower level.

## Program Adherence

The median relative training adherence was 59.3% in the brochure group (IQR 0.0%-88.9%), 84.0% in the social group (IQR 77.2%-89.5%), and 80.9% (IQR 52.8%-88.9%) in the individual group. We registered 7 active (41%) and 10 inactive (59%) participants for the brochure group (n=17), 11 active (85%) and 2 inactive (15%) participants for the social group (n=13), and 8 active (57%) and 6 inactive (43%) participants for the individual group (n=14). In total, 26 of 44 participants reached the goal of 75% adherence or more and were analyzed as active (59%), whereas 18 of 44 (41%) were classified as poor compliers and inactive participants. The brochure group had more inactive participants, but this did not meet statistical significance ($U$=167, $P$=.06, $r$=.29). There were no significant differences between the 2 tablet groups. By further investigating differences in baseline characteristics between active and inactive participants, we found significantly more inactive participants with type II diabetes mellitus ($U$=178, $P$=.03, $r$=.34). There were no further differences between active and inactive participants concerning their baseline characteristics. Details on the 25% attrition rate have been previously published [53].

## Gait Analysis

Table 3 details the results of the spatiotemporal walking parameters of the 3 groups. Participants' performance in the posttest was significantly higher than in the pretest throughout all 4 conditions (preferred walking, fast walking, preferred dual task walking, fast dual task walking) for the 2 tablet groups (social group and individual group). In contrast, apart from step length during fast walking, there were no significant improvements in the brochure group observable. The active participants performed significantly better at posttests compared to pretests, whereas the inactive participants did not improve.

Differences between the brochure group and the tablet groups, between the 2 tablet groups, and between active and inactive participants are summarized in Table 4. Performance of the tablet groups differed significantly from the brochure group in the dual task walking condition with preferred walking speed: dual task preferred walking (velocity: $U$=138.5, $P$=.03, $r$=.33; cadence: $U$=138.5, $P$=.03, $r$=.34). Preferred, fast walking, and dual task preferred walking did not show significant differences between the 2 tablet groups (social group vs individual group). However, a significant difference was found for dual task fast walking (SD of step length: $U$=49, $P$=.04, $r$=.39). Comparison between active and inactive participants revealed significant differences in velocity throughout all conditions (preferred: $U$=145, $P$=.03, $r$=.32; fast: $U$=146.5, $P$=.04, $r$=0.32; dual task preferred walking: $U$=82.5, $P$>.001, $r$=.55; dual task fast walking: $U$=100.5, $P$=.001, $r$=.05). Although the active participants outperformed the inactive participants in most parameters in walking conditions, preferred walking, dual task preferred walking, and in dual task fast walking, there were no further significant differences for fast walking.

Analyses of dual task costs (DTC) with preferred walking speed revealed significant differences between pretest and posttest for the individual group (velocity: $P$=.03, $z$=–2.134; cadence: $P$=.02, $z$=–2.401; step time: $P$=.02, $z$=–2.401; double support time: $P$=.02, $z$=–2.401). In contrast, performance over time did not increase for the brochure and social groups. In the fast walking condition, DTC decreased for the brochure group (SD of step time: $P$=.047, $z$=1.988). No significant differences were reported between (1) the brochure group and the tablet groups, and (2) the social group and the individual group.

Between-group differences in DTC of walking revealed significant greater performance for the active group when compared with the inactive group (DTC preferred: velocity: $U$=151.5, $P$=.047, $r$=0.30; cadence: $U$=139.5, $P$=.02, $r$=.34; step time: $U$=149.5, $P$=.04, $r$=.31; DTC fast: SD of step time: $U$=152.5, $P$=.049, $r$=.30).

**Table 3.** Participants' single and dual task walking performance during the pretests and posttests and within-group significance calculated with Wilcoxon signed rank test.

| Condition and parameters | Single task walking, median (IQR) | | | Dual task walking, median (IQR) | | |
|---|---|---|---|---|---|---|
| | Pretest | Posttest | *P* | Pretest | Posttest | *P* |
| **Brochure group** | | | | | | |
| **Preferred** | | | | | | |
| Velocity (cm/s) | 109.9 (103.7,112.1) | 109.9 (106.8, 125.4) | .09 | 86.5 (84.3, 103.6) | 86.5 (81.3, 106.1) | .29 |
| Cadence (steps/min) | 109.7 (105.3, 110.1) | 109.7 (109.7, 114.1) | .07 | 91.9 (86.9, 105.5) | 91.9 (91.9, 108.1) | .45 |
| Step length (cm) | 60.0 (60.0, 65.4) | 60.0 (60.0, 67.2) | .06 | 55.6 (55.6, 60.0) | 55.6 (55.6, 64.1) | .11 |
| Step time (s) | 0.55 (0.55, 0.57) | 0.55 (0.52, 0,55) | .07 | 0.72 (0.57, 0.73) | 0.72 (0.56, 0.72) | .33 |
| SD step length (cm) | 2.70 (2.38, 2.74) | 2.70 (2.03, 2.70) | .24 | 2.93 (2.32, 2.93) | 2.93 (2.49, 3.14) | .88 |
| SD step time (s) | 0.022 (0.018, 0.022) | 0.022 (0.013, 0.022) | .51 | 0.107 (0.030, 0.107) | 0.107 (0.020, 0.107) | .14 |
| Double support time (s) | 0.35 (0.32, 0.36) | 0.35 (0.32, 0.35) | .14 | 0.50 (0.36, 0.50) | 0.50 (0.35, 0.50) | .45 |
| **Fast** | | | | | | |
| Velocity (cm/s) | 142.3 (139.8, 145.0) | 142.3 (142.3 (160.0) | .06 | 97.0 (87.8, 106.1) | 97.0 (97.0, 117.4) | .07 |
| Cadence (steps/min) | 127.8 (121.5, 127.8) | 127.8 (125.4, 128.7) | .20 | 97.4 (93.3, 111.3) | 97.4 (97.4, 114.6) | .20 |
| Step length (cm) | 66.7 (66.3, 70.5) | 66.6 (66.6, 74.1) | .02 | 59.3 (59.3, 64.0) | 59.3 (59.3, 66.5) | .06 |
| Step time (s) | 0.48 (0.48, 0.49) | 0.48 (0.47, 0.48) | .17 | 0.65 (0.54, 0.66) | 0.65 (0.52, 0.65) | .22 |
| SD step length (cm) | 2.96 (2.65, 2.96) | 2.96 (2.66, 3.16) | .24 | 3.44 (2.99, 4.07) | 3.44 (2.77, 3.46) | .45 |
| SD step time (s) | 0.020 (0.013, 0.020) | 0.020 (0.011, 0.020) | .65 | 0.072 (0.022, 0.072) | 0.072 (0.019, 0.072) | .11 |
| Double support time (s) | 0.27 (0.27, 0.27) | 0.27 (0.25, 0.27) | .17 | 0.42 (0.31, 0.44) | 0.42 (0.31, 0.43) | .24 |
| **Social group** | | | | | | |
| **Preferred** | | | | | | |
| Velocity (cm/s) | 108.3 (95.87, 129.73) | 121.8 (106.4, 143.3) | .004 | 91.3 (70.4, 111.8) | 115.6 (85.1, 130.5) | .02 |
| Cadence (steps/min) | 106.1 (101.1, 112.3) | 116.6 (105.7, 117.7) | .006 | 93.4 (86.9, 105.1) | 107.1 (91.6, 117.9) | .01 |
| Step length (cm) | 60.9 (54.6, 67.3) | 60.9 (58.9, 75.1) | .004 | 58.2 (50.6, 64.9) | 58.2 (50.2, 69.5) | .11 |
| Step time (s) | 0.57 (0.54, 0.59) | 0.51 (0.51, 0.57) | .01 | 0.65 (0.57, 0.69) | 0.56 (0.51, 0.66) | .01 |
| SD step length (cm) | 2.05 (1.80, 2.21) | 1.70(1.38, 2.14) | .37 | 2.38 (1.92, 2.74) | 2.40 (1.52, 2.61) | .29 |
| SD step time (s) | 0.019 (0.015, 0.021) | 0.015 (0.011, 0.020) | .14 | 0.033 (0.019, 0.041) | 0.023 (0.013, 0.040) | .03 |
| Double support time (s) | 0.33 (0.30, 0.38) | 0.32 (0.27, 0.35) | .02 | 0.38 (0.35, 0.46) | 0.33 (0.28, 0.45) | .11 |
| **Fast** | | | | | | |
| Velocity (cm/s) | 146.5 (130.6, 182.8) | 152.8(136.3, 200.5) | .03 | 117.3 (101.9, 135.5) | 141.1 (108.9, 158.7) | .003 |
| Cadence (steps/min) | 128.5 (121.2, 136.2) | 133.6 (119.8, 154.7) | .06 | 107.7 (105.7, 118.7) | 115.3 (106.5, 132.8) | .003 |
| Step length (cm) | 69.6 (59.7, 76.5) | 69.4 (65.4, 78.3) | .42 | 63.9 (56.1, 70.2) | 63.9 (58.8, 72.0) | .09 |
| Step time (s) | 0.47 (0.44, 0.49) | 0.50 (0.39, 0.50) | .05 | 0.56 (0.51, 0.59) | 0.52 (0.45, 0.57) | .003 |
| SD step length (cm) | 2.62 (20.5, 3.27) | 2.66 (1.86, 3.11) | .59 | 2.01 (1.76, 2.50) | 2.54 (2.28, 3.04) | .05 |
| SD step time (s) | 0.014 (0.011, 0.018) | 0.014 (0.010, 0.017) | .89 | 0.019 (0.014, 0.033) | 0.019 (0.015, 0.034) | .56 |
| Double support time (s) | 0.25 (0.20, 0.27) | 0.23 (0.17, 0.27) | .25 | 0.30 (0.28, 0.36) | 0.31 (0.24, 0.36) | .01 |
| **Individual group** | | | | | | |
| **Preferred** | | | | | | |
| Velocity (cm/s) | 123.0 (112.9, 137.2) | 132.8 (123.0, 156.1) | .01 | 100.8 (91.7, 109.6) | 112.3 (95.7, 140.1) | .01 |
| Cadence (steps/min) | 113.7 (109.2, 119.3) | 124.4 (113.6, 128.9) | .01 | 102.6 (91.1, 109.6) | 109.2 (90.5, 127.5) | .004 |
| Step length (cm) | 64.8 (61.6, 70.4) | 64.8 (64.1, 70.4) | .08 | 60.2 (55.7, 62.8) | 60.9 (60.0, 65.2) | .02 |
| Step time (s) | 0.53 (0.50, 0.55) | 0.48 (0.47, 0.53) | .01 | 0.59 (0.55, 0.71) | 0.57 (0.47, 0.66) | .01 |

| Condition and parameters | Single task walking, median (IQR) | | | Dual task walking, median (IQR) | | |
|---|---|---|---|---|---|---|
| | Pretest | Posttest | *P* | Pretest | Posttest | *P* |
| SD step length (cm) | 1.88 (1.68, 2.10) | 1.74 (1.48, 1.86) | .18 | 2.79 (2.13, 3.46) | 2.79 (1.99, 2.94) | .29 |
| SD step time (s) | 0.017 (0.015, 0.019) | 0.013 (0.011, 0.017) | .01 | 0.032 (0.023, 0.440) | 0.021 (0.023, 0.222) | .003 |
| Double support time (s) | 0.30 (0.27, 0.33) | 0.27 (0.23, 0.30) | .01 | 0.37 (0.32, 0.45) | 0.32 (0.25, 0.40) | .004 |
| **Fast** | | | | | | |
| Velocity (cm/s) | 179.1 (167.2, 190.9) | 183.8 (175.0, 216.1) | .03 | 134.9 (122.2, 142.6) | 140.3 (125.8, 172.0) | .11 |
| Cadence (steps/min) | 146.4 (141.4, 154.6) | 155.7 (146.4, 171.1) | .01 | 123.3 (113.1, 132.0) | 125.8 (118.0, 144.1) | .09 |
| Step length (cm) | 73.6 (69.7, 75.4) | 73.6 (70.2, 76.6) | .53 | 68.4 (61.8, 68.7) | 67.4 (66.3, 68.7) | .79 |
| Step time (s) | 0.41 (0.39, 0.42) | 0.39 (0.35, 0.41) | .01 | 0.49 (0.45, 0.56) | 0.48 (0.42, 0.53) | .11 |
| SD step length (cm) | 2.72 (2.34, 3.04) | 2.72 (2.34, 3.97) | .79 | 2.96 (2.18, 4.02) | 2.87 (2.53, 3.02) | .33 |
| SD step time (s) | 0.014 (0.011, 0.017) | 0.012 (0.010, 0.014) | .37 | 0.029 (0.018, 0.051) | 0.018 (0.014, 0.036) | .02 |
| Double support time (s) | 0.19 (0.16, 0.20) | 0.16 (0.12, 0.19) | .04 | 0.24 (0.28, 0.29) | 0.24 (0.19, 0.27) | .13 |
| **Active** | | | | | | |
| **Preferred** | | | | | | |
| Velocity (cm/s) | 117.1 (104.5, 129.3) | 128.1 (107.8, 153.5) | >.001 | 104.3 (68.8, 114.0) | 121.0 (93.3, 136.1) | >.001 |
| Cadence (steps/min) | 109.1 (102.1, 118.4) | 107.1 (116.7, 126.1) | >.001 | 102.6 (88.1, 109.0) | 111.7 (93.2, 126.3) | >.001 |
| Step length (cm) | 64.6 (58.4, 69.3) | 65.8 (60.8, 74.4) | >.001 | 59.9 (52.2, 66.7) | 64.1 (56.3, 69.5) | .001 |
| Step time (s) | 0.55 (0.51, 0.59) | 0.51 (0.48, 0.56) | >.001 | 0.58 (0.55, 0.68) | 0.54 (0.48, 0.65) | >.001 |
| SD step length (cm) | 2.06 (1.82, 2.41) | 1.71 (1.40, 2.17) | .03 | 2.48 (2.00, 3.21) | 2.48 (1.64, 2.94) | .05 |
| SD step time (s) | 0.017 (0.014, 0.021) | 0.012 (0.011, 0.018) | .01 | 0.030 (0.019, 0.040) | 0.018 (0.013, 0.037) | >.001 |
| Double support time (s) | 0.31 (0.29, 0.37) | 0.29 (0.25, 0.38) | .001 | 0.27 (0.32, 0.48) | 0.32 (0.27, 0.42) | .001 |
| **Fast** | | | | | | |
| Velocity (cm/s) | 157.3 (141.0, 181.8) | 166.9 (145.7, 204.9) | .001 | 122.8 (99.8, 10.3) | 142.6 (106.9, 172.0) | >.001 |
| Cadence (steps/min) | 131.1 (119.8, 145.9) | 135.7 (121.7, 163.5) | .002 | 111.9 (102.1, 124.0) | 121.8 (107.2, 139.1) | >.001 |
| Step length (cm) | 71.8 (63.0, 77.6) | 72.7 (67.0, 81.6) | .03 | 64.4 (58.9, 69.8) | 66.8 (60.3, 74.4) | .02 |
| Step time (s) | 0.46 (0.41, 0.50) | 0.44 (0.37, 0.49) | .002 | 0.54 (0.48, 0.59) | 0.49 (0.43, 0.57) | >.001 |
| SD step length (cm) | 2.66 (2.13, 3.49) | 2.62 (1.93, 3.33) | .88 | 2.63 (1.80, 4.11) | 2.68 (2.12, 3.40) | .68 |
| SD step time (s) | 0.013 (0.011, 0.016) | 0.011 (0.009, 0.018) | .96 | 0.019 (0.016, 0.038) | 0.017 (0.013, 0.025) | .002 |
| Double support time (s) | 0.24 (0.19, 0.27) | 0.22 (0.13, 0.26) | .02 | 0.29 (0.26, 0.37) | 0.28 (0.20, 0.36) | .001 |
| **Inactive** | | | | | | |
| **Preferred** | | | | | | |
| Velocity (cm/s) | 109.9 (104.9, 116.7) | 109.9 (109.9, 125.4) | .09 | 86.5 (85.4, 100.1) | 86.5 (85.8, 93.5) | .87 |
| Cadence (steps/min) | 109.7 (106.9, 113.7) | 111.3 (109.7, 114.1) | .06 | 91.9 (89.9, 98.4) | 91.9 (89.1, 98.4) | .75 |
| Step length (cm) | 60.0 (60.0, 64.1) | 60.4 (60.0, 64.8) | .09 | 55.6 (55.6, 60.2) | 55.6 (55.6, 60.6) | .74 |
| Step time (s) | 0.55 (0.53, 0.56) | 0.54 (0.53, 0.55) | .04 | 0.72 (0.65, 0.72) | 0.72 (0.65, 0.72) | .74 |
| SD step length (cm) | 2.56 (1.91, 2.70) | 2.39 (1.82, 2.70) | .99 | 2.79 (2.37, 2.93) | 2.93 (2.72, 2.95) | .18 |
| SD step time (s) | 0.022 (0.017, 0.022) | 0.019 (0.017, 0.022) | .31 | 0.107 (0.046, 0.184) | 0.107 (0.039, 0.184) | .40 |
| Double support time (s) | 0.35 (0.32, 0.35) | 0.34 (0.30, 0.35) | .18 | 0.48 (0.40, 0.50) | 0.50 (0.40, 0.50) | .87 |
| **Fast** | | | | | | |
| Velocity (cm/s) | 142.2 (142.2, 179.1) | 144.4 (142.2, 179.1) | .18 | 97.0 (97.0, 125.3) | 98.4 (97.0, 134.9) | .61 |
| Cadence (steps/min) | 127.8 (127.4, 144.5) | 128.2 (127.8, 146.4) | .09 | 97.4 (97.4, 119.4) | 101.7 (97.4, 119.4) | .74 |
| Step length (cm) | 66.6 (66.6, 73.6) | 67.0 (66.6, 73.6) | .61 | 59.6 (59.3, 68.3) | 60.5 (59.3, 67.7) | .99 |
| Step time (s) | 0.48 (0.42, 0.48) | 0.47 (0.41, 0.48) | .09 | 0.65 (0.53, 0.65) | 0.62 (0.53, 0.65) | .87 |

| Condition and parameters | Single task walking, median (IQR) | | | Dual task walking, median (IQR) | | |
|---|---|---|---|---|---|---|
| | Pretest | Posttest | *P* | Pretest | Posttest | *P* |
| SD step length (cm) | 2.93 (2.70, 2.96) | 2.96 (2.72, 2.96) | .31 | 3.24 (2.61, 3.44) | 3.25 (2.78, 3.44) | .87 |
| SD step time (s) | 0.017 (0.014, 0.020) | 0.018 (0.014, 0.020) | .50 | 0.071 (0.033, 0.072) | 0.060 (0.032, 0.072) | .74 |
| Double support time (s) | 0.027 (0.019, 0.027) | 0.026 (0.019, 0.027) | .18 | 0.42 (0.29, 0.42) | 0.39 (0.25, 0.42) | .99 |

**Table 4.** *P* values of participants' walking performance (between-groups differences after intervention phase calculated with Mann-Whitney *U* test).

| Condition/parameters | Brochure vs social and individual | | Social vs individual | | Active vs inactive | |
|---|---|---|---|---|---|---|
| | *P* | *r* [a] | *P* | *r* [a] | *P* | *r* [a] |
| **Preferred** | | | | | | |
| Velocity | .08 | .26 | .96 | .01 | .03 | .32 |
| Cadence | .09 | .26 | .63 | .09 | .06 | .29 |
| Step length | .22 | .18 | .53 | .12 | .02 | .36 |
| Step time | .14 | .22 | .92 | .02 | .06 | .28 |
| SD step length | .91 | .02 | .99 | .00 | .03 | .33 |
| SD step time | .08 | .26 | .44 | .15 | .04 | .30 |
| Double support time | .19 | .20 | .53 | .12 | .01 | .38 |
| **Fast** | | | | | | |
| Velocity | .37 | .14 | .96 | .01 | .04 | .32 |
| Cadence | .09 | .25 | .66 | .08 | .08 | .27 |
| Step length | .38 | .13 | .96 | .01 | .07 | .27 |
| Step time | .24 | .18 | .90 | .02 | .10 | .25 |
| SD step length | .53 | .10 | .96 | .01 | .66 | .07 |
| SD step time | .40 | .13 | .44 | .15 | .58 | .08 |
| Double support time | .36 | .14 | .72 | .07 | .12 | .23 |
| **Dual task preferred** | | | | | | |
| Velocity | .03 | .33 | .44 | .15 | <.001 | .55 |
| Cadence | .03 | .33 | .37 | .17 | <.001 | .57 |
| Step length | .37 | .14 | .99 | .00 | .003 | .45 |
| Step time | .05 | .29 | .47 | .14 | .001 | .48 |
| SD step length | .28 | .16 | .92 | .02 | .01 | .40 |
| SD step time | .20 | .19 | .47 | .14 | .002 | .47 |
| Double support time | .11 | .24 | .17 | .26 | .003 | .47 |
| **Dual task fast** | | | | | | |
| Velocity | .20 | .19 | .59 | .10 | .001 | .49 |
| Cadence | .07 | .28 | .59 | .10 | .001 | .50 |
| Step length | .58 | .08 | .20 | .25 | .10 | .25 |
| Step time | .14 | .22 | .47 | .14 | .001 | .48 |
| SD step length | .30 | .16 | .04 | .39 | .76 | .05 |
| SD step time | .61 | .08 | .38 | .17 | .01 | .42 |
| Double support time | .22 | .18 | .96 | .01 | .002 | .47 |

[a]Effect size (small effect: *r*=.1; medium effect: *r*=.3; large effect: *r*=.5).

### Physical Performance and Fear of Falling

Table 5 demonstrates changes over time for fear of falling (FES-I) and physical performance (SPPB) for the 3 groups. The SPPB showed significant improvements for all groups. There were no differences between pretest and posttest for FES-I. Significant group differences for FES-I were observed between the brochure group and tablet groups (*U*=151.5, *P*=.04, *r*=.31); however, not between the 2 tablet groups (*U*=89.5, *P*=.94, *r*=.01) or the active and inactive participants (*U*=210.5, *P*=.53, *r*=.09). We found a significant difference between active and inactive participants in SPPB (*U*=139, *P*=.02, *r*=.36).

**Table 5.** Physical performance and fear of falling during the pretest and the posttest and significance of within-group differences pre-post calculated with Wilcoxon signed rank test.

| Test | Brochure group, median (IQR) | | | Social group, median (IQR) | | | Individual group, median (IQR) | | |
|---|---|---|---|---|---|---|---|---|---|
| | Pretest | Posttest | *P* | Pretest | Posttest | *P* | Pretest | Posttest | *P* |
| SPPB | 9.8 (9.4, 11.0) | 11.0 (9.8, 12.0) | .02 | 9.7 (8.0, 11.0) | 12.0 (9.7, 12.0) | .02 | 9.9 (8.8, 11.0) | 11.0 (9.9, 12.0) | .02 |
| FES-I | 17.9 (16.0, 17.9) | 17.9 (17.0, 17.9) | .49 | 20.0 (17.0, 21.5) | 20.0 (17.0, 20.6) | .23 | 18.9(17.5, 20.0) | 18.0 (16.0, 18.9) | .27 |

### Social Interaction

We registered the number of dispatched messages. The total number of messages dispatched to the bulletin board was 31 from the social group participants sent by 8 of 13 social group participants. The caregivers dispatched a total of 37 messages to the bulletin board. Six of 13 social group participants wrote 13 messages to another participant. Participants received 84 messages from caregivers; 93 messages were dispatched by 11 social group participants to caregivers. Thus, most interaction occurred between caregivers and participants and not between participants, indicating the importance of social support from caregivers.

## Discussion

### Principal Findings

This study compared 3 different home-based training programs and their effect on measures of gait quality while considering adherence to the training program. We hypothesized that there would be differing results for (1) the tablet-based groups when compared to the brochure group, (2) the tablet group with social motivation strategies when compared to the tablet group with individual motivation strategies, and (3) active participants when compared to inactive participants. The outcomes of interest were gait quality and lower extremity physical performance. Furthermore, the aim was to assess the influence of different motivation strategies offered to the trainees.

### Gait Analysis

From previous studies, we know that home-based exercise training can have beneficial effects on physical performance outcomes [1,75], provided the program is adhered to [76]. Our results of the walking quality analysis show significant improvements from pretest to posttest, especially in the training groups that showed high adherence rates. The tablet groups reached higher adherence rates compared to the brochure group. Furthermore, participants in the tablet groups were able to improve gait velocity throughout all walking conditions (preferred and fast single task walking, preferred and fast dual task walking), whereas the brochure group failed to increase this performance aspect following 12 weeks of training. Usual gait speed is a predictor for disability, falls, and mortality [26]. In comparison to our brochure group and the inactive participants, the tablet groups and the active participants reached improvements of 10 cm/s or more. Such improvements represent clinically meaningful change in gait speed [26]. Walking at fastest speed may serve as a useful diagnostic measure for people at higher risk for multiple falls. In the fast walking condition, shorter step length relates to falls [77]. We reported an improvement in step length during walking in our group of active participants, but not in the inactive participants. Both the tablet groups and the active participants improved velocity during fastest walking. Compared to literature reference values where an expected preferred and fast walking speed for independently living elderly would be approximately 133 cm/s and 207 cm/s, respectively [78], our samples performed worse pretraining. Following training, however, the tablet groups improved toward these reference values.

Frail elderly people and elderly people who tend to fall exhibit increased variability in measures of gait [23,79,80]. Elderly nonfallers present low rates of variability of temporal variables [20,24]. Decreased leg strength explains greater variability [81]. This study shows that tablet-based exercise may decrease gait variability provided the trainees adhere to the training plan. The brochure group demonstrated no decrease in gait variability after the intervention. In contrast, the tablet groups showed significantly lower variability throughout all measurement conditions. This especially holds true for the group with individual motivation strategies and for step time variability. Step time and double support time—factors that have been previously related to falls [35]—decreased throughout all conditions, again solely in the tablet groups. Thus, our trial underpins the importance of training program compliance in preventive exercise programs for elderly and indicates that an appropriate targeted tablet-based exercise application is able to positively influence exercise adherence in independent-living elderly training at home. Because of the higher training adherence, the tablet-based exercise groups improved their single and dual task walking to a larger extent compared to a group trained with a more conventional type of brochures-based training.

Dual task walking (ie, the ability to perform a second task while walking) is a key element to remain independent because this is an ability required for many activities in daily life. Daily activities pose high cognitive demands and safe walking should be practicable under cognitively distractive or otherwise challenging conditions. Our findings in dual task walking are similar to some extent to the findings of Pichierri et al [82], who reported no improvements in dual task walking with an isolated motor training program. This finding was in-line with previous studies that investigated the effect of an isolated physical training program that were not able to demonstrate improvements in walking under attention-demanding circumstances [83,84]. Our intervention did not consist of a cognitive training part and it can be speculated that an extension of our program with a cognitive challenge will be more effective in influencing walking under attention-demanding circumstances. Future research should be directed to investigating the value of additional cognitive elements to the training program to substantiate these assumptions.

### Physical Performance

We found a significant improvement in SPPB scores within all groups, reflecting enhanced lower extremity function and walking ability [85]. On average, a person that reaches less than 10 points on the SPPB is almost 3.5 times more susceptible to suffer from mobility disability than a person scoring the maximum of 12 points [85]. All 3 groups reached a median relative score of 11 points or more in the posttests, compared to a median relative score of less than 10 points in the pretests.

### Program Adherence

An important issue in the field of exercise interventions with elderly people is adherence to the training plan [76]. Elderly people will only be able to reap the gains from exercise under the precondition that they comply with and progress through the exercise plan. A systematic review investigating adherence to multifactorial interventions in falls prevention in community settings for clinical trials reported rates ranging between 28% and 95%. The general range was approximately 75%, which was the reason we chose this level to divide our training group into active versus inactive participants. Compared with these values [86], we achieved better or similar rates as 75% adherence; however, this was for the tablet-based training groups only. Furthermore, we observed the most prominent differences in training effects between the active and the inactive participants. Active participants demonstrated significantly higher performance in several spatial-temporal walking parameters compared to the inactive participants. This supports findings from other studies showing that better compliance leads to significantly higher training-related benefits [87,88] and indicates that adherence moderated treatment effectiveness. We report on values after 3 training months, but Nyman and Victor [64] reported values that may be expected by 12 months. In a future phase III trial, the follow-up period for the assessment of adherence and attrition should preferably be extended to a similar time frame to facilitate comparability of this future study with reference values.

Social support [48] and commitment to or advice from health experts, physicians, or caregivers are reasons for higher compliance rates and more moderate exercise conduction [44,89]. In an analysis of compliance in home-based exercise programs, an increase in compliance was registered in a brochure-based group compared with the outcome of a control group who did not receive any recommendations [90]. Moreover, a DVD-supported training program reported better adherence compared to brochures [89]. DVDs might help to overcome motivational problems [89] and enhance exercise correctness [91] compared to brochure-guided exercise programs. The amount of messages dispatched indicates that most interactions occurred between caregivers and participants and not between participants. This reflects the importance of social support of caregivers to the trainees.

Motivation is an important parameter for home-based exercise performance [92] and should be explicitly considered in the design of interventions. The program used in our study explicitly considered motivational elements and allowed participants contacting experts and training partners. The most active participants were found in the social group, whereas the most inactive participants belonged to the brochure group (although this did not meet statistical significance). This result supports our assumption that social motivation strategies enhance compliance. Apart from that, there seems to be no direct gain from social motivation strategies on walking quality compared with individual motivation strategies because the results of the 2 tablet groups did not differ in the outcome measures.

### Limitations

An obvious limitation of this study is that the groups were only partly randomized. Therefore, this study only reveals first estimates and warrants further research with a properly randomized model. A further limitation is the rather small sample size. Measurements of compliance are based on written information of participants, which cannot be seen as an instrument that guarantees the participants followed the exercises. Better control instruments would be a useful extension to further studies.

Additionally, correctness of the exercise was not controlled. To overcome this problem, further research should include technologies to control posture and movement pattern. Video analysis with 3-dimensional motion tracking equipment or microelectromechanical systems (MEMS) can offer opportunities to link clinicians and potential users [93]. Another option is the Health Hub (HH) software that allows recognition and analysis of motion [93].

We treated the dropouts of this study as part of the treatment group to which they were assigned even if they did not receive the full intervention. Intention-to-treat is a recommended approach to several types of nonadherence to the study protocol [94], able to reduce the potential dropout bias effect [95]. We replaced missing data with the mean values of the groups, thus allowing complete case analysis. A drawback of this approach is reduced variability and weakening of covariance and correlation estimates in the data. Future adequately powered studies with larger samples should be performed with both intention-to-treat and per-protocol analysis.

### Conclusions

The findings of this study are in-line with previous research that demonstrated improvements in gait quality and physical performance of older adults after strength-balance exercises.

This study adds useful information about home-based training programs for older adults. Our participants adhered better to the weekly physical intervention when provided with the ActiveLifestyle app. This clearly described exercise program, including motivational aspects, an attractive design, automated reminders, and the opportunity to give feedback about performed exercises to training supervisors, seems to contain important elements to enhance adherence and compliance rates, which leads to training-related improvements. The trainees that complied with the training plan improved gait and physical performance. The tablet-based program resulted in higher rates of adherence compared to the brochure-based program. These findings suggest that in older adults a tablet-based intervention may enhance compliance and potentially offers an effective way to improve gait.

## Acknowledgments

This work was carried out with the support of Maria Messmer-Capaul and her team of the Fachstelle für präventive Beratung Spitex-Zürich, Claudia Nüesch of the Senioren Begegnungszentrum Baumgärtlihof, and Data Quest who provided tablets for the study. We would like to thank all the participants for their great enthusiasm and support. This work is partially sponsored by the project Anchise funded by the Autonomous Province of Trento, Italy, and the EIT project Virtual Social Gym and performed in collaboration with Tomsk Polytechnic University within the project Evaluation and enhancement of social, economic and emotional well-being of older adults under the Agreement No:14.Z50.31.0029.

## Conflicts of Interest

None declared.

## References

1. Singh MA. Exercise comes of age: rationale and recommendations for a geriatric exercise prescription. J Gerontol A Biol Sci Med Sci 2002 May;57(5):M262-M282. [Medline: 11983720]
2. Spirduso WW, Cronin DL. Exercise dose-response effects on quality of life and independent living in older adults. Med Sci Sports Exerc 2001 Jun;33(6 Suppl):S598-608; discussion S609. [Medline: 11427784]
3. Ferrucci L, Izmirlian G, Leveille S, Phillips CL, Corti MC, Brock DB, et al. Smoking, physical activity, and active life expectancy. Am J Epidemiol 1999 Apr 1;149(7):645-653 [FREE Full text] [Medline: 10192312]
4. Haskell WL, Lee IM, Pate RR, Powell KE, Blair SN, Franklin BA, et al. Physical activity and public health: updated recommendation for adults from the American College of Sports Medicine and the American Heart Association. Med Sci Sports Exerc 2007 Aug;39(8):1423-1434. [doi: 10.1249/mss.0b013e3180616b27] [Medline: 17762377]
5. Kesaniemi YK, Danforth E, Jensen MD, Kopelman PG, Lefèbvre P, Reeder BA. Dose-response issues concerning physical activity and health: an evidence-based symposium. Med Sci Sports Exerc 2001 Jun;33(6 Suppl):S351-S358. [Medline: 11427759]
6. Warburton DE, Nicol CW, Bredin SS. Health benefits of physical activity: the evidence. CMAJ 2006 Mar 14;174(6):801-809 [FREE Full text] [doi: 10.1503/cmaj.051351] [Medline: 16534088]
7. Deslandes A. The biological clock keeps ticking, but exercise may turn it back. Arq Neuropsiquiatr 2013 Feb;71(2):113-118 [FREE Full text] [Medline: 23392323]
8. Deslandes A, Moraes H, Ferreira C, Veiga H, Silveira H, Mouta R, et al. Exercise and mental health: many reasons to move. Neuropsychobiology 2009;59(4):191-198 [FREE Full text] [doi: 10.1159/000223730] [Medline: 19521110]
9. Binder EF, Schechtman KB, Ehsani AA, Steger-May K, Brown M, Sinacore DR, et al. Effects of exercise training on frailty in community-dwelling older adults: results of a randomized, controlled trial. J Am Geriatr Soc 2002 Dec;50(12):1921-1928. [Medline: 12473001]
10. Abate M, Di Iorio A, Di Renzo D, Paganelli R, Saggini R, Abate G. Frailty in the elderly: the physical dimension. Eura Medicophys 2007 Sep;43(3):407-415 [FREE Full text] [Medline: 17117147]
11. Katzmarzyk PT, Janssen I. The economic costs associated with physical inactivity and obesity in Canada: an update. Can J Appl Physiol 2004 Feb;29(1):90-115. [Medline: 15001807]
12. American College of Sports Medicine, Chodzko-Zajko WJ, Proctor DN, Fiatarone Singh MA, Minson CT, Nigg CR, et al. American College of Sports Medicine position stand. Exercise and physical activity for older adults. Med Sci Sports Exerc 2009 Jul;41(7):1510-1530. [doi: 10.1249/MSS.0b013e3181a0c95c] [Medline: 19516148]
13. Rizzuto D, Orsini N, Qiu C, Wang H, Fratiglioni L. Lifestyle, social factors, and survival after age 75: population based study. BMJ 2012 Aug 30;345(aug29 2):e5568-e5568. [doi: 10.1136/bmj.e5568]
14. Barnett A, Smith B, Lord SR, Williams M, Baumand A. Community-based group exercise improves balance and reduces falls in at-risk older people: a randomised controlled trial. Age Ageing 2003 Jul;32(4):407-414 [FREE Full text] [Medline: 12851185]
15. Campbell AJ, Robertson MC, Gardner MM, Norton RN, Tilyard MW, Buchner DM. Randomised controlled trial of a general practice programme of home based exercise to prevent falls in elderly women. BMJ 1997 Oct 25;315(7115):1065-1069 [FREE Full text] [Medline: 9366737]

16. Buchner DM, Cress ME, de Lateur BJ, Esselman PC, Margherita AJ, Price R, et al. The effect of strength and endurance training on gait, balance, fall risk, and health services use in community-living older adults. J Gerontol A Biol Sci Med Sci 1997 Jul;52(4):M218-M224. [Medline: 9224433]
17. Landi F, Abbatecola AM, Provinciali M, Corsonello A, Bustacchini S, Manigrasso L, et al. Moving against frailty: does physical activity matter? Biogerontology 2010 Oct;11(5):537-545. [doi: 10.1007/s10522-010-9296-1] [Medline: 20697813]
18. Studenski S, Perera S, Patel K, Rosano C, Faulkner K, Inzitari M, et al. Gait speed and survival in older adults. JAMA 2011 Jan 5;305(1):50-58 [FREE Full text] [doi: 10.1001/jama.2010.1923] [Medline: 21205966]
19. Brandes M, Schomaker R, Möllenhoff G, Rosenbaum D. Quantity versus quality of gait and quality of life in patients with osteoarthritis. Gait Posture 2008 Jul;28(1):74-79. [doi: 10.1016/j.gaitpost.2007.10.004] [Medline: 18054233]
20. Hausdorff JM. Gait variability: methods, modeling and meaning. J Neuroeng Rehabil 2005;2:19 [FREE Full text] [doi: 10.1186/1743-0003-2-19] [Medline: 16033650]
21. Gabell A, Nayak US. The effect of age on variability in gait. J Gerontol 1984 Nov;39(6):662-666. [Medline: 6491179]
22. Maki BE. Gait changes in older adults: predictors of falls or indicators of fear. J Am Geriatr Soc 1997 Mar;45(3):313-320. [Medline: 9063277]
23. Maki BE. Gait changes in older adults: predictors of falls or indicators of fear. J Am Geriatr Soc 1997 Mar;45(3):313-320. [Medline: 9063277]
24. Hausdorff JM, Rios DA, Edelberg HK. Gait variability and fall risk in community-living older adults: a 1-year prospective study. Arch Phys Med Rehabil 2001 Aug;82(8):1050-1056. [doi: 10.1053/apmr.2001.24893] [Medline: 11494184]
25. Cesari M, Kritchevsky SB, Penninx BW, Nicklas BJ, Simonsick EM, Newman AB, et al. Prognostic value of usual gait speed in well-functioning older people--results from the Health, Aging and Body Composition Study. J Am Geriatr Soc 2005 Oct;53(10):1675-1680. [doi: 10.1111/j.1532-5415.2005.53501.x] [Medline: 16181165]
26. Abellan van Kan G, Rolland Y, Andrieu S, Bauer J, Beauchet O, Bonnefoy M, et al. Gait speed at usual pace as a predictor of adverse outcomes in community-dwelling older people an International Academy on Nutrition and Aging (IANA) Task Force. J Nutr Health Aging 2009 Dec;13(10):881-889. [Medline: 19924348]
27. Hardy SE, Perera S, Roumani YF, Chandler JM, Studenski SA. Improvement in usual gait speed predicts better survival in older adults. J Am Geriatr Soc 2007 Nov;55(11):1727-1734. [doi: 10.1111/j.1532-5415.2007.01413.x] [Medline: 17916121]
28. Bootsma-van der Wiel A, Gussekloo J, De Craen AJ, Van Exel E, Bloem BR, Westendorp RG. Common chronic diseases and general impairments as determinants of walking disability in the oldest-old population. J Am Geriatr Soc 2002 Aug;50(8):1405-1410. [Medline: 12164998]
29. Ostir GV, Berges I, Kuo YF, Goodwin JS, Ottenbacher KJ, Guralnik JM. Assessing gait speed in acutely ill older patients admitted to an acute care for elders hospital unit. Arch Intern Med 2012 Feb 27;172(4):353-358 [FREE Full text] [doi: 10.1001/archinternmed.2011.1615] [Medline: 22371922]
30. Alexander NB, Goldberg A. Gait disorders: search for multiple causes. Cleve Clin J Med 2005 Jul;72(7):586, 589-590, 592 [FREE Full text] [Medline: 16044655]
31. Inzitari M, Newman AB, Yaffe K, Boudreau R, de Rekeneire N, Shorr R, et al. Gait speed predicts decline in attention and psychomotor speed in older adults: the health aging and body composition study. Neuroepidemiology 2007;29(3-4):156-162 [FREE Full text] [doi: 10.1159/000111577] [Medline: 18042999]
32. Oberg T, Karsznia A, Oberg K. Basic gait parameters: reference data for normal subjects, 10-79 years of age. J Rehabil Res Dev 1993;30(2):210-223. [Medline: 8035350]
33. Lord SR, Lloyd DG, Li SK. Sensori-motor function, gait patterns and falls in community-dwelling women. Age Ageing 1996 Jul;25(4):292-299 [FREE Full text] [Medline: 8831874]
34. Ferrandez AM, Pailhous J, Durup M. Slowness in elderly gait. Exp Aging Res 1990;16(1-2):79-89. [doi: 10.1080/07340669008251531] [Medline: 2265670]
35. Mbourou GA, Lajoie Y, Teasdale N. Step length variability at gait initiation in elderly fallers and non-fallers, and young adults. Gerontology 2003;49(1):21-26. [Medline: 12457046]
36. Shin S, Valentine RJ, Evans EM, Sosnoff JJ. Lower extremity muscle quality and gait variability in older adults. Age Ageing 2012 Sep;41(5):595-599 [FREE Full text] [doi: 10.1093/ageing/afs032] [Medline: 22417983]
37. Alexander NB. Gait disorders in older adults. J Am Geriatr Soc 1996 Apr;44(4):434-451. [Medline: 8636592]
38. Verghese J, LeValley A, Hall CB, Katz MJ, Ambrose AF, Lipton RB. Epidemiology of gait disorders in community-residing older adults. J Am Geriatr Soc 2006 Feb;54(2):255-261 [FREE Full text] [doi: 10.1111/j.1532-5415.2005.00580.x] [Medline: 16460376]
39. Alexander BH, Rivara FP, Wolf ME. The cost and frequency of hospitalization for fall-related injuries in older adults. Am J Public Health 1992 Jul;82(7):1020-1023. [Medline: 1609903]
40. de Bruin ED, Murer K. Effect of additional functional exercises on balance in elderly people. Clin Rehabil 2007 Feb;21(2):112-121. [doi: 10.1177/0269215506070144] [Medline: 17264105]
41. Sherrington C, Whitney JC, Lord SR, Herbert RD, Cumming RG, Close JC. Effective exercise for the prevention of falls: a systematic review and meta-analysis. J Am Geriatr Soc 2008 Dec;56(12):2234-2243. [doi: 10.1111/j.1532-5415.2008.02014.x] [Medline: 19093923]

42. Mian OS, Baltzopoulos V, Minetti AE, Narici MV. The impact of physical training on locomotor function in older people. Sports Med 2007;37(8):683-701. [Medline: 17645371]
43. Liu-Ambrose T, Donaldson MG, Ahamed Y, Graf P, Cook WL, Close J, et al. Otago home-based strength and balance retraining improves executive functioning in older fallers: a randomized controlled trial. J Am Geriatr Soc 2008 Oct;56(10):1821-1830. [doi: 10.1111/j.1532-5415.2008.01931.x] [Medline: 18795987]
44. Schutzer KA, Graves BS. Barriers and motivations to exercise in older adults. Prev Med 2004 Nov;39(5):1056-1061. [doi: 10.1016/j.ypmed.2004.04.003] [Medline: 15475041]
45. Kingston G, Gray MA, Williams G. A critical review of the evidence on the use of videotapes or DVD to promote patient compliance with home programmes. Disabil Rehabil Assist Technol 2010 May;5(3):153-163. [doi: 10.3109/17483101003671709] [Medline: 20205545]
46. Chao D, Foy CG, Farmer D. Exercise adherence among older adults: challenges and strategies. Control Clin Trials 2000 Oct;21(5 Suppl):212S-217S. [Medline: 11018578]
47. Bandura A. Self-efficacy: toward a unifying theory of behavioral change. Psychol Rev 1977 Mar;84(2):191-215. [Medline: 847061]
48. Fraser SN, Spink KS. Examining the role of social support and group cohesion in exercise compliance. J Behav Med 2002 Jun;25(3):233-249. [Medline: 12055775]
49. King AC, Taylor CB, Haskell WL, Debusk RF. Strategies for increasing early adherence to and long-term maintenance of home-based exercise training in healthy middle-aged men and women. Am J Cardiol 1988 Mar 1;61(8):628-632. [Medline: 3344690]
50. Eckert JK, Morgan LA, Swamy N. Preferences for receipt of care among community-dwelling adults. J Aging Soc Policy 2004;16(2):49-65. [doi: 10.1300/J031v16n02_04] [Medline: 15148044]
51. Geraedts H, Zijlstra A, Bulstra SK, Stevens M, Zijlstra W. Effects of remote feedback in home-based physical activity interventions for older adults: a systematic review. Patient Educ Couns 2013 Apr;91(1):14-24. [doi: 10.1016/j.pec.2012.10.018] [Medline: 23194823]
52. Thabane L, Ma J, Chu R, Cheng J, Ismaila A, Rios LP, et al. A tutorial on pilot studies: the what, why and how. BMC Med Res Methodol 2010;10:1 [FREE Full text] [doi: 10.1186/1471-2288-10-1] [Medline: 20053272]
53. Silveira P, van de Langenberg R, van Het Reve E, Daniel F, Casati F, de Bruin ED. Tablet-based strength-balance training to motivate and improve adherence to exercise in independently living older people: a phase II preclinical exploratory trial. J Med Internet Res 2013;15(8):e159 [FREE Full text] [doi: 10.2196/jmir.2579] [Medline: 23939401]
54. Silveira P, van het Reve E, Daniel F, Casati F, de Bruin ED. Motivating and assisting physical exercise in independently living older adults: a pilot study. Int J Med Inform 2013 May;82(5):325-334. [doi: 10.1016/j.ijmedinf.2012.11.015] [Medline: 23273420]
55. Mian OS, Baltzopoulos V, Minetti AE, Narici MV. The impact of physical training on locomotor function in older people. Sports Med 2007;37(8):683-701. [Medline: 17645371]
56. Paterson DH, Jones GR, Rice CL. Ageing and physical activity: evidence to develop exercise recommendations for older adults. Can J Public Health 2007;98 Suppl 2:S69-108. [Medline: 18213941]
57. Kenny RAM, Rubenstein LZ, Tinetti ME, Brewer K, Cameron KA, Capezuti EA. Summary of the updated American Geriatrics Society/British Geriatrics Society clinical practice guideline for prevention of falls in older persons. Journal of the American Geriatrics Society 2011 Jan;59(1):148-157. [doi: 10.1111/j.1532-5415.2010.03234.x]
58. Kraemer WJ, Adams K, Cafarelli E, Dudley GA, Dooly C, Feigenbaum MS, American College of Sports Medicine. American College of Sports Medicine position stand. Progression models in resistance training for healthy adults. Med Sci Sports Exerc 2002 Feb;34(2):364-380. [Medline: 11828249]
59. Rogers ME, Sherwood HS, Rogers NL, Bohlken RM. Effects of dumbbell and elastic band training on physical function in older inner-city African-American women. Women Health 2002;36(4):33-41. [doi: 10.1300/J013v36n04_03] [Medline: 12555800]
60. Cress ME, Buchner DM, Prohaska T, Rimmer J, Brown M, Macera C, et al. Best practices for physical activity programs and behavior counseling in older adult populations. J Aging Phys Act 2005 Jan;13(1):61-74. [Medline: 15677836]
61. Borg G. Borg's Perceived Exertion and Pain Scales. Champaign, IL: Human Kinetics; 1998.
62. Thabane L, Ma J, Chu R, Cheng J, Ismaila A, Rios LP, et al. A tutorial on pilot studies: the what, why and how. BMC Med Res Methodol 2010;10:1 [FREE Full text] [doi: 10.1186/1471-2288-10-1] [Medline: 20053272]
63. van Tulder M, Furlan A, Bombardier C, Bouter L, Editorial Board of the Cochrane Collaboration Back Review Group. Updated method guidelines for systematic reviews in the cochrane collaboration back review group. Spine (Phila Pa 1976) 2003 Jun 15;28(12):1290-1299. [doi: 10.1097/01.BRS.0000065484.95996.AF] [Medline: 12811274]
64. Nyman SR, Victor CR. Older people's recruitment, sustained participation, and adherence to falls prevention interventions in institutional settings: a supplement to the Cochrane systematic review. Age Ageing 2011 Jul;40(4):430-436 [FREE Full text] [doi: 10.1093/ageing/afr016] [Medline: 21502163]
65. Menz HB, Latt MD, Tiedemann A, Mun San Kwan M, Lord SR. Reliability of the GAITRite walkway system for the quantification of temporo-spatial parameters of gait in young and older people. Gait Posture 2004 Aug;20(1):20-25. [doi: 10.1016/S0966-6362(03)00068-7] [Medline: 15196515]

66. Kressig RW, Beauchet O, European GAITRite Network Group. Guidelines for clinical applications of spatio-temporal gait analysis in older adults. Aging Clin Exp Res 2006 Apr;18(2):174-176. [Medline: 16702791]
67. McDonough AL, Batavia M, Chen FC, Kwon S, Ziai J. The validity and reliability of the GAITRite system's measurements: A preliminary evaluation. Arch Phys Med Rehabil 2001 Mar;82(3):419-425. [doi: 10.1053/apmr.2001.19778] [Medline: 11245768]
68. McDowd JM. The effects of age and extended practice on divided attention performance. J Gerontol 1986 Nov;41(6):764-769. [Medline: 3772053]
69. Coppin AK, Shumway-Cook A, Saczynski JS, Patel KV, Ble A, Ferrucci L, et al. Association of executive function and performance of dual-task physical tests among older adults: analyses from the InChianti study. Age Ageing 2006 Nov;35(6):619-624 [FREE Full text] [doi: 10.1093/ageing/afl107] [Medline: 17047008]
70. Guralnik JM, Simonsick EM, Ferrucci L, Glynn RJ, Berkman LF, Blazer DG, et al. A short physical performance battery assessing lower extremity function: association with self-reported disability and prediction of mortality and nursing home admission. J Gerontol 1994 Mar;49(2):M85-M94. [Medline: 8126356]
71. Guralnik JM, Ferrucci L, Simonsick EM, Salive ME, Wallace RB. Lower-extremity function in persons over the age of 70 years as a predictor of subsequent disability. N Engl J Med 1995 Mar 2;332(9):556-561. [doi: 10.1056/NEJM199503023320902] [Medline: 7838189]
72. Yardley L, Beyer N, Hauer K, Kempen G, Piot-Ziegler C, Todd C. Development and initial validation of the Falls Efficacy Scale-International (FES-I). Age Ageing 2005 Nov;34(6):614-619 [FREE Full text] [doi: 10.1093/ageing/afi196] [Medline: 16267188]
73. Moher D, Hopewell S, Schulz KF, Montori V, Gøtzsche PC, Devereaux PJ, et al. CONSORT 2010 explanation and elaboration: updated guidelines for reporting parallel group randomised trials. BMJ 2010;340:c869 [FREE Full text] [Medline: 20332511]
74. Hollis S, Campbell F. What is meant by intention to treat analysis? Survey of published randomised controlled trials. BMJ 1999 Sep 11;319(7211):670-674 [FREE Full text] [Medline: 10480822]
75. Campbell AJ, Robertson MC, Gardner MM, Norton RN, Tilyard MW, Buchner DM. Randomised controlled trial of a general practice programme of home based exercise to prevent falls in elderly women. BMJ 1997 Oct 25;315(7115):1065-1069 [FREE Full text] [Medline: 9366737]
76. Woodard CM, Berry MJ. Enhancing adherence to prescribed exercise: structured behavioral interventions in clinical exercise programs. J Cardiopulm Rehabil 2001;21(4):201-209. [Medline: 11508179]
77. Callisaya ML, Blizzard L, McGinley JL, Srikanth VK. Risk of falls in older people during fast-walking--the TASCOG study. Gait Posture 2012 Jul;36(3):510-515. [doi: 10.1016/j.gaitpost.2012.05.003] [Medline: 22682610]
78. Bohannon RW. Comfortable and maximum walking speed of adults aged 20-79 years: reference values and determinants. Age Ageing 1997 Jan;26(1):15-19 [FREE Full text] [Medline: 9143432]
79. Hausdorff JM, Rios DA, Edelberg HK. Gait variability and fall risk in community-living older adults: a 1-year prospective study. Arch Phys Med Rehabil 2001 Aug;82(8):1050-1056. [doi: 10.1053/apmr.2001.24893] [Medline: 11494184]
80. Dubost V, Kressig RW, Gonthier R, Herrmann FR, Aminian K, Najafi B, et al. Relationships between dual-task related changes in stride velocity and stride time variability in healthy older adults. Hum Mov Sci 2006 Jun;25(3):372-382. [doi: 10.1016/j.humov.2006.03.004] [Medline: 16714067]
81. Kang HG, Dingwell JB. Separating the effects of age and walking speed on gait variability. Gait Posture 2008 May;27(4):572-577. [doi: 10.1016/j.gaitpost.2007.07.009] [Medline: 17768055]
82. Pichierri G, Murer K, de Bruin ED. A cognitive-motor intervention using a dance video game to enhance foot placement accuracy and gait under dual task conditions in older adults: a randomized controlled trial. BMC Geriatr 2012;12:74 [FREE Full text] [doi: 10.1186/1471-2318-12-74] [Medline: 23241332]
83. Hartmann A, Murer K, de Bie RA, de Bruin ED. The effect of a training program combined with augmented afferent feedback from the feet using shoe insoles on gait performance and muscle power in older adults: a randomised controlled trial. Disabil Rehabil 2010;32(9):755-764. [Medline: 20491152]
84. Hartmann A, Murer K, de Bie RA, de Bruin ED. The effect of a foot gymnastic exercise programme on gait performance in older adults: a randomised controlled trial. Disabil Rehabil 2009;31(25):2101-2110. [doi: 10.3109/09638280902927010] [Medline: 19888840]
85. Vasunilashorn S, Coppin AK, Patel KV, Lauretani F, Ferrucci L, Bandinelli S, et al. Use of the Short Physical Performance Battery Score to predict loss of ability to walk 400 meters: analysis from the InCHIANTI study. J Gerontol A Biol Sci Med Sci 2009 Feb;64(2):223-229 [FREE Full text] [doi: 10.1093/gerona/gln022] [Medline: 19182232]
86. Nyman SR, Victor CR. Older people's participation in and engagement with falls prevention interventions in community settings: an augment to the Cochrane systematic review. Age Ageing 2012 Jan;41(1):16-23 [FREE Full text] [doi: 10.1093/ageing/afr103] [Medline: 21875865]
87. Bagwell DK, West RL. Assessing compliance: active versus inactive trainees in a memory intervention. Clin Interv Aging 2008;3(2):371-382 [FREE Full text] [Medline: 18686759]
88. Näslund GK, Fredrikson M, Hellénius ML, de Faire U. Determinants of compliance in men enrolled in a diet and exercise intervention trial: a randomized, controlled study. Patient Educ Couns 1996 Dec;29(3):247-256. [Medline: 9006240]

89. Khalil H, Quinn L, van Deursen R, Martin R, Rosser A, Busse M. Adherence to use of a home-based exercise DVD in people with Huntington disease: participants' perspectives. Phys Ther 2012 Jan;92(1):69-82 [FREE Full text] [doi: 10.2522/ptj.20100438] [Medline: 21960468]
90. Burke L, Lee AH, Jancey J, Xiang L, Kerr DA, Howat PA, et al. Physical activity and nutrition behavioural outcomes of a home-based intervention program for seniors: a randomized controlled trial. Int J Behav Nutr Phys Act 2013;10:14 [FREE Full text] [doi: 10.1186/1479-5868-10-14] [Medline: 23363616]
91. Marhadour T, Saraux A. WITHDRAWN: Ivory vertebra and systemic mastocytosis. Comments on the article by Frenzel et al. Joint Bone Spine 2013 Jun 2:79-86. [doi: 10.1016/j.jbspin.2013.04.006] [Medline: 23731643]
92. Jolly K, Taylor R, Lip GY, Greenfield S, Raftery J, Mant J, et al. The Birmingham Rehabilitation Uptake Maximisation Study (BRUM). Home-based compared with hospital-based cardiac rehabilitation in a multi-ethnic population: cost-effectiveness and patient adherence. Health Technol Assess 2007 Sep;11(35):1-118 [FREE Full text] [Medline: 17767899]
93. Kuusik A, Sarna K, Reilent E. Home rehabilitation system supported by the safety model. Stud Health Technol Inform 2013;189:145-151. [Medline: 23739374]
94. Petkova E, Teresi J. Some statistical issues in the analyses of data from longitudinal studies of elderly chronic care populations. Psychosom Med 2002;64(3):531-547. [Medline: 12021427]
95. Ferrucci L, Guralnik JM, Studenski S, Fried LP, Cutler GB, Walston JD, Interventions on Frailty Working Group. Designing randomized, controlled trials aimed at preventing or delaying functional decline and disability in frail, older persons: a consensus report. J Am Geriatr Soc 2004 Apr;52(4):625-634. [doi: 10.1111/j.1532-5415.2004.52174.x] [Medline: 15066083]

## Abbreviations

**DTC:** dual task costs
**FES-I:** Falls Efficacy Scale International
**HH:** Health Hub
**MEMS:** microelectromechanical systems
**SPPB:** Short Physical Performance Battery

*Edited by G Eysenbach; submitted 28.10.13; peer-reviewed by E Stanmore, S Yang, S Boerema; comments to author 05.02.14; revised version received 19.03.14; accepted 31.05.14; published 25.06.14.*

*Please cite as:*
*van het Reve E, Silveira P, Daniel F, Casati F, de Bruin ED*
*Tablet-Based Strength-Balance Training to Motivate and Improve Adherence to Exercise in Independently Living Older People: Part 2 of a Phase II Preclinical Exploratory Trial*
*J Med Internet Res 2014;16(6):e159*
*URL: http://www.jmir.org/2014/6/e159/*
*doi:10.2196/jmir.3055*
*PMID:24966165*

Original Paper

# Paging "Dr. Google": Does Technology Fill the Gap Created by the Prenatal Care Visit Structure? Qualitative Focus Group Study With Pregnant Women

Jennifer L Kraschnewski[1], MD, MPH; Cynthia H Chuang[1], MSc, MD; Erika S Poole[2], PhD; Tamara Peyton[2]; Ian Blubaugh[1]; Jaimey Pauli[1], MD; Alyssa Feher[3]; Madhu Reddy[2], PhD

[1]Penn State University College of Medicine, Hershey, PA, United States

[2]The Pennsylvania State University, State College, PA, United States

[3]Family Health Council of Central Pennsylvania, Carlisle, PA, United States

**Corresponding Author:**
Jennifer L Kraschnewski, MD, MPH
Penn State University College of Medicine
500 University Drive, HO34
Hershey, PA, 17036
United States
Phone: 1 717 531 8161
Fax: 1 717 531 7726
Email: jkraschnewski@hmc.psu.edu

## *Abstract*

**Background:** The prenatal care visit structure has changed little over the past century despite the rapid evolution of technology including Internet and mobile phones. Little is known about how pregnant women engage with technologies and the interface between these tools and medical care, especially for women of lower socioeconomic status.

**Objective:** We sought to understand how women use technology during pregnancy through a qualitative study with women enrolled in the Women, Infants, and Children (WIC) program.

**Methods:** We recruited pregnant women ages 18 and older who owned a smartphone, at a WIC clinic in central Pennsylvania. The focus group guide included questions about women's current pregnancy, their sources of information, and whether they used technology for pregnancy-related information. Sessions were audiotaped and transcribed. Three members of the research team independently analyzed each transcript, using a thematic analysis approach. Themes related to the topics discussed were identified, for which there was full agreement.

**Results:** Four focus groups were conducted with a total of 17 women. Three major themes emerged as follows. First, the prenatal visit structure is not patient-centered, with the first visit perceived as occurring too late and with too few visits early in pregnancy when women have the most questions for their prenatal care providers. Unfortunately, the educational materials women received during prenatal care were viewed as unhelpful. Second, women turn to technology (eg, Google, smartphone applications) to fill their knowledge gaps. Turning to technology was viewed to be a generational approach. Finally, women reported that technology, although frequently used, has limitations.

**Conclusions:** The results of this qualitative research suggest that the current prenatal care visit structure is not patient-centered in that it does not allow women to seek advice when they want it most. A generational shift seems to have occurred, resulting in pregnant women in our study turning to the Internet and smartphones to fill this gap, which requires significant skills to navigate for useful information. Future steps may include developing interventions to help health care providers assist patients early in pregnancy to seek the information they want and to become better consumers of Internet-based pregnancy resources.

***(J Med Internet Res 2014;16(6):e147)*** doi:10.2196/jmir.3385

**KEYWORDS**

qualitative research; prenatal care; pregnancy resources; Women, Infants, and Children Program; mhealth; mobile phones; smartphones; Internet; patient education; consumer health informatics

## Introduction

Little is known about how pregnant women are currently using Internet technologies (eg, websites, smartphone applications) and how these tools interface with medical care [1]. The Maternity Experiences Survey, a 2006-2007 national survey of postpartum women in Canada, found that women considered the most useful source of information during pregnancy to be their health care provider (32.2%), followed by books (22.3%), and personal experiences from a prior pregnancy (17.1%), although family and friends, the Internet, and prenatal classes were also noted [2]. Since that survey, the Internet and smartphones have become much more popular and, although patients report that physicians are their preferred source for information, the Internet is often the first resource accessed for health information because of its accessibility, wide availability, and low cost [3,4]. Women, in particular, are more likely to be health information seekers and to report that information obtained from the Internet helped them cope with their health conditions, including pregnancy [4,5]. Pregnant women who search the Internet for health information have a variety of resources from which to choose. One study investigating search terms for common obstetrical terms (eg, birth trauma, epidural, etc) found millions of websites, less than 4% of which were created or sponsored by physicians [6].

Given the wide availability of online resources for pregnant women, it is not surprising that nearly half (44%) of pregnant women are using these tools [1]. However, what remains less clear is the role technology has during pregnancy and the interaction between online resources and prenatal care. In this study, we sought to understand how women use technology during pregnancy through a qualitative study of pregnant women enrolled in the Women, Infants, and Children (WIC) program.

## Methods

### Setting and Participants

In spring 2013, we recruited pregnant women through posted advertisements at a Women, Infants, and Children (WIC) clinic in central Pennsylvania. The focus groups were conducted at the Cumberland/Perry Tapestry of Health (CP TOH) WIC clinic. The CP TOH provides the WIC program to over 3500 clients per month in both Cumberland and Perry counties in central Pennsylvania. Recruitment materials invited women to participate in a 90-minute focus group to discuss how smartphones may help women have healthier pregnancies. Interested women were screened in person at the clinic or by phone for eligibility. The eligibility criteria included being 18 years old or older, currently pregnant, and owning a smartphone. Women who met eligibility criteria and agreed to participate were scheduled for a focus group. Informed consent was obtained at the start of the focus group session. Each woman was compensated for her participation and childcare was provided. This study was approved by the Penn State University College of Medicine’s Institutional Review Board.

### Procedures

We conducted four focus groups, ranging between 2-6 participants each, with a total of 17 participants. The focus groups were conducted by 3 of the investigators (JLK, CHC, EP). The groups were held in a conference room at the WIC clinic. Prior to each session, participants completed a brief self-administered written questionnaire to assess demographic data (eg, race, ethnicity, weight, and height), adapted from the National Health and Nutrition Examination Survey, and smartphone use characteristics, adapted for our population from the Pew Research Internet Project [7].

The primary purpose of the focus groups was to determine participants’ requirements for a smartphone application aimed at helping them achieve a healthy pregnancy, while the current analysis reports on the subset of questions related to current technology use. Women were asked when they found out they were pregnant, when they called for prenatal care, and where they sought information prior to the first prenatal care visit. The focus group guide also included questions about the positive experiences and challenges they were having during their current pregnancy and how they had been using their smartphones and other sources of technology during the current pregnancy. Textbox 1 presents the questions from the interview guide analyzed in this manuscript. All sessions were audiotaped and transcribed. Members of the research team debriefed following each focus group session and focus groups were continued until it was agreed that thematic saturation was reached.

**Textbox 1.** Focus group interview guide.

1. What’s been one of the most challenging things so far about this pregnancy?
    a. Are these challenges your prenatal care providers have helped you with?
    b. When did you have your first prenatal visit?
2. Tell us about something you’ve done to keep track of your pregnancy.
3. Do you talk about your pregnancy with others online (eg, on Facebook, Twitter, YouTube, or websites for expecting moms)?
4. You may or may not have seen them before, but there are a lot of smartphone applications that are about pregnancy. Have you downloaded any pregnancy applications?
    a. What were your experiences with them?

### Data Analysis

Frequencies for data reported on the brief questionnaire are presented. Three members of the research team (JLK, IB, CHC) independently analyzed each transcript, using a thematic analysis approach. Data from the notes and transcripts were reviewed and codes were generated. Codes were then analyzed and categorized into over-arching themes independently by investigators and discussed, resulting in full agreement. Illustrative examples of the themes were selected and presented.

## Results

### Participant Characteristics

Table 1 displays the characteristics of the focus group participants. Women had an average age of 28 years and most were white. There were women representing all pregnancy trimesters. The vast majority reported using online social networking sites at least once a day (82%, 14/17).

**Table 1.** Participant characteristics (n=17).

| Characteristics | | n (%) |
|---|---|---|
| Age, years, median (range) | | 28 (21-38) |
| **Race** | | |
| | White | 14 (82) |
| | Other | 3 (18) |
| **Parity** | | |
| | Nulliparous | 5 (29) |
| | Parous | 12 (71) |
| **Number of weeks pregnant** | | |
| | First trimester | 7 (41) |
| | Second trimester | 4 (24) |
| | Third trimester | 6 (35) |
| **Pre-pregnancy weight category** | | |
| | Normal weight | 8 (47) |
| | Overweight | 6 (35) |
| | Obese | 3 (18) |
| **Smartphone operating system** | | |
| | iOS | 6 (35) |
| | Android | 8 (47) |
| | Other | 3 (18) |
| **Frequency of use of online social networking** | | |
| | At least once a day | 14 (82) |
| | At least once a week | 3 (18) |

### Themes

#### *Overview*

Technology use, either through Internet or smartphone applications, was the standard among our participants. Women sought the Internet and smartphone applications, in part because the prenatal care visit structure and how pregnancy-related information was delivered during prenatal care visits was not meeting their needs. Specifically, women reported using search engines (eg, Google) to answer pregnancy-related questions, which ranged from, "Am I pregnant?" to specific pregnancy-related symptoms (eg, abdominal pain, constipation, fatigue, heartburn). Women also frequently described using pregnancy-tracking smartphone applications (eg, BabyCenter) to follow their baby's progress (eg, current size, organ development). Further, women used social media sites, including Facebook, to share their pregnancy experience and learn about the experiences of others (eg, videos of different birthing methods). The analysis of the women's responses resulted in the identification of three overarching themes: (1) prenatal care structure is not patient-centered, (2) women used technology to fill gaps, and (3) technology has limitations in supporting their pregnancy-related needs.

#### *Prenatal Care Structure Was Not Patient-Centered*

In general, most women reported that the structure of their prenatal care did not meet their needs and thus was not patient-centered (ie, responsive to individual preference, needs, and values) in several key ways. First, the timing of the prenatal visits did not reflect when women wanted to see their provider. Multiple women commented that the first visit occurs too late and that there are too few visits early in pregnancy, when women had the most questions for their prenatal care providers:

> *They expected me to wait 13 weeks until I had a conversation with my doctor.*
>
> *I know we can't change the health care system…but on your first appointment, they say, "We'll see you in 8 weeks…" and uh…That's 2 months! What am I going to do?* [Focus Group 1, Participant C; FG1, C]

In contrast, women felt the clinic visit structure required too many visits toward the end of pregnancy. One woman suggested that the prenatal care visit structure was upside down:

> *I'm at 10 weeks, they don't want to see me for another 6 weeks…they see you more at the end than at the beginning…they don't have to see you so much at the end. [At the] beginning there are more questions about health and weight gain—that should be the priority.* [FG1, D]

In addition to the timing of clinic visits, women expressed that the supplemental information provided during these visits was not useful to them:

> *Today they gave me a whole bag of pamphlets and flyers and didn't explain or go over them with me…and now I have to go home and try to go through them, while I have a kid running around…and when you're a new mom, that's overwhelming.* [FG1, D]

Another woman echoed this opinion:

> *They gave me pamphlets on my first appointment…here's this one…here's this one…and they bombard you with all this information.* [FG2, B]

Interestingly, the book of "What to Expect When Expecting", previously considered a must-read for pregnant women, was unfamiliar to many of the women. Some women said they were given a copy of the book by their prenatal care provider but had not opened it because they found using a reference book to be outdated and not how they wanted to receive information. Those who had used the book expressed that much of the information it contained lacked usefulness:

> *[The book] says how to take care of your second child, well, I don't need that—I'm a first time mother!* [FG2, D]

Another woman agreed,

> *Half that book doesn't pertain to anyone or anything. Or it tells you about how you conceived the baby…I know this much already!* [FG2, C]

Another way in which women described how prenatal care lacked patient-centeredness was that the visits themselves felt structured around the clinics' needs and not individualized toward the patients' needs. For example, when discussing gestational weight gain:

> *It [the target weight to gain] wasn't even my goal, it was theirs…They just gave me a paper. What good does that do at 28 weeks? I'm almost already there.* [FG1, A]

Another woman also commented on how her prenatal care felt routine and inconvenient:

> *I found out [I was pregnant] at 4 weeks…but I was new with this, so I was on it. They took me in for a blood test. That was it. They called to say, 'Yes, congratulations' and then called me at 9 weeks for a sonogram and a whole slew of blood work, and I asked specifically if I was going to see my doctor there and they said no. So I had to make a separate appointment following that, just to see my doctor, and pay for that visit.* [FG1, C]

The structure of the prenatal care led most of the participants to turn to Internet resources to provide them with pregnancy-related information.

### *Women Sought Technology to Fill Information Gaps and Share Their Pregnancy Experiences*

Participants reported turning to technology to fill gaps largely attributed to limitations in their prenatal care, primarily the inability to ask their provider questions during their pregnancy. Most frequently, women reported using Google and smartphone applications (eg, Babycenter) as a means of finding information. One woman reported turning to Google to fill information gaps largely because of the prenatal visit limitations:

> *I did a lot of Google searches and Pinterest, my little mommy blog things, just looking at different things…my doctor didn't tell me about round ligament pain, until, gosh, maybe 4 weeks ago…but I was having [the pain] from 13 weeks on.* [FG1, C]

Another woman echoed these thoughts:

> *I think they should see you at 6 [weeks pregnant]. Just because, with new moms, they'll have all types of questions…they're getting sick, feeling miserable. So they can get helpful tips, instead of getting all the info late...so women are going on Google to get their own answers because their doctors won't see them.* [FG1, D]

Even when women had established care with their prenatal care provider, they almost all turned to Google first to answer their questions but would follow up with their provider if they still had concerns:

> *I'll go on Google first. Then [if I don't really understand], I'll call my doctor.* [FG3, C]

Women also saw their use of technology during pregnancy as something unique to their generation.

Overall, Internet resources were used frequently and for a variety of pregnancy-related informational needs. When asked to recall a time when the Internet was used to look up things about pregnancy, one woman responded: "Every day!" [FG2, B]. More specific situations women reported included searching for different symptoms of pregnancy as well as baby-related information. These findings were similar across focus groups.

Some women believed that finding information online led them to read more, rather than less, about their pregnancy. For example, one woman reported:

> *I'm not a reader and I know this is going to sound really strange…I read more on my phone, tablet, or*

> *laptop than I would a book or magazine or pamphlet.* [FG2, B]

The Internet also offered resources in media formats typically not provided during prenatal care, yet desired by pregnant women. For example, some women reported watching videos of different types of births on the Internet. Another mother used videos of the developing baby to engage her family in the pregnancy: "I would show the kids the little video clips of the baby developing. Those are really good videos" [FG4, A]. In addition to filling information gaps for themselves, many of the women reported using technology as a way of connecting with their partners on the pregnancy, particularly for first-time dads:

> *Then I get the emails [from a pregnancy tracking website]…and I forward them to my husband, so that I feel like we're both synced on what is going on.* [FG1, D]

Social media also provided opportunities for most women to learn about and share symptoms of pregnancy. Facebook, Instagram, and blogs were all mentioned as sources of obtaining information from others women who had similar experiences. Additionally, these venues were frequently reported as ways of sharing their personal pregnancy updates:

> *[Facebook plug-in program] automatically posts on your wall, so you don't even have to worry about it…it does it for you, like every week, and it shows the progression of your baby.* [FG1, D]

However, many women reported being cautious about how much they shared on Facebook:

> *Some people share way too much…I put little things, like '20 week check…everything was doing really good'…I'm not friends with 18,000 people.* [FG2, C]

Overall, participants desired information, particularly early in their pregnancy prior to prenatal care and sought it independently through Google and other Internet applications.

### *Technology Had Limitations*

Although all of the women in the focus groups reported using technology sources for pregnancy-related information, they did recognize significant limitations with this approach. For example, women reported needing to exercise caution when searching about symptoms they were having, to avoid receiving inaccurate information:

> *Sometimes you can Google something, like when I was having my round ligament pain for the first time…some things that came up were terrifying…you want to go to the ER right away! You definitely have to be careful and smart about your Google searches.* [FG1, C]

Women reporting using the Internet required multiple searches to find the specific information they were looking for:

> *I just add more keywords…or put my quotes in there…just a more specific, more refined search. And then it usually has a better answer. 'Cause sometimes when you're just searching something, you just put in a very simple general description of what you want to search and it brings up all these different things.* [FG1, C]

Most women reported using a smartphone application to help keep track of their pregnancy progress, but that had significant limitations as well. For example, some women tracked their weight gain during pregnancy through a smartphone application, but when they found that they were gaining too much weight, there was no specific advice given to help women achieve weight gain goals:

> *The weight tracker I used…I stopped using it. It tells you where you should be [with weight gain], but it doesn't make any sense. It says this is 'you' and this is where you should be, but what do I do [to get there]?* [FG2, E]]

Another woman echoed that simply tracking weight data without useful feedback on how to stay on track was unhelpful:

> *It's like Google maps…saying you're supposed to get there, but it doesn't give you directions [on how to get there]* [FG2, D]

Other noted limitations included lacking a food diary to record what women eat.

Even though participants reported widespread use of technology sources for finding and sharing pregnancy-related information, they identified significant limitations leading some women to avoid using technology all together.

## Discussion

### Principal Findings

Our results suggest that women use the Internet and other sources of technology frequently during pregnancy in part because the current prenatal care visit structure does not allow women to seek advice when they want it the most, and thus is not patient-centered. Our findings echo those of a global study by Lagan and colleagues, who concluded that "the use of the Internet by pregnant women to seek health information and advice suggests a lack of information available from health professionals" [8]. National efforts to provide patient-centered care, described by the Institute of Medicine (IOM) as health care that is both respectful and responsive to a patient's needs, preferences, and values, have begun in primary care with the creation of the Patient-Centered Medical Home [9]. As one of the most frequently used preventive health care services in the United States, prenatal care has not yet experienced a similar overhaul.

Given the lack of evidence on how prenatal care should ideally be delivered, the traditional model for prenatal care delivery in the United States has changed little over the last century and has been described as more "ritualistic than rational" [10-13]. The prenatal care visit structure typically starts with an initial prenatal visit (usually no earlier than 8 weeks of pregnancy), followed by infrequent visits until the third trimester. The more frequent visits toward the end of pregnancy support increased surveillance for signs of preeclampsia and preterm birth, which can change rather rapidly later in pregnancy. However, the importance of healthy behaviors during pregnancy is now better appreciated, especially in the presence of chronic disease (eg, diabetes, obesity, and hypertension) and detrimental health habits (eg, smoking alcohol use, nutritional) that require management as early as possible [14], preferably prior to conception.

Perhaps moving in the opposite direction, interventions have attempted to modify the current prenatal visit structure by actually reducing the number of visits [15,16]. A meta-analysis of seven trials with 60,724 women found that, despite no increase in adverse health outcomes, women were less satisfied with their care when the number of prenatal visits was reduced [10]. Further efforts to disseminate novel prenatal care approaches should demonstrate improved patient satisfaction as well as effectiveness as a challenger to the status quo, despite a lack of demonstrated effectiveness of traditional prenatal care [11]. One such effort is "CenteringPregnancy", a group visit approach to prenatal care involving a care-provider physical examination (similar to the traditional appointment) followed by 90 minutes of a care provider-led educational group with women at similar pregnancy stages [17]. Although the prenatal care visit number is unchanged in CenteringPregnancy, the longer visits offer significant opportunity for information exchange and increased patient-centeredness and satisfaction.

Largely due to the lack of patient-centeredness in prenatal care, pregnant women in our study turned to technology for timely answers to their questions. This change appears to represent a generational shift compared to years prior, with women now using the Internet more and finding it to be more useful than family and friends [1]. Unlike their mothers, women in our study tended to ask "Dr. Google" first when investigating pregnancy questions, ranging from determining if they are pregnant, the etiologies of abdominal pain, and different birthing methods. Although most women utilized Internet resources, many commented on the challenges of finding reliable information that was helpful, instead of scary. Further, most women in our study used the Internet before contacting their prenatal care provider. Despite this extensive use of online resources, it is important that women still feel they can contact their provider for questions that remain.

Although technology use is widespread, online resources have significant limitations in meeting the informational needs for pregnant women. Importantly, there is a nearly complete lack of interaction between online resources and medical care. Kaimal and colleagues found in their study of online resources for obstetrics that fewer than 4% of websites were created and/or sponsored by physicians [6]. This suggests that the vast majority of online resources women utilize may be created in the absence of expert knowledge. As a result, significant skills are required by users to navigate the Internet for useful information. Internet-based tools may help improve access to pregnancy-related information; however, the benefit may be limited in certain populations due to lower rates of eHealth literacy, defined as "the ability to seek, find, understand, and appraise health information from electronic sources and apply the knowledge gained to addressing or solving a health problem" [18]. A recent study by Neter and Brainin found that eHealth literacy was higher among younger, more educated adults and that those with higher eHealth literacy were more likely to have positive outcomes from the information searched (ie, greater gains in health behaviors and positive interactions with their health care provider) [19]. Pregnant women tend to be younger, but those with lower socioeconomic status, such as the women in our study, may not derive equal benefit from these resources. Further research is necessary to determine how best to design technology to better serve this population.

However, this also presents a tremendous opportunity for medical systems to leverage the technology already available as well as further developing appropriate connections with medical expertise. For example, all of the women in our study used a pregnancy application to track their pregnancy. The limitations of these applications could easily be met by integrating evidence-based information from medical experts, such as including a discussion of the IOM's guidelines for appropriate gestational weight gain instead of simply tracking weight gain.

Fortunately, women may be discussing questionable Internet information with their health care provider. Lagan and colleagues studied 303 midwives to assess their understanding of their patients' use of the Internet and found that most (86%) had experienced a pregnant woman discussing information from the Internet with them in the past year [20]. Unfortunately, care providers may not be able to systematically evaluate such information: only 15% of midwives in Lagan's study were aware of and able to describe indicators for quality online health information evaluation [20].

### Study Strengths and Limitations

Our study has several strengths. First, the role technology plays during pregnancy has been minimally explored in the literature, despite the growing use of technology. Additionally, to our knowledge, this is the only qualitative study investigating technology's role in pregnancy for women enrolled in WIC, a health disparate population at greater risk for pregnancy complications. Our study also has limitations, including the recruitment of a convenience sample of volunteer pregnant women enrolled in WIC in Central Pennsylvania. As a result, volunteer bias is likely. Further, this population may be significantly different from women with higher socioeconomic status who experience fewer barriers to care access and may have different sources of information support. Therefore, our results may not be generalizable to pregnant women's experiences in other settings. However, given the ubiquity of the Internet and largely standardized approach to prenatal care, we expect these results will be useful across the country. In addition, this study did not aim to compare technology with other information sources pregnant women use. Further qualitative and quantitative research on this topic is necessary in a large, more diverse group of women.

### Conclusions

Our results suggest several important next steps. Given how critical patient-provider communication is to the therapeutic relationship, the Internet should be considered by more providers as a forum for both dissemination of evidence-based education information and integration into the prenatal care structure. Importantly, none of the women in our study mentioned receiving online resources from their prenatal care provider, although it is established that providers are aware of and perhaps have even created such resources for their patients. Greater efforts are necessary to connect women with such resources, particularly early in pregnancy and prior to initiating prenatal care. For example, letting women know of reliable online resources when they first call in for an appointment to be scheduled weeks away may be useful. Further, as the role of technology is increasing in importance for pregnant women, understanding how best to leverage existing resources to facilitate healthy pregnancies will be necessary to meet women's informational needs. Future steps may include developing interventions to help health care providers assist patients early in pregnancy seek the information they want and become better consumers of Internet-based pregnancy resources.

## Acknowledgments

This research was supported by the National Center for Research Resources and the National Center for Advancing Translational Sciences, National Institutes of Health, through Grant UL1 TR000127. Dr Kraschnewski is supported by Grants UL1 TR000127 and KL2 TR000126.

## Conflicts of Interest

None declared.

## References

1. Grimes HA, Forster DA, Newton MS. Sources of information used by women during pregnancy to meet their information needs. Midwifery 2014 Jan;30(1):e26-e33. [doi: 10.1016/j.midw.2013.10.007] [Medline: 24246969]
2. Public Health Agency of Canada. What Mothers Say: The Canadian Maternity Experiences Survey. 2009. URL: http://www.phac-aspc.gc.ca/rhs-ssg/survey-eng.php [accessed 2014-05-28] [WebCite Cache ID 6PudMEJdu]
3. Hesse BW, Nelson DE, Kreps GL, Croyle RT, Arora NK, Rimer BK, et al. Trust and sources of health information: the impact of the Internet and its implications for health care providers: findings from the first Health Information National Trends Survey. Arch Intern Med 2005;165(22):2618-2624. [doi: 10.1001/archinte.165.22.2618] [Medline: 16344419]
4. Ybarra M, Suman M. Reasons, assessments and actions taken: sex and age differences in uses of Internet health information. Health Educ Res 2008 Jun;23(3):512-521 [FREE Full text] [doi: 10.1093/her/cyl062] [Medline: 16880222]
5. Shieh C, Broome ME, Stump TE. Factors associated with health information-seeking in low-income pregnant women. Women Health 2010 Jul;50(5):426-442. [doi: 10.1080/03630242.2010.506152] [Medline: 20853218]
6. Kaimal AJ, Cheng YW, Bryant AS, Norton ME, Shaffer BL, Caughey AB. Google obstetrics: who is educating our patients? Am J Obstet Gynecol 2008 Jun;198(6):682.e1-682.e5. [doi: 10.1016/j.ajog.2008.03.030] [Medline: 18538152]
7. Duggan M, Smith A. Pew Research Internet Project. 2013 Dec 30. Social Media Update 2013 URL: http://www.pewinternet.org/2013/12/30/social-media-update-2013/ [accessed 2014-05-28] [WebCite Cache ID 6PudjKue7]
8. Lagan BM, Sinclair M, Kernohan WG. What is the impact of the Internet on decision-making in pregnancy? A global study. Birth 2011 Dec;38(4):336-345. [doi: 10.1111/j.1523-536X.2011.00488.x] [Medline: 22112334]
9. Institute of Medicine. In: Briere R, editor. Crossing the Quality Chasm. Washington, D.C: National Academy Press; 2001.
10. Dowswell T, Carroli G, Duley L, Gates S, Gülmezoglu AM, Khan-Neelofur D, et al. Alternative versus standard packages of antenatal care for low-risk pregnancy. Cochrane Database Syst Rev 2010(10):CD000934. [doi: 10.1002/14651858.CD000934.pub2] [Medline: 20927721]
11. Novick G. CenteringPregnancy and the current state of prenatal care. J Midwifery Womens Health 2004;49(5):405-411. [doi: 10.1016/j.jmwh.2004.06.001] [Medline: 15351330]
12. Alexander GR, Kotelchuck M. Assessing the role and effectiveness of prenatal care: history, challenges, and directions for future research. Public Health Rep 2001;116(4):306-316 [FREE Full text] [Medline: 12037259]
13. Kirkham C, Harris S, Grzybowski S. Evidence-based prenatal care: Part I. General prenatal care and counseling issues. Am Fam Physician 2005 Apr 1;71(7):1307-1316 [FREE Full text] [Medline: 15832534]
14. Johnson K, Posner SF, Biermann J, Cordero JF, Atrash HK, Parker CS, CDC/ATSDR Preconception Care Work Group, Select Panel on Preconception Care. Recommendations to improve preconception health and health care--United States. A report of the CDC/ATSDR Preconception Care Work Group and the Select Panel on Preconception Care. MMWR Recomm Rep 2006 Apr 21;55(RR-6):1-23 [FREE Full text] [Medline: 16617292]
15. Sikorski J, Wilson J, Clement S, Das S, Smeeton N. A randomised controlled trial comparing two schedules of antenatal visits: the antenatal care project. BMJ 1996 Mar 2;312(7030):546-553 [FREE Full text] [Medline: 8595286]
16. McDuffie RJ, Beck A, Bischoff K, Cross J, Orleans M. Effect of frequency of prenatal care visits on perinatal outcome among low-risk women. A randomized controlled trial. JAMA 1996 Mar 20;275(11):847-851. [Medline: 8596222]
17. Shakespear K, Waite PJ, Gast J. A comparison of health behaviors of women in centering pregnancy and traditional prenatal care. Matern Child Health J 2010 Mar;14(2):202-208. [doi: 10.1007/s10995-009-0448-3] [Medline: 19184385]
18. Norman CD, Skinner HA. eHealth Literacy: Essential Skills for Consumer Health in a Networked World. J Med Internet Res 2006;8(2):e9 [FREE Full text] [doi: 10.2196/jmir.8.2.e9] [Medline: 16867972]

19. Neter E, Brainin E. eHealth literacy: extending the digital divide to the realm of health information. J Med Internet Res 2012;14(1):e19 [FREE Full text] [doi: 10.2196/jmir.1619] [Medline: 22357448]
20. Lagan BM, Sinclair M, Kernohan WG. A Web-based survey of midwives' perceptions of women using the Internet in pregnancy: a global phenomenon. Midwifery 2011 Apr;27(2):273-281. [doi: 10.1016/j.midw.2009.07.002] [Medline: 19700228]

## Abbreviations

**CP TOH:** Cumberland/Perry Tapestry of Health
**IOM:** Institute of Medicine
**WIC:** Women, Infants, and Children

*Edited by G Eysenbach; submitted 06.03.14; peer-reviewed by D Kingston, K Hameen-Anttila; comments to author 28.03.14; revised version received 07.04.14; accepted 19.05.14; published 03.06.14.*

*Please cite as:*
*Kraschnewski JL, Chuang CH, Poole ES, Peyton T, Blubaugh I, Pauli J, Feher A, Reddy M*
*Paging "Dr. Google": Does Technology Fill the Gap Created by the Prenatal Care Visit Structure? Qualitative Focus Group Study With Pregnant Women*
*J Med Internet Res 2014;16(6):e147*
*URL: http://www.jmir.org/2014/6/e147/*
*doi:10.2196/jmir.3385*
*PMID:24892583*

Original Paper

# Smartphone-Enabled Health Coach Intervention for People With Diabetes From a Modest Socioeconomic Strata Community: Single-Arm Longitudinal Feasibility Study

Noah Wayne[1*], MSc; Paul Ritvo[1,2,3,4,5,6*], PhD, CPsych

[1]School of Kinesiology & Health Science, Faculty of Health, York University, Toronto, ON, Canada
[2]Department of Psychology, Faculty of Health, York University, Toronto, ON, Canada
[3]Research, Prevention and Cancer Control, Cancer Care Ontario, Toronto, ON, Canada
[4]Department of Psychiatry, Faculty of Medicine, University of Toronto, Toronto, ON, Canada
[5]Department of Family and Community Medicine, Faculty of Medicine, University of Toronto, Toronto, ON, Canada
[6]Division of Epidemiology and Biostatistics, Ontario Cancer Institute, Princess Margaret Hospital, Toronto, ON, Canada
[*]all authors contributed equally

**Corresponding Author:**
Paul Ritvo, PhD, CPsych
School of Kinesiology & Health Science
Faculty of Health
York University
136 Chemistry Building
4700 Keele Street
Toronto, ON, M3J1P3
Canada
Phone: 1 416 736 2100 ext 22396
Fax: 1 416 736 5774
Email: pritvo@yorku.ca

## Abstract

**Background:** Lower socioeconomic strata (SES) populations have higher chronic disease risks. Smartphone-based interventions can support adoption of health behaviors that may, in turn, reduce the risks of type 2 diabetes-related complications, overcoming the obstacles that some patients may have with regular clinical contact (eg, shiftwork, travel difficulties, miscommunication).

**Objective:** The intent of the study was to develop and test a smartphone-assisted intervention that improves behavioral management of type 2 diabetes in an ethnically diverse, lower SES population within an urban community health setting.

**Methods:** This single-arm pilot study assessed a smartphone application developed with investigator assistance and delivered by health coaches. Participants were recruited from the Black Creek Community Health Centre in Toronto and had minimal prior experience with smartphones.

**Results:** A total of 21 subjects consented and 19 participants completed the 6-month trial; 12 had baseline glycosylated hemoglobin (HbA1c) levels >7.0% and these subjects demonstrated a mean reduction of 0.43% (SD 0.63) ($P$<.05) with minimal changes in medication.

**Conclusions:** This project supported the feasibility of smartphone-based health coaching for individuals from lower SES with minimal prior smartphone experience.

***(J Med Internet Res 2014;16(6):e149)*** doi:10.2196/jmir.3180

**KEYWORDS**

diabetes mellitus; type 2; health coaching; telehealth

## Introduction

### Background

A consensus of medical professionals and academic researchers indicates that type 2 diabetes mellitus (T2DM) is a chronic condition that progresses to more debilitating complications if certain unhealthy behaviors persist [1]. Regular exercise conversely prevents deteriorating health and disease onset [2] and has measurable benefits for T2DM-diagnosed populations [3,4]. Because high carbohydrate diets increase risks for diabetes-related complications due to chronic hyperglycemia, dietary modification can also result in risk reductions [5]. The adoption of optimal health behaviors in those diagnosed with T2DM requires behavior change and support for diabetic individuals from lower socioeconomic strata (SES) is especially important as this population confronts additional challenges in maintaining good health [6]. Data from the Canadian Healthy Community Survey (2005) suggest individuals from the lowest income group are over four times more likely to have T2DM [7]. Furthermore, education and personal wealth variables, typically viewed as SES proxies, are the strongest predictors of premature death associated with T2DM [8]. Despite recent surges of interest in disease incidence related to SES, little attention has been paid to urban, low SES immigrant/minority groups. As our experience indicates, these individuals are often less willing to volunteer for research and are less reliable subjects after enrollment. This is mainly related to the competing demands they confront and the lack of flexibility in their working conditions.

Health coaches promote adoption and maintenance of health behaviors, using validated theoretical frameworks (eg, motivational interviewing [9] and cognitive behavioral therapy [10]). Health coaches primarily focus on helping patients define and attain personal goals and discover intrinsic health-oriented motivations [11]. Recent trials involving health coaching in chronic disease demonstrate positive gains for patients, such as increased exercise and medication adherence [11,12], improved psychological functioning [11], and more positive illness-coping strategies [11].

Mobile technologies complement health coaching by enabling patients and coaches to maintain multiple channels of contact via remote monitoring, voice, and text message communications. The use of mobile phones potentially provides unprecedented precision in supporting health-related behavior since it facilitates responses to immediate needs and serves to maintain communication consistency. Once an individual decides on the intensity, frequency, and duration of contacts with the health coach, it is possible to detect non-adherence lapses quickly to the point where supportive-corrective responses can be provided while the non-adherent pattern is still unfolding. Reminder and reinforcement messages of different types can be sent to patients at any hour of day or evening, enabling interactions that purposefully blend with the patient's daily lifestyle.

Remote monitoring has been associated in numerous controlled studies with significant benefits in improving blood pressure and blood glucose regulation [13-16], exercise adherence [17], and dietary control [18,19]. Mobile technologies enable immediate and inexpensive communication with patients, exemplified in the use of text messages (SMS) to boost medication adherence and decrease viral load in HIV-positive Kenyan populations [20], and to deliver supportive SMS to patients at risk for developing type 2 diabetes [21], and have demonstrated results with a variety of other chronic medical conditions [22].

### NexJ Connected Health and Wellness Platform (CHWP)

The Connected Health and Wellness Platform (CHWP) Health Coach app is designed to support multi-channel communications between clients and health coaches and supportive family members. The app was collaboratively designed by software developers (NexJ Systems Inc.) and study investigators to support participants in electronically tracking health behaviors (eg, exercise, diet, stress reduction practices) and self-monitoring health data (eg, blood glucose, blood pressure, mood, pain, energy). Provider-client communications require two-way, certificate-based authentication and passwords stored in encrypted columns, with entered data recalled by client and health coach through a secure online portal.

## Methods

### Study Design

This experimental pre/post, single-arm trial assessed a 24-week intervention where interactions in person, by phone, and by smartphone (eg, secure messaging, email) with a personal health coach supported adoption of and adherence to self-generated health-behavior change goals. The primary study outcome was glycosylated hemoglobin (HbA1c) assessed at baseline and 24 weeks. HbA1c is a clinical indicator of glucose regulation correlated with debilitating and costly diabetic complications. The clinical goal for self-management of diabetes is an HbA1c of 7.0% or less, although further reductions are preferred. Interventions that reduce HbA1c in elevated risk populations are of significant value in diabetes care.

### Health Coaching Intervention

The health coach intervention was carried out by a graduate student trained in behavior change techniques. After obtaining informed consent and collecting demographic information, baseline lab reports, and psychometric measures, the participants and the health coach communicated about eating, physical activity patterns, and overall health goals. Wellness plans were collaboratively created in multiple interactions focused on exercise instruction and reviews of electronic monitoring entries, with diet and medication guidelines set by primary care physicians and dieticians.

### Recruitment

Participants were recruited at the Black Creek Community Health Centre in Toronto, Ontario, Canada. Recruitment was through health care provider referral and poster advertising. Eligible participants were patients over 18 years old, diagnosed with type 2 diabetes, and able to read and speak English. Participants were excluded if their baseline HbA1c was greater than 9.5%. All study procedures were approved by the York

University Human Participants Research Committee and participants signed an informed consent.

## NexJ Health Coach App Access

All clients were given access to the custom smartphone app, Health Coach, on a loaned Blackberry Curve 8900 with full data access for the duration of the trial (n=19), unless they possessed a smartphone (n=2).

## App Feedback and Development

Research staff collected participant experience with version 1.0 of the Health Coach app, reporting errors and overall feedback. Feedback was organized and relayed back to the software design team as described in Figure 1.

As the Health Coach app was version 1.0, periodic malfunctions hindered client communications during the trial. Due to the close relationship between the health coach and software production team, the feedback and user experience was communicated as received, resulting in upgrades installed on the server at frequent intervals. This feedback loop led to significant improvements in the software throughout the trial. Some of the most important modifications included user-interface enhancements, general usability, and solution of software instability issues. Screenshots of the mobile phone app with an explanation of the various trackers and functions are found in Figures 2-11.

**Figure 1.** Software improvement cycle. Feedback loop conveys user experience and smartphone software redesign.

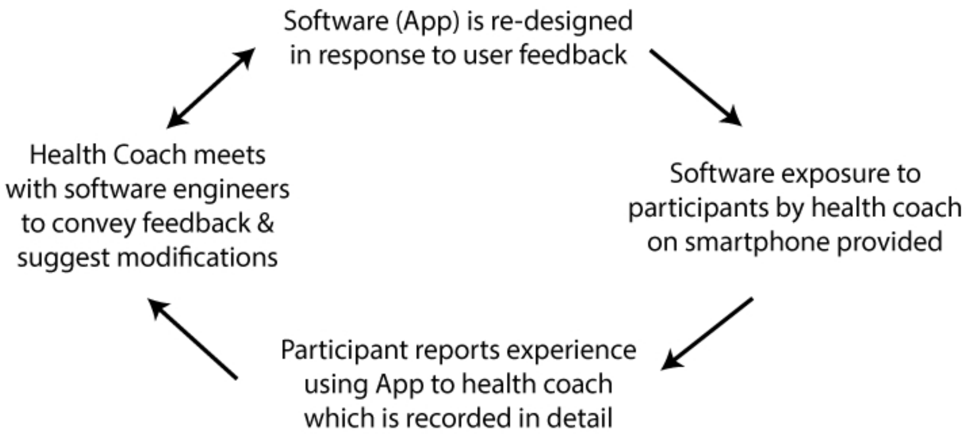



**Figure 2.** Exercise Tracker is designed to easily track multiple exercise modalities. Users can log duration of exercise, rate perceived intensity (light, moderate, vigorous), and enter additional text comments.

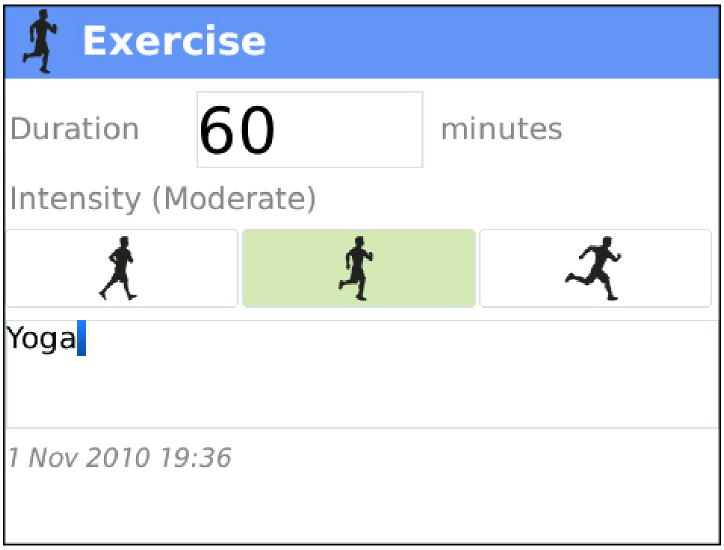


**Figure 3.** Food Tracker automatically triggers the smartphone's camera, enabling photo capture of meals. Users can subjectively rate food portion (small, moderate, large), source (home-made, packaged, restaurant served), and healthiness (not so healthy, moderately healthy, very healthy).


**Figure 4.** Satisfaction survey: at a customizable timeframe (usually 20 minutes), the program prompts for reports on satiety level (not enough, just right, too full).

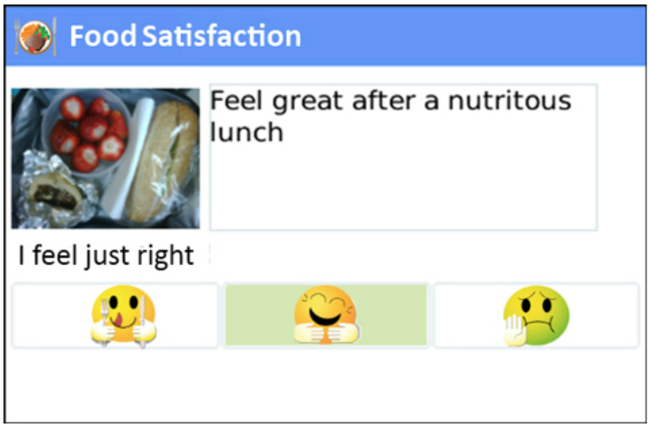



**Figure 5.** Blood Glucose Tracker: Clients enter blood glucose level and comments on readings.

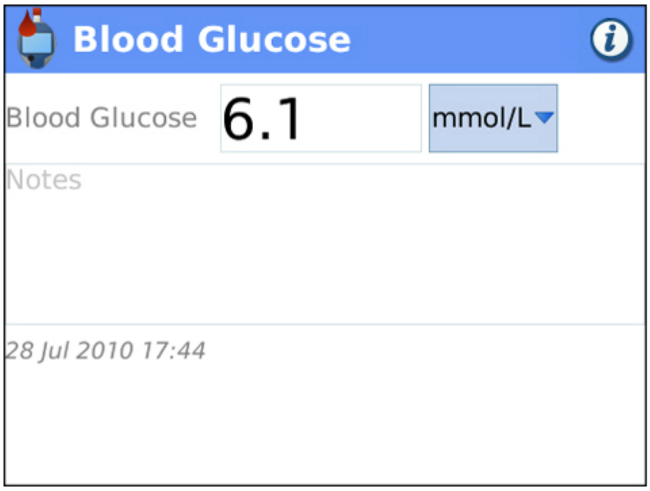


**Figure 6.** Mood Tracker: Clients enter “How They Feel” using a simple 5-pt scale: I feel (great, very good, good, bad, very bad) and comment on entry, which is time-stamped.

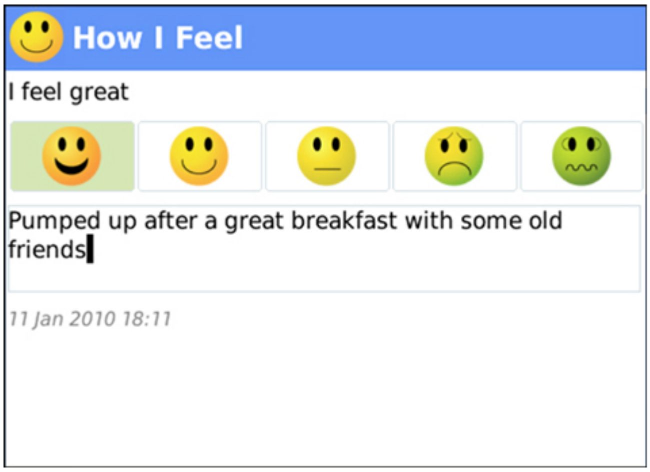



**Figure 7.** Weight Tracker: Clients enter weight and enter comments on the reading.


**Figure 8.** Pain Tracker: Clients can enter subjective pain ratings using a 5-pt scale: pain level is (none, mild, moderate, severe, very severe).

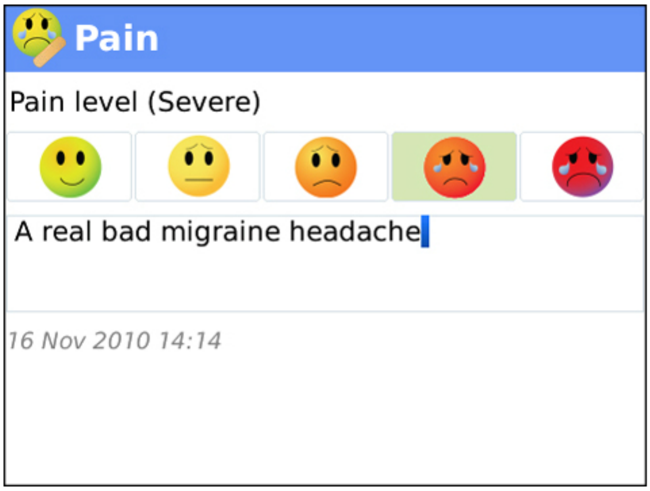


**Figure 9.** Blood Pressure Tracker: Clients enter blood pressure including systolic, diastolic, and heart rate and are able to comment on the reading.

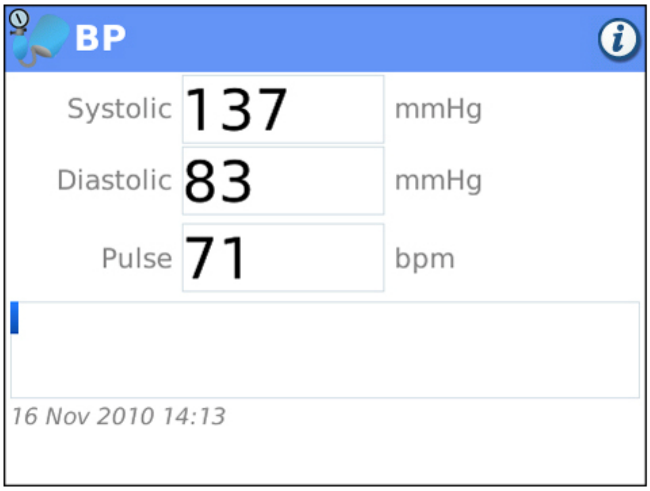



**Figure 10.** Messaging allows for two-way secure messaging between participant and health coach who can selectively promote healthy choices at pivotal times of client decision-making, providing support immediately after healthy behaviors have been logged, and/or addressing questions and/or sending relevant materials.

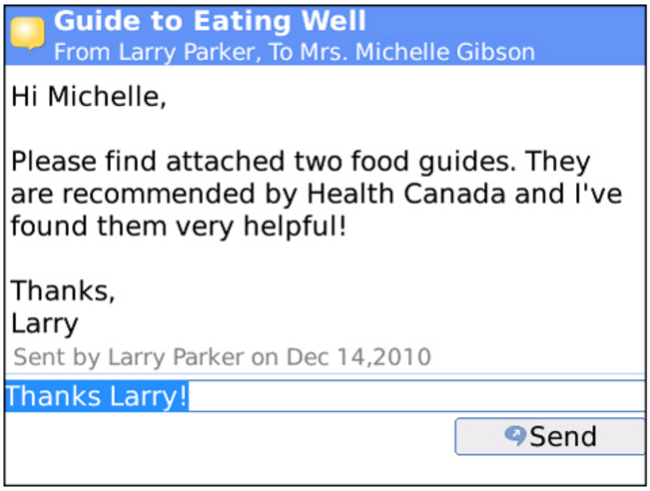



**Figure 11.** Reminders: The trackers use employ alarm-type entry reminders, which provide convenient ways to prompt clients to engage in health behaviors like exercise, dietary modifications, stress reduction, and self-reported mood. Reminders can be turned on and off easily by health coach and/or participant.


## Statistical Analysis

Data was analyzed using SPSS (version 21.0, 2012, IBM, Chicago, IL). Descriptive statistics are reported (means and standard deviations). Differences in outcome variables (baseline to 24 weeks) were analyzed using a paired samples *t* test. Participants were split into groupings according to baseline assessments (HbA1c≥7.0% and HbA1c<7.0%). Significance was set to $P<.05$.

## Results

Of the 21 participants, final outcome variables were collected for 19. The primary reason for missing data was primary care physician failure to forward lab results (n=2).

Demographics are summarized in Table 1. There was a mean reduction of 0.28% (SD 0.57) (*P*=.05) found over the entire sample. Since participant glucose control varied across optimal levels at baseline, data was re-analyzed for those who began the trial with sub-optimally managed glucose and those with optimally managed glucose. A total of 12 participants started the trial with sub-optimally managed glycemic control (HbA1c≥7.0% [Diabetes Control and Complications Trial/DCCT method] or 53 mmol/mol [International Federation of Clinical Chemistry/IFCC method]) and experienced a greater mean reduction of 0.43% (SD 0.63) (*P*=.04) (see Table 2).

**Table 1.** Demographic characteristics at baseline (n=21).

| Characteristic | | n (%) |
|---|---|---|
| Age (years), mean (SD) | | 55.6 (12.3) |
| **Sex** | | |
| | Male | 9 (43%) |
| | Female | 12 (57%) |
| **Marital status** | | |
| | Single | 5 (24%) |
| | Married or common law | 14 (67%) |
| | Widowed | 2 (10%) |
| **Children** | | |
| | Yes | 18 (86%) |
| | No | 3 (14%) |
| **Educational background** | | |
| | Less than high school | 3 (14%) |
| | Completed high school | 4 (19%) |
| | Some college/university | 7 (33%) |
| | College diploma | 6 (29%) |
| | University degree | 1 (5%) |
| **Employment** | | |
| | Full-time | 12 (57%) |
| | Part-time | 2 (10%) |
| | Not presently employed | 7 (33%) |
| **Ethno-cultural group** | | |
| | Hispanic | 3 (14%) |
| | African | 3 (14%) |
| | Caribbean | 3 (14%) |
| | South Asian | 3 (14%) |
| | Caucasian | 9 (43%) |

**Table 2.** Change in outcomes of patients participating in the Health Coach intervention.

| Outcome | | n | Baseline, mean (SD) | Post, mean (SD) | Mean change, mean (SD) | *P* value |
|---|---|---|---|---|---|---|
| **Entire sample** | | | | | | |
| | HbA1c[a] (%) | 19 | 7.58 (1.13) | 7.31 (0.95) | −0.28 (0.57) | .05 |
| | Weight (kg) | 14 | 94.6 (16.8) | 93.2 (15.8) | −1.3 (1.9) | .02 |
| | BMI[b] | 13 | 34.4 (5.5) | 33.9 (5.3) | −0.4 (0.7) | .05 |
| | Waist circumference (cm) | 11 | 109.4 (16.1) | 112.1 (16.1) | 2.7 (4.3) | .06 |
| **Baseline A1c≥7.0%** | | | | | | |
| | HbA1c (%) | 12 | 8.26 (0.80) | 7.83 (0.78) | −0.43 (0.63) | .04 |
| | Weight (kg) | 9 | 100.1 (18.0) | 98.1 (17.1) | −1.9 (1.7) | .01 |
| | BMI | 8 | 36.2 (5.8) | 35.6 (5.7) | −0.7 (0.7) | .37 |
| | Waist circumference (cm) | 7 | 114.4 (17.1) | 116.5 (16.4) | 2.1 (5.3) | .33 |
| **Baseline A1c<7.0%** | | | | | | |
| | HbA1c (%) | 7 | 6.43 (0.39) | 6.41 (0.38) | −0.01 (0.32) | .91 |
| | Weight (kg) | 5 | 84.6 (8.7) | 84.4 (8.8) | −0.2 (1.8) | .81 |
| | BMI | 5 | 31.4 (3.7) | 31.3 (3.8) | −0.1 (0.7) | .80 |
| | Waist circumference (cm) | 4 | 100.6 (11.0) | 104.4 (10.0) | 3.8 (1.6) | .02 |

[a]HbA1c: hemoglobin A1c (glycosylated hemoglobin)
[b]BMI: body mass index

## Discussion

### Principal Results

In this trial, patients with a range of glucose regulation efficacy were recruited to pilot a smartphone-based mobile software app and personal health coach program. Given the objective of demonstrating intervention efficacy in poorly managed diabetic clients, our analysis focused on subjects with a baseline HbA1c>7.0% (53 mmol/mol). These participants, who started at a poorly managed level, showed a mean reduction of 0.43% (SD 0.63) (*P*=.04), demonstrating the potential clinical relevance of the intervention.

### Socioeconomic Strata and Intervention Applicability

Lower SES populations often have difficulty navigating and accessing the health care system [23] to a degree where SES appears to be the best predictor of health status in Canada and the United States [24,25], with SES-related factors manifesting as substantial barriers to the health of many Canadians. This intervention attempted to address some of these issues by engaging participants in a health coaching relationship to overcome accessibility barriers. During the course of the intervention, it was observed that participants were sometimes prevented from attending appointments with their health care team due to familial obligations and work obligations (mainly shift work). With low workplace flexibility, when work had to be interrupted to attend a health care session, losing out on the day's pay was a significant obstacle. The intervention reduced this barrier by providing 24-hour electronic access to the health coach, enabling participants to initiate communication when possible and convenient.

Of our study sample, 34% completed either a college or university degree, compared to the 59% of Ontario's population (and 53% of Canada's population) who have a university or college level designation [26]. Education is a commonly used proxy of socioeconomic strata, but educated immigrants to Canada are frequently unable to work in their former disciplines at their achieved educational levels due to domestic policies [27]. The intervention demonstrated the effectiveness of a personalized, electronically assisted health coaching intervention in an underserved population that is not typically the focus of technology-assisted health research. Most participants (n=19) did not own a smartphone and were loaned a device for the trial duration. Nonetheless, as the costs of mobile technology decrease, mobile technology interventions will be increasingly feasible and useful at all SES levels.

### From Single-Arm Pilot to Randomized Controlled Trial

The pilot study was intended to generate results guiding the eventual design of a randomized controlled trial (RCT). Several points of guidance were readily apparent. First, the lower SES participants, according to our pilot experience, would not likely sustain participation if they perceived that randomization to the control group resulted in an inferior intervention. This was due to generic participation obstacles, especially taking time out of inflexible work schedules to attend assessment sessions. This observation combined with our interest in seeing what additional benefits were attributable to health coaching with the smartphone software vs health coaching alone. Accordingly, the health coaching intervention was designed to be fundamentally equivalent across comparison arms except for use of the smartphone plus software in the experimental group.

Second, our experience with primary care providers involved their inconsistent provision of HbA1c tests. Accordingly, we have ensured a point-of-care HbA1c Analyzer is available (via finger-prick A1c blood samples) throughout the current RCT.

### Limitations

This pilot study enrolled a small convenience sample with no control group, limiting the generalizability of intervention results. Throughout the pilot trial, temporary software malfunctions and upgrades inevitably resulted in service disruptions. Although participants could directly log healthy behaviors via smartphone, their self-report could be falsified or exaggerated. Future studies can employ Bluetooth connected technology (ie, glucometers, accelerometers) to omit some self-report biases. To more rigorously assess intervention efficacy, the RCT now in the field is being undertaken with stabilized, consistently functional software. The goal is to assess whether health coaching without vs with the use of the smartphone software is equivalent (or non-inferior). In order to address this question, subjects were randomly allocated to experimental and control groups and the same coaches delivered health coaching in both arms. This approach aims to better understand which intervention features are most important to effective intervention. We understand that there are limitations to this assessment approach but it represents an important step in investigating these interventions.

### Comparison With Prior Work

The most comparable intervention is the WellDoc diabetes trial [28-30] in which 26 primary health practices were randomized to provide one of four possible health coach intervention options to their patients. Across participating practices, 163 patients were intervened with intensities ranging from usual care to use of smartphone-assisted health coaching. Investigators found significant decreases in HbA1c in the highest intensity group. In that trial, participants on Medicaid and Medicare and those without health insurance were excluded. Our trial specifically targets individuals from a lower-resource sector of a large Canadian city, most of whom would have been excluded from the WellDoc trial. Since the association between type 2 diabetes and poverty has been well demonstrated [6,7,8], our interests focus on interventions that serve people of all SES and have demonstrated efficacy with subjects from lower SES.

### Conclusions

As mobile technology becomes more accessible, electronically assisted health coaching may emerge as a viable and effective means of managing chronic conditions through improved health behaviors across all SES. To help understand what parts of the intervention were responsible for changes in behavior (health coaching, remote monitoring), the RCT currently being conducted will assess the effectiveness of health coaching in type 2 diabetic patients both with and without the use of smartphone technology at multiple sites with diverse populations.

### Acknowledgments

NW and PR designed and carried out study. NexJ Systems Inc. provided the software. Rogers Communication provided data plans and Blackberry (formerly Research in Motion) provided smartphones. Research funding was provided by Mitacs and Ministry for Research and Innovation (Province of Ontario).

### Conflicts of Interest

None declared.

### References

1. Canadian Diabetes Association Clinical Practice Guidelines Expert Committee. Can J Diabetes. Winnipeg: Transcontinental Printing; 2013. Canadian Diabetes Association Clinical Practice Guidelines 2013 URL: http://guidelines.diabetes.ca/App_Themes/CDACPG/resources/cpg_2013_full_en.pdf [accessed 2014-05-21] [WebCite Cache ID 6PjnNnNaa]
2. Burr JF, Rowan CP, Jamnik VK, Riddell MC. The role of physical activity in type 2 diabetes prevention: physiological and practical perspectives. Phys Sportsmed 2010 Apr;38(1):72-82. [doi: 10.3810/psm.2010.04.1764] [Medline: 20424404]
3. Reid RD, Tulloch HE, Sigal RJ, Kenny GP, Fortier M, McDonnell L, et al. Effects of aerobic exercise, resistance exercise or both, on patient-reported health status and well-being in type 2 diabetes mellitus: a randomised trial. Diabetologia 2010 Apr;53(4):632-640. [doi: 10.1007/s00125-009-1631-1] [Medline: 20012857]
4. Church TS, Blair SN, Cocreham S, Johannsen N, Johnson W, Kramer K, et al. Effects of aerobic and resistance training on hemoglobin A1c levels in patients with type 2 diabetes: a randomized controlled trial. JAMA 2010 Nov 24;304(20):2253-2262 [FREE Full text] [doi: 10.1001/jama.2010.1710] [Medline: 21098771]
5. Abete I, Astrup A, Martínez JA, Thorsdottir I, Zulet MA. Obesity and the metabolic syndrome: role of different dietary macronutrient distribution patterns and specific nutritional components on weight loss and maintenance. Nutr Rev 2010 Apr;68(4):214-231. [doi: 10.1111/j.1753-4887.2010.00280.x] [Medline: 20416018]
6. Beryl Pilkington F, Daiski I, Bryant T, Dinca-panaitescu M, Dinca-panaitescu S, Raphael D. The experience of living with diabetes for low-income Canadians. Canadian Journal of Diabetes 2010 Jan;34(2):119-126. [doi: 10.1016/S1499-2671(10)42008-0]

7. Dinca-Panaitescu S, Dinca-Panaitescu M, Bryant T, Daiski I, Pilkington B, Raphael D. Diabetes prevalence and income: Results of the Canadian Community Health Survey. Health Policy 2011 Feb;99(2):116-123. [doi: 10.1016/j.healthpol.2010.07.018] [Medline: 20724018]
8. Saydah SH, Imperatore G, Beckles GL. Socioeconomic status and mortality: contribution of health care access and psychological distress among U.S. adults with diagnosed diabetes. Diabetes Care 2013 Jan;36(1):49-55 [FREE Full text] [doi: 10.2337/dc11-1864] [Medline: 22933434]
9. Miller WR, Rollnick S. Motivational interviewing: preparing people to change addictive behavior. New York: Guilford Press; 1991.
10. Sheldon B. Cognitive-behavioural therapy: Research and practice in health and social care. New York: Routledge; 2011.
11. Kreitzer MJ, Sierpina VS, Lawson K. Health coaching: innovative education and clinical programs emerging. Explore (NY) 2008;4(2):154-155. [doi: 10.1016/j.explore.2007.12.007] [Medline: 18316060]
12. Wolever RQ, Dreusicke M, Fikkan J, Hawkins TV, Yeung S, Wakefield J, et al. Integrative health coaching for patients with type 2 diabetes: a randomized clinical trial. Diabetes Educ 2010;36(4):629-639. [doi: 10.1177/0145721710371523] [Medline: 20534872]
13. Melko CN, Terry PE, Camp K, Min X, Healey ML. Diabetes health coaching improves medication adherence: A pilot study. American Journal of Lifestyle Medicine 2009 Oct 22;4(2):187-194. [doi: 10.1177/1559827609351131]
14. Cuspidi C, Meani S, Fusi V, Salerno M, Valerio C, Severgnini B, et al. Home blood pressure measurement and its relationship with blood pressure control in a large selected hypertensive population. J Hum Hypertens 2004 Oct;18(10):725-731. [doi: 10.1038/sj.jhh.1001737] [Medline: 15103315]
15. Logan AG, McIsaac WJ, Tisler A, Irvine MJ, Saunders A, Dunai A, et al. Mobile phone-based remote patient monitoring system for management of hypertension in diabetic patients. Am J Hypertens 2007 Sep;20(9):942-948. [doi: 10.1016/j.amjhyper.2007.03.020] [Medline: 17765133]
16. Halifax NV, Cafazzo JA, Irvine MJ, Hamill M, Rizo CA, McIssac WJ, et al. Telemanagement of hypertension: a qualitative assessment of patient and physician preferences. Can J Cardiol 2007 May 15;23(7):591-594 [FREE Full text] [Medline: 17534469]
17. Nguyen HQ, Wolpin S, Chiang KC, Cuenco D, Carrieri-Kohlman V. Exercise and symptom monitoring with a mobile device. AMIA Annu Symp Proc 2006:1047 [FREE Full text] [Medline: 17238666]
18. Wang DH, Kogashiwa M, Ohta S, Kira S. Validity and reliability of a dietary assessment method: the application of a digital camera with a mobile phone card attachment. J Nutr Sci Vitaminol (Tokyo) 2002 Dec;48(6):498-504. [Medline: 12775117]
19. Arsand E, Tufano JT, Ralston JD, Hjortdahl P. Designing mobile dietary management support technologies for people with diabetes. J Telemed Telecare 2008;14(7):329-332. [doi: 10.1258/jtt.2008.007001] [Medline: 18852310]
20. Lester RT, Mills EJ, Kariri A, Ritvo P, Chung M, Jack W, et al. The HAART cell phone adherence trial (WelTel Kenya1): a randomized controlled trial protocol. Trials 2009;10:87 [FREE Full text] [doi: 10.1186/1745-6215-10-87] [Medline: 19772596]
21. Abebe NA, Capozza KL, Des Jardins TR, Kulick DA, Rein AL, Schachter AA, et al. Considerations for community-based mHealth initiatives: insights from three Beacon Communities. J Med Internet Res 2013;15(10):e221 [FREE Full text] [doi: 10.2196/jmir.2803] [Medline: 24128406]
22. Free C, Phillips G, Galli L, Watson L, Felix L, Edwards P, et al. The effectiveness of mobile-health technology-based health behaviour change or disease management interventions for health care consumers: a systematic review. PLoS Med 2013;10(1):e1001362 [FREE Full text] [doi: 10.1371/journal.pmed.1001362] [Medline: 23349621]
23. Olah ME, Gaisano G, Hwang SW. The effect of socioeconomic status on access to primary care: an audit study. CMAJ 2013 Apr 2;185(6):E263-E269 [FREE Full text] [doi: 10.1503/cmaj.121383] [Medline: 23439620]
24. Chen E, Miller GE. Socioeconomic status and health: mediating and moderating factors. Annu Rev Clin Psychol 2013;9:723-749. [doi: 10.1146/annurev-clinpsy-050212-185634] [Medline: 23245339]
25. Prus SG. Comparing social determinants of self-rated health across the United States and Canada. Soc Sci Med 2011 Jul;73(1):50-59. [doi: 10.1016/j.socscimed.2011.04.010] [Medline: 21664020]
26. Statistics Canada. 2013. Education Indicators in Canada: Report of the Pan-Canadian Education Indicators Program URL: http://www.statcan.gc.ca/pub/12-581-x/2012000/edu-eng.htm [accessed 2013-12-12] [WebCite Cache ID 6LoYLDqtu]
27. Creese G, Wiebe B. 'Survival Employment': Gender and deskilling among African immigrants in Canada. International Migration 2012;50(5):56-76. [doi: 10.1111/j.1468-2435.2009.00531.x]
28. Quinn CC, Clough SS, Minor JM, Lender D, Okafor MC, Gruber-Baldini A. WellDoc mobile diabetes management randomized controlled trial: change in clinical and behavioral outcomes and patient and physician satisfaction. Diabetes Technol Ther 2008 Jun;10(3):160-168. [doi: 10.1089/dia.2008.0283] [Medline: 18473689]
29. Quinn CC, Shardell MD, Terrin ML, Barr EA, Ballew SH, Gruber-Baldini AL. Cluster-randomized trial of a mobile phone personalized behavioral intervention for blood glucose control. Diabetes Care 2011 Sep;34(9):1934-1942 [FREE Full text] [doi: 10.2337/dc11-0366] [Medline: 21788632]

30. Quinn CC, Gruber-Baldini AL, Shardell M, Weed K, Clough SS, Peeples M, et al. Mobile diabetes intervention study: testing a personalized treatment/behavioral communication intervention for blood glucose control. Contemp Clin Trials 2009 Jul;30(4):334-346. [doi: 10.1016/j.cct.2009.02.004] [Medline: 19250979]
31. Levine JA. Poverty and obesity in the U.S. Diabetes 2011 Nov;60(11):2667-2668 [FREE Full text] [doi: 10.2337/db11-1118] [Medline: 22025771]

## Abbreviations

**BMI:** body mass index
**HbA1c:** hemoglobin A1c (glycosylated hemoglobin)
**RCT:** randomized controlled trial
**SES:** socioeconomic strata
**T2DM:** type 2 diabetes mellitus

*Edited by G Eysenbach; submitted 12.12.13; peer-reviewed by H Potts, M Dogan; comments to author 11.02.14; revised version received 25.03.14; accepted 28.04.14; published 06.06.14.*

*Please cite as:*
*Wayne N, Ritvo P*
*Smartphone-Enabled Health Coach Intervention for People With Diabetes From a Modest Socioeconomic Strata Community: Single-Arm Longitudinal Feasibility Study*
*J Med Internet Res 2014;16(6):e149*
*URL: http://www.jmir.org/2014/6/e149/*
*doi:10.2196/jmir.3180*
*PMID:24907918*

Original Paper

# Detecting Disease Outbreaks in Mass Gatherings Using Internet Data

Elad Yom-Tov[1], BSc, MA, PhD; Diana Borsa[2], BSc, BMath, MSc (Hons); Ingemar J Cox[3,4], BSc, DPhil; Rachel A McKendry[5], BSc, PhD

[1]Microsoft Research Israel, Herzelia, Israel

[2]Centre of Computational Statistics and Machine Learning (CSML), Department of Computer Science, University College London, University of London, London, United Kingdom

[3]Copenhagen University, Department of Computer Science, Copenhagen, Denmark

[4]University College London, University of London, Department of Computer Science, London, United Kingdom

[5]University College London, University of London, London Centre for Nanotechnology and Division of Medicine, London, United Kingdom

**Corresponding Author:**
Diana Borsa, BSc, BMath, MSc (Hons)
Centre of Computational Statistics and Machine Learning (CSML)
Department of Computer Science
University College London, University of London
Malet Place
Gower St
London, WC1E 6BT
United Kingdom
Phone: 44 20 7679
Fax: 44 20 7387 1397
Email: d.borsa@cs.ucl.ac.uk

## Abstract

**Background:** Mass gatherings, such as music festivals and religious events, pose a health care challenge because of the risk of transmission of communicable diseases. This is exacerbated by the fact that participants disperse soon after the gathering, potentially spreading disease within their communities. The dispersion of participants also poses a challenge for traditional surveillance methods. The ubiquitous use of the Internet may enable the detection of disease outbreaks through analysis of data generated by users during events and shortly thereafter.

**Objective:** The intent of the study was to develop algorithms that can alert to possible outbreaks of communicable diseases from Internet data, specifically Twitter and search engine queries.

**Methods:** We extracted all Twitter postings and queries made to the Bing search engine by users who repeatedly mentioned one of nine major music festivals held in the United Kingdom and one religious event (the Hajj in Mecca) during 2012, for a period of 30 days and after each festival. We analyzed these data using three methods, two of which compared words associated with disease symptoms before and after the time of the festival, and one that compared the frequency of these words with those of other users in the United Kingdom in the days following the festivals.

**Results:** The data comprised, on average, 7.5 million tweets made by 12,163 users, and 32,143 queries made by 1756 users from each festival. Our methods indicated the statistically significant appearance of a disease symptom in two of the nine festivals. For example, cough was detected at higher than expected levels following the Wakestock festival. Statistically significant agreement (chi-square test, $P<.01$) between methods and across data sources was found where a statistically significant symptom was detected. Anecdotal evidence suggests that symptoms detected are indeed indicative of a disease that some users attributed to being at the festival.

**Conclusions:** Our work shows the feasibility of creating a public health surveillance system for mass gatherings based on Internet data. The use of multiple data sources and analysis methods was found to be advantageous for rejecting false positives. Further studies are required in order to validate our findings with data from public health authorities.

***(J Med Internet Res 2014;16(6):e154)*** doi:10.2196/jmir.3156

**KEYWORDS**
mass gatherings; infodemiology; infectious disease; information retrieval; data mining

## Introduction

### Background

Historically, infectious diseases have devastated societies. Examples include the "Black Death" bubonic plague of the 14th century in which between 30-40% of Europe's population is estimated to have died [1], and the influenza epidemic of 1918-1920, in which as many as 50 million are estimated to have died [2]. Despite very significant advances in medicine, infectious diseases remain potentially very serious threats to society. For example, a pandemic influenza is rated as the greatest national risk on the UK government risk register [3]. An estimated 35.3 million people are HIV-infected [4], drug-resistant Methicillin-resistant *Staphylococcus aureus* (MRSA) is a major public health concern [5], about 2 million cases of cancer are caused by infections each year [6], and infection is a major source of morbidity in primary care [7]. Moreover, emerging new infections, such as H1N1 influenza, can cause pandemics, spreading rapidly and unpredictably. Early diagnostics play a crucial role in prevention, treatment, and care but most tests require samples to be sent to specialist laboratories leading to inherent delays between tests, results, and clinical interventions. Public health intervention may be further delayed by the time lag of 1-2 weeks associated with retrospective surveillance. There are increasing national and international drivers to dramatically improve our capacity to rapidly respond to infectious diseases by widening access to tests in community settings and drive innovative real-time surveillance

Protection against infectious diseases includes the development of new medicines, vaccination programs, improved hygiene, and promotion of behavioral modifications. While together these efforts may reduce the risk of infectious diseases, the risk cannot be eliminated. Consequently, infectious disease surveillance networks at national and international levels have been established. The purpose of public health surveillance networks is to provide "Ongoing systematic collection, analysis, interpretation and dissemination of data regarding a health-related event for use in public health action to reduce morbidity and mortality and to improve health" [8].

The most reliable sources of data for public health surveillance networks are confirmed diagnoses of diseases. Unfortunately, confirming a diagnosis may take days or weeks, due to a variety of delays including (1) time to ship a patient sample to a testing laboratory, (2) time to perform the test, and (3) time to report the results.

Delays in identifying the onset of an infectious epidemic result in delayed responses, which can significantly exacerbate the impact of the epidemic on a society. Consequently, there is strong interest in reducing delays. One way to accomplish this is through syndromic surveillance, which emphasizes "the use of near 'real-time' data and automated tools to detect and characterize unusual activity for further public health investigation" [9]. There is a range of pre-diagnostic data that can and has been used, including clinical data such as nurse advice line activity, school nurse visits, poison control center data, EMS records, emergency department visits, outpatient records, laboratory/radiology orders and results, prescription medication sales, and electronic health records, and non-clinical data such as over-the-counter (OTC) medications, work and school absenteeism records, ambulance dispatch data, zoonotic surveillance data (eg, dead birds from West Nile virus activity), health-related Web searches, and other data from online social networks.

The use of syndromic surveillance systems dates back to at least 1977, when Welliver et al [10] reported the use of OTC medication sales in Los Angeles. The early 2000s saw renewed interest in syndromic surveillance as a result of a US Defense Advanced Research Projects Agency (DARPA) initiative called ENCOMPASS (ENhanced COnsequence Management Planning And Support System) to provide an early warning system to protect against bioterrorism. As early as 2001, it was suggested to use query logs associated with health care websites as one form of syndromic data [11]. The advantage of online data sources is that the data collection is usually straightforward and very timely, that is, the lag between data creation, collection, and analysis can be very short (possibly seconds). We are therefore interested in online syndromic surveillance, which is discussed in more detail in the next section.

The World Health Organization (WHO) states that "an organized or unplanned event can be classified as a mass gathering if the number of people attending is sufficient to strain the planning and response resources of the community, state, or nation hosting the event" [12]. Examples of mass gatherings include very large religious gatherings such as the Hajj (approximately 2 million people) and the Hindu Kumbh Mela (estimated at 80-100 million people), large international sporting events such as the Olympics, and national music festivals such as Glastonbury in the United Kingdom. Mass gatherings have been sources for the spread of infectious diseases. The spread of cholera from a well in Mecca was documented as far back as 1883 [13]. More recently, during the 1992 Glastonbury music festival attended by 70,000 people in the United Kingdom, 72 cases of Campylobacter infection were reported due to drinking unpasteurized milk [14]. In 2009, [15] reported an outbreak of H1N1 influenza at the Rock Werchter festival in Belgium. Also in 2009, [16] reported outbreaks of H1N1 influenza at a sports event and at a music festival, called EXIT, where 62 confirmed cases were identified. In the same year, a further case was reported at a music festival in Hungary [17]. The issue of mass gatherings, medicine, and global health security was the subject of a series of reports in *The Lancet* in 2012.

In the next section, we provide a discussion of prior work on syndromic surveillance based on online social networks and search engine query logs.

### Related Work

In 2001, Wagner et al [11] first suggested the utility of query terms to detect infectious diseases. In particular, they presented data on the number of queries to a health website (WebMD) using words such as “cold” and “flu”. Though no quantitative assessment was provided, qualitatively a correlation is visible between the query frequency and measures of infectious disease. A related quantitative analysis was documented in subsequent work [18], which took “the weekly counts of the number of accesses of selected influenza-related articles on the Healthlink website and measured their correlation with traditional influenza surveillance data from the Centers for Disease Control and Prevention (CDC)”. The results showed a clear correlation; however, interestingly, the Web log data was no more timely than that of the CDC, that is, the Web log data did not allow an influenza outbreak to be detected any sooner than with traditional surveillance methods.

Later, Eysenbach [19] used information from Google’s AdSense to indirectly estimate the number of queries for particular search terms that contained keywords related to influenza. Specifically, Eysenbach reported correlations between the “number of clicks on a keyword-triggered influenza link” and traditional measures such as (1) the number of lab tests, and (2) the number of positive lab test results (cases). Pearson correlation scores of between .85 and .91 are reported. Interestingly, the higher correlation score was obtained when correlating with the number of cases reported for the next week, indicating the Web-based information was more timely.

A number of systems have been developed to gather and analyze unstructured information that is openly available on the Web. The earliest example of this is Global Public Health Intelligence Network (GPHIN) developed by the Canadian government and the WHO [20]. A number of systems have subsequently been deployed, including BioCaster [21,22], EpiSPIDER [23], and HealthMap [24,25]. Comparisons of these various systems can be found in [26,27].

Interest in Web-based surveillance increased significantly with the publication by Polgreen et al [28] and Ginsberg et al [29] of relationships between query search terms and influenza-like illness (ILI) based on Yahoo and Google search logs, respectively. Polgreen et al showed that it was possible to estimate the percentage of positive cultures for influenza and the deaths attributable to pneumonia and influenza in the United States, and to do so several weeks ahead of actual culture results. Ginsberg et al reported similar findings. A further contribution of [29] was to automatically determine the best set of query search terms that correlate with CDC estimates. The work by Ginsberg et al has subsequently been developed as Google Flu Trends and its more generic service, Google Trends [30].

A large body of research has since been developed that utilizes data from online social network or query logs to infer health information. This includes work on mining blog posts that mention influenza. For example, Corley et al [31,32] describe collecting blogs from a variety of sources and looking for the frequency of occurrence of keywords such as “influenza”. After normalization, they reported Pearson correlation scores of .77 and .55 for two datasets with corresponding ILI reports from the CDC (CDC ILINet reports). This work also discusses the possibility of identifying relevant online communities and developing associated targeted intervention strategies.

The analysis of microblogging data from Twitter for health purposes has recently received attention [33-40]. Inspired by the approach in Ginsberg et al [29], Cullota et al [35] applies a similar approach to Twitter data revealing the benefits of having longer, more complete messages as opposed to unstructured search query entries. This allows for simpler classification algorithms that can also filter out many of the erroneous messages that typically occur and would sometimes overwhelm the classifier predictions [38]. Lampos and Cristianini [33,34] performed an analysis of tracking influenza rates throughout the United Kingdom. Their major contribution to the existing regression-based models was proposing a new automatic way of selecting the keywords used by the classifier. These were learned from a large pool of candidates extracted from Web articles related to influenza, imposing a scarcity constraint via an L1 norm penalty in the least squares prediction error. This method yielded a correlation of 97% with respect to the reported influenza rates. Unfortunately, the proposed way of automatically building the vocabulary is based solely on correlation and sometimes produces terms that, although highly correlated with the flu trends, may not make good candidates to track for future predictions: for instance, automatically selected keywords “phone”, “nation”, or “mention” might not be good indicators of the presence of ILI conditions.

## Methods

### Data

We examined 10 events, nine of which were in the United Kingdom and one (the annual Hajj in Mecca) that had significant participation from people in the United Kingdom. All events took place in the second half of 2012.

We extracted two datasets for each event, one from the entire set of Twitter users and the other from that of the Microsoft Bing search engine. The population of Twitter users relevant to an event was defined as any user who mentioned a hashtag associated with an event at least twice between 30 days before and 30 days after the event. We refer to the relevant users as the target population. We also identified a population of users who could be used as a reference population (see Analysis Algorithms below) for each event by randomly sampling 1% of users who did not mention the event in their Twitter messages, but had the United Kingdom listed as their location in their profile. It comprised 345,849 users over the entire study period. For each Twitter message, we extracted an anonymized user identifier, the date and time of the message, and its text.

We followed a similar methodology for detecting relevant users according to queries made on the Bing search engine by users who agreed to share their queries, and marked as relevant any user who mentioned an event at least twice in their queries. For each query made by the relevant users, we extracted the query text, time and date, and an anonymized user identifier. In order to maintain user privacy, data were first anonymized by hashing, before the investigators had access to them. They were then aggregated prior to analysis and no individual-level user datum was examined by the experimenters.

On average, we identified approximately 14,000 Twitter users and 5650 Bing users. The list of events and basic statistics concerning the events are shown in Table 1, including the number of Twitter users who mentioned the event more than twice, the number of tweets that mentioned each event, the number of users who queried for each event, and the number of queries.

We extracted all queries and Twitter messages for the relevant users from 30 days before an event until 30 days after it. The queries and messages were stemmed using a Porter stemmer [41]. We then marked each query and Twitter message as to whether it contained one or more words or phrases describing medical symptoms given in a list of 195 medical symptoms and 457 corresponding synonyms described in Yom-Tov and Gabrilovich [42]. This list of terms was derived from a set of terms in *International Statistical Classification of Diseases and Related Health Problems, 10th Revision (ICD-10)*, expanded to include ways in which non-specialist people frequently refer to the medical terms. The expansion is based on terms that people use in order to reach the Wikipedia page referring to a medical symptom and the terms frequently associated with it in Web documents. A complete explanation of how the list was constructed can be found in Yom-Tov and Gabrilovich [42].

A table listing the number of tweets that contained each of the symptom words or their synonyms in each of the festivals analyzed is provided in Multimedia Appendix 1.

**Table 1.** List of analyzed events and statistics.

| Event | Dates | Capacity[a] | Twitter | | Bing | |
|---|---|---|---|---|---|---|
| | | | Number of users | Number of festival mentions | Number of users | Number of festival queries |
| Wakestock | 6-8 July | 10,000 | 3878 | 12,180 | 1177 | 3750 |
| Wireless Festival | 6-8 July | 50,000 | 23,105 | 191,762 | 2309 | 6909 |
| T in the Park | 6-8 July | 85,000 | 24,746 | 175,881 | 11,899 | 44,416 |
| V Festival | 17-19 August | 90,000 | 22,018 | 92,722 | 14,704 | 50,796 |
| Bestival | 6-9 September | 30,000 | 13,359 | 104,550 | 6715 | 23,330 |
| Creamfields | 24-26 August | 80,000 | 21,703 | 191,663 | 5533 | 19,071 |
| Hajj | 24-27 October | 3,161,573 | 17,473 | 129,137 | 3402 | 13,892 |
| Isle of Wight Festival | 22-24 June | 60,000 | 6276 | 1398 | 4400 | 14,222 |
| Download Festival | 8-10 June | 120,000 | 9360 | 1497 | 4598 | 17,267 |
| RockNess | 8-10 June | 35,000 | 12,935 | 1068 | 1764 | 6266 |
| Median | | 70,000 | 15,416 | 98,636 | 4499 | 15,744 |

[a]Capacity information from Wikifestivals and Wikipedia websites.

## Analysis Algorithms

### *Overview*

We analyzed each dataset using three methods, described below. Briefly, Method 1 tests how well the probability of a word occurring as a function of time fits a lognormal distribution with variance between 1.2 and 1.5, since this is the epidemiological distribution predicted in [43] for spread of infectious disease. Method 2 compares the number of times a symptom was mentioned before and after the date of an event, and uses a statistical test based on the False Discovery Rate (FDR) to determine significance. Method 3 computes the likelihood that symptoms would be measured at an observed frequency in a target population compared to what would be expected by chance. All three methods are described in detail below.

### *Method 1: Comparison to Background With Epidemiological Profile*

Let $P^T_i(w,t)$ be the probability that the *i*-th word will appear in the target population on day *t*, where, in our data $t\in[-30,-29,...,29,30]$. Similarly, we denote $P^R_i(w,t)$ as the same probability in the reference population, that is, in a population that is disjointed from the target population, but is located in a similar geographic area.

We assume that if there is an epidemic of an infectious disease in the population, users mention its symptoms in their text (eg, Twitter messages). In that case, a word $P^T_i(w,t)$ describing a symptom of the disease should follow the appearance profile of such a disease, which takes into account its incubation period. This profile should fit a lognormal distribution with a variance of between 1.2 and 1.5 [43].

Thus, for each of the symptom words, we compute its probability over time and normalize this by the same probability for the reference population, in order to exclude diseases that are unrelated to the event. Therefore, for each symptom word (and its synonyms), we compute a score given by $P^T_i(w,t)/P^R_i(w,t)$, and fit to it a lognormal distribution with a center that varies from the first day of the event and until 14 days later. The day on which the best fit is found (in the least squares sense) is chosen to represent the distribution of this word.

In order to ascertain if the fit of the distribution is statistically significant, we employ the FDR procedure [44] and conduct the same procedure for a random set of 1950 non-symptom words (10 times larger than the symptom list) and display a symptom only if its fit to the lognormal distribution is greater than would be expected at an FDR of 1%.

This method should work well if there is a large enough target population to generate information pertaining to the epidemic and should enable not only the identification of the outbreak but also its temporal profile.

### Method 2: Comparison to Background and Time

Here, we follow Yom-Tov and Gabrilovich [42] and construct a 2×2 contingency table that measures the number of times a symptom was mentioned before and after the date of the event (see Table 2 for an example), for either the target or reference population. Each symptom is then scored according to the chi-square score computed from the table.

A threshold for statistical significance is computed using FDR [44] with a random set of non-symptom words. We report symptoms with a chi-square score higher than that expected at an FDR of 1%.

**Table 2.** The 2x2 contingency table for computing the chi-square score of Method 2.

| Number of times that the user mentioned/queried for the symptom or its synonym | User queried for or tweeted about the festival? | |
|---|---|---|
| | No | Yes |
| Before Day 0 | $N_{11}$ | $N_{12}$ |
| After Day 0 | $N_{21}$ | $N_{22}$ |

### Method 3: What's Strange About Recent Events

Following the approach in [45] (What's Strange About Recent Events [WSARE]), for each day after the mass gathering, $t \in [1, ,30]$, we compute a one-term rule score for each symptom in our vocabulary. The score is computed using a hypothesis test in which the null hypothesis is the independence between history records and current day counts. We apply the Fisher's exact test on a 2×2 contingency table, as shown in Table 3, made out of the current day's symptom count and the number of times the symptom was mentioned in the time prior to the festivals.

The test generates a *P* value, given by $P(x=k)=C(K, k)C(N-K, n-k)/C(N, n)$, with $C(n, k)$ being the binomial coefficient ("n choose k") – $C(n,k)=n!/k!(n-k)!$ and where $k$ is the number of tweets containing the keyword $w_i$ today, $K$ is the number of times the keyword $w_i$ was mentioned in the period before the festival, $n$ is the number of tweets today, and $N$ is the number of tweets in the period before the festival.

Since we are computing a score for each day, we consider as baseline the corresponding weekdays in the 30-day time window (ie, if the current day is Tuesday, we will look back to all Tuesdays in the time before the mass gathering and take that as our history baseline). This is done primarily to eliminate false detection due to periodic weekly trends in Twitter postings.

**Table 3.** The 2×2 contingency table (rule $w_i$=1: tweet contains keyword $w_i$) for Fisher's exact test.

| | $C$ today | $C$ history |
|---|---|---|
| $w_i$=1 | # today tweets containing $w_i$, $(k)$[a] | # history tweets containing $w_i(K)$[b] |
| $w_i$=0 | # today tweets not mentioning $w_i$, $(n-k)$ | # history tweets not mentioning $w_i(N-K)$ |
| | $n$[c] | $N$[d] |

[a] $k$: the number of tweets containing the keyword $w_i$ today.

[b] $K$: the number of times the keyword $w_i$ was mentioned in the period before the festival.

[c] $n$: the number of tweets today.

[d] $N$: the number of tweets in the period before the festival.

## Results

As noted above, the target population was defined as any user who tweeted a hashtag related to the event during the data period. To validate this heuristic, a random sample of 200 twitter users who mentioned the Wakestock festival in their tweets were analyzed. Their tweets were labeled as to whether or not the tweets of a user implied that they were at the event. The area under the receiver operating characteristic (ROC) curve for this label as a function of the number of tweets a user made that had the event hashtag was 0.91 and the true detection rate at the threshold of two tweets was 0.70. Therefore, the majority of people who were detected by our heuristic did, in fact, attend the festival. The remaining users either did not attend the event, and thus added noise to our analysis, or did not mention their attendance in their tweets.

Table 4 shows the list of statistically significant symptoms (at $P<.01$) identified in the Twitter data for each of the 10 events. Several observations are in order. First, though most identified symptoms are mild (eg, tired), in some events, the symptoms could be a cause for concern. For example, in the Bestival event, the symptom was "tremor".

In only two of the events (Wakestock and V Festival) did all three methods identify the same symptoms. Anecdotally, once "cough" was identified as a possible symptom after the Wakestock festival, we found tweets such as "anyone else still suffering from the wakestock cough? can't be only me", which were made by people who were identified as having been to the festival, suggesting that this is a true symptom that was also self-identified as due to the event. This, together with the fact that it was identified by all three analysis methods, indicates that this symptom is very unlikely to be a spurious false positive, especially as it was identified by making different comparisons within the data (eg, target vs control population and before vs after the event in the target population). Thus, the use of more than one analysis method strengthens the analysis and reduces the likelihood of false positives.

We tested the agreement between all pairs of analysis methods for each of the events using a chi-square test at a threshold of $P$=.01. Methods 2 and 3 had a statistically significant agreement in six of the 10 events, Methods 1 and 3 in two of eight events (two of the events had no identified symptoms), and Methods 1 and 2 in three of eight of the events. We also found a statistically significant agreement between sources for three of the events: Wakestock, V Festival, and T in the Park. The agreement rate expected by chance, as computed using an FDR procedure, is 5 of 1000 comparisons. Therefore, these agreements are much higher than expected by chance and lend support to the hypothesis that the different methods identified real signals, through alternative means.

Table 5 shows the list of statistically significant symptoms (at $P$<.01) identified in the Bing data for each of the 10 events using Method 2. We applied only this method because there was insufficient daily activity in the Bing data to allow the application of Methods 1 and 3. As this table shows, the symptoms identified in the Bing data were potentially more serious (eg, "diarrhea" and "vomiting") and also more personally sensitive. This is probably because users tend to share more sensitive information in anonymous media [46]. Thus, the use of Bing data complements Twitter data in the kinds of symptoms that are identified. However, the relative sparseness of this data, which is at least partly related to the number of Bing users in the United Kingdom, also means that not all methods are applicable to it.

In order to validate whether our methods might result in false positive symptoms, we also applied our methods to an event with a small physical footprint, but one that had significant media attention. Specifically, we chose the opening of The Shard building in London (the tallest building in the European Union) on July 5, 2012. This event was mentioned by 2007 users in 5553 tweets. No symptoms were reported at statistically significant levels by any of these methods. This provides evidence that when no symptoms exist, our methods will not report spurious symptoms.

**Table 4.** Statistically significant symptoms[a] from Twitter data for each event and three analysis methods.

| Event | Method 1 | Method 2 | Method 3 |
|---|---|---|---|
| Wakestock | Cough | Cough | Tired, cough |
| Wireless Festival | None | Tired, pain, tremor | Tired, flatulence |
| T in the Park | Tired | Tired, pain, cough | Tired, cough |
| V Festival | Depression | Tired, pain, depression | Depression |
| Bestival | None | Tired, pain, tremor | Tired, fever |
| Creamfields | None | Tired, pain, blindness | None |
| Hajj | Rash, wound | Tired | Tired |
| Isle of Wight Festival | None | Bleeding | None |
| Download Festival | None | None | None |
| RockNess | None | Phobia, swelling | None |

[a]When more than three symptoms were significant, only the top three are shown.

**Table 5.** Statistically significant symptoms[a] from Bing data for each event using Method 2.

| Event | Method 2 |
|---|---|
| Wakestock | Pain |
| Wireless Festival | Pain |
| T in the Park | Wound, cough, diarrhea |
| V Festival | Perspiration, edema, wound |
| Bestival | Vomiting, diarrhea |
| Creamfields | Wound, rash, itch |
| Hajj | Fever, flatulence, pain |
| Isle of Wight Festival | Headache, fever, flatulence |
| Download Festival | Diarrhea, wound, headache |
| RockNess | Fever |

[a]When more than three symptoms were significant, only the top three are shown.

## Discussion

### Principal Findings

Mass gatherings are potentially significant to the spread of infectious diseases. However, traditional surveillance methods are challenged by the fact the participants may congregate and disperse very quickly. In this paper, we investigated whether syndromic surveillance based on Twitter and query logs could be used to monitor mass gatherings.

We looked at nine music festivals that took place in the United Kingdom in 2012 as well as the 2012 Hajj religious gathering in Mecca. When analyzing the Twitter data, we considered three different statistical methods. The three methods did not always give the same results, with Methods 1 and 3 finding no statistically significant symptoms almost half of the time. However, when all three methods did identify statistically significant symptoms at the same concert, there was almost always agreement with at least one of the symptoms.

Each of the three methods compares different attributes of the data in order to detect medical symptoms. Because of this, each method might be better in the analysis of data from some festivals, while for others it will perform less accurately. By using more than one method, we afford two benefits. First, if more than one method discovers a symptom has appeared with an unexpectedly high probability (as noted above), this strengthens the evidence that this symptom has indeed appeared in festival participants. Second, at the cost of higher false positive rates (but also higher true positives), health authorities might choose to use symptoms discovered by any of the methods as possible candidates for further investigation.

The relative lack of data provided by the Bing query logs permitted only Method 2 to be used. Generally, the statistically significant symptoms that were identified were different from the symptoms identified by Twitter. We hypothesized that this is because users rightly perceive that tweets are public, while queries are private. Consequently, the symptoms identified by the query log describe more private indicators such as “flatulence” and “diarrhea”. Nevertheless, for two concerts, namely “Wirelessfest” and “T in the Park”, using Method 2 for both Tweets and query logs, the same symptoms were identified as “pain” and “cough” respectively.

### Limitations and Conclusions

To the best of our knowledge, no infectious outbreaks at mass gatherings were reported to health authorities during the last 18 months, the period for which query logs are available. While this is, of course, fortunate, it prevents any comparison with ground truth data. Future work is needed to compare results from Internet data with results obtained from traditional methods. Note, however, that the use of traditional surveillance methods can be challenging in the context of mass gatherings due to the combination of an incubation period prior to onset of symptoms and dispersal of participants to their home regions.

An additional drawback of our method is that some of the identified symptoms (eg, tired) might not be a symptom of a disease, but instead the outcomes of going to specific types of events. Therefore, an additional filtering stage might be required so as to remove symptoms that regularly appear in similar events.

### Acknowledgments

The work described here was supported by an Engineering and Physical Sciences Research Council Interdisciplinary Research Collaboration (EPSRC IRC) in Early Warning Sensing Systems for Infectious Diseases EP/K031953/1, the and School of the Built Environment, Engineering and Mathematical and Physical Sciences (BEAMS), University College London, and a Royal Society Wolfson Merit Award for RM BEAMS. We thank these institutions for their support. The authors would also like thank Dame Anne Johnson of University College London for suggesting the problem and for many useful discussions.

## Conflicts of Interest

None declared.

## Multimedia Appendix 1

Number of tweets containing symptom words for each festival.

[PDF File (Adobe PDF File), 160KB - jmir_v16i6e154_app1.pdf ]

## References


1. Perry RD, Fetherston JD. Yersinia pestis--etiologic agent of plague. Clin Microbiol Rev 1997 Jan;10(1):35-66 [FREE Full text] [Medline: 8993858]
2. Johnson NP, Mueller J. Updating the accounts: global mortality of the 1918-1920 "Spanish" influenza pandemic. Bull Hist Med 2002;76(1):105-115. [Medline: 11875246]
3. Cabinet Office National Risk Register of Civil Emergencies 2012 Edition. URL: https://www.gov.uk/government/publications/national-risk-register-for-civil-emergencies-2012-update [accessed 2014-06-06] [WebCite Cache ID 6Q79v6EPN]
4. Global Report: UNAIDS report on the global AIDS epidemic 2013. URL: http://www.unaids.org/en/resources/campaigns/globalreport2013/index.html [accessed 2014-06-06] [WebCite Cache ID 6Q7A04zh2]
5. Grundmann H, Aires-de-Sousa M, Boyce J, Tiemersma E. Emergence and resurgence of meticillin-resistant Staphylococcus aureus as a public-health threat. Lancet 2006 Sep 2;368(9538):874-885. [doi: 10.1016/S0140-6736(06)68853-3] [Medline: 16950365]
6. Parkin DM. The global health burden of infection-associated cancers in the year 2002. Int J Cancer 2006 Jun 15;118(12):3030-3044. [doi: 10.1002/ijc.21731] [Medline: 16404738]
7. Davies SC. Infections and the rise of antimicrobial resistance. 2011. URL: http://antibiotic-action.com/resources/chief-medical-officer-annual-report-volume-two-201-infections-and-the-rise-of-antimicrobial-resistance/ [accessed 2014-06-05] [WebCite Cache ID 6Q7ADsur0]
8. German RR, Lee LM, Horan JM, Milstein RL, Pertowski CA, Waller MN, Guidelines Working Group Centers for Disease Control Prevention (CDC). Updated guidelines for evaluating public health surveillance systems: recommendations from the Guidelines Working Group. MMWR Recomm Rep 2001 Jul 27;50(RR-13):1-35; quiz CE1. [Medline: 18634202]
9. May L, Chretien JP, Pavlin JA. Beyond traditional surveillance: applying syndromic surveillance to developing settings--opportunities and challenges. BMC Public Health 2009;9:242 [FREE Full text] [doi: 10.1186/1471-2458-9-242] [Medline: 19607669]
10. Welliver RC, Cherry JD, Boyer KM, Deseda-Tous JE, Krause PJ, Dudley JP, et al. Sales of nonprescription cold remedies: a unique method of influenza surveillance. Pediatr Res 1979 Sep;13(9):1015-1017. [Medline: 503653]
11. Wagner MM, Tsui FC, Espino JU, Dato VM, Sittig DF, Caruana RA, et al. The emerging science of very early detection of disease outbreaks. J Public Health Manag Pract 2001 Nov;7(6):51-59. [Medline: 11710168]
12. Barbeschi M, Healing T. World Health Organization. 2008. Communicable disease alert and response for mass gatherings: Key considerations URL: http://www.who.int/csr/Mass_gatherings2.pdf [accessed 2014-06-05] [WebCite Cache ID 6Q7AIIRht]
13. Donkin H. The Cholera and Hagar's Well at Mecca. The Lancet 1883 Aug;122(3128):256-257. [doi: 10.1016/S0140-6736(02)35905-1]
14. Morgan D, Gunneberg C, Gunnell D, Healing TD, Lamerton S, Soltanpoor N, et al. An outbreak of Campylobacter infection associated with the consumption of unpasteurised milk at a large festival in England. Eur J Epidemiol 1994 Oct;10(5):581-585. [Medline: 7859858]
15. Gutiérrez I, Litzroth A, Hammadi S, Van Oyen H, Gerard C, Robesyn E, et al. Community transmission of influenza A (H1N1)v virus at a rock festival in Belgium, 2-5 July 2009. Euro Surveill 2009 Aug 6;14(31):1 [FREE Full text] [Medline: 19660245]
16. Loncarevic G, Payne L, Kon P, Petrovic V, Dimitrijevic D, Knezevic T, et al. Public health preparedness for two mass gathering events in the context of pandemic influenza (H1N1) 2009 - Serbia, July 2009. Eurosurveillance 2009;14(31):A4 1-A4 3. [Medline: 19660246]
17. Botelho-Nevers E, Gautret P, Benarous L, Charrel R, Felkai P, Parola P. Travel-related influenza A/H1N1 infection at a rock festival in Hungary: one virus may hide another one. J Travel Med 2010;17(3):197-198. [doi: 10.1111/j.1708-8305.2010.00410.x] [Medline: 20536890]
18. Johnson HA, Wagner MM, Hogan WR, Chapman W, Olszewski RT, Dowling J, et al. Analysis of Web access logs for surveillance of influenza. Stud Health Technol Inform 2004;107(Pt 2):1202-1206. [Medline: 15361003]
19. Eysenbach G. Infodemiology: Tracking flu-related searches on the Web for syndromic surveillance. AMIA Annual Symposium Proceedings 2006:244-248. [Medline: 17238340]
20. Mykhalovskiy E, Weir L. The Global Public Health Intelligence Network and early warning outbreak detection: a Canadian contribution to global public health. Can J Public Health 2006;97(1):42-44. [Medline: 16512327]

21. Collier N, Kawazoe A, Jin L, Shigematsu M, Dien D, Barrero RA, et al. A multilingual ontology for infectious disease surveillance: rationale, design and challenges. Lang Resources & Evaluation 2007 Jun 26;40(3-4):405-413. [doi: 10.1007/s10579-007-9019-7]
22. Collier N, Doan S, Kawazoe A, Goodwin RM, Conway M, Tateno Y, et al. BioCaster: detecting public health rumors with a Web-based text mining system. Bioinformatics 2008 Dec 15;24(24):2940-2941 [FREE Full text] [doi: 10.1093/bioinformatics/btn534] [Medline: 18922806]
23. Tolentino H, Kamadjeu R, Fontelo P, Liu F, Matters M, Pollack M, et al. Scanning the emerging infectious diseases horizon-visualizing ProMED emails using EpiSPIDER. Advances in Disease Surveillance 2007;2:169.
24. Brownstein JS, Freifeld CC, Madoff LC. Digital disease detection--harnessing the Web for public health surveillance. N Engl J Med 2009 May 21;360(21):2153-2157 [FREE Full text] [doi: 10.1056/NEJMp0900702] [Medline: 19423867]
25. Freifeld CC, Mandl KD, Reis BY, Brownstein JS. HealthMap: global infectious disease monitoring through automated classification and visualization of Internet media reports. J Am Med Inform Assoc 2008;15(2):150-157 [FREE Full text] [doi: 10.1197/jamia.M2544] [Medline: 18096908]
26. Keller M, Blench M, Tolentino H, Freifeld CC, Mandl KD, Mawudeku A, et al. Use of unstructured event-based reports for global infectious disease surveillance. Emerg Infect Dis 2009 May;15(5):689-695 [FREE Full text] [doi: 10.3201/eid1505.081114] [Medline: 19402953]
27. Lyon A, Nunn M, Grossel G, Burgman M. Comparison of Web-based biosecurity intelligence systems: BioCaster, EpiSPIDER and HealthMap. Transbound Emerg Dis 2012 Jun;59(3):223-232. [doi: 10.1111/j.1865-1682.2011.01258.x] [Medline: 22182229]
28. Polgreen PM, Chen Y, Pennock DM, Nelson FD. Using Internet searches for influenza surveillance. Clin Infect Dis 2008 Dec 1;47(11):1443-1448 [FREE Full text] [doi: 10.1086/593098] [Medline: 18954267]
29. Ginsberg J, Mohebbi MH, Patel RS, Brammer L, Smolinski MS, Brilliant L. Detecting influenza epidemics using search engine query data. Nature 2009 Feb 19;457(7232):1012-1014. [doi: 10.1038/nature07634] [Medline: 19020500]
30. Carneiro HA, Mylonakis E. Google Trends: a Web-based tool for real-time surveillance of disease outbreaks. Clin Infect Dis 2009 Nov 15;49(10):1557-1564 [FREE Full text] [doi: 10.1086/630200] [Medline: 19845471]
31. Corley CD, Cook DJ, Mikler AR, Singh KP. Text and structural data mining of influenza mentions in Web and social media. Int J Environ Res Public Health 2010 Feb;7(2):596-615 [FREE Full text] [doi: 10.3390/ijerph7020596] [Medline: 20616993]
32. Corley CD, Mikler AR, Singh KP, Cook DJ. Monitoring influenza trends through mining social media. 2009 Presented at: International Conference on Bioinformatics and Computational Biology; July 2009; Las Vegas, NV p. 340-346.
33. Lampos V, Cristianini N. Tracking the flu pandemic by monitoring the social web. 2010 Presented at: Cognitive Information Processing (CIP); 14-16 June 2010; Elba, Italy p. 411-416. [doi: 10.1109/CIP.2010.5604088]
34. Lampos V, De Bie T, Cristianini N. Flu detector-tracking epidemics on Twitter. 2010 Presented at: Machine Learning and Knowledge Discovery in Databases; 2010; Barcelona, Spain p. 599-602.
35. Culotta A. Towards detecting influenza epidemics by analyzing Twitter messages. In: Proceedings of the First Workshop on Social Media Analytics. 2010 Presented at: The 16th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining; 2010; Washington DC, District of Columbia p. 115-122. [doi: 10.1145/1964858.1964874]
36. Chew C, Eysenbach G. Pandemics in the age of Twitter: content analysis of Tweets during the 2009 H1N1 outbreak. PLoS One 2010;5(11):e14118 [FREE Full text] [doi: 10.1371/journal.pone.0014118] [Medline: 21124761]
37. Signorini A, Segre AM, Polgreen PM. The use of Twitter to track levels of disease activity and public concern in the U.S. during the influenza A H1N1 pandemic. PLoS One 2011;6(5):e19467 [FREE Full text] [doi: 10.1371/journal.pone.0019467] [Medline: 21573238]
38. Culotta A. Lightweight methods to estimate influenza rates and alcohol sales volume from Twitter messages. Lang Resources & Evaluation 2012 May 13;47(1):217-238. [doi: 10.1007/s10579-012-9185-0]
39. de Quincey E, Kostkova P. Early warning and outbreak detection using social networking websites: The potential of Twitter. In: Electronic Healthcare. Berlin: Springer; 2010:21-24.
40. Szomszor M, Kostkova P, De Quincey E. #swineflu: Twitter predicts swine flu outbreak in 2009. : Electronic Healthcare; 2010 Dec Presented at: eHealth; 13-15 December 2010; Casablanca, Morocco. [doi: 10.1007/978-3-642-23635-8_3]
41. Porter MF. An algorithm for suffix stripping. Program: electronic library and information systems 1980;14(3):130-137. [doi: 10.1108/eb046814]
42. Yom-Tov E, Gabrilovich E. Postmarket drug surveillance without trial costs: discovery of adverse drug reactions through large-scale analysis of web search queries. J Med Internet Res 2013;15(6):e124 [FREE Full text] [doi: 10.2196/jmir.2614] [Medline: 23778053]
43. Sartwell PE. The distribution of incubation periods of infectious disease. Am J Epidemiol 1950 May;51(3):310-318. [Medline: 15413610]
44. Benjamini Y, Hochberg Y. Controlling the False Discovery Rate - a new and powerful approach to multiple testing. J Roy Stat Soc B 1995;57(1):289-300. [doi: 10.2307/2346101]
45. Moore A, Cooper G, Wagner M. WSARE: What's strange about recent events? J Urban Health 2003;80(1):i66-i75. [doi: 10.1007/PL00022317]

46. Pelleg D, Yom-Tov E, Maarek Y. Can you believe an anonymous contributor? On truthfulness in Yahoo! Answers. 2012 Presented at: ASE/IEEE International Conference on Social Computing; 3-6 September 2012; Amsterdam, The Netherlands p. 411-420. [doi: 10.1109/SocialCom-PASSAT.2012.13]

## Abbreviations

**CDC:** Centers for Disease Control and Prevention
**EMS:** Emergency Medical Services
**FDR:** false discovery rate
**ILI:** influenza-like illness
**OTC:** over the counter
**WHO:** World Health Organization

*Edited by G Eysenbach; submitted 02.12.13; peer-reviewed by T Sakaki, J Jiang, C Freifeld; comments to author 14.03.14; revised version received 14.04.14; accepted 18.05.14; published 18.06.14.*

*Please cite as:*
*Yom-Tov E, Borsa D, Cox IJ, McKendry RA*
*Detecting Disease Outbreaks in Mass Gatherings Using Internet Data*
*J Med Internet Res 2014;16(6):e154*
*URL: http://www.jmir.org/2014/6/e154/*
*doi:10.2196/jmir.3156*
*PMID:24943128*

Original Paper

# Common Cold Symptoms in Children: Results of an Internet-Based Surveillance Program

Emanuel Troullos[1], DMD, MPH; Lisa Baird[1], MS; Shyamalie Jayawardena[1], PhD

Pfizer Consumer Healthcare, Global Clinical Development, Madison, NJ, United States

**Corresponding Author:**
Emanuel Troullos, DMD, MPH
Pfizer Consumer Healthcare
Global Clinical Development
1 Giralda Farms
Madison, NJ, 07940
United States
Phone: 1 973 660 5137
Fax: 1 943 660 8513
Email: emanuel.troullos@pfizer.com

## Abstract

**Background:** Conducting and analyzing clinical studies of cough and cold medications is challenging due to the rapid onset and short duration of the symptoms. The use of Internet-based surveillance tools is a new approach in clinical studies that is gradually becoming popular and may become a useful method of recruitment. As part of an initiative to assess the safety and efficacy of cough and cold ingredients in children 6-11 years of age, a surveillance program was proposed as a means to identify and recruit pediatric subjects for clinical studies.

**Objective:** The objective of the study was to develop an Internet-based surveillance system and to assess the feasibility of using such a system to recruit children for common cold clinical studies, record the natural history of their cold symptoms, and determine the willingness of parents to have their children participate in clinical studies.

**Methods:** Healthy potential subjects were recruited via parental contact online. During the 6-week surveillance period, parents completed daily surveys to record details of any cold symptoms in their children. If a child developed a cold, symptoms were followed via survey for 10 days. Additional questions evaluated the willingness of parents to have their children participate in a clinical study shortly after onset of symptoms.

**Results:** The enrollment target of 248 children was reached in approximately 1 week. Children from 4 distinct geographic regions of the United States were recruited. Parents reported cold symptoms in 163 children, and 134 went on to develop colds. The most prevalent symptoms were runny nose, stuffed-up nose, and sneezing. The most severe symptoms were runny nose, stuffed-up nose, and sore/scratchy throat. The severity of most symptoms peaked 1–2 days after onset. Up to 54% of parents expressed willingness to bring a sick child to a clinical center shortly after the onset of symptoms. Parents found the Internet-based surveys easy to complete.

**Conclusions:** Internet-based surveillance and recruitment can be useful tools to follow colds in children and enroll subjects in clinical studies. However, study designs should account for a potentially high dropout rate and low rate of adherence to study procedures.

***(J Med Internet Res 2014;16(6):e144)*** doi:10.2196/jmir.2868

**KEYWORDS**

common cold; pediatric; sleep; surveillance; symptoms

## Introduction

The common cold is one of the most prevalent illnesses in the world [1]. Adults may experience 2-5 colds per year, and children may experience 7-10 colds per year [2]. Owing to the high rate of incidence, especially among children, the common cold creates a significant economic and social burden [1,3,4]. Symptoms of the common cold in children typically reach peak intensity shortly after the onset of illness [5]. Symptom duration is approximately 7-10 days but may range from 2-14 days [3,4]. Diagnosis of the common cold can be problematic in young children and infants who are not able to communicate their symptoms. Because colds are of limited duration and clinical studies of cough and cold medications rely on self-reported assessment of symptoms, the conduct and analysis of such studies is highly challenging. Evaluating the efficacy of over-the-counter cough and cold products is therefore equally challenging. Given these hurdles, optimizing clinical design is paramount to fully assess the efficacy of current and future cough and cold products. One design element that has proven important in cold studies is the ability to enroll subjects at the earliest stages of a cold [3,5,6]. As part of an initiative to assess the safety and efficacy of cough and cold ingredients in children 6-11 years of age, a surveillance program was proposed as a means to identify and recruit pediatric subjects for participation in clinical studies. Surveillance systems have been used to monitor daily health and to study infectious disease dynamics in a daycare setting [7,8]. Engaging parents with a surveillance program was thought to be a way of generating a pool of potential patients for recruitment into a clinical study within the first 2 days of the appearance of cold symptoms. The present study was undertaken to develop and test Internet-based surveillance methodology designed to recruit and prescreen children aged 6-11 years, monitor these children on a daily basis for the first onset of cold symptoms, determine the feasibility of enrolling them into a clinical study within approximately 24 hours of the onset of cold symptoms, identify potential recruitment issues, and assess the proposed recruitment strategy.

## Methods

### Subjects

Eligible subjects were children 6-11 years of age. We required a history of 3 or more colds per winter season in either of the past 2 winters as reported by parents ("parent" includes parents and legally authorized representative), and/or a history of living with 3 or more siblings or other children, in order to increase the likelihood that the child would develop a cold during the 6-week surveillance period. Each subject's parent was required to have access to a home computer with an Internet connection. Major exclusion criteria included cardiovascular or thyroid disease, asthma requiring daily medication, chronic bronchitis, glaucoma, use of sedatives or tranquilizers, use of monoamine oxidase inhibitors, smoking, and history of attention deficit disorder or attention deficit hyperactivity disorder. Concomitant medications, apart from these exclusions, were allowed. Only 1 child per household was permitted into the study. The study was conducted in accordance with the requirements specified in the US Code of Federal Regulations (21 CFR Parts 50, 56, 312) and the International Conference on Harmonization Good Clinical Practice Guidelines, and informed consent was provided by parents before initiation of any study procedures. The final protocol and informed consent documentation were reviewed and approved by an independent institutional review board (Copernicus Group).

### Study Design

This was a noninterventional surveillance study in school-age children (ages 6-11 years). Potential subjects were identified through the resources of a patient recruitment provider with an extensive database of individuals who had chosen to receive new health information and clinical study invitations. Letters were sent to individuals in the network in 4 geographically diverse metropolitan areas (Austin, TX; Boston, MA; Portland, OR; Raleigh, NC) informing them of the study and directing them to a website if they wished to obtain additional information about enrolling their child in the study. Screening and evaluations were performed online by parents. Once the subjects were enrolled, parents recorded the presence or absence of 10 cold symptoms each evening for up to 6 weeks by completing a Well Child Daily Survey (WCDS) (see Multimedia Appendix 1). Cold symptoms included in the survey were runny nose, stuffed-up nose, sneezing, sore/scratchy throat, dry cough (no mucus), wet cough (with mucus), chest congestion, headache, muscle/body ache, and feverishness/chilliness. On the first day that parents reported their child was experiencing cold symptoms, they were asked questions designed to evaluate their willingness and availability to bring their child to a clinic and to participate in a clinical study of cough/cold medication. If the child developed a cold, the parent recorded details of the symptoms by using a Daily Cold Symptom Severity Survey (DCSSS; see Multimedia Appendix 2). Parents rated each of the 10 individual cold symptoms on a 4-point categorical rating scale. Additionally, parents recorded whether they believed the symptoms were related to a cold as opposed to a different upper respiratory illness, such as allergy or flu. At the end of the surveillance period, parents were asked to complete an End of Study Survey (EOSS) that included questions about the effect of cold symptoms on the child's sleep and the ability of the parent to use the Internet-based tools to identify and evaluate cold symptoms and comply with the requirements of the study. Because no therapeutic intervention was planned, safety and adverse event data were not collected (Multimedia Appendix 1 and 2).

### Statistical Analysis

No formal hypotheses were tested; all outcome measures are described by summary statistics.

## Results

### Subject Characteristics

Between January 5 and January 11, 2011, 2543 parents entered the system by visiting the website. Of those, 425 completed the prescreening questionnaire, 346 completed the informed consent form, and 248 children were enrolled. Demographic characteristics of the study population are presented in Table 1.

**Table 1.** Demographic characteristics of enrolled children (N=248).

| Characteristic | | n (%) |
|---|---|---|
| **Gender** | | |
| | Male | 160 (64.5) |
| | Female | 88 (35.5) |
| **Age, years** | | |
| | 6 | 36 (14.5) |
| | 7 | 60 (24.2) |
| | 8 | 61 (24.6) |
| | 9 | 48 (19.4) |
| | 10 | 23 (9.3) |
| | 11 | 20 (8.1) |
| **Race** | | |
| | White | 183 (73.8) |
| | Black | 34 (13.7) |
| | American Indian or Alaskan native | 6 (2.4) |
| | Asian | 5 (2.0) |
| | Mixed race | 16 (6.5) |
| | Did not answer | 4 (1.6) |
| **Ethnicity** | | |
| | Not Hispanic or Latino | 222 (89.5) |
| | Hispanic or Latino | 23 (9.3) |
| | Did not answer | 3 (1.2) |
| **Geographic region** | | |
| | Austin, TX | 56 (22.6) |
| | Boston, MA | 71 (28.6) |
| | Portland, OR | 67 (27.0) |
| | Raleigh, NC | 54 (21.8) |
| **Number of other children in the home** | | |
| | 0 | 72 (29.0) |
| | 1 | 31 (12.5) |
| | 2 | 43 (17.3) |
| | ≥3 | 102 (41.1) |
| **Highest education level of parent** | | |
| | Did not graduate high school | 4 (1.6) |
| | High school graduate (or equivalent) | 35 (14.1) |
| | Some college education | 85 (34.3) |
| | Bachelor’s degree | 92 (37.1) |
| | Master’s degree | 26 (10.5) |
| | Doctorate degree | 5 (2.0) |
| | Did not answer | 1 (0.4) |
| **Household income** | | |

| Characteristic | | n (%) |
| --- | --- | --- |
| | <$25,000 | 18 (7.3) |
| | $25,001–$50,000 | 53 (21.4) |
| | $50,001–$100,000 | 138 (55.6) |
| | >$100,000 | 37 (14.9) |
| | Did not answer | 2 (0.8) |

## Survey Results

### *Natural History of Colds in Enrolled Children*

Using the WCDS, parents reported cold symptoms in 65.7% (163/248) of the enrolled children. Using the DCSSS, parents reported that 54.0% (134/248) of the children developed colds and asserted in their opinion that the symptoms were not related to a different upper respiratory condition, such as allergy or flu. In this study, development of a cold was defined as at least 1 entry in the DCSSS with symptoms present and confirmation that the parent believed the symptoms were related to a cold. Symptoms were ranked in severity on a 4-step scale: “symptom not present”, “mild”, “moderate”, and “severe.” Of the 10 symptoms evaluated, the most commonly reported as severe were runny nose (65/134, 48.5%), stuffed-up nose (65/134, 48.5%), and sore/scratchy throat (62/134, 46.3%). All symptoms were most severe in the first 1-2 days after onset and declined thereafter (Figure 1). Moderate-to-severe runny nose in the first 24 hours after onset was reported in 64.2% (86/134) of the children who suffered colds; moderate-to-severe chest congestion within 48 hours was reported in 51.5% (69/134) of the children.

The most prevalent symptoms among children with colds, regardless of severity, were runny nose, stuffed-up nose, dry cough, sore throat/scratchy throat, and sneezing; at least 75% of subjects experienced these symptoms on Day 1. The time course of symptom prevalence had a profile similar to that of symptom severity, with a peak on Day 1 or 2 followed by a decline (Figure 2). The least prevalent symptoms were muscle ache/body ache and feverishness/chilliness, which were reported in 55.2% (74/134) and 54.4% (73/134) of children, respectively, on Day 1. Most symptoms were largely resolved by Day 10 (reported in <15% of children).

**Figure 1.** Average daily severity of individual cold symptoms. Parents of children with colds (n=134) were asked to score symptoms on a scale from 0 (not present) to 3 (severe). To calculate the average daily severity, a value of zero was assigned for those subjects who did not provide a symptom severity rating on a given day during the 10-day follow-up period because the parent was not required to complete the symptom severity questionnaire after all symptoms had resolved.

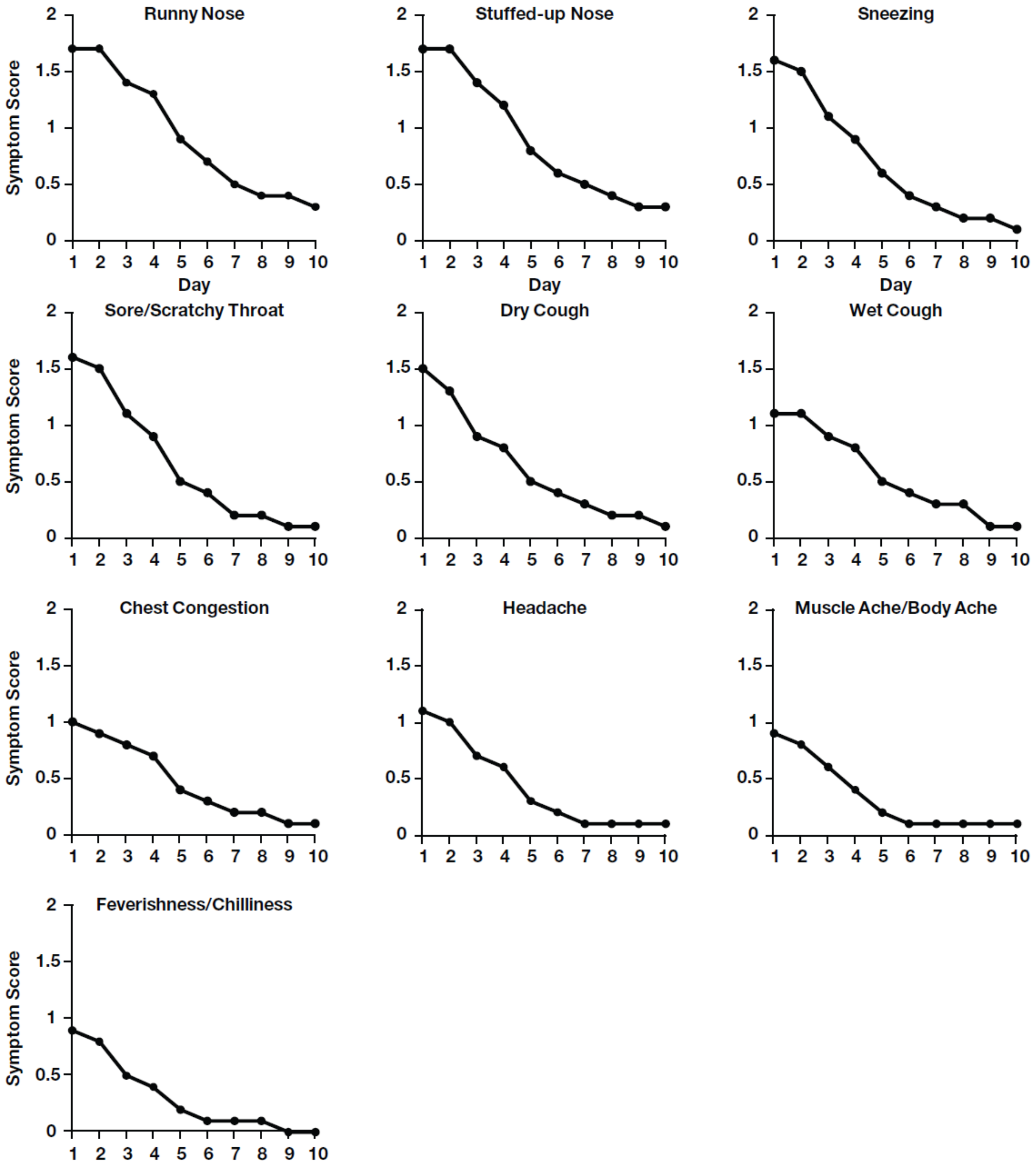
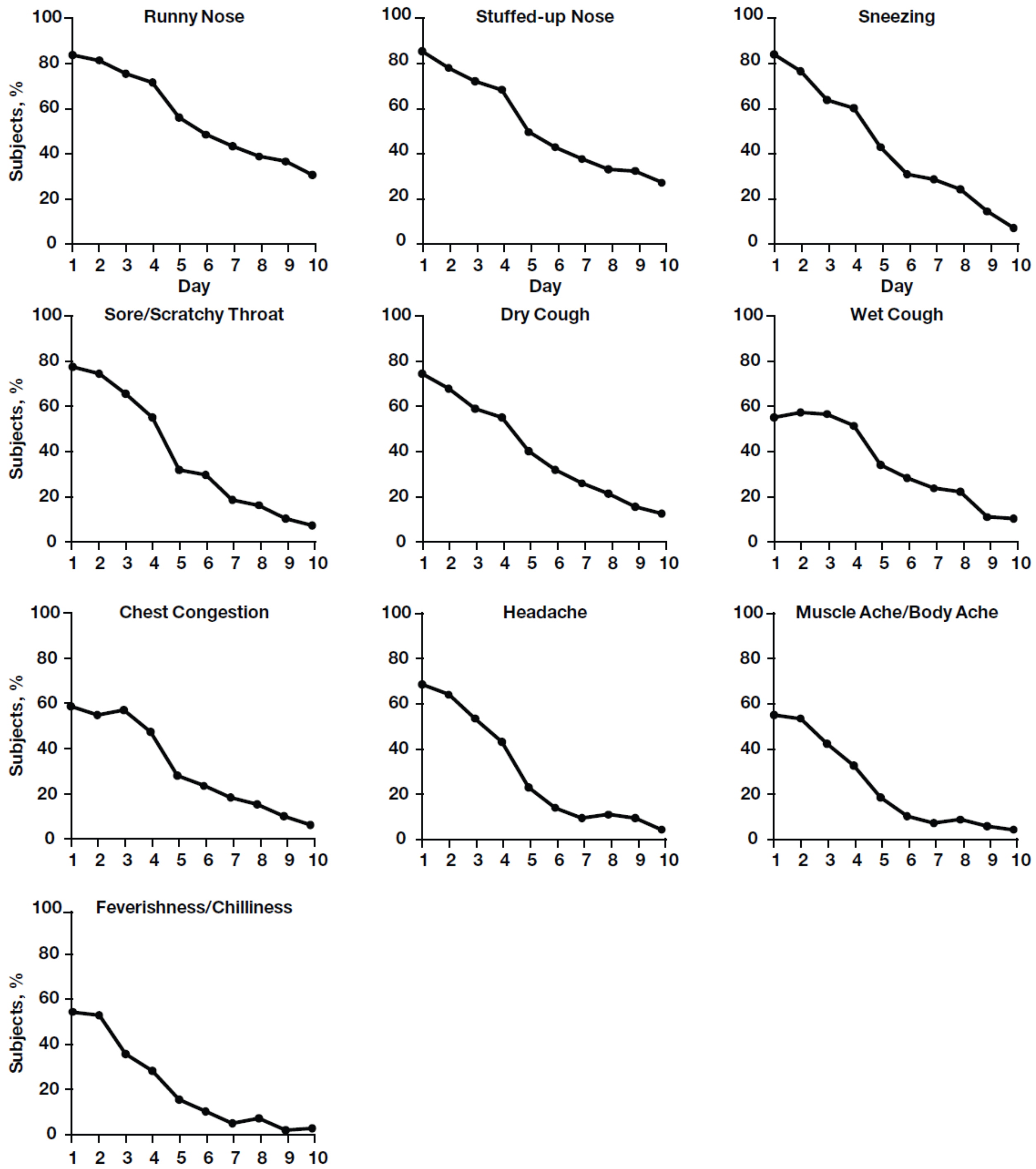


**Figure 2.** Average daily prevalence of individual cold symptoms. From the day of onset, parents of children with colds (n=134) were asked to report whether a symptom was present or absent.




### Effect on Sleep

Of those parents whose children developed colds during the surveillance period, 81.3% (109/134) completed the EOSS. An additional aspect of the survey was to assess the effect of a cold on a child's sleep, and the EOSS asked parents to record the effect of a cold on their child's sleep on the night that cold symptoms were at their worst. Of the parents who completed the sleep questionnaire for a child who developed a cold, nearly two-thirds (55/93, 59.1%) reported that their child's sleep quality was somewhat worse than usual. Nearly three-quarters of parents (69/93, 74.2%) reported that their child had at least some difficulty falling asleep. A large majority of parents (81/93, 87.1%) reported that their child woke at least once during the night.

Parents reported that the majority of children who developed colds were given medication for their cold symptoms. A similar percentage of children were given nonprescription medicine (50/134, 37.3%) or prescription medicine (49/134, 36.6%). In addition, 12.7% (17/134) were given both non-prescription and prescription medication.

### Parental Willingness to Participate in Clinical Studies

When a parent observed that their child was experiencing the first occurrence of symptoms and they believed that the child was experiencing a cold, the parent was asked a series of questions regarding their willingness to comply with certain procedures that might be necessary for participation in a clinical study; 65.7% (163/248) parents replied (Table 2). Among parents who responded on the same day that symptoms appeared, 26.4% (43/163) expressed willingness and availability to bring their child to a clinical site. Including respondents who answered within 1 day of the appearance of symptoms, the number of parents who would be willing/available to bring the child to a clinical site rose to 54.0% (88/163). Only 12.3% (20/163) of the respondents indicated a willingness to allow the child to remain home from school. Somewhat more parents, 29.4% (48/163) reported willingness to score symptoms and administer a study medication to the child during lunch breaks at school, and 30.7% (50/163) reported that they were willing to allow the child to remain home from school and/or score symptoms and administer study medications at school.

**Table 2.** Parent willingness to participate in clinical study procedures (N=163).

| Procedure | | Willing, n (%) | Not willing, n (%) |
|---|---|---|---|
| **Visit a clinical site (response on same day as the appearance of symptoms in the child)** | | | |
| | Total | 43 (26.4) | 120 (73.6) |
| | Before 11 am the next day | 14 (8.6) | |
| | Before the clinical site closes the next day | 15 (9.2) | |
| | Within the next 3 days | 21 (12.9) | |
| | Within the next 5 days | 20 (12.3) | |
| **Visit a clinical site (response within 1 day of appearance of symptoms in the child)** | | | |
| | Total | 88 (54.0) | 75 (46.0) |
| | Before 11 am the next day | 29 (17.8) | |
| | Before the clinical site closes the next day | 35 (21.5) | |
| | Within the next 3 days | 32 (19.6) | |
| | Within the next 5 days | 30 (18.4) | |
| Permit a child to remain out of school to participate in a study | | 20 (12.3) | 143 (87.7) |
| Score symptoms and administer medication to the child at school | | 48 (29.4) | 115 (70.6) |
| Permit a child to remain out of school and/or score symptoms and administer medication to the child at school | | 50 (30.7) | 113 (69.3) |

### Ease of Participation

In addition to evaluating the quality of sleep in enrolled children, the EOSS asked parents to rate how easy or difficult it was for them to participate in this Internet-based program. Among parents who completed the EOSS, 89.0% (97/109) reported that it was easy or very easy to use the website on a daily basis, and the majority were able to complete all surveys with little difficulty. Respondents consistently reported that it was easy or very easy to rate individual cold symptoms in their children (78/109, 71.6% to 93/109, 85.3%, depending on the symptom), and 85.3% (93/109) felt that it was easy or very easy to decide whether the child had a cold rather than some other illness.

## Discussion

### Principal Findings

This study examined the suitability of an Internet-based surveillance program to recruit and prescreen school-age children for common cold clinical studies, monitor the natural history of their colds, and evaluate their parents' willingness to quickly enroll them in clinical studies. The results demonstrated that the Internet-based methodology was efficient and effective. Of enrolled children, 54.0% (134/248) developed colds, and parents monitored the severity and duration of 10 individual symptoms. The single most prevalent symptom was runny nose, which was reported in 94.8% (127/134) of children with colds. Other highly prevalent symptoms were stuffed-up nose, sneezing, dry cough, and scratchy/sore throat, which were reported in 86.6% (116/134) or more of children. The symptoms that were most highly prevalent also were frequently rated as severe. Runny nose and stuffed-up nose remained present after 6 days or more in 85.5% (106/124) or more of children who experienced those symptoms. The symptoms that were least prevalent and resolved most quickly were muscle/body ache and feverishness/chilliness. Because these symptoms are more commonly associated with influenza, this observation suggests that children were suffering colds and that their parents were able to differentiate between the 2 conditions.

The patterns of symptom prevalence, severity, and duration observed in the present study are in accord with those previously reported in adults and children [2,4,9-11]. In a study of colds in children, runny nose and nasal congestion were found to be the most common symptoms and 73% of children remained symptomatic 10 days after onset of the cold [5]. An early study of colds in adults found that runny nose, sneezing, and sore throat were the most common symptoms and the mean duration of a cold was 7.4 days [11]. A more recent study reported that runny nose, stuffy nose, and sore throat were the most bothersome symptoms in adults; median duration of symptoms was 11 days [9]. The severity of cold symptoms has been reported to reach a peak 2-3 days after onset [2,10].The results presented here are consistent with these earlier investigations and suggest that the natural history of colds is similar in adults and in children and that an Internet-based program is an effective way to collect data on cold symptoms.

The enrollment data from the present study indicate that the Internet-based strategy was effective at reaching a wide population of potential subjects in different geographic areas. An enrollment target of approximately 250 subjects was arbitrarily selected for this pilot surveillance study, and the surveillance enrollment target was reached in approximately 1 week. Achieving the target enrollment of 248 subjects required that an approximately 10-fold larger number of parents enter the system, as only 16.71% (425/2543) completed the screening questionnaire. While the enrollment target was rapidly reached in this study, Internet-based recruitment is not always successful. Koo et al found a disappointing recruitment rate in a survey of teenagers and identified challenges, including concerns about the legitimacy of the website as a barrier to enrollment [12]. Similarly, Dobrow et al found that overall response rates to Internet-based surveys were low [13].

It is encouraging that more than half of the parents who entered the system eventually provided informed consent and enrolled in the study. This observation, coupled with the fact that the pool of subjects obtained with this Internet-based recruitment technology was generally representative of the US population in terms of race and ethnicity—white, black, and Hispanic or Latino subjects in this study 73.8% (183/248), 13.7% (34/248), and 9.3% (23/248), respectively, vs US population 77.9%, 13.1%, and 16.9%, respectively [14]—supports the use of such a strategy to enroll pediatric subjects in clinical studies. Along with the benefits, however, Internet-based surveillance strategies have challenges. Consideration should be given to the representativeness of the subject population with regard to socioeconomic factors. Education level of parents in this study, for example, tended to skew higher than has been reported for the US population. A greater percentage of parents in this study were high school graduates or higher compared to the US population, 98.4% (244/248) vs 85.7%, respectively, and a greater percentage held a bachelor's degree or higher, 49.6% (123/248) vs 28.5%, respectively [14]. Also, network security, subject privacy, set-up costs, and operating costs need to be addressed when creating an Internet surveillance tool.

Ideally, studies designed to evaluate cough and cold therapies should recruit subjects and begin treatment within 24 hours of the appearance of symptoms [3,5]. However, only 26.4% (43/163) of parents who responded on the same day that symptoms appeared indicated they would be willing to bring their child to a clinical center to participate in a clinical study, and only 8.6% (14/163) reported that they would bring the child to a center the following morning. Among parents who responded either the same day or the following day that symptoms appeared, the proportion willing to bring the child to a clinical center increased to 54.0% (88/163). Thus, it appears that recruitment within 24 hours may be a significant barrier to overcome in the design of a study.

Another potential challenge that emerged from the survey results was low willingness to comply with clinical study requirements involving school and the need to record symptoms and administer study medication multiple times during the day. Only 12.3% (20/163) of parents indicated that they would permit their child to remain out of school to participate in a study. Although more parents, 29.4% (48/163), were willing to administer study drugs and collect symptom scores at school, these responses suggest that parental adherence to a study protocol that requires multiple doses during the day will be a major obstacle. In addition, there was a substantial decline in adherence to the protocol throughout this study. Fewer than half of all parents of enrolled children successfully completed the WCDS and DCSSS (43.5% (108/248) and 44.8% (111/248), respectively), and only 22.6% (56/248) completed all surveys.

## Conclusion

The results of this investigation suggest that Internet-based surveillance and recruitment can be useful tools to follow the natural history of colds in children and to enroll subjects in clinical studies of therapies for the treatment of cough and cold.

## Acknowledgments

This study was sponsored by Pfizer Consumer Healthcare. The sponsor thanks participating members of the CHPA Pediatric Cough Cold Products Task Group for their support. Medical editorial support was provided by William Sinkins, PhD, ProEd Communications, Inc, and editorial support was provided by Carla Resvanis of Peloton Advantage, LLC, and was funded by Pfizer, Inc.

## Authors' Contributions

All authors were involved in the design of the study. ET and LB were involved in study conduct. ET and SJ were involved in data analyses. All authors were involved in manuscript development, and all authors provided final approval of the manuscript.

## Conflicts of Interest

The authors are employees of Pfizer Consumer Healthcare.

## Multimedia Appendix 1

Well child daily survey.

[JPG File, 85KB - jmir_v16i6e144_app1.JPG ]

## Multimedia Appendix 2

Daily cold symptom severity survey.

[JPG File, 127KB - jmir_v16i6e144_app2.JPG ]

## Multimedia Appendix 3

CHERRIES checklist.

[PDF File (Adobe PDF File), 59KB - jmir_v16i6e144_app3.pdf ]

## References

1. Fendrick AM, Monto AS, Nightengale B, Sarnes M. The economic burden of non-influenza-related viral respiratory tract infection in the United States. Arch Intern Med 2003 Feb 24;163(4):487-494. [Medline: 12588210]
2. Eccles R. Understanding the symptoms of the common cold and influenza. Lancet Infect Dis 2005 Nov;5(11):718-725. [doi: 10.1016/S1473-3099(05)70270-X] [Medline: 16253889]
3. Heikkinen T, Järvinen A. The common cold. Lancet 2003 Jan 4;361(9351):51-59. [doi: 10.1016/S0140-6736(03)12162-9] [Medline: 12517470]
4. National Institute of Allergy and Infectious Diseases. Common cold URL: http://www.niaid.nih.gov/topics/commoncold/Pages/default.aspx [accessed 2014-02-13] [WebCite Cache ID 6NMLwRbPg]
5. Pappas DE, Hendley JO, Hayden FG, Winther B. Symptom profile of common colds in school-aged children. Pediatr Infect Dis J 2008 Jan;27(1):8-11. [doi: 10.1097/INF.0b013e31814847d9] [Medline: 18162930]
6. Tilston NL, Eames KT, Paolotti D, Ealden T, Edmunds WJ. Internet-based surveillance of Influenza-like-illness in the UK during the 2009 H1N1 influenza pandemic. BMC Public Health 2010;10:650 [FREE Full text] [doi: 10.1186/1471-2458-10-650] [Medline: 20979640]
7. Enserink R, Noel H, Friesema IH, de Jager CM, Kooistra-Smid AM, Kortbeek LM, Sentinel Surveillance Network of Infectious diseases in Child Day Care Centers (the KIzSS network). The KIzSS network, a sentinel surveillance system for infectious diseases in day care centers: study protocol. BMC Infect Dis 2012;12:259 [FREE Full text] [doi: 10.1186/1471-2334-12-259] [Medline: 23066727]
8. Sugiura H, Ohkusa Y, Akahane M, Sugahara T, Okabe N, Imamura T. Construction of syndromic surveillance using a web-based daily questionnaire for health and its application at the G8 Hokkaido Toyako Summit meeting. Epidemiol Infect 2010 Oct;138(10):1493-1502. [doi: 10.1017/S095026880999149X] [Medline: 20067657]
9. Arruda E, Pitkäranta A, Witek TJ, Doyle CA, Hayden FG. Frequency and natural history of rhinovirus infections in adults during autumn. J Clin Microbiol 1997 Nov;35(11):2864-2868 [FREE Full text] [Medline: 9350748]
10. Gwaltney JM. Viral respiratory infection therapy: historical perspectives and current trials. Am J Med 2002 Apr 22;112 Suppl 6A:33S-41S. [Medline: 11955458]
11. Gwaltney JM, Hendley JO, Simon G, Jordan WS. Rhinovirus infections in an industrial population. II. Characteristics of illness and antibody response. JAMA 1967 Nov 6;202(6):494-500. [Medline: 4293015]
12. Koo M, Skinner H. Challenges of internet recruitment: a case study with disappointing results. J Med Internet Res 2005;7(1):e6 [FREE Full text] [doi: 10.2196/jmir.7.1.e6] [Medline: 15829478]
13. Dobrow MJ, Orchard MC, Golden B, Holowaty E, Paszat L, Brown AD, et al. Response audit of an Internet survey of health care providers and administrators: implications for determination of response rates. J Med Internet Res 2008;10(4):e30 [FREE Full text] [doi: 10.2196/jmir.1090] [Medline: 18926979]
14. US Census Bureau. People QuickFacts 2014 URL: http://quickfacts.census.gov/qfd/states/00000.html [accessed 2014-02-13] [WebCite Cache ID 6NMLsfYco]

## Abbreviations

**DCSSS:** Daily Cold Symptom Severity Survey
**EOSS:** End of Study Survey
**WCDS:** Well Child Daily Survey

*Edited by G Eysenbach; submitted 12.09.13; peer-reviewed by D Pappas, R Enserink; comments to author 31.10.13; accepted 09.04.14; published 19.06.14.*

*Please cite as:*
*Troullos E, Baird L, Jayawardena S*
*Common Cold Symptoms in Children: Results of an Internet-Based Surveillance Program*
*J Med Internet Res 2014;16(6):e144*
*URL: http://www.jmir.org/2014/6/e144/*
*doi:10.2196/jmir.2868*
*PMID:24945090*

Original Paper

# Characterizing the Followers and Tweets of a Marijuana-Focused Twitter Handle

Patricia Cavazos-Rehg[1], PhD; Melissa Krauss[1], MPH; Richard Grucza[1], PhD; Laura Bierut[1], MD

Washington University School of Medicine, St. Louis, MO, United States

**Corresponding Author:**
Patricia Cavazos-Rehg, PhD
Washington University School of Medicine
660 South Euclid, Box 8134
St. Louis, MO, 63110
United States
Phone: 1 314 362 2152
Fax: 1 314 362 4247
Email: rehgp@psychiatry.wustl.edu

## Abstract

**Background:** Twitter is a popular social media forum for sharing personal experiences, interests, and opinions. An improved understanding of the discourse on Twitter that encourages marijuana use can be helpful for tailoring and targeting online and offline prevention messages.

**Objectives:** The intent of the study was to assess the content of "tweets" and the demographics of followers of a popular pro-marijuana Twitter handle (@stillblazingtho).

**Methods:** We assessed the sentiment and content of tweets (sent from May 1 to December 31, 2013), as well as the demographics of consumers that follow a popular pro-marijuana Twitter handle (approximately 1,000,000 followers) using Twitter analytics from Demographics Pro. This analytics company estimates demographic characteristics based on Twitter behavior/usage, relying on multiple data signals from networks, consumption, and language and requires confidence of 95% or above to make an estimate of a single demographic characteristic.

**Results:** A total of 2590 tweets were sent from @stillblazingtho during the 8-month period and 305 (11.78%) replies to another Twitter user were excluded for qualitative analysis. Of the remaining 2285 tweets, 1875 (82.06%) were positive about marijuana, 403 (17.64%) were neutral, and 7 (0.31%) appeared negative about marijuana. Approximately 1101 (58.72%) of the positive marijuana tweets were perceived as jokes or humorous, 340 (18.13%) implied that marijuana helps you to feel good or relax, 294 (15.68%) mentioned routine, frequent, or heavy use, 193 (10.29%) mentioned blunts, marijuana edibles, or paraphernalia (eg, bongs, vaporizers), and 186 (9.92%) mentioned other risky health behaviors (eg, tobacco, alcohol, other drugs, sex). The majority (699,103/959,143; 72.89%) of @stillblazingtho followers were 19 years old or younger. Among people ages 17 to 19 years, @stillblazingtho was in the top 10% of all Twitter handles followed. More followers of @stillblazingtho in the United States were African American (323,107/759,407; 42.55%) or Hispanic (90,732/759,407; 11.95%) than the Twitter median average (African American 22.4%, inter-quartile ratio [IQR] 5.1-62.5%; Hispanic 5.4%, IQR 3.0-10.8%) and among Hispanics, @stillblazingtho was in the top 30% of all Twitter handles followed.

**Conclusions:** Young people are especially responsive to social media influences and often establish substance use patterns during this phase of development. Our findings underscore the need for surveillance efforts to monitor the pro-marijuana content reaching young people on Twitter.

***(J Med Internet Res 2014;16(6):e157)*** doi:10.2196/jmir.3247

**KEYWORDS**

Twitter; social media; marijuana

## Introduction

Social media use is common among young persons. The majority of Internet users in the United States (72%) use social media platforms like Facebook, Twitter, LinkedIn, MySpace, YouTube, and others [1]. The rate of social media use is even higher among young adults aged 18-29 years old in the United States (89%) [2,3]. Many US social media sites have high levels of user engagement: 63% of Facebook users check the site at least daily, followed by 57% of Instagram users, and 46% of Twitter users [3]. This is especially true for youth and young adults who are the most likely age group to use Twitter. Typical users of Twitter are quite young [4]: nearly half are under the age of 34 and only 30% are over 45. While Facebook continues to dominate social media engagement, more US teens rated Twitter (26%) as the most important social media site than Facebook (23%) [5]. Focus groups revealed that teens dislike the increasing adult presence, inane details, drama, and the need to maintain their reputation on Facebook, but can better express themselves on sites like Twitter [6]. Continued growth from 1.1 billion social media users worldwide in 2013 to 2.3 billion users in 2017 is projected [7].

The term “infodemiology” was coined by Eysenbach and underscores the communication patterns on the Internet that have important implications for the study of population health and public policy [8]. Emerging evidence in the infodemiology of online substance use risk behavior content that is being viewed and posted online via social media platforms is concerning. For instance, up to 83% of US college students’ social networking sites, such as Facebook and MySpace, reference alcohol use [9]. Also, a recent study found that 39% of 15-24 year olds reported having a friend who posted online pictures of themselves smoking marijuana on Facebook or MySpace [10]. In addition, findings suggest that explicit and/or illegal online content on social media is relatively common among adolescents who are 18 years of age and under. Specifically, studies of US college students have found that underage young adults commonly post pictures of themselves drinking alcohol on Facebook [11-13]. Related studies also found references to sexual risk-taking, alcohol use, and drug use behaviors on US adolescents’ (ages 16-18 years old) public online MySpace social media profiles [9,14]. Taken together, the studies indicate a high likelihood for youth and young adults to consume and create online content about risk behaviors via social media platforms.

Like Facebook and MySpace, Twitter is a popular social media forum among youth and young adults [15]. Tweets are messages that are ≤140 characters and are sent from a user profile (“handle”) to a network of “followers” who have chosen to “follow” that particular handle. Followers receive tweets in real time via mobile phones and/or email. Twitter advertises itself as a freedom of speech social media platform and seldom removes tweets that are not illegal or spam. Therefore, it is possible for tweets that encourage deleterious health behaviors to reach youth and other vulnerable populations (eg, current substance abusers); yet, the research that addresses this topic is scant. In one study that examined exposure to alcohol beverage advertisements and marketing via Twitter, it was found that youth who were not yet of the legal drinking age could easily access alcohol marketing campaigns [16]. Similarly, underage youth were able to view and post tweets that promoted trendy tobacco products like hookah and e-cigarettes [17]. In a related study, Twitter users whose tweets identified them as prescription drug abusers tended to be “socially surrounded” (via tweets) with other Twitter users who similarly Tweeted about prescription drug abuse [18]. These findings suggest that Twitter users, even those who are young in age and cannot legally purchase substances like alcohol or tobacco, engage in Twitter activities that promote substance use behaviors.

Young people are responsive to social media influences and often establish substance use patterns during this phase of development [19-21]. In fact, the Media Practice Model (MPM) was developed to explain how individuals can use social media messages for guidance on life choices and accordingly disclose information on social media that reflects actual behaviors and traits or behavioral intent [22-25]. The MPM further postulates that youth and young adults consume and engage with media based on who they are and who they want to be at the moment [22-26]. It is therefore important to increase knowledge about the substance use-related online content that is connecting with youth and young adults.

The current study presents timely analysis of a popular Twitter handle that streams marijuana-related content. Marijuana is one of the most commonly used substances among young people in the United States. The US National Survey on Drug Use and Health (NSDUH) provides data on marijuana use across individuals ages 12 and older and the latest data indicate that past month marijuana use is highest for young adults ages 18-25 years old (18.7% in 2012 versus 19.0% in 2011) followed by 26-29 year olds (11.9% in 2012 and 12.3% in 2011) [27]. Marijuana use often begins in young adulthood with the average age being 17.9 years old in 2012.

Trends in marijuana use are important to monitor given the current shift in the marijuana policy landscape with the liberalizing of marijuana policies [28]. Currently, 19 US states and the District of Columbia now provide legal protection for the possession and supply of marijuana for medicinal purposes. A number of states and community jurisdictions have also reduced penalties for possession and use of small amounts of marijuana from criminal sanctions to fines or civil penalties. In November 2012, Colorado and Washington legalized the sale and possession of marijuana for recreational purposes. In addition, recent self-report data suggest more relaxed views toward marijuana use across both youth and adults. Specifically, population-level data indicate that most youth (60% of high school seniors) do not believe that regular marijuana use is harmful [29] and most Americans (52%) now favor legalizing the recreational use of marijuana [30].

In the US states where it is legal, medical marijuana can be used to treat various conditions including cachexia, cancer, glaucoma, human immunodeficiency virus infection/acquired immune deficiency syndrome, muscle spasms, seizures, severe nausea, severe pain, and sleep disorders [31]. Pain and muscle spasms are the most common reasons that medical marijuana is used: 89% (Arizona) and 94% (Colorado) of patients are registered for severe or chronic pain and 14% (Arizona) and 17% (Colorado) are registered for muscle spasms [32]. Nevertheless, the benefits of medical marijuana use remain uncertain with much of the evidence for marijuana's efficacy being anecdotal [33,34]. Therefore, marijuana regulation continues to be important from a medical perspective given the known risks that are associated with its use. In 2011, marijuana contributed to over 455,000 visits to the emergency department in the United States; 13% of these patients were between the ages of 12 and 17 [35]. Additionally, there are numerous harmful short-term and long-term effects of marijuana use including short-term memory damage, impairment in attention, judgment and other cognitive functions, worsened coordination and balance, and psychotic episodes [36-39]. Persistent marijuana effects include impaired long-term memory, learning skills, and sleep, while chronic abuse can lead to addiction and increased risk for chronic cough, bronchitis, and several mental disorders including schizophrenia, anxiety, and depression [38,40].

Nevertheless, content about marijuana use is likely to have a presence on social media given its recent increased use among youth and both youths' and adults' more relaxed views toward marijuana use. In the present study, we assess the content of tweets and demographics of consumers who are following a popular Twitter handle (approximately 1,000,000 followers) that streams daily tweets about marijuana-related content.

## Methods

### Overview

The Twitter data in the current study is public. The Washington University Institutional Review Board reviewed our study protocol and our research was deemed exempt from human subjects review.

### Twitter Handle

We searched Twitter for popular accounts related to "marijuana" or "weed" and chose the account with the most followers: "Weed Tweets" (@stillblazingtho) with approximately 1 million followers. The next most popular marijuana-related accounts had approximately 200,000 to 300,000 followers; thus, the above account had by far the highest number of followers. The profile summary of Weed Tweets, @stillblazingtho, is shown in Figure 1.

**Figure 1.** Profile summary of Weed Tweets @stillblazingtho.


### Tweet Engagement, Sentiment, and Content

Tweets from @stillblazingtho were collected historically for eight months (May 1, 2013-December 31, 2013). Analytics platform "SimplyMeasured" was used to access the Twitter "firehose" via Gnip (a social data firm that provides access to the Twitter "firehose" stream of every tweet ever sent) and collect all tweets sent from @stillblazingtho for the time period of interest [41]. A total of 2590 unique tweets (an average of 11 tweets per day) was sent from @stillblazingtho during the 8-month period. SimplyMeasured also provides a "Klout" score for the Twitter handle (the Klout score ranges from 1 to 100 with higher scores representing higher influence) and analysis of Twitter engagement, including the number of retweets and replies for each tweet and the number of potential impressions (total number of times a tweet from @stillblazingtho or a tweet mentioning @stillblazingtho appeared in someone's Twitter feed during the time period).

Tweets sent from @stillblazingtho were qualitatively analyzed for sentiment and topics/themes. Tweets that were replies to another Twitter user (305/2590, 11.78% of the total tweets) were removed from the dataset because the original tweets would also need to be reviewed in order to understand the context of replies. This resulted in 2285 tweets for qualitative analysis. Tweets were coded for sentiment: positive sentiment about marijuana, negative sentiment about marijuana, neutral/unknown. Topics or themes included in tweets were additionally coded, such as whether the tweet was a joke/humorous, implied that marijuana use is not harmful or dangerous (or less harmful than other substances like alcohol), explicitly encouraged legalization, included a motivational message or quote, implied that marijuana use is good for friendship/promotes getting along, implied that you can still be successful or a good person if you use marijuana, and whether it mentioned other risky health behaviors (eg, tobacco, alcohol, other drugs, sex), the relaxing or de-stressing effects of marijuana use, frequent, regular/routine, or heavy use, blunts, marijuana edibles, or paraphernalia (eg, bongs, vaporizers), and the health benefits of marijuana or medical marijuana use. The sentiment of each tweet was coded and the topic/theme of the tweet was subsequently coded when applicable. Each tweet could be coded for more than one topic/theme if necessary.

We used crowdsourcing to code the tweets with the services of "CrowdFlower" [42]. Crowdsourcing involves using a large network of workers to complete micro-tasks. Kim et al also used crowdsourcing via CrowdFlower to analyze sentiment of tweets about US health care reform, similar to methods used for this study, and found a high level of agreement between trained coders from the research team and crowdsourced coders (82.4% for positive sentiment, 100% for negative sentiment) [43]. The tweets to be analyzed and instructions with codebook and detailed definitions (including example tweets) were provided to the CrowdFlower contributors via the online CrowdFlower platform. All tweets were coded by at least three people. Sentiment codes were a Likert scale: 1=strongly negative, 2=slightly negative, 3=neutral/unknown, 4=slightly positive, 5=strongly positive. The presence of topics/themes of interest was coded as yes/no. A set of 108 tweets (from the total 2285 tweets) coded by two trained members of the research team was considered gold standard and these were used as test questions for the CrowdFlower contributors. Only coders who scored highly on a subset of the test sample questions could begin the project. Gold standard tweets were also intermingled throughout the tweets in order to monitor coder performance throughout the project. Coders who did not perform well were dropped from the project, all prior codes from those coders were discarded, and new coders were assigned in their place.

Because tweets were coded by multiple coders, the numeric values for sentiment coding were first averaged and then collapsed into negative (values 1 to 2.4), neutral/unknown (values 2.5 to 3.4), and positive (3.5 to 5.0). For the yes/no items, the response from the most "trusted" coder (based on coding accuracy compared to gold standard questions) was chosen; when "trust" scores among the coders were close, the most popular response was chosen. Based on our own coding of 108 test questions compared to final codes from CrowdFlower contributors, overall level of agreement was high. Percent agreement was 91% for sentiment, and ranged from 76% to 100% for topic codes (76% was for the joke/humorous code, which would be expected to have lower agreement due to the subjective nature of the code).

Hashtags (symbol #) are used before a relevant keyword or phrase in a tweet to categorize the tweet so that people can find them more easily in their Twitter search. We also extracted tweets that included hashtags and two members of the research team coded the hashtags as being related to marijuana or not related to marijuana.

### Demographics of Followers

We used "Demographics Pro for Twitter" [44], described in detail below, to report on the predicted demographic characteristics of followers of @stillblazingtho and the characteristics of the average Twitter user. Inferred characteristics of followers included geographic location, gender, marital status, age, race, income, occupation, other likes and interests, and other Twitter handles followed. We also report on the followers' level of Twitter activity (eg, number of tweets/day, number of handles followed, number of their own followers), which is not inferred or predicted but rather taken from explicit Twitter data or metadata.

Inferred demographics data on current followers of @stillblazingtho on December 9, 2013 at 2:30pm EST were obtained from Demographics Pro [44], which provides analysis of followers of Twitter accounts for a fee. Demographics Pro estimates demographic characteristics based on Twitter behavior/usage, relying on multiple data signals from networks (signals imparted by the nature and strength of ties between individuals on Twitter), consumption (consumption of information on Twitter revealed by accounts followed and real-world consumption revealed by Twitter usage), and language (words and phrased used in tweets and bios). A random sample of 50,000 followers of @stillblazingtho was analyzed, regardless of whether they posted or commented to @stillblazingtho. The data signals were filtered and amplified using large proprietary knowledge bases of established correlations between data points and demographic characteristics. The multiple amplified signals were combined using a series of algorithms to estimate or infer the likely demographic characteristics. Demographics Pro has used their methodology to profile some 300 million Twitter users to date. The methodologies used in the prediction of demographic characteristics of Twitter followers include big data, natural language processing, entity identification, image analyses, and network theory. Demographics Pro requires confidence of 95% or above to make an estimate of a single demographic characteristic [44]. For example, if 10,000 predictions are made, 9500 would need to be correct in order to accept the methodology used to make the prediction. The success of the Demographics Pro analytic predictions relies on the relatively low covariance of multiple amplified signals. Iterative evaluation testing the methodologies on training sets of established samples of Twitter users with verified demographics allows the calibration of balance between depth of coverage (the number of demographic predictions made) and required accuracy. The size of these established samples of Twitter users with verified demographics varies from 10,000 to 200,000 people depending on the specific demographic characteristic to be inferred. For comparison purposes, Demographics Pro also reports the distributions of the median average and inter-quartile range [IQR] for follower demographic characteristics across a sample of approximately 250,000 Twitter accounts from 10 million Twitter accounts analyzed by Demographics Pro. Inter-quartile ranges are not presented for age or income because the median averages for these categorical variables are weighted so that the sum of the weighted medians over all categories totals 100%.

Characteristics of @stillblazingtho followers were descriptively compared to the median average of the characteristics distributions for Twitter users. Finally, we also report on the popularity of the @stillblazingtho Twitter account within demographic groups based on rankings by Demographics Pro. To examine the popularity of the Twitter handle of interest within demographic groups, Demographics Pro ranks a subset (approximately 250,000 handles with 1000 or more followers) of the 10,000,000 Twitter handles they have analyzed by number of followers within specific demographic groups.

## Results

### Tweet Engagement, Sentiment, and Content

A total of 2590 tweets (2285 regular tweets and 305 replies) were sent from @stillblazingtho from May 1, 2013 to December 31, 2013 (average of 11 tweets per day). The Klout score for @stillblazingtho was 77.8. Regarding engagement, there were a total of 1,964,908 retweets of @stillblazingtho tweets and 135,797 replies to @stillblazingtho during the 8-month time period. Total potential impressions, or total number of times a tweet from @stillblazingtho or a tweet mentioning @stillblazingtho appeared in someone's Twitter feed, was 2,898,866,761 during the 8-month period.

Qualitative analysis was performed on the 2285 regular tweets sent from @stillblazingtho (305 replies representing 11.78% of total tweets were excluded). Of these tweets that excluded replies, 1875 (82.06%) were positive about marijuana, 403 (17.64%) were either neutral in sentiment or were not specifically about marijuana, and 7 (0.31%) appeared negative about marijuana. Percentages for sentiment of tweets included in the qualitative analysis (excluding replies) and also among total tweets (including replies) are presented in Table 1.

The distribution of specific topics for the positive marijuana tweets along with example tweets are presented in Figure 2. Most of the positive marijuana tweets were viewed as jokes or humorous (1101/1875, 58.72%) followed by tweets that implied that marijuana helps you to feel good, relax, or chill (340/1875, 18.13%); 15.68% (294/1875) of the tweets mentioned routine, frequent, or heavy use, and 193 (10.29%) mentioned blunts, marijuana edibles, or paraphernalia (eg, bongs, vaporizers). Approximately 186 (9.92%) of the 1875 positive marijuana tweets mentioned other risky health behaviors (eg, tobacco, alcohol, other drugs, sex). Additional results are shown in Figure 2.

Of the 403 neutral tweets, 70 (17.4%) were inspirational or motivational quotes/messages and 58 (14.4%) were jokes/humorous; for example, "If you are always worried about what others think of you, you will never be happy" or "Sitting there wondering why someone hasn't texted you back, and realizing you never finished sending the message". Examples of the seven negative tweets include, "If you smoke weed to be cool, you're a fucking loser" or "I know too many people who have died from drug overdoses. When the fuck are people going to learn #RIP".

Of the total 2590 tweets sent from @stillblazingtho, 135 (5.21%) contained the use of a hashtag. Only 26 (19.26%) of these hashtags were marijuana specific (eg, #weed, #staystoned, and #stayhigh), while tweets including general hashtags that were non-marijuana related were 109 (80.74%) (eg, #ThingsIWillTeachMyChild, #firstdayofsummer, and #TheSecretToLifeIs).

**Figure 2.** Topics and themes present in positive marijuana Tweets.

| Topic/theme | Pro-marijuana (N=1,875) n (%) | Example Tweets | |
|---|---|---|---|
| Joke/humorous | 1,101 (58.72) | Happy Hump Day. Get high and hump someone. | Facebook makes me hate people I actually know. Twitter makes me want to smoke a lot of blunts with people I've never met. |
| Marijuana helps you to feel good, de-stress, relax, chill out | 340 (18.13) | Stress can pull you down, but weed can lift you right back up. | A little herb can calm a lot of nerve. |
| Frequent, regular/routine, or heavy marijuana use | 294 (15.68) | I need a joint. Or two. Or three. | Weed is my morning cup of coffee. |
| Blunts, marijuana edibles, or paraphernalia (e.g., bongs, vaporizers) | 193 (10.29) | If at first you don't succeed, roll a blunt and smoke some weed. | How to Make Weed Brownies  |
| Other risky health behaviors (tobacco, alcohol, other drugs, sex) | 186 (9.92) | Drugs tear friends apart. Weed brings them closer. | The best thing about getting high and having sex. Is getting high and having sex. |
| Inspiring or motivational message/quote | 150 (8.00) | "Herb is the unification of mankind." — Bob Marley | Truth pic.twitter.com/4yyFmz2bt0  |
| Friendship/getting along when using marijuana | 140 (7.47) | Relationships are better if there's weed involved. | "You smoke?" "Smoke what?" Boom, new friendship. |
| Marijuana is not harmful or dangerous. | 94 (5.01) |   | Fast food kills more people than weed. |
| You can smoke marijuana and still be successful | 92 (4.91) | Fact: You can be an educated, intelligent person and still smoke marijuana. | You can succeed & smoke weed. |
| Encourages legalization | 83 (4.43) | Honestly though, just legalize weed already. | An accurate map of the U.S. pic.twitter.com/7eokchiasN   |
| Health benefits or medical marijuana use | 30 (1.60) | Weed is my sleep medicine. | Marijuana saves lives. #medicine |

## Demographics of @stillblazingtho Followers

Characteristics of @stillblazingtho followers, other than Twitter activity (eg, tweets per day, number of followers, number of accounts followed), were inferred by Demographics Pro. Of the 959,143 followers of @stillblazingtho, 759,407 (79.17%) were in the United States, 60,211 (6.28%) in the United Kingdom, 41,716 (4.35%) in Canada, and <1% in each of South Africa (n=5460; 0.88%), Netherlands (n=7785; 0.81%), and Mexico (n=6885; 0.72%). Within the United States, @stillblazingtho was in the top 20% of all Twitter accounts. The Twitter followers were active: 34.01% (326,242/959,143) had >5 tweets/day and 36.71% (352,148/959,143) had 1-5 tweets/day. Approximately 82.19% (788,310/959,143) followed a total of 101-1000 of Twitter accounts, and 68.34% (655,489/959,143) of users had a high number of their own followers (101-1000). A total of 54.03% (518,184/959,143) of @stillblazingtho followers were female, which is similar to the Twitter median average (52.6%, IQR 40.7-67.6%). Approximately 81.14% (778,240/959,143) of the followers were single, compared to the Twitter median average of only 38.1% (IQR 9.5-75.1%).

Followers of @stillblazingtho were younger than the Twitter median average age distribution (Figure 3). Most followers of @stillblazingtho were 17-19 years old (518,430/959,143; 54.05%); 18.84% (180,673/959,143) were 16 years old or younger, 22.0% (210,799/959,143) were 20-24 years old, and only 5.11% (49,047/959,143) were 25 years old or older. The Twitter median average age distribution was: 14.2% were 16 years old or younger, 17.8% were 17 to 19 years old, 21.4% were 20-24 years old, 16.0% were 25-29 years old, 15.8% were 30-39 years old, 11.2% were 40-49 years old, and 3.5% ≥50 years old. Among people aged 17 to 19 years, @stillblazingtho was in the top 10% of all Twitter accounts followed.

More followers of @stillblazingtho in the United States were African American (323,107/759,407; 42.55%) or Hispanic (90,732/759,407; 11.95%) than the Twitter median average (African American 22.4%, IQR 5.1-62.5%; Hispanic 5.4%, IQR 3.0-10.8%) (Figure 4). Among Hispanics, @stillblazingtho was in the top 30% of all Twitter accounts followed. Personal income among all followers of @stillblazingtho was somewhat lower than the Twitter median average, with 93.53% (897,041/959,143) under US$30,000 per year (Twitter median average 76.9% under $30,000 per year).

More @stillblazingtho followers were students (267,855/959,143; 27.93%) and musicians (205,967/959,143; 21.47%) than the Twitter median average (9.1% students, IQR 4.9-15.0%; 8.2% musicians, IQR 3.3-17.7%). Among students and musicians, @stillblazingtho was in the top 10% and top 20%, respectively, of all Twitter accounts. Music (290,228/959,143; 30.26%) and basketball (274,514/959,143; 28.62%) were the most common interests of @stillblazingtho followers, compared to Twitter median averages of 14.0% music (IQR 9.0-22.9%) and 10.1% basketball (IQR 4.6-19.7%). Many followers of @stillblazingtho also followed rappers and recording artists such as Wiz Khalifa (453,477/959,143; 47.28%), Drake (327,645/959,143; 34.16%), Lil Wayne (323,616/959,143; 33.74%), Mac Miller (277,592/959,143; 28.94%), Nicki Minaj (256,961/959,143; 26.79%), Rihanna (248,927/959,143; 25.95%), and Eminem (234,884/959,143; 24.49%). Twitter median averages for the above recording artists ranged from 7.0% (for Mac Miller, IQR 4.9-8.8%) to 12.6% (for Rihanna, IQR 5.6-24.5%).

**Table 1.** Characteristics of “Weed Tweets @stillblazingtho” tweets, 5/1/2013-12/31/2013.

| Sentiment of tweets[a] | Total tweets | Replies | Tweets excluding replies |
|---|---|---|---|
| | n=2590 | n=305 | n=2285 |
| n (%) | n (%) | | n (%) |
| Positive | 1875 (72.39) | - | 1875 (82.06) |
| Neutral | 403 (15.56) | - | 403 (17.64) |
| Negative | 7 (0.27) | - | 7 (0.31) |

[a]Sentiment of tweets was determined only for regular tweets. Direct replies were excluded because the context of the conversation was difficult to determine without additional information.

**Figure 3.** Age distribution of @stillblazingtho followers and Twitter median average.

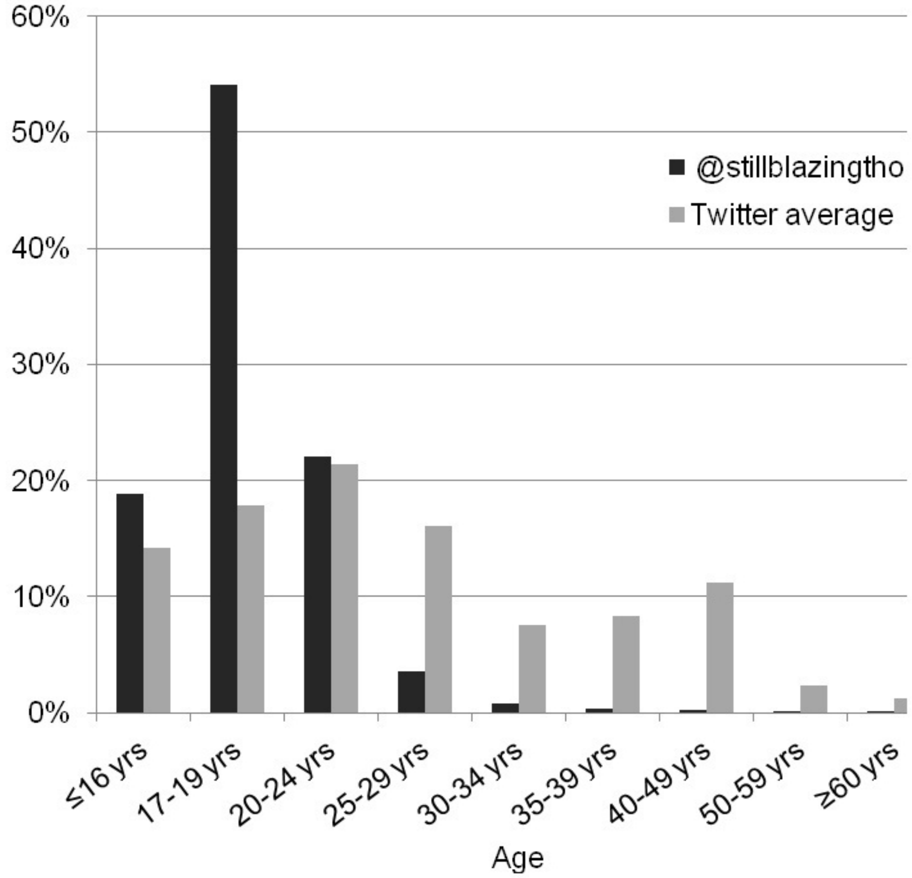
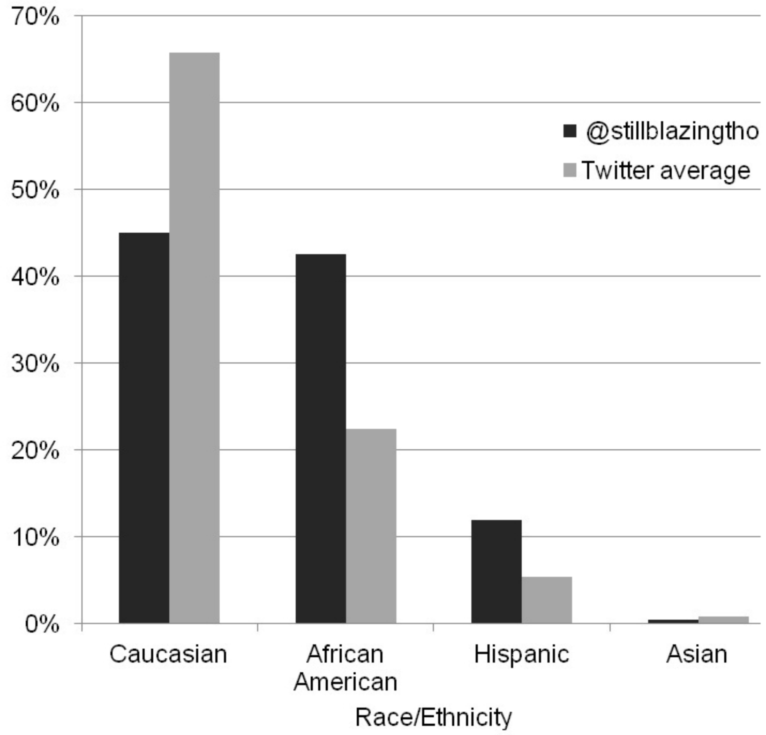



**Figure 4.** Race/ethnicity distribution of @stillblazingtho followers and Twitter median average.



## Discussion

### Principal Findings

The @stillblazingtho is a popular Twitter handle with approximately 1 million followers. This Twitter handle sends an average of 11 tweets per day, the vast majority of which promote marijuana use. Most tweets generated from @stillblazingtho contain humorous content about marijuana use followed by tweets that suggested that marijuana helps you to feel good, relax, or chill. This Twitter handle encourages favorable attitudes toward marijuana by distributing a high number of tweets normalizing the routine use of marijuana and promoting its relaxation effects. It additionally engages followers about pro-marijuana culture by tweeting about such content as marijuana edibles (eg, recipes for brownies) and paraphernalia commonly used to smoke marijuana, like bongs and vaporizers. Tweets that minimize the harmful effects of marijuana use and associate its use with health benefits and/or stronger peer relationships are also distributed by @stillblazingtho. In addition, tweets that encourage the legalization of marijuana are sent by this Twitter handle, but this is done to a lesser degree. While tweets from @stillblazingtho comprised a number of themes and topics, most tweets were alike in their overarching positive sentiment toward marijuana use.

The majority of the followers of @stillblazingtho who are being exposed to this pro-marijuana content are predicted to be under 20 years of age (approximately 73%) and 19% are under 17 years old. The average age at which marijuana use begins in the United States is currently at 17.9 years old [27]; therefore, our results call attention to the majority of Twitter followers of @stillblazingtho who are either approaching or are very near the average age at which marijuana use is first initiated. Moreover, young people are especially responsive to social media influences and often establish substance use patterns during this phase of development [19-21]. Thus, it is of concern that so many youth and young adults are following a Twitter handle that depicts marijuana use as a popular and normal social activity. In addition, past research has found that young Twitter users can become exposed to tweets promoting alcohol use via interactive features such as hashtags on other unrelated sites [45-46]. The extent of hashtags in tweets from @stillblazingtho was relatively low. Nevertheless, the inclusion of general hashtags (non-marijuana related) in any of the tweets sent by this Twitter handle have the potential to reach a much wider audience of youth and young adults beyond the followers that we analyzed in the current study.

Another primary finding of our study is that African American and Hispanic Twitter users disproportionately follow @stillblazingtho versus Caucasians. This finding signals a disparity in exposure to social media promoting marijuana use in that the pro-marijuana tweets delivered by this handle are disproportionately consumed by minority Twitter users. Our findings match concerning differences in marijuana use by race/ethnicity reported in previous studies [47-49]. The frequency of marijuana abuse and dependence among African American adults is about twice the rate of Caucasians and Hispanics [50]. With regard to Hispanics, marijuana abuse and dependence rates are closer to the rates of Caucasians, but the latest reports show that Hispanic youth now have the highest rates of marijuana use versus Caucasians and African Americans [51]. Accordingly, our findings underscore the critical need to improve understanding on how African Americans and Hispanics engage with social media outlets like Twitter in ways that may exacerbate their marijuana use.

The @stillblazingtho followers receive pro-marijuana use content from this Twitter handle and could be receiving similar marijuana-related content from other handles. For instance, many of the @stillblazingtho followers are alike in that they follow the same celebrity Twitter handles. One or more of these celebrities could also be tweeting favorably about recreational marijuana use. To illustrate this point, we provide a sample tweet from Wiz Khalifa who is a recording artist followed by many of @stillblazingtho followers (47.3%). On February 8, 2014, Wiz Khalifa tweeted, “Those who don’t understand the beauty of weed, purchasing weed, rolling and sharing of weed are outsiders and have no business in our world.” This tweet demonstrates the likelihood for pro-marijuana content to be distributed by multiple Twitter handles to a cluster of followers. A study of all the pro-marijuana content that is being consumed by the followers of @stillblazingtho is beyond the scope of this study; nevertheless, it is important for public health professionals to consider all of the tweets and Twitter handles that promote harmful norms toward substance use and are connecting with young people. Prevention efforts can use this information to connect with Twitter users in a strategic and meaningful way. One such strategy would be for public health professionals to consider partnering with a popular celebrity who is willing to tweet health promoting messages about the harms associated with marijuana use. Likewise, many of the followers of @stillblazingtho are students and/or musicians, and have interests in music and basketball. Perhaps, these data could be used to distinguish persons who are at increased risk for marijuana use and/or to identify appropriate settings where marijuana use prevention messages could be delivered (eg, music concerts).

### Limitations

Some limitations should be considered when interpreting the results. First, demographics of followers are not actual reported demographics but rather inferred based on Twitter behavior/usage. However, Demographics Pro uses sophisticated methodology (reported in the Methods section) to make such inferences and requires confidence of 95% or above to make an estimate of a single demographic characteristic [44]. Second, we report on only one of many marijuana-related Twitter handles. Demographics of other specific marijuana-related handles could differ from the one we chose to analyze. Nevertheless, we reported on a very popular marijuana-related Twitter handle, whose followers greatly outnumbered those of other handles. Our study did not examine Twitter marijuana discourse in a general way, where both favorable and unfavorable tweets are considered in analysis. Such a study would entail a data collection and analysis of countless tweets that contain any and all marijuana-related terms, and is beyond the scope of our study. We nevertheless encourage future studies to work toward understanding marijuana-related communication on Twitter utilizing a more general approach where both favorable and unfavorable content is considered. Finally, we have no way of inferring whether followers of @stillblazingtho are themselves marijuana users or are non-marijuana users. Non-marijuana users might be different from marijuana users in their reasons for following @stillblazingtho; it is, therefore, challenging to make broad-stroke conclusions about why the followers of @stillblazingtho have opted to receive tweets from this handle.

### Conclusions

Despite these limitations, our results stress the need for continued research and surveillance on the pro-marijuana content that is currently being delivered via Twitter. We found that youth and young adults as well as minority Twitter users are disproportionately more likely to follow @stillblazingtho, which is a popular Twitter handle that distributes a high number of tweets encouraging favorable attitudes toward marijuana use. Our findings provide a snapshot of the pro-marijuana content that is reaching young people. Twitter use has expanded exponentially, especially among youth and young adults; therefore, an improved understanding of the discourse on Twitter that encourages marijuana use can be helpful for tailoring and targeting online and offline prevention messages.

## Acknowledgments

This publication was made possible by grant numbers UL1 RR024992 and KL2 RR024994 from the National Center for Research Resources (NCRR), a component of the National Institutes of Health (NIH), and NIH Roadmap for Medical Research. Other support includes an NIH Career Development Award awarded to Dr Cavazos-Rehg (NIDA, K01DA025733) and NIDA, R01 DA032843, an NIH Midcareer Investigator Award awarded to Dr Bierut (K02 DA021237), and R01 DA031288 awarded to Dr Grucza.

## Conflicts of Interest

Dr Bierut is listed as an inventor on Issued US Patent 8,080,371,"Markers for Addiction" covering the use of certain single nucleotide polymorphisms (SNPs) in determining the diagnosis, prognosis, and treatment of addiction.

## References

1. Brenner J, Smith A. Pew Research Internet Project. 2013. 72% of online adults are social networking site users URL: http://www.pewinternet.org/2013/08/05/72-of-online-adults-are-social-networking-site-users/ [accessed 2014-06-11] [WebCite Cache ID 6QGDK8hCH]
2. Brenner J. Pew Research Internet Project. 2013. Social networking fact sheet URL: http://www.pewinternet.org/fact-sheets/social-networking-fact-sheet/ [accessed 2014-06-11] [WebCite Cache ID 6QGDMhoxG]
3. Duggan M, Smith A. Pew Research Internet Project. 2013. Social media update URL: http://www.pewinternet.org/2013/12/30/social-media-update-2013/ [accessed 2014-06-11] [WebCite Cache ID 6QGDO5hJf]
4. Buffer. 2013. Social media in 2013: User demographics for Twitter, Facebook, Pinterest and Instagram URL: http://blog.bufferapp.com/social-media-in-2013-user-demographics-for-twitter-facebook-pinterest-and-instagram [accessed 2014-06-11] [WebCite Cache ID 6QGDPWwGn]
5. Edwards J. Business Insider. 2013. Facebook is no longer the most popular social network for teens URL: http://www.businessinsider.com/facebook-and-teen-user-trends-2013-10 [accessed 2014-06-11] [WebCite Cache ID 6QGDR4GkM]
6. Madden M, Lenhart A, Cortesi S, Gasser U, Duggan M, Smith A, et al. Pew Research Internet Project. 2013. Teens, social media, and privacy URL: http://www.pewinternet.org/2013/05/21/teens-social-media-and-privacy/ [accessed 2014-06-11] [WebCite Cache ID 6QGDVLDHk]
7. eMarketer. 2013. India leads worldwide social networking growth URL: http://www.emarketer.com/Article/India-Leads-Worldwide-Social-Networking-Growth/1010396 [accessed 2014-06-11] [WebCite Cache ID 6QGDboeth]
8. Eysenbach G. Infodemiology and infoveillance: framework for an emerging set of public health informatics methods to analyze search, communication and publication behavior on the Internet. J Med Internet Res 2009;11(1):e11 [FREE Full text] [doi: 10.2196/jmir.1157] [Medline: 19329408]
9. Moreno MA, Parks MR, Zimmerman FJ, Brito TE, Christakis DA. Display of health risk behaviors on MySpace by adolescents: prevalence and associations. Arch Pediatr Adolesc Med 2009 Jan;163(1):27-34. [doi: 10.1001/archpediatrics.2008.528] [Medline: 19124700]
10. Morgan EM, Snelson C, Elison-Bowers P. Image and video disclosure of substance use on social media websites. Comput Hum Behav 2010 Nov;26(6):1405-1411.
11. Glassman T. Implications for college students posting pictures of themselves drinking alcohol on Facebook. J Alcohol Drug Educ 2012;56(1):38.
12. Egan KG, Moreno MA. Alcohol references on undergraduate males' Facebook profiles. Am J Mens Health 2011 Sep;5(5):413-420 [FREE Full text] [doi: 10.1177/1557988310394341] [Medline: 21406490]

13. Moreno MA, Christakis DA, Egan KG, Brockman LN, Becker T. Associations between displayed alcohol references on Facebook and problem drinking among college students. Arch Pediatr Adolesc Med 2012 Feb;166(2):157-163 [FREE Full text] [doi: 10.1001/archpediatrics.2011.180] [Medline: 21969360]
14. Moreno MA, Parks M, Richardson LP. What are adolescents showing the world about their health risk behaviors on MySpace? MedGenMed 2007;9(4):9. [Medline: 18311359]
15. Smith A, Brenner J. Pew Research Internet Project. 2012. Twitter use URL: http://www.pewinternet.org/2012/05/31/twitter-use-2012/ [accessed 2014-06-11] [WebCite Cache ID 6QGDjKDkO]
16. Winpenny EM, Marteau TM, Nolte E. Exposure of children and adolescents to alcohol marketing on social media websites. Alcohol Alcohol 2014;49(2):154-159 [FREE Full text] [doi: 10.1093/alcalc/agt174] [Medline: 24293506]
17. Myslín M, Zhu SH, Chapman W, Conway M. Using twitter to examine smoking behavior and perceptions of emerging tobacco products. J Med Internet Res 2013;15(8):e174 [FREE Full text] [doi: 10.2196/jmir.2534] [Medline: 23989137]
18. Hanson CL, Cannon B, Burton S, Giraud-Carrier C. An exploration of social circles and prescription drug abuse through twitter. J Med Internet Res 2013;15(9):e189 [FREE Full text] [doi: 10.2196/jmir.2741] [Medline: 24014109]
19. Chen P, Jacobson KC. Developmental trajectories of substance use from early adolescence to young adulthood: gender and racial/ethnic differences. J Adolesc Health 2012 Feb;50(2):154-163 [FREE Full text] [doi: 10.1016/j.jadohealth.2011.05.013] [Medline: 22265111]
20. Stone AL, Becker LG, Huber AM, Catalano RF. Review of risk and protective factors of substance use and problem use in emerging adulthood. Addict Behav 2012 Jul;37(7):747-775. [doi: 10.1016/j.addbeh.2012.02.014] [Medline: 22445418]
21. Sher KJ, Grekin ER, Williams NA. The development of alcohol use disorders. Annu Rev Clin Psychol 2005;1:493-523. [doi: 10.1146/annurev.clinpsy.1.102803.144107] [Medline: 17716097]
22. Steele JR. Children, teens, families, and mass media: The millennial generation. Journalism Mass Comm 2005;82(1):199-203.
23. Steele JR. Kids and media in America. Journalism Mass Comm 2005;82(1):199-203.
24. Steele JR, Brown JD. Adolescent room culture: Studying media in the context of everyday life. J Youth Adolescence 1995 Oct;24(5):551-576. [doi: 10.1007/BF01537056]
25. Brown JD, Dykers CR, Steele JR, White AB. Teenage room culture: Where media and identities intersect. Communication Research 1994 Dec 01;21(6):813-827. [doi: 10.1177/009365094021006008]
26. Moreno MA, Whitehill JM. New media, old risks: toward an understanding of the relationships between online and offline health behavior. Arch Pediatr Adolesc Med 2012 Sep;166(9):868-869. [doi: 10.1001/archpediatrics.2012.1320] [Medline: 22751783]
27. Results from the 2012 National Survey on Drug Use and Health: Summary of national findings. Rockville, MD: Substance Abuse and Mental Health Services Administration; 2013 Sep. URL: http://www.samhsa.gov/data/NSDUH/2012SummNatFindDetTables/Index.aspx [accessed 2014-06-12] [WebCite Cache ID 6QHHATbXN]
28. Pacula RL, Sevigny EL. Marijuana liberalization policies: Why we can't learn much from policy still in motion. J Pol Anal Manage 2013 Oct 22;33(1):212-221 [FREE Full text] [doi: 10.1002/pam.21726]
29. Johnston LD, O'Malley PM, Bachman JG, Schulenberg JE. Monitoring the future. National results on drug use. Ann Arbor, MI: Institute for Social Research, The University of Michigan; 2012:1-93.
30. Pew Research Center. 2013. Public opinion and marijuana: Shifting attitudes, events and laws URL: http://www.people-press.org/2013/04/04/marijuana-timeline/ [accessed 2014-06-11] [WebCite Cache ID 6QGEAQDZ5]
31. Thompson JW, Koenen MA. Physicians as gatekeepers in the use of medical marijuana. J Am Acad Psychiatry Law 2011;39(4):460-464. [Medline: 22159973]
32. Borgelt LM, Franson KL, Nussbaum AM, Wang GS. The pharmacologic and clinical effects of medical cannabis. Pharmacotherapy 2013 Feb;33(2):195-209. [doi: 10.1002/phar.1187] [Medline: 23386598]
33. Kleber HD, DuPont RL. Physicians and medical marijuana. Am J Psychiatry 2012 Jun;169(6):564-568. [doi: 10.1176/appi.ajp.2012.12030373] [Medline: 22684592]
34. Kondrad E, Reid A. Colorado family physicians' attitudes toward medical marijuana. J Am Board Fam Med 2013 Feb;26(1):52-60 [FREE Full text] [doi: 10.3122/jabfm.2013.01.120089] [Medline: 23288281]
35. Drug Abuse Warning Network, 2011: National estimates of drug-related emergency department visits. Rockville, MD: Substance Abuse and Mental Health Services Administration; 2011. URL: http://www.samhsa.gov/data/2k13/DAWN2k11ED/DAWN2k11ED.htm [accessed 2014-06-12] [WebCite Cache ID 6QHIfhlZU]
36. Hall W, Degenhardt L. Adverse health effects of non-medical cannabis use. The Lancet 2009 Oct 17;374(9698):1383-1391. [doi: 10.1016/S0140-6736(09)61037-0] [Medline: 19837255]
37. Caspi A, Moffitt TE, Cannon M, McClay J, Murray R, Harrington H, et al. Moderation of the effect of adolescent-onset cannabis use on adult psychosis by a functional polymorphism in the catechol-O-methyltransferase gene: longitudinal evidence of a gene X environment interaction. Biol Psychiatry 2005 May 15;57(10):1117-1127. [doi: 10.1016/j.biopsych.2005.01.026] [Medline: 15866551]
38. National Institute on Drug Abuse. Marijuana. 2012. URL: http://www.drugabuse.gov/publications/research-reports/marijuana [accessed 2014-06-11] [WebCite Cache ID 6QGEEqk6E]
39. Schweinsburg AD, Brown SA, Tapert SF. The influence of marijuana use on neurocognitive functioning in adolescents. Curr Drug Abuse Rev 2008 Jan;1(1):99-111 [FREE Full text] [Medline: 19630709]

40. Polen MR, Sidney S, Tekawa IS, Sadler M, Friedman GD. Health care use by frequent marijuana smokers who do not smoke tobacco. West J Med 1993 Jun;158(6):596-601 [FREE Full text] [Medline: 8337854]
41. Simply Measured. URL: http://simplymeasured.com/ [accessed 2014-06-11] [WebCite Cache ID 6QGEINoPq]
42. CrowdFlower. URL: http://www.crowdflower.com/ [accessed 2014-06-11] [WebCite Cache ID 6QGEJc0ur]
43. Kim A, Murphy J, Richards A, Hansen H, Powell R, Haney C. Can tweets replace polls? A U.S. health-care reform case study. In: Hill C , Dean E , Murphy J , editors. Social Media, Sociality, and Survey Research. New Jersey: John Wiley & Sons; 2013:61-86.
44. Demographics Pro. URL: http://www.demographicspro.com/ [accessed 2014-06-11] [WebCite Cache ID 6QGER3DOd]
45. Burton SA, Dadich AM, Soboleva A. Competing voices: Marketing and counter-marketing alcohol on Twitter. Journal of Nonprofit & Public Sector Marketing 2013 Apr;25(2):186-209. [doi: 10.1080/10495142.2013.787836]
46. Dadich AM, Burton SM, Soboleva A. Promotion of alcohol on Twitter. Med J Aust 2013 Sep 2;199(5):327-329. [Medline: 23992187]
47. Anthony JC, Warner LA, Kessler RC. Comparative epidemiology of dependence on tobacco, alcohol, controlled substances, and inhalants: Basic findings from the National Comorbidity Survey. Experimental and Clinical Psychopharmacology 1994;2(3):244-268. [doi: 10.1037/1064-1297.2.3.244]
48. Stinson FS, Grant BF, Dawson DA, Ruan WJ, Huang B, Saha T. Comorbidity between DSM-IV alcohol and specific drug use disorders in the United States: results from the National Epidemiologic Survey on Alcohol and Related Conditions. Drug Alcohol Depend 2005 Oct 1;80(1):105-116. [doi: 10.1016/j.drugalcdep.2005.03.009] [Medline: 16157233]
49. Compton WM, Grant BF, Colliver JD, Glantz MD, Stinson FS. Prevalence of marijuana use disorders in the United States: 1991-1992 and 2001-2002. JAMA 2004 May 5;291(17):2114-2121. [doi: 10.1001/jama.291.17.2114] [Medline: 15126440]
50. Pacek LR, Malcolm RJ, Martins SS. Race/ethnicity differences between alcohol, marijuana, and co-occurring alcohol and marijuana use disorders and their association with public health and social problems using a national sample. Am J Addict 2012;21(5):435-444 [FREE Full text] [doi: 10.1111/j.1521-0391.2012.00249.x] [Medline: 22882394]
51. Johnston LD, O'Malley PM, Bachman JG, Schulenberg JE. Demographic subgroup trends among adolescents for forty-six classes of licit and illicit drugs (Monitoring the Future Occasional Paper No. 79). Ann Arbor, MI: Institute for Social Research; 2013. URL: http://www.monitoringthefuture.org/pubs/occpapers/mtf-occ79.pdf [accessed 2014-06-12] [WebCite Cache ID 6QHKbS39k]

## Abbreviations

**IQR:** inter-quartile range
**MPM:** Media Practice Model

*Edited by G Eysenbach; submitted 15.01.14; peer-reviewed by M Conway, S Burton, C Hanson, T Hernández; comments to author 11.02.14; revised version received 16.03.14; accepted 28.04.14; published 27.06.14.*

*Please cite as:*
*Cavazos-Rehg P, Krauss M, Grucza R, Bierut L*
*Characterizing the Followers and Tweets of a Marijuana-Focused Twitter Handle*
*J Med Internet Res 2014;16(6):e157*
*URL: http://www.jmir.org/2014/6/e157/*
*doi:10.2196/jmir.3247*
*PMID:24974893*

Original Paper

# Assessment of the Cost-Effectiveness and Clinical Outcomes of a Fourth-Generation Synchronous Telehealth Program for the Management of Chronic Cardiovascular Disease

Yi-Lwun Ho[1,2], MD, PhD; Jiun-Yu Yu[3], PhD; Yen-Hung Lin[2], MD, PhD; Ying-Hsien Chen[1,2], MD; Ching-Chang Huang[1,2], MD; Tse-Pin Hsu[1,4], MSN; Pao-Yu Chuang[1,4], MSN; Chi-Sheng Hung[1,2], MD; Ming-Fong Chen[1,2], MD, PhD

[1]Telehealth Center, National Taiwan University Hospital, Taipei, Taiwan

[2]Department of Internal Medicine, National Taiwan University Hospital, Taipei, Taiwan

[3]National Taiwan University, Taipei, Taiwan

[4]Department of Nursing, National Taiwan University Hospital, Taipei, Taiwan

**Corresponding Author:**
Chi-Sheng Hung, MD
Telehealth Center
National Taiwan University Hospital
No 7, Chung-Shan S Road,
Taipei, 100
Taiwan
Phone: 886 972651696
Fax: 886 227044688
Email: petrehcs@gmail.com

## Abstract

**Background:** Telehealth programs are a growing field in the care of patients. The evolution of information technology has resulted in telehealth becoming a fourth-generation synchronous program. However, long-term outcomes and cost-effectiveness analysis of fourth-generation telehealth programs have not been reported in patients with chronic cardiovascular diseases.

**Objective:** We conducted this study to assess the clinical outcomes and cost-effectiveness of a fourth-generation synchronous telehealth program for patients with chronic cardiovascular diseases.

**Methods:** We retrospectively analyzed 575 patients who had joined a telehealth program and compared them with 1178 patients matched for sex, age, and Charlson comorbidity index. The program included: (1) instant transmission of biometric data, (2) daily telephone interview, and (3) continuous decision-making support. Data on hospitalization, emergency department (ED) visits, and medical costs were collected from the hospital's database and were adjusted to the follow-up months.

**Results:** The mean age was 64.5 years (SD 16.0). The mean number of monthly ED visits (mean 0.06 SD 0.13 vs mean 0.09 SD 0.23, $P$<.001), hospitalizations (mean 0.05 SD 0.12 vs mean 0.11 SD 0.21, $P$<.001), length of hospitalization (mean 0.77 days SD 2.78 vs mean 1.4 SD 3.6, $P$<.001), and intensive care unit admissions (mean 0.01 SD 0.07 vs mean 0.036 SD 0.14, $P$<.001) were lower in the telehealth group. The monthly mean costs of ED visits (mean US$20.90 SD 66.60 vs mean US$37.30 SD 126.20, $P$<.001), hospitalizations (mean US$386.30 SD 1424.30 vs mean US$878.20 SD 2697.20, $P$<.001), and all medical costs (mean US$587.60 SD 1497.80 vs mean US$1163.60 SD 3036.60, $P$<.001) were lower in the telehealth group. The intervention costs per patient were US$224.80 per month. Multivariate analyses revealed that age, telehealth care, and Charlson index were the independent factors for ED visits, hospitalizations, and length of hospitalization. A bootstrap method revealed the dominant cost-effectiveness of telehealth care over usual care.

**Conclusions:** Better cost-effectiveness and clinical outcomes were noted with the use of a fourth-generation synchronous telehealth program in patients with chronic cardiovascular diseases. The intervention costs of this new generation of telehealth program do not increase the total costs for patient care.

***(J Med Internet Res 2014;16(6):e145)*** doi:10.2196/jmir.3346

**KEYWORDS**

cardiovascular disease; cost-benefit analysis; telehealth

## Introduction

Cardiovascular disease (CVD), one of the main chronic diseases, is the leading cause of death and disability worldwide [1]. Chronic CVD is characterized by a high rate of co-morbidities and a high risk for acute deterioration [2], both of which contribute to adverse clinical outcomes and economic burden on society. Hospitalization due to acute deterioration represents the main cost component of CVD care [3]. To reduce hospitalization and improve long-term care for CVD, disease management programs, defined as multidisciplinary approaches that coordinate care strategies to manage patients with chronic disease, have been applied to patients with chronic CVD [4,5]. Despite the beneficial results, disease management programs are limited by their high cost and modest efficiency.

Recently, advances in telemonitoring devices have improved the efficiency and reduced the labor costs of disease management programs. With the help of remote telemonitoring, biometric parameters can be monitored closely and acute episodes of deterioration can be detected early, both of which make timely interventions possible. Telehealth programs, which incorporate telemonitoring and disease management programs, have been shown to improve the results of long-term care in patients with chronic diseases including heart failure, chronic respiratory disease, and diabetes [6-10]. However, not all studies on telehealth programs revealed beneficial results. A recent randomized controlled trial of a telehealth program, which used a non-immediate data analysis system, failed to reduce hospitalizations in elderly patients with chronic diseases (hospitalization and emergency department [ED] visits: telemonitoring group 63.7% vs usual care group 57.3%, $P$=.35) [11]. Patients enrolled in this study were elderly with a mean age of 80.3 years and at high risk for rehospitalization. Another study on a telehealth program among patients with chronic illness including heart failure, diabetes, or chronic obstructive pulmonary disease in the United Kingdom also revealed unfavorable results. The cost-effectiveness study of this telehealth program revealed a slightly higher total cost in the telehealth group (telehealth group, £1596.10 vs usual care group, £1389.70, $P$>.05) but relatively high costs per quality adjusted life year (QALY) gain (£92,000, n=969), and concluded that the telehealth program was not cost effective [12]. A review article published recently also argues that evidence for the benefit of telehealth programs in managing chronic diseases is inadequate and contradictory [13]. These contrasting results raise a serious concern about the use of telehealth programs in the management of patients with chronic CVD.

One possible explanation to these contrasting results is the difference in the level of care provided by telehealth programs. Based on the level of data analysis, decision ability, and integration of care, Anker and coworkers classified telehealth programs into four generations: (1) non-reactive data collection programs, (2) programs with non-immediate analytical structure, (3) remote patient management programs, and (4) fully integrated remote management programs [14]. According to this classification, the fourth-generation telehealth program provides the highest level of patient care: round-the-clock presence of a physician and nursing staff to analyze and respond “synchronously” to the data transferred from patients. It is probable that the different levels of monitoring, staff, and response provided by these four generations of telehealth program contribute directly to the aforementioned contrasting results in the literature. However, the clinical benefit of the fourth-generation telehealth program has not been validated.

Based on these reasons, we hypothesized that a fourth-generation telehealth program would be effective in patients with chronic CVD. To test this hypothesis, we first reported reductions in costs and hospitalization rates for patients with chronic CVD 6 months after vs before receiving a fourth-generation telehealth program in a quasi-experiment study [15]. We then conducted this retrospective cohort study to elucidate whether the patients with chronic CVD who received the fourth-generation telehealth program may have better clinical outcomes and cost-effectiveness compared with those who received standard care in a longer follow-up period.

## Methods

### Study Design

This was a single center, retrospective study, and was approved by the Institutional Review Board at National Taiwan University Hospital, Taipei, Taiwan.

### Recruitment

The study was conducted from December 2009 to April 2013 at the Telehealth Center of the hospital, and was conducted by the Taiwan ELEctroHEALTH study group (TELEHEALTH study group). Patients aged 20 years or over receiving the telehealth program at our telehealth center were enrolled as the case group. The control group included subjects who visited our cardiovascular center during the same period but did not participate in the telehealth care program (received usual care only), and were matched for age, gender, and Charlson comorbidity index. Data on sex, gender, and diagnosis were obtained from the electronic database of our center. There were 7742 patients who visited our cardiovascular center during this period. After matching age, gender, and Charlson comorbidity index, 604 case patients and 1208 controls were selected. Follow-up data and medical costs of these subjects were then obtained from the electronic database. After excluding subjects with incomplete follow-up and cost data, a total of 576 cases and 1178 controls were finally enrolled in this study.

### Telehealth Care Program

The fourth-generation telehealth program at our telehealth center is a synchronized, structured, and integrated remote management program of chronic diseases [15]; it is an Internet-based system. Briefly, this telehealth program provided four major components. The first component was real-time transmission of biometric data from the patients to the telehealth center. The biometric data included single-lead electrocardiography, blood pressure, heart rate, oximetry, and glucometry (in patients with diabetes and those with impaired fasting glucose and impaired glucose tolerance). These biometric data were transmitted via the Internet and stored in the electronic health record system at our hospital. The data was processed immediately after transmission by the nurse case manager. Second, there were daily and on-demand telephone interviews between the telehealth care team and the patients for communication and health promotion. Third, full-time nurse case managers and cardiologists were in charge of care 24 hours a day. The nurse case managers reviewed the clinical and biometric data immediately and were empowered to adjust the dosage of medications or to stop a medication with potentially harmful side effects after consulting physicians. A screenshot of our telehealth platform is shown in Figure 1. The clinical information was relayed to the cardiology specialist who made the final judgment and suggestions regarding care. Fourth, the long-term medication and monitoring plan were discussed with the patients' primary care physician after acute episodes. This telehealth program bridged between institute care and home care on an individualized approach, emphasized the prevention and early detection of clinical deterioration, and then managed the patient at the outpatient department (OPD) or emergency department (ED), rather than by hospitalization. The service and characteristics of this telehealth program did not change during the study period. All clinical information and biometric data were provided to the primary care physician at the regular OPD visit. Additional visits to the OPD were encouraged if adjustments to medications were frequently required or if inadequate control of symptoms was noted by the nurse case manager. An ED visit was suggested if acute deterioration of a chronic condition was suspected. The clinical information was relayed to the ED before the patient arrived at the ED. The decision to hospitalize was determined by primary care physicians and/or ED physicians.

**Figure 1.** Screenshot of telehealth platform. All biometric and clinical data of patients receiving telehealth care can be assessed from this Internet-based database. Abnormal value marked in red.


## Usual Care

Patients in the control group received usual care provided by the cardiovascular center according to updated guidelines, including, but not limited to, the American Heart Association's guidelines on lifestyle management to reduce cardiovascular risk, guidelines for the management of stable ischemic heart disease, and the American Diabetes Association's guidelines for the management of diabetes. Patients in the control group received routine OPD visits to primary care physicians. ED visits were determined by patients and/or caregivers. The decisions for hospitalization were determined by primary care physicians and/or ED physicians. There was no contact between telehealth center and patients receiving usual care.

## Data Collection

All of the demographic, hospitalization, and payment data were collected from the electronic database of the hospital. The diagnosis of chronic diseases was also based on the electronic database. A discharge diagnosis was recorded if the outpatient and discharge diagnoses were different.

## Outcomes

The primary outcomes were hospitalization, length of hospitalization, and ED visits adjusted by the follow-up period (month). Data on hospitalization, length of stay, and ED visits were collected using an administrative billing system.

## Costs

### Medical Costs

Taiwan launched a single-payer National Health Insurance program in 1995, which covers most of the medical costs from primary care to hospitalization. This study used a third-party payer perspective and included only direct medical costs in the cost analysis, including: medication, pharmacological service, examinations, diagnostic tests, physician visits, operations, anesthesia, blood product, ward, nursing, and specialized equipment during visits to the OPD and ED, and hospitalization. Self-paid medical costs (not covered by National Health Insurance program) were also included. Costs were adjusted to the US$ average exchange rate for 2012.

### Telehealth Care Program Costs (Intervention Costs)

The total intervention costs of the telehealth care program included direct costs (in-house staff costs, contract costs, and fees to other organizations) and indirect costs (marketing, business development, and administrative costs). The costs for the telehealth equipment were included in the fees to other organizations. The intervention cost per patient-month was calculated by the total intervention costs in 2011 and 2012 divided by the active participants and duration (months).

### Total Costs

The total costs were defined as the sum of medical costs and intervention costs in the telehealth group; the total costs were the same as medical costs in the control group.

## Cost-Effectiveness

Cost-effectiveness was evaluated by the cost saved for each hospitalization that was avoided and the cost per hospitalization day that was avoided. Uncertainty was calculated by the bootstrap method and plotted in a cost-effectiveness plane.

## Statistical Analysis

Discrete data are expressed as count and percentages. Continuous data are presented as mean and standard deviation (SD) or median and interquartile range (IQR) for data with normal or skewed distribution, respectively. The chi-square test was used to compare categorical data. The Student's *t* test or Mann-Whitney test was applied to compare continuous unpaired data with normal or skewed distribution, respectively. A Wilcoxon rank-sum test was applied to compare the outcome data and costs, which were not normally distributed.

Linear regression models for the number of ED visits, hospitalizations, hospitalization days, and number of intensive care unit admissions were developed with age, sex, participation in the telehealth care program, and Charlson comorbidity index as the independent variables. To evaluate the variables that were significantly associated with cost, a two-part gamma model was adapted. First, logistic regression analysis was performed to evaluate the probability of the cost of the clinical factors being greater than zero. The significant variables were then entered into the second part, for which we use a generalized linear model (GLM) with gamma distribution and logarithmic link function to evaluate the variables in the patients with costs larger than zero.

The time to first ED visit or hospitalization-free survival was estimated according to the Kaplan-Meier method. The effect of participation in the telehealth program was estimated using a Cox proportional hazards model. Repeat hospitalizations were examined using Cox regression analysis for recurrent events, accounting for the possibility of multiple readmissions occurring over the follow-up period.

Cost-effectiveness was measured by:

$(\text{cost}_{\text{case}}-\text{cost}_{\text{control}}) / (\text{effect}_{\text{case}}-\text{effect}_{\text{control}})$

The incremental cost-effectiveness ratio (ICER) provided the payments per hospital episode averted or per hospital day averted. Non-parametric bootstraps were used to simulate 5000 ICERs that were plotted on a cost-effectiveness plane. Each simulated ICER fell into one of the four quadrants of the ICER plane (increased or decreased cost vs better or worse health result). Strong dominance applied when the telehealth program was both more effective and less costly than usual care.

Because there was difference in the follow-up duration in two study groups, we performed sensitivity analyses by different follow-up durations. We repeated the analyses for the comparisons of clinical events, Cox regression for time-to-first admission free survival, comparisons of medical costs, and cost-effective plane by the different follow-up durations (<3 months, <6 months, <1 year, <2 years, 3 months-1year, 1-2 years, and without adjustment for duration).

A *P* value of less than .05 was considered to be statistically significant. Stata/SE 11.0 for Windows (StataCorp LP, College Station, TX, USA) was used for all statistical analyses.

# Results

## Descriptive Statistics

A total of 1754 patients (576 in the telehealth group and 1178 in the control group) were enrolled in this study. The average age was 64.5 (SD 16.0) years; 61.17% (1073/1754) of the subjects were male. The diagnosis of chronic CVD included hypertension (79.99%, 1403/1754), heart failure (16.99%, 298/1754), stroke (10.32%, 181/1754), myocardial infarction (7.13%, 125/1754), and peripheral artery diseases (5.19%, 91/1754). The mean Charlson comorbidity index was 1.26 (IQR 0-2). At baseline, age, sex, and Charlson comorbidity index were matched between the two groups (Table 1). There were slightly more patients with heart failure, stroke, dementia, chronic obstructive pulmonary disease, diabetes, and peptic ulcer disease in the telehealth group (Table 1). There was no difference in hemoglobin A1c level between two study groups. There was no difference in the duration of education between two study groups. The median follow-up time was 694 days (IQR 338-1163). The follow-up time in the control group (879 days, IQR 334-1190) was longer than that in the telehealth group (572 days, IQR 349-809). Because of the different follow-up times, the costs and events were divided by the follow-up time (months) in the subsequent analysis.

**Table 1.** Baseline characteristics.

| Characteristic | Cases | Controls | *P* value |
|---|---|---|---|
| Patients, n | 576 | 1178 | |
| Age, year, mean (SD) | 64.6 (16.3) | 64.5 (16.1) | .8 |
| Sex (male), n (%) | 356 (61.81%) | 717 (60.87%) | .7 |
| Systolic blood pressure, mmHg, mean (SD) | 124.3 (20) | 123.3 (27) | .5 |
| Diastolic blood pressure, mmHg, mean (SD) | 70.4 (12.6) | 70.6 (16.4) | .8 |
| **Comorbidity** | | | |
| Charlson comorbidity index | 1.35 (1.65) | 1.21 (1.52) | .07 |
| Myocardial infarction, n (%) | 44 (7.64%) | 81 (6.88%) | .5 |
| Heart failure, n (%) | 112 (19.44%) | 186 (15.79%) | .05 |
| Peripheral artery disease, n (%) | 61 (10.59%) | 30 (2.55%) | .9 |
| Stroke, n (%) | 71 (12.33%) | 110 (9.34%) | .05 |
| Dementia, n (%) | 13 (2.26%) | 10 (0.85%) | .01 |
| Chronic obstructive pulmonary disease, n (%) | 49 (8.51%) | 67 (5.69%) | .02 |
| Diabetes, n (%) | 165 (28.65%) | 273 (23.17%) | .01 |
| Peptic ulcer disease, n (%) | 28 (4.86%) | 34 (2.89%) | .03 |
| Chronic kidney disease, n (%) | 57 (9.90%) | 117 (9.93%) | .9 |
| Chronic liver disease, n (%) | 15 (2.60%) | 26 (2.21%) | .6 |
| Malignancy, n (%) | 44 (7.64%) | 120 (10.19%) | .08 |
| **Hemoglobin A1c, %, mean (SD)** | | | |
| Overall | 6.6 (1.4) | 6.7 (1.5) | .15 |
| With diabetes | 7.2 (1.6) | 4.7 (1.5) | .33 |
| With ICU[a] admission | 6.8 (1.5) | 6.9 (1.7) | .65 |
| **Duration of education, n (%)** [b] | | | .09 |
| <9 years | 102 (31.58%) | 259 (47.01%) | |
| 9-16 years | 200 (61.92%) | 266 (48.28%) | |
| >16 years | 21 (6.50%) | 26 (4.72%) | |
| **Medications, n (%)** | | | |
| Anti-hypertension | 475 (82.47%) | 932 (79.11%) | .1 |
| Oral-anti-diabetes | 93 (16.15%) | 157 (13.33%) | .1 |
| Insulin | 47 (8.16%) | 47 (3.99%) | <.001 |
| Statin | 74 (12.85%) | 120 (10.19%) | .1 |
| Aspirin | 117 (20.31%) | 249 (21.14%) | .7 |
| Clopidogrel | 128 (22.22%) | 238 (20.20%) | .3 |

[a]ICU: intensive care unit.

[b]Not all patients provided their education information—data was obtained for 874 participants (323 in the telehealth program and 551 in the control group).

## Outcomes

There were significantly fewer ED visits, hospitalizations, hospitalization days, and intensive care unit admissions per month in the telehealth group compared to the control group (Table 2). The hospitalization-free survival was significantly longer in the telehealth group (*P*=.01, log-rank test). In the Cox regression analysis, age (hazard ratio [HR] 1.01, *P*<.001), telehealth (HR 0.76, *P*=.001), and Charlson comorbidity index (HR 1.23, *P*<.001) were independent predictors for re-hospitalization (Table 3). The ED visit-free survival was not significantly longer in the telehealth group (*P*=.08, log-rank test). In the Cox regression analysis, only age (HR 1.01, *P*<.001) and Charlson comorbidity index (HR 1.3, *P*<.001) were independent predictors for an ED visit. Repeated events Cox regression analysis also demonstrated significantly longer hospitalization-free survival for the telehealth group. Age (HR 1.01, *P*=.013), telehealth (HR 0.5, *P*=.001), and Charlson comorbidity index (HR 1.41, *P*<.001) were independent predictors for repeated hospitalizations (Table 3).

**Table 2.** Clinical events, adjusted by follow-up months.

| Events | Cases (n=576) mean (SD) | Controls (n=1178) | *P* value |
|---|---|---|---|
| Follow-up months | 20.4 (11.4) | 25.8 (14.5) | <.001 |
| ED[a] visits | 0.06 (0.13) | 0.09 (0.23) | <.001 |
| Hospitalizations | 0.05 (0.12) | 0.11 (0.21) | <.001 |
| Hospitalization days | 0.77 (2.78) | 1.4 (3.6) | <.001 |
| ICU[b] admissions | 0.01 (0.07) | 0.04 (0.14) | <.001 |
| OPD[c] visits | 1.57 (1.12) | 1.66 (1.78) | .75 |

[a]ED: emergency department

[b]ICU: intensive care unit

[c]OPD: outpatient department

**Table 3.** Multivariate Cox regression analysis for event-free survival.

| | Time to first hospitalization | | Time to first emergency department visit | | Hospitalization, multiple event | |
|---|---|---|---|---|---|---|
| | Hazard ratio | *P* | Hazard ratio | *P* | Hazard ratio | *P* |
| Age | 1.01 (1.01-1.02) | <.001 | 1.01 (1.0-1.01) | <.001 | 1.01 (1.0-1.02) | .013 |
| Sex | 1.11 (0.97-1.29) | .13 | 1.01 (0.86-1.19) | .9 | 0.94 (0.69-1.29) | .71 |
| Telehealth | 0.76 (0.65-0.89) | .001 | 1.11 (0.94-1.35) | .19 | 0.5 (0.34-0.74) | .001 |
| Charlson comorbidity index | 1.23 (1.19-1.28) | <.001 | 1.3 (1.25-1.35) | <.001 | 1.41 (1.32-1.52) | <.001 |

## Costs

The monthly intervention costs in the telehealth group were US$224.80 per patient (Table 4). The personnel costs comprised 77.97% (27,348.50/35,075.50) of the intervention costs. The average medical costs were US$587.60 (SD 1497.80) per month in the telehealth group and US$1163.60 (SD 3036.60) per month in the control group (*P*=.02; Table 5). Generalized linear model (GLM) analysis revealed that telehealth (OR 0.4, 95% CI 0.32-0.55, *P*<.001), heart failure (OR 1.56, 95% CI 1.11-2.19, *P*=.001), and cancer (OR 1.86, 95% CI 1.23-2.8, *P*<.001) were significantly associated with the total costs (all medical + intervention costs; Table 6). Hospitalization costs accounted for the largest portion of the total costs and were significantly higher in the control group (mean US$878.20 SD 2697.20 per month) compared with the telehealth group (mean US$386.30 SD 1424.30 per month; Table 5). GLM analysis also revealed that only telehealth (OR 0.67, 95% CI 0.46-0.95, *P*=.009) was significantly associated with the hospitalization costs (Table 6). The OPD costs were also higher in the control group (mean US$248.20 SD 984.60 per month) compared with the telehealth group (mean US$180.40 SD 248.20 per month; Table 5). GLM analysis further revealed that age (OR 1.01, 95% CI 1.0-1.01, *P*=.01), telehealth (OR 0.72, 95% CI 0.57-0.9, *P*=.05), heart failure (OR 1.61, 95% CI 1.2-2.17, *P*=.002), and liver cirrhosis (OR 4, 95% CI 2.0-8.1, *P*<.001) were significantly associated with the OPD costs. The ED costs were higher in the control group (mean US$20.90 SD 66.60 per month) compared with the telehealth group (mean US$37.30 SD 126.20 per month; Table 5). GLM analysis revealed that age (OR 1.02, 95% CI 1.01-1.03, *P*<.001), heart failure (OR 1.47, 95% CI 1.01-2.12, *P*=.05), and cancer (OR 2.3, 95% CI 1.48-3.6, *P*<.001) were significantly associated with the ED cost.

**Table 4.** Intervention cost (2011-2012).

| Cost category | Amount (US$/month) |
|---|---|
| In-house staff | $27,348.50 |
| Contract costs/Fees to other organizations | $5213.70 |
| Total direct costs | $32,562.20 |
| Marketing and business development | $15.50 |
| Selling, general and administrative | $2451.20 |
| Other expenses | $46.70 |
| Total intervention cost | $35,075.50 |
| Total intervention cost per patient | $224.80 |

**Table 5.** Medical cost (US$ per patient/month).

| Medical costs | | Case mean (SD) | Control mean (SD) | *P* value |
|---|---|---|---|---|
| **By clinical setting** | | | | |
| | Emergency department costs | $20.90 (66.60) | $37.30 (126.20) | <.001 |
| | Hospitalization costs | $386.30 (1424.30) | $878.20 (2697.20) | <.001 |
| | Outpatient clinic visit costs | $180.40 (278.60) | $248.20 (984.60) | .06 |
| | Total medical costs | $587.60 (1497.80) | $1163.60 (3036.60) | <.001 |
| | Total health care costs | $812.40 (1497.80) | $1163.00 (3036.60) | <.001 |
| **By items** | | | | |
| | Laboratory examinations | $66.10 (171.10) | $120.2 (270.90) | <.001 |
| | Imaging | $20.00 (56.20) | $56.40 (150.10) | <.001 |
| | Medication | $130.00 (304.00) | $226.60 (864.50) | .009 |
| | Other treatment and management | $56.10 (286.60) | $81.30 (315.00) | .11 |
| | Physician visit | $16.10 (65.20) | $26.40 (69.40) | .003 |
| | Nursing | $42.60 (224.30) | $69.40 (244.60) | .03 |
| | General ward | $51.90 (240.00) | $59.70 (212.40) | .49 |
| | ICU[a] ward | $19.20 (135.70) | $30.30 (146.10) | .13 |

[a]ICU: intensive care unit.

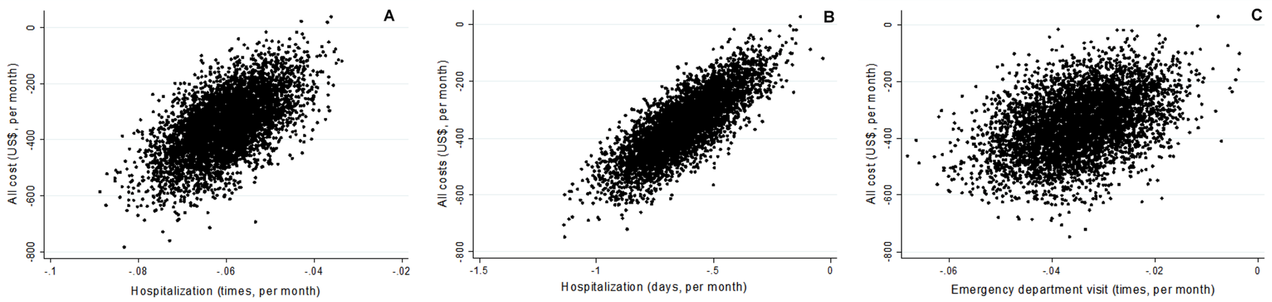
**Table 6.** Generalized linear models for costs.

| Costs/Factors | Outpatient department | | Emergency department | | Hospitalization | | Total (medical + intervention) | |
|---|---|---|---|---|---|---|---|---|
| | OR | *P* | OR | *P* | OR | *P* | OR | *P* |
| Age | 1.01 (1.0-1.01) | .01 | 1.02 (1.01-1.03) | <.001 | 1.00 (0.99-1.01) | .33 | 1.0 (0.99-1.01) | .7 |
| Telehealth | 0.72 (0.57-0.9) | .05 | 0.72 (0.51-1.01) | .06 | 0.67 (0.46-0.95) | .009 | 0.4 (0.32-0.55) | <.001 |
| Heart failure | 1.61 (1.2-2.17) | .002 | 1.47 (1.01-2.12) | .05 | - | - | 1.56 (1.11-2.19) | .009 |
| Diabetes | 1.32 (1.02-1.7) | .03 | - | - | - | - | | |
| Liver cirrhosis | 4.0 (2.0-8.1) | <.001 | - | - | - | - | - | - |
| Cancer | - | - | 2.3 (1.48-3.6) | <.001 | 1.48 (0.97-2.28) | .07 | 1.86 (1.23-2.8) | .003 |

## Cost-Effectiveness

Figure 2 shows the 5000 bootstrapped replicates of incremental costs versus hospitalizations, hospitalization days averted, and ED visits averted on a cost-effectiveness plane. Because of the different follow-up times, the cost, number of hospitalizations, and hospitalization days were divided by the follow-up months. In this bootstrap analysis, 99.9% of the 5000 replicates were in the cost-saving quadrant in all three analyses, which indicated that the telehealth program was a dominant strategy.

**Figure 2.** Cost-effectiveness planes for hospitalization times, hospitalization days, and emergency department visits averted.




### Sensitivity Analyses

The sensitivity analyses by different follow-up durations revealed consistent results. There were no differences in age, sex, and Charlson comorbidity score in the two study groups by different follow-up durations. The clinical events were significantly less in the telehealth group over different follow-up durations. In the Cox regression analyses for time to first admission-free survival, the telehealth was a significant protective factor over different follow-up durations. The total medical costs were significantly lower in the telehealth group over different follow-up durations. In the cost-effectiveness analyses, the 1000-times bootstrap revealed that telehealth was a cost-saving strategy (99.9% of the simulations were in the cost-saving quadrant over different follow-up durations, except for the duration of 1-2 years where 96.6% of the simulations were in the cost-saving quadrant).

## Discussion

### Principal Results

The results of the current study revealed that our fourth-generation telehealth program was associated with lower total costs, lower rate of hospitalizations, and shorter hospitalization length of stay in patients with chronic CVD during the 2-year follow-up period. The total costs of US$811 per month (medical costs: US$587, intervention costs: US$224) in the telehealth group were less than the total costs of US$1163 (medical costs only) per month in the control group. In multivariate analyses, the telehealth program was an independent predictor for a longer time to first hospitalization and repeated hospitalization-free survival. In the GLM analysis, the telehealth program was independently associated with fewer OPD visits and lower hospitalization medical costs and total health care costs (medical + intervention cost). Sensitivity analysis revealed that the telehealth program was a cost-saving strategy from the health care system perspective.

This cost-saving conclusion was consistent over different endpoints, including hospitalization times and durations. Our intervention costs at US$224.80 per month (or US$2697 per year) were reasonable compared to those reported in two recent telehealth studies: US$3010 per year in a UK study and US$2177 per year in a US study [11,12]. Our synchronous telehealth program adopted a strategy to manage patients in OPD or ED without delay to avoid hospitalization, if an acute event was detected. This strategy showed a 38% reduction in hospitalizations without significant increase in OPD or ED visits in the telehealth group (Table 2). The non-significantly less ED visit-free survival in the telehealth group (Figure 1B) did not translate into higher costs or more hospitalizations. Based on these advantages in costs and event reduction, our telehealth program was demonstrated to be cost-effective.

### Comparison With Prior Work

Until now, research on telehealth programs in chronic diseases management has had mixed results [13,16]. Telehealth care has been shown to reduce hospitalizations in patients with chronic conditions such as asthma [6], chronic obstructive pulmonary disease [7], and heart failure [8,9]. Data also shows that telehealth care can achieve better blood pressure [17,18] and glycemic control [19]. Two large randomized controlled trials published recently, however, questioned the benefits and cost-effectiveness of telemedicine in patients with chronic diseases [11,12]. The first trial enrolled 205 elderly adults aged 60 years or above, with multiple illnesses and a higher risk of hospitalization [11]. Half of the participants (51.2%) had chronic CVD. The results showed a neutral effect of asynchronous telemonitoring on the composite endpoint of hospitalization and ED visits in 12 months (63.7% vs 57.3%, *P*=.35). A higher mortality rate was reported in the telemonitoring group compared to the control group unexpectedly (14.7% vs 3.9%, *P*=.008). Although the study was carefully designed and conducted, only 40% of the subjects screened were enrolled in the trial. This low rate of enrollment may limit its generalizability. Another factor that may limit its generalizability is the asynchronous telemonitoring used in this trial.

The second randomized controlled trial (Whole System Demonstrator trial [WSD]) enrolled 3230 people with heart failure (37.8%), chronic obstructive pulmonary disease (33.5%), or diabetes (28.7%) in the United Kingdom. The results showed the hospitalization rate (OR 0.85, *P*=.017), length of hospital stay, and mortality (4.6% vs 8.3%, *P*<.001) were reduced in the telehealth group [20]. These reductions in hospitalization and length of hospital stay in the telehealth group were similar to our results. A cost-effectiveness analysis of this trial included 965 of the original 3230 subjects, among them 36.4% had heart failure. The result derived an ICER of £92,000 per QALY gained. This value was considered not to be cost-effective compared with the current threshold of willingness to pay [12]. The medical costs in the telehealth group were lower than those in the usual care group (not including the intervention costs). This indicates that the cost of intervention is the major determinant for the cost-effectiveness of a telehealth care program. The intervention costs in our study were lower than those in the WSD trial. This difference in intervention costs may account for the difference in cost-effectiveness between our study and the WSD trial.

The causes of these inconsistent results between different trials are not totally clear. Our data provide three potential implications for the causes. First, our data imply that the level of care provided by a telehealth program affects its efficacy. Different telehealth programs should not be compared directly without analyzing their basic structure. An effective telehealth program relies on the premise that routinely monitoring biometrics and symptoms will facilitate early detection of clinical deterioration and trigger timely intervention [21]. To achieve this goal, our fourth-generation telehealth program has the ability to detect deterioration early by synchronous data analyses and to initiate timely intervention by round-the-clock presence of a physician. Our telehealth program implemented an electronic platform to integrate all the biometrics measured and to notify the nurse case managers immediately if abnormal values were received. The nurse case managers could respond more rapidly to abnormal biometric values, compared with the stored-and-forward system used in other trials [11,22]. The nurse case managers were trained to deliberately seek and track the symptoms and signs of early deterioration during the daily telephone interview. This strategy may detect early deterioration more efficiently in patients with a wide range of comorbidities, compared with the patients answering predetermined screening questions to automated systems used in other trials [11,22]. Prior research has shown that the benefit of a telehealth program in patients with heart failure can be lost after changing from a small-scale, nurse case manager-led program to a large-scale, automated monitoring system without one-to-one telephone interviews [22,23]. These results highlight the role of nurse case managers in a telehealth program. The round-the-clock presence of a physician for therapeutic decisions and the synchronous type of telehealth program adopted in our study were not formally tested in other trials. Although we did not directly compare our telehealth program with an earlier generation, our data imply that level of care provided by a telehealth program makes a difference in efficacy. Future research on telehealth programs should clearly address the level of care provided by the program. We suggest a synchronous telehealth program should be considered in a population with multiple comorbidities and high risk for acute deterioration, as the program implemented in our study.

The second implication of our data is that the composition of the total health care costs is crucial to the balance of cost-effectiveness in a telehealth program. The intervention costs accounted for 27% of the total cost in the telehealth group in our study; the personnel cost accounted for 78% of the intervention costs. This result indicates that one-fifth of the total health care cost of the patients receiving our telehealth program will pay for the personnel costs. The personnel costs may not change much if a specific level of care is determined. The medical costs, however, increased significantly with older age and more comorbid conditions, as demonstrated by our GLM analyses. Given a patient population with fewer comorbid conditions than the patients in our study, the expected annual medical costs would be much lower. If the medical costs are much lower than the intervention costs, the cost-saving feature of the telehealth program may not exist. The same problem will also be encountered in a patient population with a greater number of comorbid conditions and higher expected medical costs. Therefore, choosing the appropriate patient population would have a major influence on the balance of cost-effectiveness. According to our data and prior trials in telehealth programs [12] or disease management programs [24], the intervention costs should be less than US$2500-3000 per year to be cost-saving in a patient population with moderate chronic comorbidities. With advances in information technologies such as automatic data analysis algorithms, the personnel costs might be lowered in the future.

The third implication of our data is that the patient population that will benefit from a telehealth program extends to patients with chronic CVD and multiple chronic conditions. In CVD, telehealth programs have been tested mostly in patients with heart failure [14,22,23,25]. In our study, 24% of our patients had heart failure or myocardial infarction. The mean Charlson comorbidity index in our study was 1.26, which was lower than that reported in some of the recent research [11,12]. The overall severity in our study may be less than that in the studies in patients with heart failure. Our study provided the data of a telehealth program for a patient population with established CVD and multiple comorbidities but without advanced heart failure.

### Limitations

There are several limitations to this study. First, because this was not a randomized controlled study, confounding factors and bias may not have been detected. Although we matched the patients and controls by age, sex, and Charlson comorbidity index, each item of the Charlson comorbidity index was not completely matched. However, because the disease severity was higher in the telehealth group, we do not think that this artificially increased the benefits of telehealth care. Moreover, a protocol-driven use of resources did not exist in this study, making the costs more reflective of the real-world situation. Other confounding factors such as socioeconomic status were not fully detected in this study. Second, only direct medical costs and intervention costs were reported in our study; however, travel and time costs are two major direct non-health-related costs. These two types of cost are difficult to compare between different societies and health care systems, and therefore we did not include these two costs in our analysis. Third, the clinical outcomes were derived from the electronic billing and medical records of our hospital, and the patients who received care outside of our hospital were not recorded. Resources that were used but not billed may also have been overlooked when extracting data from our billing system. Fourth, long-term follow-up data were not available in our study, so the cost-effectiveness over a longer time frame is unknown. Finally, we did not measure the QALY in our study, although many cost-effectiveness studies have reported this. Although frequently used in health economic research, QALY is not without drawbacks [26]. One of the major problems is that the use of QALY rests on the assumption that all QALYs are of equivalent value in the perspective of society. However, this assumption is not necessarily true in all circumstances [27].

QALYs derived from different societies and cultural backgrounds may not be suitable for a direct comparison. Hence, we reported the cost per hospitalization avoided.

### Conclusions

Our data support that a fourth-generation telehealth program is associated with a reduction in the rate of hospitalizations, the length of hospital stay, and the accompanying medical costs in patients with chronic CVD and multiple comorbidities. The intervention costs of this new generation of telehealth program do not increase the total costs for patient care. Randomized trials should be considered in this new generation of telehealth program for the management of chronic CVD.


## Acknowledgments

Funding was provided by Taiwan National Science Council (grant no. NSC 102-2220-E-002-008-), National Taiwan University (grant no. 10R71608-1) and National Science Council for the Center for Dynamical Biomarkers and Translational Medicine, National Central University, Taiwan (NSC 102-2911-I-008-001-).


## Conflicts of Interest

None declared.

## References


1. Kung HC, Hoyert DL, Xu J, Murphy SL. Deaths: final data for 2005. Natl Vital Stat Rep 2008 Apr 24;56(10):1-120 [FREE Full text] [Medline: 18512336]
2. Go AS, Mozaffarian D, Roger VL, Benjamin EJ, Berry JD, Borden WB, American Heart Association Statistics Committee and Stroke Statistics Subcommittee. Executive summary: heart disease and stroke statistics--2013 update: a report from the American Heart Association. Circulation 2013 Jan 1;127(1):143-152 [FREE Full text] [doi: 10.1161/CIR.0b013e318282ab8f] [Medline: 23283859]
3. Mahoney EM, Wang K, Cohen DJ, Hirsch AT, Alberts MJ, Eagle K, REACH Registry Investigators. One-year costs in patients with a history of or at risk for atherothrombosis in the United States. Circ Cardiovasc Qual Outcomes 2008 Sep;1(1):38-45 [FREE Full text] [doi: 10.1161/CIRCOUTCOMES.108.775247] [Medline: 20031786]
4. McAlister FA, Lawson FM, Teo KK, Armstrong PW. A systematic review of randomized trials of disease management programs in heart failure. Am J Med 2001 Apr 1;110(5):378-384. [Medline: 11286953]
5. Faxon DP, Schwamm LH, Pasternak RC, Peterson ED, McNeil BJ, Bufalino V, American Heart Association's Expert Panel on Disease Management. Improving quality of care through disease management: principles and recommendations from the American Heart Association's Expert Panel on Disease Management. Circulation 2004 Jun 1;109(21):2651-2654 [FREE Full text] [doi: 10.1161/01.CIR.0000128373.90851.7B] [Medline: 15173048]
6. McLean S, Chandler D, Nurmatov U, Liu J, Pagliari C, Car J, et al. Telehealthcare for asthma. Cochrane Database Syst Rev 2010(10):CD007717. [doi: 10.1002/14651858.CD007717.pub2] [Medline: 20927763]
7. McLean S, Nurmatov U, Liu JL, Pagliari C, Car J, Sheikh A. Telehealthcare for chronic obstructive pulmonary disease. Cochrane Database Syst Rev 2011(7):CD007718. [doi: 10.1002/14651858.CD007718.pub2] [Medline: 21735417]
8. Clark RA, Inglis SC, McAlister FA, Cleland JG, Stewart S. Telemonitoring or structured telephone support programmes for patients with chronic heart failure: systematic review and meta-analysis. BMJ 2007 May 5;334(7600):942 [FREE Full text] [doi: 10.1136/bmj.39156.536968.55] [Medline: 17426062]
9. Clarke M, Shah A, Sharma U. Systematic review of studies on telemonitoring of patients with congestive heart failure: a meta-analysis. J Telemed Telecare 2011;17(1):7-14. [doi: 10.1258/jtt.2010.100113] [Medline: 21097564]
10. Inglis SC, Clark RA, McAlister FA, Ball J, Lewinter C, Cullington D, et al. Structured telephone support or telemonitoring programmes for patients with chronic heart failure. Cochrane Database Syst Rev 2010(8):CD007228. [doi: 10.1002/14651858.CD007228.pub2] [Medline: 20687083]
11. Takahashi PY, Pecina JL, Upatising B, Chaudhry R, Shah ND, Van Houten H, et al. A randomized controlled trial of telemonitoring in older adults with multiple health issues to prevent hospitalizations and emergency department visits. Arch Intern Med 2012 May 28;172(10):773-779. [doi: 10.1001/archinternmed.2012.256] [Medline: 22507696]
12. Henderson C, Knapp M, Fernández JL, Beecham J, Hirani SP, Cartwright M, Whole System Demonstrator evaluation team. Cost effectiveness of telehealth for patients with long term conditions (Whole Systems Demonstrator telehealth questionnaire study): nested economic evaluation in a pragmatic, cluster randomised controlled trial. BMJ 2013;346:f1035 [FREE Full text] [Medline: 23520339]
13. Wootton R. Twenty years of telemedicine in chronic disease management--an evidence synthesis. J Telemed Telecare 2012 Jun;18(4):211-220 [FREE Full text] [doi: 10.1258/jtt.2012.120219] [Medline: 22674020]
14. Anker SD, Koehler F, Abraham WT. Telemedicine and remote management of patients with heart failure. Lancet 2011 Aug 20;378(9792):731-739. [doi: 10.1016/S0140-6736(11)61229-4] [Medline: 21856487]

15. Chen YH, Lin YH, Hung CS, Huang CC, Yeih DF, Chuang PY, et al. Clinical outcome and cost-effectiveness of a synchronous telehealth service for seniors and nonseniors with cardiovascular diseases: quasi-experimental study. J Med Internet Res 2013;15(4):e87 [FREE Full text] [doi: 10.2196/jmir.2091] [Medline: 23615318]
16. Ekeland AG, Bowes A, Flottorp S. Effectiveness of telemedicine: a systematic review of reviews. Int J Med Inform 2010 Nov;79(11):736-771. [doi: 10.1016/j.ijmedinf.2010.08.006] [Medline: 20884286]
17. McKinstry B, Hanley J, Wild S, Pagliari C, Paterson M, Lewis S, et al. Telemonitoring based service redesign for the management of uncontrolled hypertension: multicentre randomised controlled trial. BMJ 2013;346:f3030 [FREE Full text] [Medline: 23709583]
18. Margolis KL, Asche SE, Bergdall AR, Dehmer SP, Groen SE, Kadrmas HM, et al. Effect of home blood pressure telemonitoring and pharmacist management on blood pressure control: a cluster randomized clinical trial. JAMA 2013 Jul 3;310(1):46-56. [doi: 10.1001/jama.2013.6549] [Medline: 23821088]
19. Weinstock RS, Teresi JA, Goland R, Izquierdo R, Palmas W, Eimicke JP, IDEATel Consortium. Glycemic control and health disparities in older ethnically diverse underserved adults with diabetes: five-year results from the Informatics for Diabetes Education and Telemedicine (IDEATel) study. Diabetes Care 2011 Feb;34(2):274-279 [FREE Full text] [doi: 10.2337/dc10-1346] [Medline: 21270184]
20. Steventon A, Bardsley M, Billings J, Dixon J, Doll H, Hirani S, Whole System Demonstrator Evaluation Team. Effect of telehealth on use of secondary care and mortality: findings from the Whole System Demonstrator cluster randomised trial. BMJ 2012;344:e3874 [FREE Full text] [Medline: 22723612]
21. Desai AS, Stevenson LW. Connecting the circle from home to heart-failure disease management. N Engl J Med 2010 Dec 9;363(24):2364-2367. [doi: 10.1056/NEJMe1011769] [Medline: 21080836]
22. Chaudhry SI, Mattera JA, Curtis JP, Spertus JA, Herrin J, Lin Z, et al. Telemonitoring in patients with heart failure. N Engl J Med 2010 Dec 9;363(24):2301-2309 [FREE Full text] [doi: 10.1056/NEJMoa1010029] [Medline: 21080835]
23. Krumholz HM, Amatruda J, Smith GL, Mattera JA, Roumanis SA, Radford MJ, et al. Randomized trial of an education and support intervention to prevent readmission of patients with heart failure. J Am Coll Cardiol 2002 Jan 2;39(1):83-89. [Medline: 11755291]
24. Hebert PL, Sisk JE, Wang JJ, Tuzzio L, Casabianca JM, Chassin MR, et al. Cost-effectiveness of nurse-led disease management for heart failure in an ethnically diverse urban community. Ann Intern Med 2008 Oct 21;149(8):540-548. [Medline: 18936502]
25. Bui AL, Fonarow GC. Home monitoring for heart failure management. J Am Coll Cardiol 2012 Jan 10;59(2):97-104 [FREE Full text] [doi: 10.1016/j.jacc.2011.09.044] [Medline: 22222071]
26. Neumann PJ, Weinstein MC. Legislating against use of cost-effectiveness information. N Engl J Med 2010 Oct 14;363(16):1495-1497. [doi: 10.1056/NEJMp1007168] [Medline: 20942664]
27. McGregor M, Caro JJ. QALYs: are they helpful to decision makers? Pharmacoeconomics 2006;24(10):947-952. [Medline: 17002477]

## Abbreviations

**CVD:** cardiovascular disease
**ED:** emergency department
**GLM:** generalized linear model
**ICER:** incremental cost-effectiveness ratio
**IQR:** interquartile range
**OPD:** outpatient department
**QALY:** quality-adjusted life year
**TELEHEALTH:** Taiwan ELEctroHEALTH study group
**WSD:** Whole System Demonstrator trial

*Edited by G Eysenbach; submitted 24.02.14; peer-reviewed by C Lynch, D Smithard; comments to author 19.03.14; revised version received 24.04.14; accepted 19.05.14; published 10.06.14.*

*Please cite as:*
*Ho YL, Yu JY, Lin YH, Chen YH, Huang CC, Hsu TP, Chuang PY, Hung CS, Chen MF*
*Assessment of the Cost-Effectiveness and Clinical Outcomes of a Fourth-Generation Synchronous Telehealth Program for the Management of Chronic Cardiovascular Disease*
*J Med Internet Res 2014;16(6):e145*
*URL: http://www.jmir.org/2014/6/e145/*
*doi:10.2196/jmir.3346*
*PMID:24915187*

Original Paper

# Click “Like” to Change Your Behavior: A Mixed Methods Study of College Students’ Exposure to and Engagement With Facebook Content Designed for Weight Loss

Gina Merchant[1], MA; Nadir Weibel[2], PhD; Kevin Patrick[1], MD, MS; James H Fowler[3], PhD; Greg J Norman[1], PhD; Anjali Gupta[4], MS, MBA; Christina Servetas[4], RD, MPH; Karen Calfas[1], PhD; Ketaki Raste[4], BS; Laura Pina[2], MS; Mike Donohue[1], PhD; William G Griswold[2], PhD; Simon Marshall[1], PhD

[1]Center for Wireless and Population Health Systems, The Qualcomm Institute/Calit2, Department of Family and Preventive Medicine, University of California San Diego, La Jolla, CA, United States

[2]Center for Wireless and Population Health Systems, The Qualcomm Institute/Calit2, Department of Computer Science and Engineering, University of California San Diego, La Jolla, CA, United States

[3]Center for Wireless and Population Health Systems, The Qualcomm Institute/Calit2, Department of Medicine, School of Medicine, University of California San Diego, La Jolla, CA, United States

[4]Center for Wireless and Population Health Systems, The Qualcomm Institute/Calit2, University of California San Diego, La Jolla, CA, United States

**Corresponding Author:**
Gina Merchant, MA
Center for Wireless and Population Health Systems, The Qualcomm Institute/Calit2
Department of Family and Preventive Medicine
University of California San Diego
Center for Wireless and Population Health Systems, Calit2, 6th Floor, Room 6105
9500 Gilman Drive #0436
La Jolla, CA,
United States
Phone: 1 858 246 1371
Fax: 1 858 534 9338
Email: gmerchant@ucsd.edu

## Abstract

**Background:** Overweight or obesity is prevalent among college students and many gain weight during this time. Traditional face-to-face weight loss interventions have not worked well in this population. Facebook is an attractive tool for delivering weight loss interventions for college students because of its popularity, potential to deliver strategies found in successful weight loss interventions, and ability to support ongoing adaptation of intervention content.

**Objective:** The objective of this study was to describe participant exposure to a Facebook page designed to deliver content to overweight/obese college students in a weight loss randomized controlled trial (N=404) and examine participant engagement with behavior change campaigns for weight loss delivered via Facebook.

**Methods:** The basis of the intervention campaign model were 5 self-regulatory techniques: intention formation, action planning, feedback, goal review, and self-monitoring. Participants were encouraged to engage their existing social network to meet their weight loss goals. A health coach moderated the page and modified content based on usage patterns and user feedback. Quantitative analyses were conducted at the Facebook post- and participant-level of analysis. Participant engagement was quantified by Facebook post type (eg, status update) and interaction (eg, like) and stratified by weight loss campaign (sequenced vs nonsequenced). A subset of participants were interviewed to evaluate the presence of passive online engagement or “lurking.”

**Results:** The health coach posted 1816 unique messages to the study’s Facebook page over 21 months, averaging 3.45 posts per day (SD 1.96, range 1-13). In all, 72.96% (1325/1816) of the posts were interacted with at least once (eg, liked). Of these, approximately 24.75% (328/1325) had 1-2 interactions, 23.39% (310/1325) had 3-5 interactions, 25.13% (333/1325) had 6-8 interactions, and 41 posts had 20 or more interactions (3.09%, 41/1325). There was significant variability among quantifiable (ie, visible) engagement. Of 199 participants in the final intervention sample, 32 (16.1%) were highly active users and 62 (31.2%) never visibly engaged with the intervention on Facebook. Polls were the most popular type of post followed by photos, with 97.5% (79/81) and 80.3% (386/481) interacted with at least once. Participants visibly engaged less with posts over time (partial *r*=–.33; *P*<.001). Approximately 40% of the participants interviewed (12/29, 41%) reported passively engaging with the Facebook posts by reading but not visibly interacting with them.

**Conclusions:** Facebook can be used to remotely deliver weight loss intervention content to college students with the help of a health coach who can iteratively tailor content and interact with participants. However, visible engagement with the study's Facebook page was highly variable and declined over time. Whether the level of observed engagement is meaningful in terms of influencing changes in weight behaviors and outcomes will be evaluated at the completion of the overall study.

***(J Med Internet Res 2014;16(6):e158)*** doi:10.2196/jmir.3267

**KEYWORDS**

overweight; obesity; students; social networking; behavior; social behavior

## Introduction

Approximately 1 in 3 college students are overweight or obese [1] and most students gain weight during college [2]. Total weight gain over 3 years has been estimated at 10 pounds and is characterized by a significant increase in percent body fat and a decrease in lean muscle mass [3]. Weight gain during this time can initiate a trend toward long-term weight gain [4] and increase ones' risk for developing Type 2 diabetes [5], coronary heart disease [6-8], and depression [9] in adulthood. Weight gain in young adults is also associated with psychological distress, such as low self-satisfaction and a loss of identity [10].

Commonly used approaches to weight loss may not be effective for this population [11,12]. For example, more than half of the college students enrolled in a study that required just 1 on-campus counseling session per week quit after 3 months with 75% citing lack of time as their reason for leaving [11]. College students may be less likely to drop out of interventions delivered via the Internet (eHealth) [13] or mobile/social media (mHealth) [14] because these interventions can be delivered remotely and conveniently. At least one Internet-based randomized controlled trial (RCT) demonstrated good retention with just 18 of 159 participants lost to follow-up during the intervention [15].

Both mHealth and eHealth interventions have the potential to engage college students because online, social, and mobile tools are already integrated into their lives. The young adult population, age 18-29 years, has the highest smartphone penetration [16] and 88% of college students connect to the Internet using a mobile device [17]. College students are also highly connected via online social networks [17] with Facebook being the most popular [18]. Compared with other Facebook user groups, young adults more frequently access the site each day to update their status, comment, and "like" their friends' content [19].

In addition to its popularity, Facebook is an attractive platform for health promotion because it fosters interactivity among users and encourages content creation [20]. The Facebook user experience is a combination of human-computer interaction and computer-mediated communication [21]. Therefore, health behavior interventions should consider how participants use Facebook (ie, human-computer interaction) as well as anticipate how participants communicate through Facebook (ie, computer-mediated communication). Facebook mediates communication between friends by facilitating the sharing of personal content and the provision of feedback. Friends virtually interact with one another by posting photos, messages, and links, and by liking and commenting on friends' posts. This creates a community where social interactions account for much of the time spent on the site. Health interventions can leverage this community by creating a Facebook page to reach participants while they interact in real time. A complete review of Facebook's features in the context of behavioral research was published by Wilson et al [22].

Similar to being part of an online health community, Facebook users can motivate one another to achieve their goals [23]. However, Facebook users differ from online health community members in terms of motives for site use, strength of social ties on the site, and activities engaged in while on the site. For example, Facebook users are frequently members of many different nonoverlapping friendship networks and, within each, preferences for sharing personal health information may vary [24]. Thus, users are selective about how and what they share on Facebook, balancing the need for impression management and social support [24,25].

Users commonly "lurk" online, passively reviewing content without visibly connecting to other users or information [26]. Lurking behavior can be prompted by a desire for privacy, a function of individuals' virtual behavior tendencies, or some combination of factors. Benefiting from membership in online social networks, however, may not require visible participation: individuals who passively engage have reported receiving high levels of social support for weight loss [27]. Online interventions encouraging social support may increase engagement [28] and exchanging social support on social networking sites (ie, Twitter) has been linked to weight loss [29].

Facebook enables the provision of timely social support as well as the giving and receiving of behavioral feedback, which is also important for weight loss. Meta-analytic data suggest that interventions that give participants' feedback on their diet and physical activity are more effective than those that do not (pooled effect size: Cohen's $d$=0.42) [30] and that delivering personally relevant feedback improves adherence to online interventions (pooled effect size: Cohen's $d$=0.22) [31]. Qualitatively, individuals have referred to their mobile devices as "virtual companions" that provide real-time support and feedback [32].

Another way that Facebook might be leveraged to change weight loss behaviors is through normative influence. For example, individuals who received messages on Facebook encouraging them to vote in a presidential election that were based on social norms were significantly more likely to vote than those who received an informational message [33]. Moreover, this message spread within individuals' social networks, increasing the likelihood that the recipients' friends and friends of friends would vote [33]. Thus, weight loss interventions using Facebook might be able to capitalize on participants' social networks to promote the spread of healthy dietary and physical activity behaviors [34].

Although Facebook enables the delivery of evidence-based behavior change techniques, such as the provision of social support and positive normative influence, deploying interventions based on traditional theoretical frameworks via this medium may not work. Facebook interactions are intermittent (asynchronous), involve multiple actors, and social norms dictate observable communication among users. As a result, interventions delivered through Facebook are inherently dynamic and fluid, requiring an adaptable theoretical approach.

An alternative to using traditional theories to design online intervention content is to use a behavior change technique framework, such as the one formulated by Michie and colleagues [35,36]. Behavior change techniques represent the smallest identifiable components of an intervention and can be used flexibly, which is ideal for a technology-based intervention [37]. For example, multimedia learning highlights the importance of "scaffolding," or adjusting the degree of difficulty of the presentation of information based on the learner's status (ie, novice to expert). During the course of an intervention, participants develop mastery and messages delivered at the outset may no longer prove useful [37]. In addition, behavior change techniques support specific instructions on how to prompt behavior change, facilitating their adaptation to technology-based interventions [38]. Also, the specificity of behavior change techniques makes clear the competencies required to deliver the technique. For example, modeling/demonstrating the behavior is a behavior change technique that is more difficult to deliver remotely than prompting action planning, which involves detailing when, where, and how often a behavior will be performed [36].

To our knowledge, no published studies have used a behavior change technique framework to design and deliver intervention content via Facebook. However, Michie and colleagues' framework has been used to analyze the content of Internet-based interventions [39] and has been incorporated into instruments used to analyze the theoretical content of mobile apps [40] and online intervention adherence [31]. This framework has also been used to conduct a meta-regression of 129 diet and physical activity interventions, which found that interventions using self-monitoring plus at least one other self-regulatory technique from control theory [41] were the most effective at changing behavior (Cohen's $d$=0.42) [30]. A recent review found that the most effective Internet-based interventions used the most behavior change techniques [39], suggesting that delivering multiple behavior change techniques through Facebook may be a valuable approach to improving health behaviors.

In addition to developing an appropriate intervention framework, it is equally important to consider how using Facebook will impact the acceptability of and adherence to the intervention. The few studies published to date suggest that young adults accept behavioral interventions that use Facebook. For example, Cavallo et al [42] tested the feasibility of a Facebook-based social support intervention to increase physical activity among sedentary college students and found that two-thirds of participants would recommend the program to friends. However, they did not find the Facebook condition to be more effective than the control condition in increasing students' perceived social support for physical activity or self-reported physical activity [42]. Similarly, Napolitano et al [43] demonstrated that a Facebook intervention for weight loss was popular among college students, but did not find Facebook intervention elements alone to be effective. However, neither of these studies fully leveraged Facebook's capacity to serve as a dynamic 2-way communication channel between the participants and the study, and between participants and their existing friendship network.

Whether social networking sites can be used as a novel setting for health promotion is currently a matter of debate with some concluding that the dearth of evidence linking online participation with offline health activities and/or positive health outcomes suggests investigators should proceed with caution [20]. What is largely missing from this conversation, however, is the recognition that standardized and validated metrics for evaluating intervention exposure and engagement are required before Facebook intervention efficacy can be addressed.

Evaluating exposure and engagement requires accurately capturing metrics of intervention delivery and adherence, yet most early Facebook research has either tallied these data manually [42,43] or used publically available Facebook Insights data [44]. Manually entered data are prone to human error and unlikely to be comprehensive. Facebook Insights data are limited because they are aggregated up to the page level and individual participants' data cannot be visualized. In addition, all fans of the page are included in Insights' capture, which contaminates analyses of open pages because nonstudy participants may be responsible for some/most of the page interactions. Also, Insights' data can have questionable internal validity. For example, Insights' data defines *reach* as the message being visible on one's personal page (ie, news feed) despite the fact that there is no evidence that the individual has attended to this information. An alternative to objectively capturing engagement and exposure data is to ask participants to self-report their Facebook use during the course of an intervention. Participants in at least 1 Facebook-based intervention self-reported on the frequency with which they saw the study's posts in their newsfeed, how often they visited the study page, and other metrics [45]. These self-report data may be particularly useful for capturing data on lurking [26].

Also prior to assessing Facebook intervention efficacy, it is important to consider what defines a satisfactory level of exposure and engagement. Paradata (eg, number of website log-ins) have been used to explore participant involvement and identify the more/less popular components of online interventions [46]. However, extending this type of data capture to online social networking sites in the context of a weight loss RCT has not been reported.

The present study had 2 goals. First, to present a way to objectively quantify and qualitatively explore participant exposure to and engagement with the Facebook page that is currently being used in a weight loss RCT of 404 overweight/obese college students. Second, to describe participant exposure to and engagement with various weight loss campaigns grounded in a behavior change technique model and delivered through Facebook. This study defined overall exposure as the number of Facebook posts delivered by the health coach (ie, dose delivered) and engagement as the number of posts participants interacted with (ie, dose received) as well as participant-initiated posts. These data are based on an interim analysis of a 2-year RCT evaluating a weight loss program for young adults [47].

## Methods

### Participants

The study used a rolling recruitment strategy whereby participants were recruited over a year's time. From May 2011 to May 2012, 404 students were recruited from 3 Southern California universities to participate in a weight loss intervention delivered through social and mobile technologies called project SMART (social and mobile approach to reduce weight). SMART is 1 of 7 studies funded by the National Heart, Lung, and Blood Institute to target weight loss/weight control in young adults. The primary outcome of SMART is weight loss at 24 months from baseline.

Inclusion criteria were: (1) age 18 to 35 years, (2) body mass index (BMI) 25-40 kg/m$^2$, (3) owns a personal computer, (4) owns a mobile phone and uses text messaging, and (5) a Facebook user or willing to join. Exclusion criteria were: (1) comorbidities of obesity that require clinical referral (eg, diabetes), (2) psychiatric or medical conditions that could prohibit study compliance (eg, bipolar disorder), (3) taking weight-altering medications, (4) pregnant or intending to get pregnant over the next 2 years, and (5) enrolled in or planning to enroll in another weight loss program.

### Procedures

Online and in-person recruitment strategies included banner ads on campus websites, a Facebook page, listservs, health fairs, and student orientations. These recruitment channels directed potential participants to the study website where they could take an eligibility survey and learn more about the study. Eligible participants were randomized into 1 of 2 groups: social and mobile intervention (n=202) or online education-only control (n=202). All participants provided written informed consent and the university's Institutional Review Board approved the study protocol (University of California San Diego, California State University San Marcos, and San Diego State University).

Participants attended a measurement visit at baseline and every 6 months for 24 months, conducted at the students' university. Self-report data collected at the visit included demographics, dietary and physical activity habits, psychological symptoms/states, quality of life, Facebook usage, and information about participants' social networks. University health center staff also measured participants' height, weight, waist circumference, and blood pressure at every visit. Participant compensation increased by US $5 after each completed visit, from US $20 at baseline to US $50 at 24 months. Participants who completed their visit within a 2-week window of their scheduled visit (1 week prior to 1 week after) received double the compensation (eg, US $100 for their final visit at 24 months).

### Intervention and Control Conditions

The intervention group had access to a study-specific website, blog, apps, Facebook page, text-messaging component, and a health coach. Upon entering the study, all intervention participants were asked to like the Facebook page. After liking the page, users were considered fans of the page and could see all posts in their news feed. Because the Facebook page was open, nonstudy participants could also become fans and view and engage with its content.

A health coach (a registered dietitian) remotely delivered all intervention content to the 202 intervention participants. The health coach moderated the Facebook page, and posted to the blog. Participants could contact the health coach up to 10 times (Lifelines) via Skype, email, phone, or text. Alternatively, the health coach could reach out to participants a maximum of 10 times (Lifesavers). The health coach used Lifesavers when participants gained >5 pounds since study entry or had not logged into at least 1 of the study's tools in >1 month.

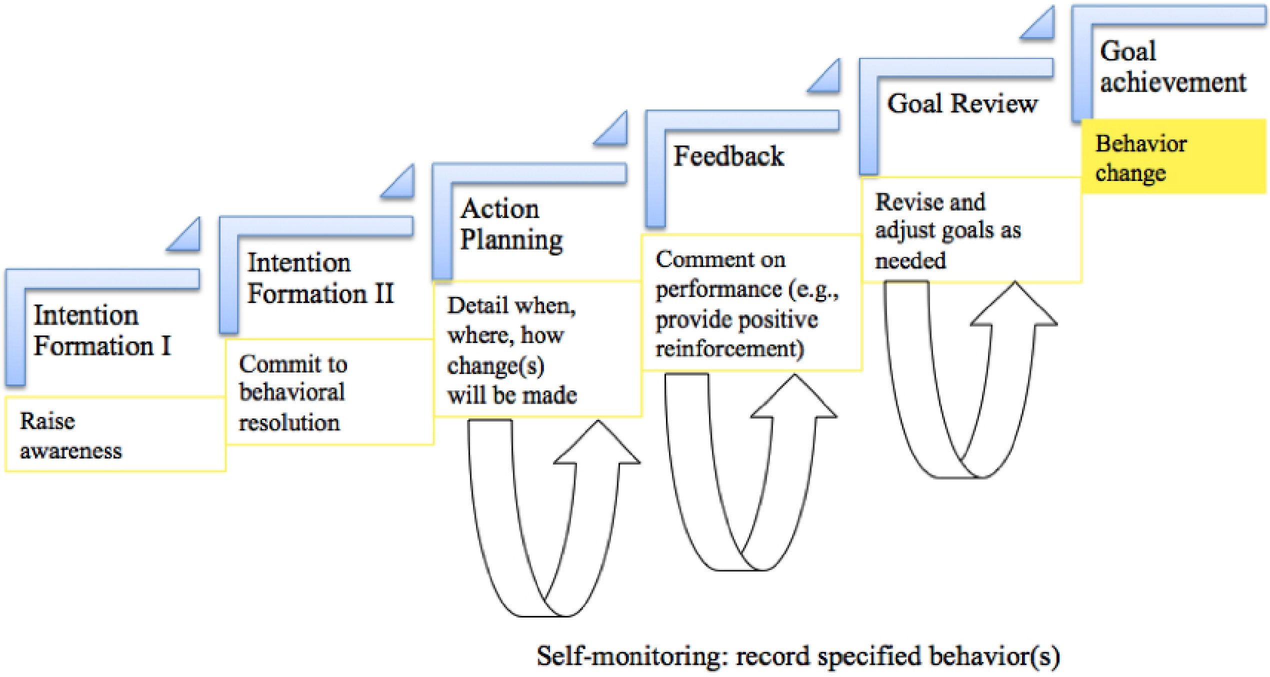
SMART intervention tools were branded as ThreeTwoMe, symbolizing the role of the college student within a broader social ecological context [48,49]. *Three* represents the student in his/her community, *Two* represents the student in his/her friendship network, and *Me* represents the student's individual behavior change needs. All intervention tools used the same ThreeTwoMe brand identity (ie, logo, imagery, colors). The control group received a self-guided educational program called SMART Health Tools that offered standard-of-care information disseminated via a different study website with minimal interactive features. Online log-ins were monitored weekly to detect possible contamination of control group participants (ie, exposure to the intervention). Additional details about the intervention's methods have been published elsewhere [47].

### Facebook

#### *Conceptual Model*

Abraham and Michie's 26-item behavior change taxonomy [35] was used to create a conceptual model called iSIMPLE (intention formation, self-monitor, make plans, execute) for the Facebook campaigns (see Figure 1). The taxonomy is grounded in theory known to enhance behavior change, including the theory of reasoned action [50], social cognitive theory [51], control theory [41], operant conditioning [52], theories of social comparison [53], and theories of social support [54]. iSIMPLE was based on the 5 most effective behavior change techniques identified in a meta-regression analysis [30]. These techniques are intention formation, action planning, feedback, goal review, and self-monitoring.

**Figure 1.** Conceptual model iSIMPLE (Intention formation, Self-monitor, Make plans, Execute) used in the design of the SMART study's Facebook campaigns for weight loss behaviors.




### *Facebook Campaigns*

Campaigns were intervention periods (eg, week of Thanksgiving) with a specific relevant theme (eg, mindless eating). iSIMPLE was used to design Facebook campaigns that were either sequenced or nonsequenced. Sequenced campaigns implemented the behavior change techniques in a hierarchical manner, consistent with a temporal sequence in how behavior change is thought to occur [55,56]. For example, participants were first asked to join the campaign and pledge to change their behavior (ie, intention formation). Pledge requests were followed with action planning wherein participants were prompted to describe when, where, and how they would change their behavior. Throughout the campaign, the health coach provided feedback and conducted goal reviews, prompting participants to revise and adjust their goals as needed. While participants worked toward behavior change, the health coach also prompted for self-monitoring. Participants were prompted to observe and record their diet and physical activity behaviors on Facebook (eg, Facebook poll) as well as on the study website and apps. For example, participants were asked to record their daily steps during a pedometer campaign by posting their steps on Facebook (public option) or via text message (private option).

Nonsequenced campaigns used the same behavior change techniques, but participants were not explicitly asked to join the campaign and messages pushed to participants were not systematically ordered. Nonsequenced campaigns exposed participants to similar content as sequenced campaigns, but the posts did not outline an explicit campaign-based goal the participant should work toward. For example, an unstructured January campaign delivered motivational posts that mapped onto various behavior change techniques, but participants were not asked to complete specific tasks to meet a campaign goal.

Designing and delivering sequenced and nonsequenced campaigns enables the comparison of ordered behavior change techniques. It was theorized that having 2 different campaign structures may maximize overall participant engagement. Some users may be more interested in being challenged and pledging to participate in a campaign, whereas others may prefer to receive content that asks less of them in terms of overt online participation. It also may be the case that delivering too much dynamic content is problematic: there is some evidence that adding layers of complexity to online interventions can decrease participant engagement and intervention effectiveness [57], exacerbating the problem of reduced motivation to engage with online tools over time [31].

Behavior change techniques not specified in iSIMPLE were also used as needed. For example, the ThreeTwoMe health coach could provide contingent rewards (ie, prizes based on completion of an activity) and model behavior (eg, post a link on how to correctly do a push-up). The health coach also delivered behavioral cues to action messages [58,59] alongside/in place of preplanned messages (ie, Facebook posts that were designed a priori as part of a campaign) dependent upon user engagement and participant feedback. For example, the message "30 minutes of exercise per day is recommended, even if it's split apart. That's only 3% of your day, so start moving!" was sent as a behavioral cue message in the late morning after students' gave feedback that this was a good time to remind them to plan for their day. The health coach also delivered "filler" messages that included posts tailored to our audience, such as "Good luck with finals this week!"

Although the iSIMPLE model is focused on the individual, it is supported by the social support platform inherent to Facebook's architecture. Some of the Facebook campaigns asked participants to engage their social networks to make successful behavior change more likely. For example, Facebook posts often prompted participants to be active with their friends and discuss their goals with them. In-between campaigns, Facebook content was often less theoretically informed and did not necessarily map onto behavior change techniques. For example, a post to promote eating vegetables was an infographic of the actor Patrick Dempsey holding a bushel of kale.

## Process Measures and Analysis Plan

The findings presented here represent a way in which exposure to and engagement with Facebook can be conceptualized for the purposes of health behavior intervention research. These analyses focused on Facebook posts delivered by the health coach and posts received by study participants. The measures used to define exposure and engagement are presented subsequently.

The study's Facebook page was created on August 7, 2011, the same day the first participant was randomized. General posts aimed at helping participants lose weight and be healthy were delivered for the first ~45 weeks of the intervention. During this time, the research team focused on integrating the various channels (eg, apps, text messaging, Facebook) and testing various Facebook messages. The first campaign was launched on June 21, 2012.

For purposes of the present study, Facebook data from August 7, 2011 and May 27, 2013 were collected. These dates include the first (August 7, 2011) and last day (May 27, 2012) of participant randomization. It is important to point out that because of rolling recruitment, participants were exposed to varying amounts of Facebook content delivered before the start of the first campaign. For example, participants randomized in the first month of recruitment were exposed to approximately 10 months of noncampaign content, whereas participants randomized in the last month of recruitment were exposed to approximately 2 months of noncampaign content. However, all participants were exposed to the same 8 campaigns analyzed here as well as the same noncampaign content posted in-between campaigns (ie, noncampaign content delivered after the start of the first campaign).

For participant-level analyses, the first 12 months of data based on each participant's start date were used. For post-level analyses, all 21 months of data were used so that the first 8 campaigns could be evaluated.

Facebook query language was used to retrieve data from Facebook's social graph. Data were downloaded in JavaScript Object Notation (JSON) format. Given that this study's Facebook page was open, nonstudy participants could like it and become a fan. Therefore, the exported data contained some nonparticipant Facebook activity. However, these data were excluded by only including data associated with Facebook identification numbers belonging to study participants. The data obtained via Facebook's social graph were merged with baseline survey data in SPSS version 20 (IBM Corp, Armonk, NY, USA).

### Exposure

#### *Dose Delivered*

*Dose delivered* was defined at the Facebook post-level unit of analysis as the number of unique posts made by the health coach to the study's Facebook page. The number of health coach posts was summed over the course of the study's first 21 months (August 7, 2011-May 27, 2013). Therefore, this metric includes posts made both during and outside of campaigns. An example of a status update made by the health coach outside of a campaign was: “This is a great checklist for a healthy pantry. Are you in good shape??” This post included a link to an article about tips for keeping a healthy pantry. Campaign versus noncampaign posts were not always qualitatively different when considered individually; rather, posts made during campaigns were qualitatively different in aggregate (ie, because they were part of a cohesive message/plan).

#### *Feedback Delivered*

The number of comments the health coach made on participant posts and the number of times the health coach liked participant posts were summed and used as a measure of the dose of feedback delivered.

### Engagement

#### *Dose Received*

Dose received was defined at the post-level and the participant-level unit of analysis. *Post-level dose received* was defined as the number of posts made by the ThreeTwoMe health coach that participants interacted with. Participants could interact with a post by liking, commenting, sharing, or answering (if the post was a poll). Post-level dose received was analyzed as a binary variable (post was interacted with: yes or no) as well as a continuous variable (total number of interactions with the post). *Participant-level dose received* was defined as the number of participant interactions stratified by interaction type (eg, like). For example, a participant who liked a photo on the ThreeTwoMe page was said to have “received” that post.

#### *Participant-Initiated Posts*

The number of posts participants made to the study's Facebook page was summed. These data represent participant activity that was either motivated by the participant independent of the health coach prompting for it or the health coach calling for participants to post. For example, a participant may have heard about a diet from a friend and sought the health coach's advice by posting about it. Differently, a participant may have posted a picture of a meal he/she recently made that met a challenge the health coach put to participants. Both types of participant-driven communications made directly on the ThreeTwoMe page may represent a higher level of engagement than dose received because they involve participant-initiated contact with the study as opposed to study-initiated contact with participants. For example, a participant who proactively visited the ThreeTwoMe page and posted a message about how many steps he/she took that day may be more engaged than a participant who only liked messages posted by the health coach that show up in his/her news feed.

Facebook posts can extend into a long thread of comments and corresponding likes, representing interactivity between participants and the health coach and/or participants and participants. For the purposes of this study, only interactions between participants and the health coach were considered. *Interactions* were defined as participant comments, etc, made to posts originating from the health coach (dose received) and likes or comments from the health coach to participants' posts (feedback delivered). Participant comments, etc, that were made to participant-initiated posts were not considered because the focus was on dose received from the health coach, not dose received from fellow participants. Table 1 summarizes the aforementioned definitions of exposure and engagement.

Participants who interacted with the ThreeTwoMe Facebook page at least once per week were categorized as highly active and those who interacted at least twice per month were categorized as active. The remaining participants were categorized as either somewhat active (interacts >once per month) or minimally active (interacts <once per month). These mutually exclusive cut points were based upon Facebook user patterns seen in this intervention, but are similar to categorizations delineated in earlier work. For example, a previous study categorized participants as active if they posted to Twitter at least once per week [29].

**Table 1.** Defining measures of intervention exposure and engagement on Facebook.

| Intervention | Definition | Types of posts/interactions | Direction of posts/interactions |
| --- | --- | --- | --- |
| **Exposure** | | | |
| Dose delivered | Posts made by the health coach on the ThreeTwoMe Facebook page | Posts: status update, photo, link, poll,[a] video | Health coach to ThreeTwoMe page |
| Feedback delivered | Health coach interactions with posts made by participants on the ThreeTwoMe Faceook page; also can be health coach interactions with comments made by participants in response to ThreeTwoMe posts | Interactions: like, comment | Health coach to participant |
| **Engagement** | | | |
| Dose received[b] | Participant interactions with ThreeTwoMe Facebook posts delivered by the health coach | Interactions: like, comment, poll response, share | Participant to ThreeTwoMe page |
| Participant-initiated posts | Posts made by participants on the ThreeTwoMe Facebook page | Posts: post, photo, video, link | Participant to ThreeTwoMe page |

[a]Facebook removed the poll feature in April 2013.

[b]Dose received was analyzed at the post-level (post interacted with: yes/no) and at the participant-level (number of participant interactions stratified by interaction type).

### *Semistructured Interviews*

A total of 29 participants (15 treatment, 14 control) were interviewed between May and July of 2013 as part of a qualitative study. Participants were "intercepted" at the end of one of their measurement visits and those who agreed to be interviewed were provided with an additional US $25 incentive (gift card to Target). Intercepted participants comprise a convenience sample; however, a concerted effort was made to sample from males and females, and students from all 3 universities. Although participants from all 3 universities were approached, most of the sample came from the University of California San Diego (23/29, 80%). Most participants interviewed were female (17/29, 59%). Interviews lasted between 30 and 60 minutes. Interviewees were asked about how they used the study's tools and how they engaged in their social network to meet their health-related goals. All interviews were tape recorded and transcribed. Two investigators independently reviewed the interviews using principles from grounded theory [60].

To explore the common practice of lurking in online health communities [26], selective results from participants' semistructured interviews are described here. Approximately 40% (12/29, 41%) of participants interviewed described lurking on Facebook. *Lurking* is defined as members of online health communities passively receiving social support and information by reading messages without visibly interacting [23,26,27,61]. On Facebook, lurking can be defined as users viewing posts but not interacting with them in a way that is visible to their social network. For example, commenting on a post makes the post visible to other members of the network and the content and source of the post becomes public, whereas reading or clicking on a post does not make it public. Previous work has found that approximately half of online health community members interact passively and that this type of engagement may play an important role in weight loss efforts [23,27].

## Results

### Overview

Table 2 provides descriptive statistics for the intervention group stratified by gender. A total of 3 of the 202 participants randomized to the intervention group were missing data (final N=199).

At baseline, 16.6% (33/199) of participants self-reported logging onto Facebook zero times per day on either a laptop, desktop, or mobile device, followed by 39.0% (77/199) logging on 1-3 times, 27.6% (55/199) logging on 4-8 times, and 17.1% (34/199) logging on 8 or more times per day. Participants reported spending an average of 60 minutes per day on Facebook (median 60) on both week (IQR 90 min/day) and weekend days (IQR 120 min/day).

**Table 2.** Baseline characteristics of the intervention group by gender (N=199).

| Demographics | Total N=199 | Men n=59 | Women n=140 |
|---|---|---|---|
| Age (years), mean (SD) | 22.0 (3.8) | 23.0 (4.6) | 21.6 (3.3) |
| **Race, n (%)** | | | |
| White | 85 (42.7) | 22 (37.3) | 63 (45.0) |
| Black | 7 (3.5) | 0 (0) | 7 (5.0) |
| Asian | 45 (22.6) | 17 (28.8) | 28 (20.0) |
| Pacific Islander | 9 (4.5) | 4 (6.8) | 5 (3.6) |
| American Indian | 1 (0.5) | 0 (0) | 1 (0.7) |
| Other | 52 (26.1) | 16 (27.1) | 36 (25.7) |
| **Ethnicity, n (%)** | | | |
| Hispanic | 63 (31.7) | 17 (28.8) | 46 (32.9) |
| Undergraduate (yes), n (%) | 159 (79.9) | 45 (76.3) | 114 (81.4) |
| **Relationship status, n (%)** | | | |
| Single | 100 (50.3) | 33 (55.9) | 77 (55.0) |
| Engaged, committed relationship, married | 88 (45) | 26 (44.1) | 62 (44.3) |
| Separated, divorced, widowed | 0 (0) | 0 (0) | 0 (0) |
| **Anthropometrics, mean (SD)** | | | |
| Body mass index (BMI) | 28.7 (3.5) | 28.5 (4.7) | 28.8 (3.0) |
| Waist circumference (cm) | 87.0 (10.8) | 93.1 (7.7) | 84.5 (10.9) |

## Exposure

### *Dose Delivered*

Table 3 presents the dose delivered and received of Facebook data by post type. The ThreeTwoMe health coach posted 1816 unique messages to the study's Facebook page over the first 21 months of the intervention, averaging 3.45 posts per day (SD 1.96, range 1-13). Overall, 72.96% (1325/1816) of the posts were interacted with at least once (eg, liked). Most posts were status updates followed by photos, links, polls, and videos. Most messages were posted on a weekday (86.01%, 1562/1816).

**Table 3.** Posts delivered by the ThreeTwoMe health coach and posts received by participants where received is defined as the post having been interacted with at least once.

| Dose delivered and received | Total[a] | Type of Facebook post | | | | |
|---|---|---|---|---|---|---|
| | | Status update | Photo | Link | Poll | Video |
| Dose delivered, n (% of total) | 1816 (100.00) | 802 (44.16) | 481 (26.49) | 400 (22.03) | 81 (4.46) | 52 (2.86) |
| Number of posts delivered per day, mean (SD) | 3.45 (1.96) | 1.92 (1.11) | 1.60 (1.02) | 1.44 (0.70) | 0.20 (0.30) | 1.18 (0.58) |
| Dose received, n (% of total delivered) | 1325 (72.96) | 605 (75.44) | 386 (80.25) | 228 (57.00) | 79 (97.53) | 27 (51.92) |

[a]Data represent posts made since the start of the study's Facebook page to the end of the eighth campaign (August 2, 2011 to May 27, 2013).

### *Feedback Delivered*

The ThreeTwoMe health coach provided ongoing feedback to participants by liking and commenting on their posts. Over the course of the first 21 months of the intervention, the health coach made 675 comments and 389 likes to participant-initiated posts and participant comments to ThreeTwoMe posts.

## Engagement

### *Dose Received-Quantitative Results*

Table 3 presents the post-level dose received results. Defining dose received as a binary variable (post interacted with the post: yes/no), intervention participants received 72.96% of the posts (1325/1816 posts were interacted with). Participants interacted most with polls (97.5%, 79/81 of polls posted) and photos (80.3%, 386/481) and the least with videos (51.9%, 27/52). Of the 1816 unique posts, there were 8967 interactions for an average of 4.94 (SD 5.37) interactions per post. Only considering posts that were received (n=1325), there was an average of 6.77 (SD 5.21) participant interactions per post (range 1-37). Approximately 25% (328/1325, 24.75%) of the posts received had 1 or 2 interactions, 23.39% (310/1325) had 3 to 5 interactions, and 25.13% (333/1325) had 6 to 8 interactions. A total of 41 posts had 20 or more interactions (3.09%, 41/1325).

Table 4 presents participant-level dose received by interaction type and participant engagement category. There was high variability among participant engagement with the ThreeTwoMe Facebook page with a range of 0-653 total interactions per participant. In all, 62 participants never engaged with the Facebook page (31.2%, 62/199). There were 32 highly active users (16.1%, 32/199). Likes were the most common type of participant interaction with the ThreeTwoMe posts (69.86%, 4385/6277), followed by comments (22.45%, 1409/6277), and poll responses (4.13%, 259/6277). However, polls were more popular than these data indicate given that there were fewer opportunities to engage with polls than other post types (see message-level dose received data presented in Table 3). Although there were more women (n=26) than men (n=6) in the highly active category, women (mean 49.47, SD 99.19) did not interact with the ThreeTwoMe page significantly more than men (mean 35.17, SD 82.03) ($t_{135}$=0.77, $P$=.44).

**Table 4.** Participants' engagement with the ThreeTwoMe Facebook page by type of Facebook activity and participant engagement category of participants who ever engaged with the Facebook page (n=137).

| Engagement category[a] | Total interactions | Type of Facebook interaction[b] | | | | |
|---|---|---|---|---|---|---|
| | n=6277 | Likes n=4385 | Comments n=1409 | Poll responses n=259 | Shares n=33 | Posts to page[c] n=191 |
| Highly active (n=32), n (%) | 5070 (80.77) | 3480 (79.36) | 1201 (85.24) | 196 (75.68) | 20 (60.60) | 173 (90.57) |
| Active (n=17), n (%) | 573 (9.13) | 442 (10.08) | 95 (6.74) | 20 (7.72) | 3 (9.09) | 5 (2.62) |
| Somewhat active (n=15), n (%) | 282 (4.49) | 204 (4.65) | 63 (4.47) | 10 (3.86) | 3 (9.09) | 2 (1.05) |
| Minimally active (n=73), n (%) | 352 (5.61) | 259 (5.91) | 50 (3.55) | 25 (9.65) | 7 (21.21) | 11 (5.76) |

[a]Categories are mutually exclusive. Highly active participants: interact with the ThreeTwoMe Facebook page ≥1/week; active participants: interact with the ThreeTwoMe Facebook page ≥2/month but <1/week; somewhat active participants: interact with the ThreeTwoMe Facebook page ≥1/month but <2/month; minimally active participants: interact with the ThreeTwoMe Facebook page <1/month.

[b]Data represent quantifiable interaction with the study's Facebook page over the first year of the study based on participants' start date.

[c]Posts to page are participant-initiated posts and are independent of a post made by the health coach.

Figure 2 shows participants' average number of daily Facebook interactions after adjusting for the number of posts delivered (# of interactions per day/# of posts delivered per day).

Figure 3 shows the average contribution per person in terms of daily Facebook interactions after adjusting for the sample size, calculated as (# of interactions per day/# of posts delivered per day)/sample size on that date. The sample size was steadily increasing until May 27, 2012, at which point all 202 participants were in the study. After adjusting for the number of participants in the study on the date the post was delivered, there was a negative correlation between time (date the post was made) and engagement (number of interactions per post) indicating that participants engaged less with ThreeTwoMe posts over time (partial $r$=–.33; $P$<.001).

The decline over time may, in part, be because of decreasing engagement from all but the highly active participants who were responsible for 80.77% (5070/6277) of all Facebook interactions (see Table 4). For example, the trend for declining engagement over time observed in Figure 2 is less pronounced than in Figure 3, which considers the entire sample in the denominator of its engagement metric.

**Figure 2.** Average daily Facebook interactions per post adjusted for the number of posts delivered.

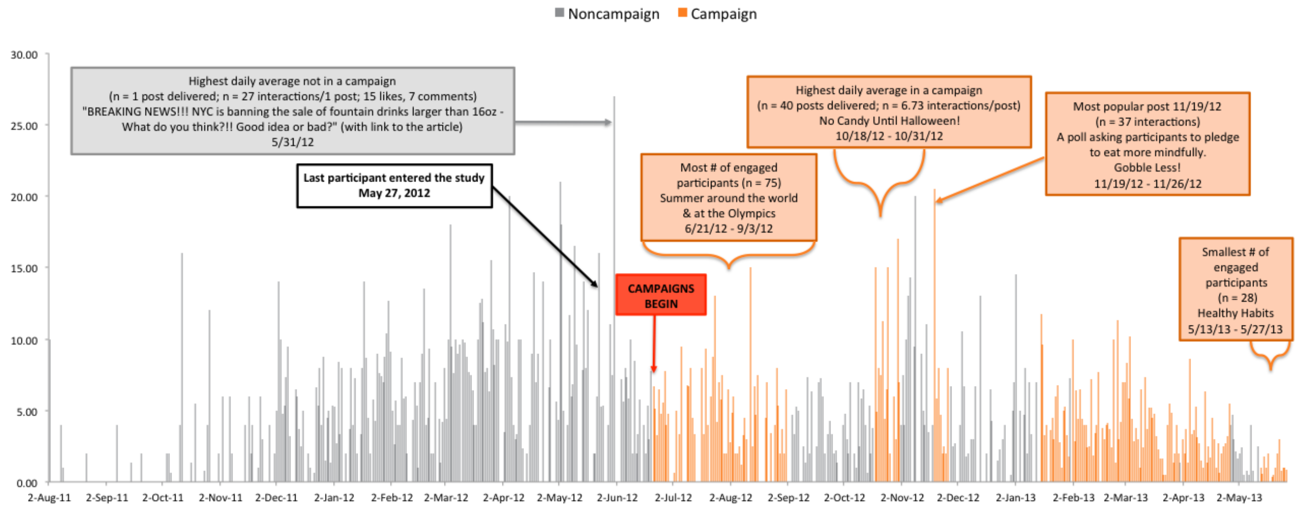
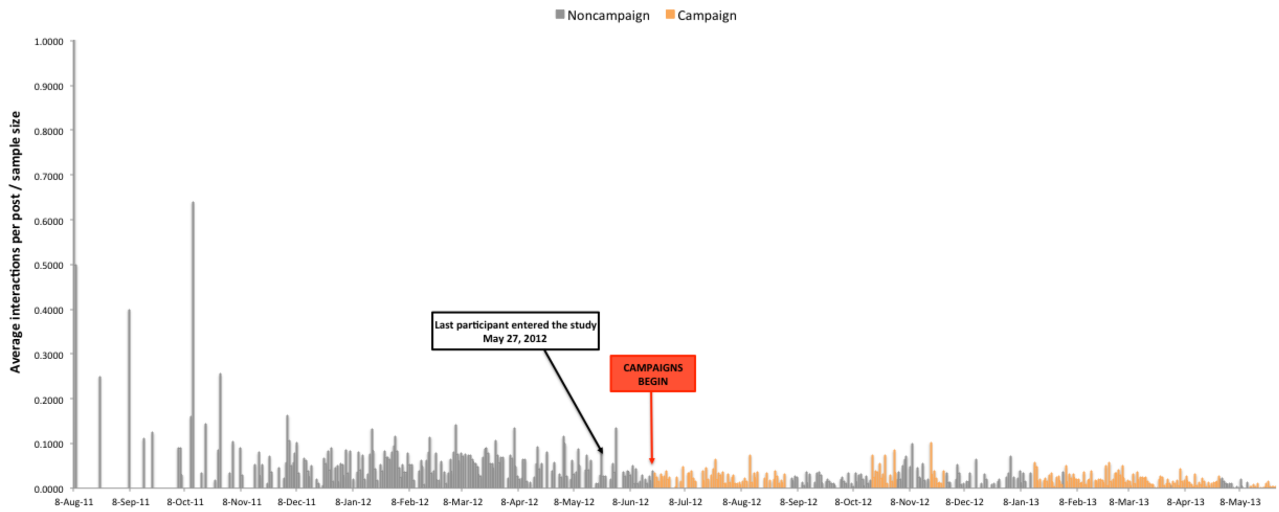



**Figure 3.** Average daily contribution per person per post delivered.




### *Dose Received-Qualitative Results*

Two themes emerged concerning participants' lurking on Facebook. Some participants lurked on Facebook when they interacted with their existing friendship network (ie, it generally characterized their overall social networking behavior), and this extended into their interactions with the study's page. Others lurked mostly on the study's page because they did not want to advertise their participation in a weight loss study.

### *"Yeah I Saw It, I Read It"*

Participants discussed how they frequently read ThreeTwoMe posts and those made by their Facebook friends without actively engaging. For example, participants said they commonly clicked on links and even if they liked the link, they did not feel obligated to like it on Facebook:

> *Just because I'm "passive" doesn't mean I'm ignoring it.*
>
> *I guess I don't post a lot on Facebook...I'm more passive...it would be more interesting if [ThreeTwoMe] posted more blogs so then I could easily read or click on [the link].*

### *"Facebook is Too Public a Place to Share My Health Information"*

A number of those interviewed talked about how they have Facebook friends they are not close with and they don't feel comfortable sharing with these people. Some participants mentioned taking ThreeTwoMe posts down from their newsfeed once they realized it was visible to their Facebook friends.

> *...[you] don't want to share weight loss with people you've met like one time in class.*
>
> *Nobody needs to know I'm in a [weight loss] study.*

## Facebook Campaigns

Over the course of the first 21 months of the study, 8 Facebook campaigns were delivered (4 sequenced and 4 nonsequenced). All participants were enrolled in the study by the time the first campaign began. Because of rolling recruitment, however, participants were exposed to the campaigns at different points in their intervention experience. For example, the first campaign began on June 21, 2012, approximately 45 weeks after the first participant entered the study, which meant that some participants were approximately halfway through the 2-year intervention whereas others had just begun the intervention. The last participant to be randomized was less than 1 month into the intervention at the start of the first campaign.

Table 5 presents participant engagement with each of the 8 campaigns. A campaign popularity score that divided the number of participant interactions by the number of unique posts delivered by the health coach was created. The health coach delivered more posts per day ($t_{3.44}$=6.13, $P$=.001) over the last 4 campaigns (mean 5.10, SD 0.14) compared to the first 4 campaigns (mean 3.40, SD 0.52).

The length of time participants' were in the study at the start of a campaign was not significantly associated with the number of Facebook interactions for the same campaign. However, there was a nonstatistically significant difference ($t_6$=2.08, $P$=.08) between the number of interactions during the first 4 campaigns (mean 4.69, SD 1.39) and the last 4 campaigns (mean 2.72, SD 1.30). Also, the number of unique participants engaged in each campaign declined over time (see Table 5).

**Table 5.** Participant engagement with the ThreeTwoMe Facebook page by Facebook campaign.

| Facebook campaigns | | | | Participant engagement,[a] n | | |
|---|---|---|---|---|---|---|
| Popularity rank | Popularity score[b] | Name[c] | Dates | Unique participants engaged | Participant interactions[d] | Unique posts delivered[e] |
| 1 | 6.73 | No candy until Halloween! (S) | 10/18/12-10/31/12 | 51 | 269 | 40 |
| 2 | 4.28 | Gobble less! (S) | 11/19/12-11/26/12 | 33 | 107 | 25 |
| 3 | 4.15 | Summer around the world & at the Olympics (NS) | 06/21/12-09/3/12 | 75 | 893 | 215 |
| 4 | 4.04 | Step it up! Pedometer challenge (S) | 02/01/13-02/28/13 | 51 | 558 | 138 |
| 5 | 3.60 | Motivation (NS) | 01/15/13-01/30/13 | 53 | 234 | 65 |
| 6 | 3.44 | Eat right your way (NS) | 03/01/13-03/30/13 | 53 | 495 | 144 |
| 7 | 2.27 | Get fit anywhere! (S) | 04/01/13-04/26/13 | 43 | 298 | 131 |
| 8 | 1.11 | Healthy habits (NS) | 05/13/13 -05/27/13 | 28 | 77 | 69 |

[a]Data represent all Facebook interactions during campaigns since the start of the study's Facebook page to the end of the eighth campaign (August 2, 2011 to May 27, 2013); total number of interactions with the ThreeTwoMe page outside of campaigns was 4965.

[b]Popularity score = # participant interactions / # unique posts delivered.

[c]S: sequenced; NS: nonsequenced.

[d]Includes all likes, comments, shares, and poll answers made in response to ThreeTwoMe posts as well as participant-initiated posts (ie, "posts to page"). Posts to page were adjusted for campaign duration and were included in this total because most posts to page were made in response to campaign requests.

[e]Unique posts delivered are consistently smaller than Participant interactions because the same post could have been interacted with more than 1 time.

Figure 4 displays sequenced Facebook campaign content stratified by behavior change technique. The health coach gave feedback in the form of likes and tailored responses to participants' posts. Goal review was frequently tailored to the individual. General goal review posts asked participants to revisit their goals and frequently included a self-monitoring element. Figure 5 shows nonsequenced campaign content and highlights participant-initiated posts. The health coach occasionally posted participants' content for them because (1) they were either unable to post directly to the page (due to changes Facebook made to their settings) or (2) participants did not want the post to be visible to their Facebook network (ie, due to privacy concerns). When this occurred, these data were counted as part of dose delivered. Note that for Figures 4 and 5 participants consented to having their images used in reports about the study and that names have been changed.

Table 6 presents sequenced and nonsequenced campaigns, describing their aims and the amount of visible participation each received.

**Table 6.** Campaign details for 2 sequenced and 1 nonsequenced campaigns.

| Name[a] | Description | Pledging | Dose received[b] |
| --- | --- | --- | --- |
| Gobble less! (S) | The campaign focused on mindful eating, encouraging participants to be more aware of what, how much, and why they were eating. Tips for how to eat more mindfully included taking eating breaks by talking with friends and family at the table, waiting until swallowing before taking a second bite, and putting the fork down between bites. | 10.6% (21/199) publically pledged to participate by responding to a poll on the ThreeTwoMe Facebook page | 76.0% (19/25) |
| Step it up! Pedometer challenge (S) | Participants were prompted to wear their pedometer to learn their baseline daily steps and encouraged to reach 10,000 steps per day by the end of the campaign by increasing their steps by 10% each week. Participants were given tables with precalculated weekly step increases. The health coach posed 3 mini-challenges during the campaign, aimed at helping participants' action plan and find fun and creative ways to increase their daily steps. | 9.0% (18/199) publically pledged to participate by posting a picture with their pedometer and/or by 'liking' a reminder post to take part in the campaign | 71.7% (99/138) |
| Summer around the world & At the Olympics[c] (NS) | The campaign focused on active travel and had a virtual scavenger hunt whereby participants earned points for completing various challenges, such as being active alone or with friends, and cooking healthy meals. Participants submitted photos or videos as proof they completed the challenge. Another campaign theme was "Take ThreeTwoMe with you all summer long!" whereby participants were asked to take pictures with a ThreeTwoMe postcard while being physically active or eating well. | There was no pledging because this was a nonsequenced campaign | 75.8% (163/215) |

[a]S: sequenced; NS: nonsequenced.

[b]Dose received is percent of posts participant(s) interacted with ≥1 time (ie, liked, commented, or shared) relative to number of posts delivered for the campaign=(# of posts interacted with/# of posts delivered)*100%.

[c]This was the study's first campaign.

**Figure 4.** Sequenced Facebook campaign content: Behavior change techniques delivered through Facebook posts.

**Figure 5.** Nonsequenced Facebook campaign content: Participant-inititated posts.

**Facebook campaign:**
Summer around the world & at the Olympics

**Participant post**


| | | | |
|---|---|---|---|
| **Participant activity** | Jen was the most active participant in this campagin with 108 interactions, which included 24 posts directly to the *ThreeTwoMe* page. | Carlos was the second most active participant in this campagin with 72 interactions, which included 3 posts directly to the *ThreeTwoMe* page. | Dianna was the third most active participant in this campagin with 63 interactions with the *ThreeTwoMe* page. |

## Discussion

### Principal Findings

This study suggests that Facebook is a promising medium to deliver theory-based weight loss content to college students. Approximately 73% (1325/1816, 72.96%) of the Facebook posts delivered were liked at least once by 68.8% (137/199) of the intervention participants. Although most of the intervention participants visibly engaged with the study's Facebook page at least once, interaction frequency was variable, including some participants who never visibly engaged, and engagement diminished over time. Our qualitative results indicate that many participants passively engaged with the page. To our knowledge, this is the first study to present Facebook process evaluation data that is stratified by post type (eg, status update, photo) as well as post interaction (eg, like, comment). These results characterize exposure to and engagement with Facebook in the context of a weight loss intervention. This characterization could be extended to define evaluation metrics in other social network-based behavioral interventions.

### Comparison With Prior Work

Despite interest in Facebook as a setting for health promotion interventions [19,34], little work has been published about how to best capture online metrics of engagement. Although the difficulty in maintaining engagement in online interventions over time is known, conclusions about a study's efficacy are often made prematurely without first considering usage patterns and nonusage attrition [62,63]. Similar to a sexual health promotion intervention that used Facebook, this study highlights the importance of defining engagement as well as developing a process evaluation plan of how it is to be measured [64]. For example, the results presented here emphasize the importance of measuring visible and nonvisible user engagement: without capturing the common practice of lurking online [26], estimates of engagement will be underestimated.

Although defining an evaluation framework enables the assessment of intervention efficacy, questions regarding the internal validity of engagement metrics remain. Interventions using social networking sites for health promotion are inherently limited by overarching social norms that govern users' visible behavior on the site [20]. For example, an individual may feel compelled to like a post because it has been liked by many others in the network (ie, social sanctioning) [20]. In addition, it remains unclear whether the like feature is an appropriate measure of engagement or if only comments should be considered as they suggest a deeper level of attention and cognitive processing [64,65]. There is evidence indicating that social network site use should not be considered homogenous; direction of interactions and which features are used differentially impacts outcomes (eg, social capital) [66]. Similarly, different motives for using Facebook predict the use of different Facebook features (eg, the like button) [67] and post type likely influences what features are used.

This study suggests that Facebook engagement metrics should not be lumped together into a single variable because this may obfuscate the interactions that are most relevant in terms of health behavior change. Similarly, metrics of exposure should be stratified so that differences in engagement by post type can be evaluated. Uncovering the most relevant feature use and post type will inform the development of better intervention frameworks.

The intervention framework analyzed in the present study differs from earlier work using Facebook in 3 ways: (1) the use of a behavior change technique framework to generate intervention content and modify content based on usage patterns and user feedback, (2) the amount of engagement and social support provided by the health coach, and (3) the amount of observed engagement with the study's Facebook page.

The iSIMPLE conceptual model used in SMART was based on behavior change techniques [35] previously demonstrated to be effective in changing weight loss behaviors [30]. Although earlier work has used theory to design message content, a behavior change technique framework has not been used to design and deliver Facebook content. Many online interventions use theory only superficially and intervention techniques are not explicitly mapped onto theory-relevant constructs [39]. Moreover, traditional health behavior theories may be underutilized in online designs because they are not flexible enough to be used in dynamic interventions [68].

In this study, intervention content was supplemented with cues to action or behavioral trigger messages [58] designed in response to participant interaction on Facebook. Delivering messages that are designed based on user feedback and/or user characteristics may be especially important for engagement with online interventions given the prominent role the user plays in computer-mediated interaction [69].

A novel aspect of this study is that the health coach delivered social support by liking and commenting on individual participants' Facebook interactions. Although Cavallo and colleagues' Facebook-based intervention had a site moderator who engaged with participants on Facebook, the moderator did not provide direct support to individual participants [42]. Previous work has shown that providing frequent and individualized support motivates overweight and obese individuals [32], and professional support from a health coach can have a significant impact on weight loss [23,70].

In addition to professional support, overweight/obese individuals' benefit from peer support [71], and peer support may be especially important for college students trying to lose weight [72]. Earlier work using Facebook has promoted the exchange of social support among participants on the study's Facebook page [42,45], an ad hoc network [34], but has not specifically involved participants' existing social networks [43].

Ad hoc networks can help individuals lose weight by providing an online space where individuals with shared goals can motivate one another [23], but some are hesitant to share with strangers. Indeed, a sizable number of participants did not visibly engage with the ThreeTwoMe Facebook page. Rather, visible engagement was high among a subset of participants and the qualitative data suggest that a number of participants interacted with the study's page passively. The proportion of participants who visibly engaged with the study's page was low but higher than has been reported in other studies. Cavallo et al [42] found that just 45% of participants interacted with the study's Facebook page once or more over the course of a 12-week intervention, and Napolitano et al [43] found that less than 25% of participants engaged with the study's Facebook page during an 8-week intervention.

## Limitations

Even though participants in the present study were more engaged compared with earlier work, it remains unknown whether Facebook is a useful medium to deliver behavior change interventions. The extent to which engagement with online interventions equates with behavior change and the mechanisms through which engagement changes behavior are not well understood [46,57,69,73]. Ritterband and colleagues' model for Internet interventions describes how behavior change is dependent upon user characteristics and the Web application with which the user interfaces [69]. Although this model was developed for more traditional top-down Internet interventions rather than social network-inspired designs, it provides a framework through which limitations of the present study can be considered. Four of the 8 areas deemed critical to intervention effectiveness are discussed in turn.

*Participation* is defined as the application's ability to interact with the user [69]. Although participants can interact with posts long after they have been posted by scrolling through their newsfeed, there is potentially an overwhelming amount of content to sort through (depending on the number of friends the user has) and posts can become more cumbersome to access over time. For example, when a participant does not actively engage with ThreeTwoMe posts, Facebook's content-personalization algorithm decreases the frequency of displaying the page's posts on his/her newsfeed—the less the user interacts with the page the less it appears on their newsfeed. In addition, participants may interact with content passively (ie, lurk) and their engagement is not captured with objectively derived quantitative metrics. Asking participants to self-report their interactions with a Facebook page can circumvent this issue and provide quantitative data on lurking behavior [45]. However, when self-report data are not captured, such as in the present study, quantitative estimates of user engagement may be underestimated.

*Burden* is defined as the ease with which the user can interact with the application [69]. Facebook is widely used [18] and may be especially easy to navigate for college students, but it may become burdensome when leveraged as a behavior change tool part of a multiyear intervention. A recent meta-analysis [31] looking at online interventions found that intervention duration is negatively associated with study adherence and intervention adherence (ie, nonusage attrition) [62], and users report disengaging from Facebook because of boredom, lack of time, or general disinterest with the site [74].

Lastly, engagement and subsequent behavior change are a function of *delivery* and *content* [69]. Although being able to use a variety of types of posts (eg, polls, photos) facilitates the delivery of diverse content, it is unclear which post(s) are most effective. For example, graphic content, such as photos, may be popular but their ability to stimulate behavior change is unknown. In addition, although the present study used an evidence-based conceptual model to design Facebook content, it is unknown the extent to which the posts mapped onto the behavior change techniques as intended. It is also unknown whether delivering more- versus less-structured Facebook campaigns has a measureable impact on behavior change. The more-structured (sequenced) campaigns had a higher average popularity score (4.33) than the less-structured (nonsequenced) campaigns (3.08), but this may be because of seasonal affects given that 2 of the 4 sequenced campaigns coincided with holidays, and/or because of the number of campaigns exposed to given that 2 of the last 3 campaigns delivered were nonsequenced.

Preliminary results from the present study indicate that participant engagement with the Facebook page declined over time. Future work will further evaluate change in engagement over time as well as qualitatively analyze the content of the Facebook interactions observed here. Analyzing the valence and words used in popular posts will inform the creation of better messages with the aim of increasing viral spread. “Going viral” is commonly mentioned as a main draw of using social networking sites for health promotion whereby messages spread among social networks, reaching a vast audience [75].

### Conclusions

Facebook can be used to deliver evidence-based weight loss intervention content designed for college students, but visible participant engagement is low. Benefits of using Facebook include the ability to iteratively tailor content and deliver timely social support and feedback to participants. Participants can engage their existing social networks as well as interact with the study network and the virtual health coach. Facebook also enables the asynchronous delivery of behavior change techniques and participants can view intervention content at their leisure, which may be especially important for RCTs among college students. Future research will examine whether Facebook campaigns based on theory-driven behavior change techniques improve behavioral outcomes and weight loss.

## Acknowledgments

Supported by grant U01 HL096715, NHLBI, NIH.

## Conflicts of Interest

None declared.

## References

1. American College Health Association. American College Health Association National College Health Assessment Spring 2006 Reference Group data report (abridged). J Am Coll Health 2007 Feb;55(4):195-206. [doi: 10.3200/JACH.55.4.195-206] [Medline: 17319325]
2. Vella-Zarb RA, Elgar FJ. The 'freshman 5': a meta-analysis of weight gain in the freshman year of college. J Am Coll Health 2009 Oct;58(2):161-166. [doi: 10.1080/07448480903221392] [Medline: 19892653]
3. Gropper SS, Simmons KP, Connell LJ, Ulrich PV. Weight and Body Composition Changes during the First Three Years of College. J Obes 2012;2012:634048 [FREE Full text] [doi: 10.1155/2012/634048] [Medline: 23050127]
4. Malhotra R, Ostbye T, Riley CM, Finkelstein EA. Young adult weight trajectories through midlife by body mass category. Obesity (Silver Spring) 2013 Sep;21(9):1923-1934. [doi: 10.1002/oby.20318] [Medline: 23408493]
5. Steinberger J, Moran A, Hong CP, Jacobs DR, Sinaiko AR. Adiposity in childhood predicts obesity and insulin resistance in young adulthood. J Pediatr 2001 Apr;138(4):469-473. [doi: 10.1067/mpd.2001.112658] [Medline: 11295707]
6. Breton ER, Fuemmeler BF, Abroms LC. Weight loss-there is an app for that! But does it adhere to evidence-informed practices? Transl Behav Med 2011 Dec;1(4):523-529 [FREE Full text] [doi: 10.1007/s13142-011-0076-5] [Medline: 24073074]
7. Cooper JN, Buchanich JM, Youk A, Brooks MM, Barinas-Mitchell E, Conroy MB, et al. Reductions in arterial stiffness with weight loss in overweight and obese young adults: potential mechanisms. Atherosclerosis 2012 Aug;223(2):485-490 [FREE Full text] [doi: 10.1016/j.atherosclerosis.2012.05.022] [Medline: 22703865]
8. Dangardt F, Chen Y, Berggren K, Osika W, Friberg P. Increased rate of arterial stiffening with obesity in adolescents: a five-year follow-up study. PLoS One 2013;8(2):e57454 [FREE Full text] [doi: 10.1371/journal.pone.0057454] [Medline: 23451232]
9. Herva A, Laitinen J, Miettunen J, Veijola J, Karvonen JT, Läksy K, et al. Obesity and depression: results from the longitudinal Northern Finland 1966 Birth Cohort Study. Int J Obes (Lond) 2006 Mar;30(3):520-527. [doi: 10.1038/sj.ijo.0803174] [Medline: 16302014]
10. Carr D, Jaffe K. The psychological consequences of weight change trajectories: evidence from quantitative and qualitative data. Econ Hum Biol 2012 Dec;10(4):419-430 [FREE Full text] [doi: 10.1016/j.ehb.2012.04.007] [Medline: 22580044]
11. Ames GE, Perri MG, Fox LD, Fallon EA, De Braganza N, Murawski ME, et al. Changing weight-loss expectations: a randomized pilot study. Eat Behav 2005 Jun;6(3):259-269. [doi: 10.1016/j.eatbeh.2005.01.003] [Medline: 15854872]
12. Donnelly JE, Hill JO, Jacobsen DJ, Potteiger J, Sullivan DK, Johnson SL, et al. Effects of a 16-month randomized controlled exercise trial on body weight and composition in young, overweight men and women: the Midwest Exercise Trial. Arch Intern Med 2003 Jun 9;163(11):1343-1350. [doi: 10.1001/archinte.163.11.1343] [Medline: 12796071]

13. Ahern DK, Kreslake JM, Phalen JM. What is eHealth (6): perspectives on the evolution of eHealth research. J Med Internet Res 2006;8(1):e4 [FREE Full text] [doi: 10.2196/jmir.8.1.e4] [Medline: 16585029]
14. Free C, Phillips G, Felix L, Galli L, Patel V, Edwards P. The effectiveness of M-health technologies for improving health and health services: a systematic review protocol. BMC Res Notes 2010;3:250 [FREE Full text] [doi: 10.1186/1756-0500-3-250] [Medline: 20925916]
15. Gow RW, Trace SE, Mazzeo SE. Preventing weight gain in first year college students: an online intervention to prevent the "freshman fifteen". Eat Behav 2010 Jan;11(1):33-39 [FREE Full text] [doi: 10.1016/j.eatbeh.2009.08.005] [Medline: 19962118]
16. Brenner J. Pew Internet: Mobile. Washington, DC: Pew Internet & American Life Project; 2013 May. URL: http://pewinternet.org/Commentary/2012/February/Pew-Internet-Mobile.aspx [accessed 2014-01-20] [WebCite Cache ID 6Mm8smnp9]
17. Smith A, Rainie L, Zickuhr K. College students and technology. Washington, DC: Pew Internet & American Life Project; 2011 Jul 19. URL: http://pewinternet.org/Reports/2011/College-students-and-technology/Report.aspx [accessed 2014-01-20] [WebCite Cache ID 6Mm9lf2eI]
18. Duggan M, Brenner J. The demographics of social media users. 2013 Feb 14. URL: http://pewinternet.org/Reports/2013/Social-media-users/Social-Networking-Site-Users/Demo-portrait.aspx [accessed 2014-01-20] [WebCite Cache ID 6Mm9pmVxU]
19. Hampton K, Goulet L, Rainie L, Purcell K. Social networking sites and our lives. Washington, DC: Pew Internet & American Life Project; 2011 Jun 16. URL: http://pewinternet.org/Reports/2011/Technology-and-social-networks/Part-2/Facebook-activities.aspx [accessed 2014-01-20] [WebCite Cache ID 6Mm9tyw35]
20. Loss J, Lindacher V, Curbach J. Online social networking sites-a novel setting for health promotion? Health Place 2014 Mar;26:161-170. [doi: 10.1016/j.healthplace.2013.12.012] [Medline: 24457613]
21. Kelders SM, Kok RN, Ossebaard HC, Van Gemert-Pijnen JE. Persuasive system design does matter: a systematic review of adherence to web-based interventions. J Med Internet Res 2012;14(6):e152 [FREE Full text] [doi: 10.2196/jmir.2104] [Medline: 23151820]
22. Wilson RE, Gosling SD, Graham LT. A review of Facebook research in the social sciences. Perspectives on Psychological Science 2012 May 16;7(3):203-220. [doi: 10.1177/1745691612442904]
23. Hwang KO, Ottenbacher AJ, Green AP, Cannon-Diehl MR, Richardson O, Bernstam EV, et al. Social support in an Internet weight loss community. Int J Med Inform 2010 Jan;79(1):5-13 [FREE Full text] [doi: 10.1016/j.ijmedinf.2009.10.003] [Medline: 19945338]
24. Lampinen AS, Tamminen S, Oulasvirta A. All my people right here, right now: Management of group co-presence on a social networking site. 2009 Presented at: ACM International Conference on Supporting Group Work; May 10-13, 2009; Sanibel Island,FL p. 281-290. [doi: 10.1145/1531674.1531717]
25. Newman MW, Lauterbach D, Munson SA, Resnick P, Morris ME. It's not that I don't have problems, I'm just not putting them on Facebook: Challenges and opportunities in using online social networks for health. 2011 Presented at: Proceedings of the ACM Conference on Computer Supported Cooperative Work; March 9-23, 2011; Hangzhou, China p. 341-350. [doi: 10.1145/1958824.1958876]
26. Rafaeli S, Ravid G, Soroka V. De-lurking in virtual communities: A social communication network approach to measuring the effects of social and cultural capital. 2004 Presented at: Proceedings of the 37th Annual Hawaii International Conference on System Sciences; January 5-8, 2004; Hawaii p. 5-8. [doi: 10.1109/HICSS.2004.1265478]
27. Ballantine PW, Stephenson RJ. Help me, I'm fat! Social support in online weight loss networks. J. Consumer Behav 2011 Dec 23;10(6):332-337. [doi: 10.1002/cb.374]
28. Brouwer W, Kroeze W, Crutzen R, de Nooijer J, de Vries NK, Brug J, et al. Which intervention characteristics are related to more exposure to internet-delivered healthy lifestyle promotion interventions? A systematic review. J Med Internet Res 2011;13(1):e2 [FREE Full text] [doi: 10.2196/jmir.1639] [Medline: 21212045]
29. Turner-McGrievy GM, Tate DF. Weight loss social support in 140 characters or less: use of an online social network in a remotely delivered weight loss intervention. Transl Behav Med 2013 Sep;3(3):287-294 [FREE Full text] [doi: 10.1007/s13142-012-0183-y] [Medline: 24073180]
30. Michie S, Abraham C, Whittington C, McAteer J, Gupta S. Effective techniques in healthy eating and physical activity interventions: a meta-regression. Health Psychol 2009 Nov;28(6):690-701. [doi: 10.1037/a0016136] [Medline: 19916637]
31. Cugelman B, Thelwall M, Dawes P. Online interventions for social marketing health behavior change campaigns: a meta-analysis of psychological architectures and adherence factors. J Med Internet Res 2011;13(1):e17 [FREE Full text] [doi: 10.2196/jmir.1367] [Medline: 21320854]
32. Fukuoka Y, Kamitani E, Bonnet K, Lindgren T. Real-time social support through a mobile virtual community to improve healthy behavior in overweight and sedentary adults: a focus group analysis. J Med Internet Res 2011;13(3):e49 [FREE Full text] [doi: 10.2196/jmir.1770] [Medline: 21752785]
33. Bond RM, Fariss CJ, Jones JJ, Kramer AD, Marlow C, Settle JE, et al. A 61-million-person experiment in social influence and political mobilization. Nature 2012 Sep 13;489(7415):295-298. [doi: 10.1038/nature11421] [Medline: 22972300]
34. Cobb NK, Graham AL. Health behavior interventions in the age of facebook. Am J Prev Med 2012 Nov;43(5):571-572. [doi: 10.1016/j.amepre.2012.08.001] [Medline: 23079184]

35. Abraham C, Michie S. A taxonomy of behavior change techniques used in interventions. Health Psychol 2008 May;27(3):379-387. [doi: 10.1037/0278-6133.27.3.379] [Medline: 18624603]
36. Michie S, Ashford S, Sniehotta FF, Dombrowski SU, Bishop A, French DP. A refined taxonomy of behaviour change techniques to help people change their physical activity and healthy eating behaviours: the CALO-RE taxonomy. Psychol Health 2011 Nov;26(11):1479-1498. [doi: 10.1080/08870446.2010.540664] [Medline: 21678185]
37. Aronson ID, Marsch LA, Acosta MC. Using findings in multimedia learning to inform technology-based behavioral health interventions. Transl Behav Med 2013 Sep;3(3):234-243 [FREE Full text] [doi: 10.1007/s13142-012-0137-4] [Medline: 24073174]
38. Hekler EB, Klasnja P, Froehlich JE, Buman MP. Mind the theoretical gap: Interpreting, using, and developing behavioral theory in HCI research. 2103 Presented at: CHI '13 Proceedings of the SIGCHI Conference on Human Factors in Computing Systems; April 27-May 2, 2013; Paris, France. [doi: 10.1145/2470654.2466452]
39. Webb TL, Joseph J, Yardley L, Michie S. Using the internet to promote health behavior change: a systematic review and meta-analysis of the impact of theoretical basis, use of behavior change techniques, and mode of delivery on efficacy. J Med Internet Res 2010;12(1):e4 [FREE Full text] [doi: 10.2196/jmir.1376] [Medline: 20164043]
40. Cowan LT, Van Wagenen SA, Brown BA, Hedin RJ, Seino-Stephan Y, Hall PC, et al. Apps of steel: are exercise apps providing consumers with realistic expectations?: a content analysis of exercise apps for presence of behavior change theory. Health Educ Behav 2013 Apr;40(2):133-139. [doi: 10.1177/1090198112452126] [Medline: 22991048]
41. Carver CS, Scheier MF. Control theory: a useful conceptual framework for personality-social, clinical, and health psychology. Psychol Bull 1982 Jul;92(1):111-135. [Medline: 7134324]
42. Cavallo DN, Tate DF, Ries AV, Brown JD, DeVellis RF, Ammerman AS. A social media-based physical activity intervention: a randomized controlled trial. Am J Prev Med 2012 Nov;43(5):527-532. [doi: 10.1016/j.amepre.2012.07.019] [Medline: 23079176]
43. Napolitano MA, Hayes S, Bennett GG, Ives AK, Foster GD. Using Facebook and text messaging to deliver a weight loss program to college students. Obesity (Silver Spring) 2013 Jan;21(1):25-31. [doi: 10.1002/oby.20232] [Medline: 23505165]
44. Pedrana A, Hellard M, Gold J, Ata N, Chang S, Howard S, et al. Queer as F**k: reaching and engaging gay men in sexual health promotion through social networking sites. J Med Internet Res 2013;15(2):e25 [FREE Full text] [doi: 10.2196/jmir.2334] [Medline: 23391459]
45. Valle CG, Tate DF, Mayer DK, Allicock M, Cai J. A randomized trial of a Facebook-based physical activity intervention for young adult cancer survivors. J Cancer Surviv 2013 Sep;7(3):355-368. [doi: 10.1007/s11764-013-0279-5] [Medline: 23532799]
46. Couper MP, Alexander GL, Zhang N, Little RJ, Maddy N, Nowak MA, et al. Engagement and retention: measuring breadth and depth of participant use of an online intervention. J Med Internet Res 2010;12(4):e52 [FREE Full text] [doi: 10.2196/jmir.1430] [Medline: 21087922]
47. Patrick K, Marshall SJ, Davila EP, Kolodziejczyk JK, Fowler JH, Calfas KJ, et al. Design and implementation of a randomized controlled social and mobile weight loss trial for young adults (project SMART). Contemp Clin Trials 2014 Jan;37(1):10-18. [doi: 10.1016/j.cct.2013.11.001] [Medline: 24215774]
48. Bronfenbrenner U. The Ecology of Human Development: Experiments by Nature and Design. Cambridge, MA: Harvard University Press; 1979.
49. Sallis JF, Cervero RB, Ascher W, Henderson KA, Kraft MK, Kerr J. An ecological approach to creating active living communities. Annu Rev Public Health 2006;27:297-322. [doi: 10.1146/annurev.publhealth.27.021405.102100] [Medline: 16533119]
50. Fishbein M, Ajzen I. Belief, Attitude, Intention, and Behavior: an Introduction to Theory and Research. Reading, MA: Addison-Wesley Pub Co; 1975.
51. Bandura A. Self-Efficacy: The Exercise of Control. New York: WH Freeman; 1997.
52. Skinner BF. About Behaviorism. New York: Vintage Books; 1974.
53. Festinger L. A theory of social comparison processes. Human Relations 1954 May 01;7(2):117-140. [doi: 10.1177/001872675400700202]
54. Berkman LF. Social support, social networks, social cohesion and health. Soc Work Health Care 2000;31(2):3-14. [doi: 10.1300/J010v31n02_02] [Medline: 11081851]
55. Webb TL, Sheeran P. Mechanisms of implementation intention effects: the role of goal intentions, self-efficacy, and accessibility of plan components. Br J Soc Psychol 2008 Sep;47(Pt 3):373-395. [doi: 10.1348/014466607X267010]
56. Rhodes RE, Dickau L. Experimental evidence for the intention-behavior relationship in the physical activity domain: a meta-analysis. Health Psychol 2012 Nov;31(6):724-727. [doi: 10.1037/a0027290] [Medline: 22390739]
57. Danaher BG, Seeley JR. Methodological issues in research on web-based behavioral interventions. Ann Behav Med 2009 Aug;38(1):28-39. [doi: 10.1007/s12160-009-9129-0] [Medline: 19806416]
58. Fogg B. A behavior model for persuasive design. 2009 Presented at: Proceedings of the 4th International Conference on Persuasive Technology; April 26-29, 2009; Claremont, CA.

59. Lacroix J, Saini P, Goris A. Understanding user cognitions to guide the tailoring of persuasive technology-based physical activity interventions. 2009 Presented at: Proceedings of the 4th International Conference on Persuasive Technology; April 26-29, 2009; Claremont, CA.
60. Glaser BG, Strauss AL. The Discovery of Grounded Theory; Strategies for Qualitative Research. Chicago, IL: Aldine Pub Co; 2012.
61. Hwang KO, Ottenbacher AJ, Lucke JF, Etchegaray JM, Graham AL, Thomas EJ, et al. Measuring social support for weight loss in an internet weight loss community. J Health Commun 2011 Feb;16(2):198-211. [doi: 10.1080/10810730.2010.535106] [Medline: 21181600]
62. Eysenbach G. The law of attrition. J Med Internet Res 2005;7(1):e11 [FREE Full text] [doi: 10.2196/jmir.7.1.e11] [Medline: 15829473]
63. Christensen H, Mackinnon A. The law of attrition revisited. J Med Internet Res 2006;8(3):e20; author reply e21 [FREE Full text] [doi: 10.2196/jmir.8.3.e20] [Medline: 17032636]
64. Gold J, Pedrana AE, Stoove MA, Chang S, Howard S, Asselin J, et al. Developing health promotion interventions on social networking sites: recommendations from The FaceSpace Project. J Med Internet Res 2012;14(1):e30 [FREE Full text] [doi: 10.2196/jmir.1875] [Medline: 22374589]
65. Koroleva K, Stimac V, Krasnova H, Kunze D. I like it because I'm like you – measuring user attitudes toward information on Facebook. 2011 Presented at: International Conference on Information Systems Proceedings; 2011; Shanghai, China.
66. Burke M, Kraut R, Marlow C. Social capital on Facebook: Differentiating uses and users. 2011 Presented at: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems; May 7-12, 2011; Vancouver, BC p. 571-580. [doi: 10.1145/1978942.1979023]
67. Smock AD, Ellison NB, Lampe C, Wohn DY. Facebook as a toolkit: A uses and gratification approach to unbundling feature use. Computers in Human Behavior 2011 Nov;27(6):2322-2329. [doi: 10.1016/j.chb.2011.07.011]
68. Riley WT, Rivera DE, Atienza AA, Nilsen W, Allison SM, Mermelstein R. Health behavior models in the age of mobile interventions: are our theories up to the task? Transl Behav Med 2011 Mar;1(1):53-71 [FREE Full text] [doi: 10.1007/s13142-011-0021-7] [Medline: 21796270]
69. Ritterband LM, Thorndike FP, Cox DJ, Kovatchev BP, Gonder-Frederick LA. A behavior change model for internet interventions. Ann Behav Med 2009 Aug;38(1):18-27 [FREE Full text] [doi: 10.1007/s12160-009-9133-4] [Medline: 19802647]
70. Leahey TM, Wing RR. A randomized controlled pilot study testing three types of health coaches for obesity treatment: Professional, peer, and mentor. Obesity (Silver Spring) 2013 May;21(5):928-934 [FREE Full text] [doi: 10.1038/oby.2012.179] [Medline: 23784896]
71. Carson TL, Eddings KE, Krukowski RA, Love SJ, Harvey-Berino JR, West DS. Examining social influence on participation and outcomes among a network of behavioral weight-loss intervention enrollees. J Obes 2013;2013:480630 [FREE Full text] [doi: 10.1155/2013/480630] [Medline: 23840944]
72. Salvy SJ, de la Haye K, Bowker JC, Hermans RC. Influence of peers and friends on children's and adolescents' eating and activity behaviors. Physiol Behav 2012 Jun 6;106(3):369-378 [FREE Full text] [doi: 10.1016/j.physbeh.2012.03.022] [Medline: 22480733]
73. Danaher BG, Boles SM, Akers L, Gordon JS, Severson HH. Defining participant exposure measures in Web-based health behavior change programs. J Med Internet Res 2006;8(3):e15 [FREE Full text] [doi: 10.2196/jmir.8.3.e15] [Medline: 16954125]
74. Rainie L, Smith A, Duggan M. Coming and Going on Facebook. Washington, DC: Pew Internet & American Life Project; 2013 Feb 05. URL: http://pewinternet.org/Reports/2013/Coming-and-going-on-facebook.aspx [accessed 2014-01-20] [WebCite Cache ID 6MmAL5jeB]
75. Woerendl M, Papagiannidis S, Bourlakis M, Li F. Internet-induced marketing techniques: Critical factors in viral marketing campaigns. Int J Bus Sci Appl Mgmt 2008;3(1):33-45.


## Abbreviations

**iSIMPLE:** intention formation, self-monitor, make plans, execute
**JSON:** JavaScript Object Notation
**RCT:** randomized controlled trial
**SMART:** social and mobile approach to reduce weight

*Edited by G Eysenbach; submitted 21.01.14; peer-reviewed by D Cavallo, C Valle; comments to author 12.02.14; revised version received 29.03.14; accepted 28.04.14; published 24.06.14.*

*Please cite as:*
*Merchant G, Weibel N, Patrick K, Fowler JH, Norman GJ, Gupta A, Servetas C, Calfas K, Raste K, Pina L, Donohue M, Griswold WG, Marshall S*
*Click "Like" to Change Your Behavior: A Mixed Methods Study of College Students' Exposure to and Engagement With Facebook Content Designed for Weight Loss*
*J Med Internet Res 2014;16(6):e158*
*URL: http://www.jmir.org/2014/6/e158/*
*doi:10.2196/jmir.3267*
*PMID:24964294*

Original Paper

# Designing for Psychological Change: Individuals' Reward and Cost Valuations in Weight Management

Anne Hsu[1], PhD; Ann Blandford[2], PhD

[1]School of Electronic Engineering and Computer Science, Queen Mary, University of London, London, United Kingdom

[2]UCL Interaction Centre, University College London, London, United Kingdom

**Corresponding Author:**
Anne Hsu, PhD
School of Electronic Engineering and Computer Science
Queen Mary, University of London
Mile End Road
London, E1 4NS
United Kingdom
Phone: 44 77 2206 2525
Fax: 44 20 7882 7997
Email: anne.hsu@eecs.qmul.ac.uk

## Abstract

**Background:** Knowledge of the psychological constructs that underlie behavior offers valuable design opportunities for persuasive systems. We use the decision theory, which describes how behavior is underpinned by reward-cost valuations, as a framework for investigating such psychological constructs to deliver design objectives for weight management technologies.

**Objective:** We applied a decision theory–based analysis in the domain of weight management to understand the rewards and costs that surround individuals' weight management behaviors, with the aim of uncovering design opportunities for weight management technologies.

**Methods:** We conducted qualitative interviews with 15 participants who were or had been trying to lose weight. Thematic analysis was used to extract themes that covered the rewards and costs surrounding weight management behaviors. We supplemented our qualitative study with a quantitative survey of 100 respondents investigating the extent to which they agreed with statements reflecting themes from the qualitative study.

**Results:** The primary obstacles to weight management were the rewards associated with unhealthy choices, such as the pleasures of unhealthy foods and unrestricted consumption in social situations, and the significant efforts required to change habits, plan, and exercise. Psychological constructs that supported positive weight management included feeling good after making healthy choices, being good to oneself, experiencing healthy yet still delicious foods, and receiving social support and encouraging messages (although opinions about encouraging messages was mixed).

**Conclusions:** A rewards-costs driven enquiry revealed a wide range of psychological constructs that contribute to discouraging and supporting weight management. The constructs extracted from our qualitative study were verified by our quantitative survey, in which the majority of respondents also reported similar thoughts and feelings. This understanding of the rewards and costs surrounding weight management offers a range of new opportunities for the design of weight management technologies that enhance the encouraging factors and alleviate the discouraging ones.

***(J Med Internet Res 2014;16(6):e138)*** doi:10.2196/jmir.3009

**KEYWORDS**

design; human-centered computing; behavior; psychology; interaction design process and methods; weight loss; health promotion

## Introduction

### Background

Obesity is one of the most serious world health problems of the 21st century. Excessive weight has been identified as the cause of many medical conditions, which have been estimated to cost $147 billion per year in the United States alone [1]. In response to this problem, a rising number of weight management technologies are being developed. Because thoughts and feelings are fundamental drivers of behavior, it is important for persuasive technologies to be informed by an understanding of the psychological underpinnings of behavior. Indeed, general frameworks for persuasive systems design have highlighted the importance of understanding the motivational landscape [2,3], or more generally, the *persuasion context*, which includes the thoughts, feelings, and attitudes of the individual being persuaded [4,5].

Psychological understanding can inform persuasive systems design at varying levels of specificity. At a macro level, there are context-general psychological principles, such as theories of behavior change. These theories describe general psychological principles and offer general strategies for influencing behavior. These include goal setting theory [6], transtheoretical model of stages of behavioral change [7], and social cognitive theory [8]. Such general behavior change theories have recently begun to influence persuasive systems design [9]. In addition to aiming to change behavior directly, persuasive technologies can also effect change by targeting the psychological constructs that underlie behaviors. Indeed, long-term behavioral changes will be sustained only when the relevant underlying psychological constructs are altered [4,5,10]. Therefore, in order to influence the psychological constructs that underpin behaviors, it is important to understand what these constructs are within a specific persuasion context. Unlike general behavior change theories, these psychological constructs are not domain general but instead capture the particular thoughts, feelings, and attitudes that surround behaviors relevant to a specific context, for example, weight loss, smoking cessation, or road safety. Thus, whereas general theories of behavior change provide the designer with strategies of *how to change*, an understanding of specific psychological constructs helps inform the designer of *what to change.* The latter has not been highlighted in the discussion of persuasive systems design. In the current work, we propose that the considerations of rewards and costs in decision theory [10] offer an appropriate framework for both extracting key context-specific psychological constructs and also for specifying how to translate knowledge of these constructs into design targets for persuasive systems.

## Persuasive Systems Design

Persuasive systems effect change through two primary (non-mutually exclusive) avenues: shaping external behaviors or internal attitudes. The overwhelming majority of existing persuasive technologies focus on external behaviors [11], for example, a tracker for calorie consumption and exercise [9,11-14]. This is because external behaviors are more tangible, measurable, and thus easier targets for change. However, the distinction between influencing behavior vs thought is blurred: often influencing behavior also promotes new thoughts and awareness. For example, exercise and calorie trackers increase user awareness of their activities and intake. There has been a recent increase in persuasive technologies designed for psychological influence by encouraging reflection and awareness about health-related choices. These include text message-based interventions that prompt self-reflection [15], a visual garden display to encourage emotional connection to one's levels of physical activity [16,17], open-ended platforms for documenting and sharing health decisions, and a shared visual journal for diet and exercise [14].

It is important for persuasive systems to change attitudes as well as behavior because attitudes and preferences underpin human choices and behavior [4,5,10]. In order to produce more robust behavioral changes, recent persuasive health technologies have started to shape people's psychological responses, attitudes, and preferences by applying theories and strategies from psychology and health research [9,11,18-20]. The pervasive quality of many technological systems, such as mobile technologies, means that they are particularly well positioned to deliver interventions that target psychological processes. These advantages of pervasive technologies are summarized through a description of the many roles that such technologies play [21]: a device of "kairos" that is always near at hand, the role of a concierge that offers guidance and information at the moment of need, a personal coach that can track personal goals and context, and a jester that can promote fun interactions (both personal and social). These properties of technological systems make them well suited for modifying psychology because they can evoke new thought processes and emotions in a timely fashion, customized to the persuasion context. For example, technologies can be synchronized with electronic diaries or sensing technologies [22] to know when contexts that prompt salient psychological states will occur. Finally, thoughts, feelings, and attitudes are highly personal, and technology-based systems have the potential to deliver personalized interventions that cater to this individual variation.

While knowledge of general context-general psychological principles is highly useful for persuasive design, it is also important to understand the specific psychological constructs that underlie the behaviors in a particular design context. Persuasive technologies can then aim to alleviate the psychological constructs that discourage and enhance the ones that encourage. We propose that decision theory provides a useful starting point for investigating these psychological constructs because its framework of reward-cost considerations naturally defines clear design objectives for persuasive systems. We provide a brief overview of decision theory below.

## Decision Theory and Reward-Cost Considerations

The term "decision theory" has been applied to a wide variety of models describing how people make choices that give rise to behavior. At one extreme are economics-inspired models of rational agents that calculate the individual utilities associated with all attributes of choice options and then maximize summed utility. More psychologically realistic models highlight the context-dependent nature of attribute valuations [23], with some models depicting choices as entirely dependent on contextual comparisons [24], or "one shot" reasoning informed by heuristics and biases [23]. From a more local perspective, a large body of recent neuroscience research [10,25] has depicted decision making as follows: Behavior is characterized as a choice among possible behavior options. The mind associates rewards and costs with each behavioral option, and the most rewarding options are most likely to be chosen. In support of this, neuroimaging and neurophysiology studies have found that before a choice is made, each behavioral option is associated with a *decision value* [10], that is, a signal in the brain that represents a mental forecast of the option's hedonic impact (the forecasted pleasure to be gained from the option). It is suggested that the brain computes decision values by summing up the predicted rewards and costs associated with each option [10,25]. A comparison is then made of the relative decision values among behavioral options, and behaviors that are assigned higher decision values are more likely to be chosen. We emphasize that decision theory focuses on *hedonic* rewards (eg, pleasure, social value, comfort) and costs (eg, pain, effort, discomfort, embarrassment). This means, for example, that a choice that has monetary cost is less desirable only because of its associated "emotional cost" of the negative feelings (eg, guilt, pain, worry) of losing money.

The decision theoretic framework we have described is broad and is consistent with a wide range of psychological-level models of decision making [25]. For example, the types of attributes considered and how they are valued have been shown to be highly modulated by context and attention [26,27], which is consistent with psychological models. Also, decision values may be informed by only a single attribute (consistent with one-shot heuristic approaches to decision making), or multiple attributes [25]. This framework is also not limited to conscious attitudes. For example, unconscious saccades in eye movements have also been described using reward-cost valuations of decision theory [24,28]. However, for the purpose of persuasive systems design, it is usually most practical to focus on the conscious attitudes that can be elicited from the user.

A key feature of reward-cost considerations, highly relevant for weight loss, is delayed discounting, where it has been observed that delayed consequences are substantially less influential than immediate ones [29]. Many studies have shown that decision values in the brain are significantly more influenced by rewards and costs that will be experienced immediately rather than far off in the future [25]. The decreased value of delayed rewards lies at the heart of most self-control struggles [30] and is highly relevant to weight management because weight change mostly occurs over long time frames. Thus weight-relevant choices (and all behavior choices) will be more influenced by immediate feelings than long-term consequences. Immediate feelings can consist of feelings of physical sensations as well as psychological feelings of satisfaction. Therefore, when a dieter chooses a healthy snack option, his or her decision values are usually less influenced by distant attributes, such as the eventual weight loss, and more influenced immediate attributes, such as the feeling of satisfaction of having made a healthy choice. This is important to bear in mind when designing persuasive systems. One possible role for persuasive systems is to transform long-term consequences into more immediate feelings (eg, show pictures of additional fat gained after a big meal).

Recent promising research shows that rewards and cost valuations can be altered to shift preferences. On a neural level, it has been found that reward associations for healthy options can be enhanced to result in preferences for healthier choices. Prompting a focus on health rather than taste increases the brain's decision values (ie, preferences) and choices, for healthier foods [27]. Prompting thoughts about future events has been shown to reduce delayed discounting and increase decision values (ie, preference) for delayed rewards [26]. Similar behavioral research has also found that preferences can be shifted towards healthier choices. Emphasizing enjoyable experiences associated with consumption of healthy foods results in these foods being chosen more often in later meals [31]. There has also been behavioral research showing that preferences for unhealthy eating behaviors can be decreased. Use of visuospatial tasks and imagery have been shown to reduce food craving levels [32].

### Applying Decision Theory to Inform Persuasive Design

We propose that the broad framework of decision theory, which considers the rewards and costs associated with behavioral options, can be used to inform persuasive systems design. This is key to behavior change as deeply rooted behaviors are likely to have strong emotional components. The framework can be used as follows. First, the designer specifies the desired and undesired behaviors within the persuasive design context. The designer then aims to identify the rewards and costs associated with these desirable and undesirable behaviors. After the rewards and costs have been identified, decision theory specifies four ways in which persuasive systems can encourage desired behaviors: (1) increase the rewards associated with desired behaviors, (2) decrease the costs associated with desired behaviors, (3) decrease the rewards associated with undesired behaviors, and (4) increase the costs associated with the undesired behaviors.

### Why Decision Theory?

Decision theory is a low-level approach to understanding behavior that underpins a large family of motivational theories, such as Theory of Planned Behavior [33], Theory of Interpersonal Behavior [34], and Theory of Normative Social Behavior [34]. Different theories of behavior capture human motivation at varying levels of abstraction, and with emphasis on different features of behavior [35]. While all levels of motivational theory can be useful for persuasive systems design, we propose that the decision theoretic approach of considering rewards and costs are at an appropriate level of abstraction to serve as a starting point for investigating the relevant psychological constructs involved. An investigation of rewards and costs over a range of weight management contexts imposes minimal assumptions and offers the most open-ended foundation for discovering design opportunities.

### Aims of Current Work

The aim of the work reported here is two-fold: (1) to test whether the decision theory framework of reward-cost valuations can be used to reveal the psychological constructs that underlie behavior and thus inform design of weight management systems, and (2) to better understand the persuasion context relevant for weight management, that is, what thoughts, feelings, and contexts encourage or discourage people's weight management efforts.

We present results from an in-depth interview study aimed at revealing the rewards and costs associated with weight management efforts. We asked individuals to share the thoughts, feelings, and contexts that surrounded their weight loss efforts. We hypothesized that (1) these interviews would reveal some key rewards and costs relevant to weight management choices, and (2) understanding of these rewards and costs would yield potential design objectives for weight management technologies. We organized the presentation of our interview results into rewards and costs surrounding behaviors that discourage versus encourage weight management. Following our qualitative study, we conducted a Web-based survey to understand the extent to which the themes from our interviews were experienced over a larger population. Finally, we discuss the implications of our results for the design of weight management technologies.

# Methods

## Summary

We sought to understand the rewards and costs associated with both negative and positive weight management behaviors. To do so, we first conducted a qualitative study consisting of semistructured interviews that aimed to identify the rewards and costs surrounding weight management behaviors. We then supplemented our qualitative study with a quantitative survey to assess the extent to which the themes we extracted from our qualitative study were experienced over a larger population.

## Methods for Qualitative Study

### *Qualitative Study Procedure*

In our qualitative study, we asked individuals about the thoughts, feelings, and contexts that surrounded behaviors that either discouraged or encouraged weight loss efforts. Semistructured interviews were conducted lasting 45-60 minutes. Questions were structured around the thoughts, feelings, actions, and situations that surrounded either successful or unsuccessful weight loss behaviors (see Multimedia Appendix 1). Participants were also asked to describe specific instances where they were either unsuccessful or successful in pursuing their weight goals and asked to elaborate on the surrounding thoughts, feelings, and circumstances. We also asked participants general weight management questions such as weight history, progress, peer involvement, and strategies used. All participants were provided with an information sheet and a consent form to sign and return to the researcher. The study materials, data collection, and methods of data storage were in accordance with human subjects guidelines set and approved by the Queen Mary University of London ethics committee.

### *Qualitative Study Recruitment*

We interviewed 15 individuals with current or previous experience of trying to lose weight. We included participants who had previously tried to lose weight so that we could capture a wider range of experiences, such as having already successfully maintained lost weight or unsuccessfully given up diet efforts. We focused on eating habits and, to a lesser extent, exercise. Interview recruitment emails were sent out through several departments within a UK university. The emails invited individuals and their friends and families who have been or are engaged in weight control efforts to talk about their experiences of weight management. The recruitment resulted in 15 respondents, 12 of whom were female. All participants recruited were actively engaged in some level of weight management activities at the time of the study, that is, they were either trying to lose weight (n=13) or just trying to maintain their current weight, having attempted weight loss in the past, either successfully (n=1) or unsuccessfully (n=1). All participants were managing their weight through some combination of watching their diet and exercise. Ages ranged from 27-68 years with a median age of 35. Body Mass Index (BMI) ranged from 21.6 to 31.2 with a median of 23.4. (We note that while all of our participants either were trying to lose weight or have lost weight previously, only 5 of our participants classified as overweight, with BMI>25, and only one those qualified as obese, with BMI>30.) Table 1 shows the demographics of gender, age, BMI, and location for each participant. Of the 15 participants, 13 were based in the United Kingdom and 2 were based in the United States (and were interviewed on Skype). They had all completed a university degree and spanned a range of professions including human resources, marketing, interior design, engineering, science, journalism, publishing, and accounting. Each participant was recompensed for their time through the award of a £6/US$9 gift voucher.

**Table 1.** Participant demographics and BMI.

| | P1 | P2 | P3 | P4 | P5 | P6 | P7 | P8 | P9 | P10 | P11 | P12 | P13 | P14 | P15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Gender | F | F | M | F | F | F | F | M\| | M | F | F | F | F | F | F |
| Age | 35 | 30 | 36 | 39 | 35 | 43 | 27 | 42 | 68 | 30 | 35 | 56 | 36 | 33 | 32 |
| BMI | 22.1 | 22.6 | 22.3 | 25.6 | 26.4 | 27.5 | 23.8 | 22.8 | 24.8 | 31.2 | 23.2 | 21.6 | 21.9 | 23.4 | 27.6 |

### *Qualitative Study Analysis*

Each interview was audio recorded and transcribed. We then employed inductive thematic analysis as described by Braun and Clarke [36]. All stages of analysis were conducted by the first author, and method and findings were discussed with the co-author at intervals.

Transcripts were initially analyzed for patterns across all interviews to extract themes about constructs that either discouraged or encouraged weight management. The data were repeatedly revisited to consolidate the main themes that were present across interviews. Once consistent themes were identified, all transcripts were re-analyzed, and all data extracts relevant to each theme were coded.

## Methods for Quantitative Study

### *Quantitative Study Procedure*

We supplemented our qualitative study with a quantitative survey to assess the extent to which the results we found in our qualitative study were valid across a larger population. While the interviews were conducted with highly educated, primarily UK-based participants, the survey was held among the general

American public. Our survey asked respondents to assess agreement with statements that represented the constructs and themes we uncovered from our qualitative study. We asked participants to rate their level of agreement on a 7-point multiple choice Likert scale ranging from Strongly Agree to Strongly Disagree. We also asked participants their age, BMI, and whether they were trying to lose weight, maintain weight, gain weight, or did not think about their weight.

### *Quantitative Study Recruitment*

Participants were 100 US-based adults recruited using Amazon Mechanical Turk. To minimize droid respondents, only participants with an approval rating of 95% or higher on Amazon Turk were allowed. They were compensated US$1 for completing our survey. Amazon Turk does not allow participants to respond twice to the same survey. Participants were provided with an information screen and a consent screen on which they had to click the "I agree" button in order to demonstrate consent for participation in the online study. The study materials, data collection, and methods of data storage were in accordance with human subjects guidelines set and approved by the Queen Mary University of London ethics committee.

# *Results*

## Qualitative Study Results

### *Summary*

Our interviews revealed a wide range of rewards and costs that were associated with both negative and positive weight management behaviors. This supports the relevance of this line of enquiry for informing the design of persuasive systems. We first describe the psychological constructs that discouraged weight management, which consist of the need to restrict rewards (positive feelings and experiences) associated with unhealthy behaviors, and the direct costs (negative feelings and experiences) associated with weight management efforts. Next we describe the psychological constructs that surrounded positive weight management behavior, which consists of emphasizing the rewards associated with weight management efforts and the costs associated with unhealthy behaviors.

### *Discouraging Weight Loss Efforts*

#### Overview

A key challenge to weight loss was the effort needed to restrict pleasure and change habits, overcome social pressures, plan ahead, and exercise. Participants also spoke of the loss of rewards associated with restricting consumption of unhealthy foods and inability to participate freely in social situations with food and drinks. Furthermore, participants felt daunted by thoughts that such weight loss efforts need to be sustained long term. Many participants voiced frustration over the fact that weight loss was a slow and unsteady process. Finally, several participants also mentioned negative associations with the general concept of dieting. We provide more details on these themes below.

#### Effort of Restricting Pleasure and Changing Habit

Most participants mentioned that modifying diet for weight loss was difficult. Circumstances where healthy eating was generally reported as being difficult included when bored, tired, stressed, busy, hungry, unhappy, and also when food was immediately present. For many, mental space and time were required for weight loss efforts. Some participants reported feeling that the effort was not worth it when life was more strenuous: "It's quite hard sometimes. You've really got to put so much energy into it and it takes up so much time and space in your life. (In the past) I just didn't want it enough" [P5] and "At the moment I just don't have headspace to be as disciplined as I'd like with my food" [P15].

#### Loss of Pleasure

Most participants described food as being a significant source of pleasure or reward, which they lose out on when trying to lose weight, for example, "I enjoy food a lot, so I'll eat if I'm not hungry…I don't like to deny myself things I enjoy" [P2].

#### Restricting Social Participation

The role of social influence in weight control has been widely acknowledged [37]. Unsurprisingly, many of our participants mentioned that social pressures made dieting difficult. About half of the participants felt that making healthy diet choices often required going against social expectations when eating among others: "I went to pub…I realized I would feel like a bit of an outcast if I had something healthy" [P11] and "There's a social pressure to everyone doing and enjoying the same type of activity" [P13].

#### Planning

About half of our participants mentioned that weight loss involved significant planning, which required mental space and time. These include planning healthy meals and snacks, workout schedules, and how to handle upcoming situations where there may be temptation to eat or drink too much, for example, "My biggest thing is you've got to plan the week ahead, you can't just wake up and think what exercise do I do today?" [P5].

#### Long-Term Commitment Is Daunting

Some participants mentioned being put off by the knowledge that weight loss efforts needed to be sustained long term. Several participants had already experienced regaining weight lost on previous diets. The need for long-term behavior changes increases the perceived costs of weight loss efforts. For P10 and P15, the likelihood of regaining the weight afterwards made weight loss efforts feel less worthwhile: "The hardest thing is kind of recognizing it's a shift in lifestyle rather than something you do for a little while and give up on" [P10] and "It's also the long-term thing that looms over me…you've got to do that for the rest of your life. Otherwise there's no point" [P15]. However, we note that this perception was not the case for all participants, and there were other participants (P8 and P13) who mentioned that maintenance was much easier than trying to lose.

#### Frustration Over Slow, Unsteady Progress

Several participants felt frustrated that they could not immediately experience rewards for their healthy behaviors.

They felt frustrated at the slow and unsteady nature of weight loss. P7 described the need to focus on motivations other than weight loss: “Don’t want to be reminded what weight I am. That’s not motivating! Because it doesn’t change quickly enough, you just don’t feel any progress from it” [P7].

P5 and P13 both voiced frustration over the fact that consistent adherence to diet and exercise regimens did not always translate to regular weight loss. They both discussed how much easier it would be if weight just decreased at a steady rate, for example, “If I’ve spent several days exercising like crazy, not eating the things and not drinking...and nothing is happening, I’m angry…Sometimes you can eat a load of food and lose weight. I think in a way we’d prefer it to be a bit fairer” [P5].

P13 expressed particular frustration over the simplistic nature of calorie and fitness tracking applications, which implicitly assume that calorie deficits readily translate to weight loss, which was not the case for her:

> *Another thing about the technology, because you keep putting the calories in, because it’s so quantitative I feel like well “shouldn’t I be losing the weight?”, and it isn’t necessarily that way, a calorie in isn’t a calorie out, there is so much else going on in the physiology, so actually just seeing the quantitative representation of what you’re eating, vs how much you should be losing weight, it’s dispiriting.* [P13]

### Notion of Diet Is Unappealing

Many participants expressed negative associations (ie, costs associated) with the concept of “being on a diet”. They expressed dislike of overemphasizing the importance of dieting and/or disliked thinking of themselves as formally being on a diet. P11 and P15 mentioned that too much focus on dieting felt superficial. P3 described dieting as pretentious: “(Dieting) feels prissy, feels pretentious. I’m a man, I have a big appetite, I do what I want when I want” [P3].

P9 and P12 felt that a focus on “dieting” would be ineffectual and even counterproductive: “If you asked me if I were on a diet, I’d say no. (To me, dieting is) this sort of deliberate pushing yourself kind of thing, and I’d say I’m not doing that, I don’t know that it would work for me” [P9] and “I’ve found that worrying about weight per se is very counterproductive, screws me up and focuses on the wrong things” [P12].

## *Encouraging Weight Loss Efforts*

### Overview

Our interviews showed that there are a variety of rewards associated with weight management. These included feeling good after making healthy choices, being good to oneself, social support, and receiving encouraging messages. (However, there were significant individual differences in response to social support and encouraging messages, which we describe below.) All participants mentioned the importance of personalization in order to find strategies that were easiest and most effective for the individual. Several participants noted that weight loss efforts eased with time. Several participants spoke of making healthy choices easier by emphasizing the costs associated with unhealthy choices. We discuss these constructs that encouraged weight loss–promoting behavior in detail below.

### Personalized Strategies for Reducing Effort

Many participants spoke of using personally tailored strategies to reduce the costs of their weight loss efforts. P2 and P5 found increased exercise most helpful for weight loss. They found exercise enjoyable and easier than restricting food. P4 had found a successful diet that consisted of low carbohydrate breakfast and lunch and no restrictions for dinner. She spoke of how this diet was surprisingly very easy to stick to because it was extremely well suited to her because she enjoyed eating meat. P9 described the strategy he adopted to fit around his unusually variable schedule, which included commuting between different cities. This erratic schedule prevented him from being able to plan ahead easily, and instead he looked to being “opportunistic” and taking advantage of circumstances in the moment, where it seemed easy to eat lighter meals rather than planning food restriction ahead of time:

> *I have to be opportunistic, I don’t think it would work if I was marking my diary ahead of time…it might just feel wrong that day. Or I might feel hungry. But on the other hand, if I’ve met my son for lunch and we had a small meal out, then I can say that’s my main meal then I can be opportunistic, that’s relatively easy to do.* [P9]

P11 talked about how she would consciously slow down her thinking to consider what she really wanted/needed to consume rather than reacting automatically to grab more unhealthy choices. She discovered that if she was mindful about what she really wanted, often she did not actually crave unhealthy foods after all and would prefer foods such as tea and salads over wine and cakes.

All participants acknowledged the importance of finding the right strategies for them. They used such phrases as “everybody’s different”, “I know other people who (are different)”, and “you have to find what works for you”. Across the interviews, personal physiologies, life circumstances, tastes, and preferences varied widely. Indeed, research has shown that individuals can have very different physiological responses to the same diet and exercise routines [38,39]. For example, people varied widely in terms of how their bodies responded to exercise and how their guts responded to foods. This variation was evident in our participants’ experiences. For example, in contrast to P5 and P13, who experienced significant periods of weight stagnation despite adhering to diet and exercise, P9 was surprised at how immediate his weight loss was—he said every time he ate lightly for one meal the night before, he could see measurable changes on the scale almost the next morning. Similarly P10 mentioned that significant weight loss happened for her only when she drastically reduced sodium intake, a phenomenon that no other participants mentioned. Variation in participants’ personal preferences obviously affected the appropriateness of particular weight loss strategies. P13 talked about how a high protein diet was difficult because she did not enjoy eating meat, in contrast to the success of P4 on such a diet. P1 spoke of how calorie restriction was far more effective than exercise, which is in contrast to the experiences of P2 and P5.

### Easier With Time

Many participants mentioned that their weight loss efforts became easier with time: "I found it was harder for first couple weeks, and then it just became a habit to track the calories and not eat. You got used to feeling hungry" [P8].

### Good Feelings, Pride, and Control

Most participants enjoyed positive feelings as a result of engaging in healthy behaviors. They mentioned feeling pleased, good, or happy after engaging in behavior that promoted weight loss. In particular, 6 participants mentioned enjoying the feeling of control and empowerment: "I feel quite empowered, feel like I own my weight, it's going the correct direction" [P5] and "I'm focused, I have the energy for it, and it feels good to say you know what I'm not going to have that, I'm going to have the good thing" [P15].

Several participants mentioned feeling proud after making weight loss promoting choices, for example, "I feel very proud of myself. This is how I should be, I should be strong, I don't really need this (cake)" [P6].

Conversely, when participants were asked how they felt immediately after having indulged in unhealthy behaviors, most reported that they enjoyed the indulgence during consumption, but the good feelings usually did not last long. Afterwards, some experienced negative feelings such as guilt or disappointment with self, or felt a bit "down". Most participants did intellectually acknowledge the unhealthiness of their choice immediately after consumption. For example, P2 felt "naughty, that you've let yourself down. You enjoyed it, but you feel like you've cheated".

### Realism

Several participants mentioned that reminding themselves to be "realistic" about the costs of unhealthy behaviors helped encourage healthy choices at moments of temptation. These thoughts included reminders of the reality of the situation of being overweight and the reality of the negative consequences of consuming excessive/unhealthy foods:

> *I've actually had to say to myself in the past "it doesn't matter what you say something is…You can pretend you have only drunk half a cup of milk but if you've drunk a whole cup that's what's going to have the impact".* [P5]
>
> *I think to be very real, "think about it, once you eat it it's going to be hard, and you know once you gain weight you will feel low esteem (and) sad"…I think it's the reality that makes me think I don't want this for myself anymore. Let's move on, let's not eat cake then.* [P6]

### Being Good to Oneself

Many participants mentioned concepts relating to being good to oneself as part of successful weight management. These included being kind to oneself, framing weight loss as a process of self-care, reassuring oneself that one is not being deprived and that healthy choices will lead to greater happiness, and savoring the pleasurable aspects of healthy choices. P5 and P10 spoke of how developing an attitude of self-kindness and forgiveness helped facilitate getting back on track after stints of excessive, unhealthy consumption: "I'm being a lot gentler with myself these day. I'm not telling myself off and being so angry with myself. So I think it's about forgiving myself for the mistakes rather than punishing myself" [P5] and "It's recognizing some days when all I want to eat is pizza and that's ok, and that doesn't ruin all the rest of the eating, and forgiving myself for the splurges and going on like I wanted to" [P10].

P10 also spoke of how recognizing that exercise and healthier eating plays into the larger purpose of general self-care and improving well-being helped her make healthier choices: "One friend said maybe the reason you're feeling crummy is you haven't had the time to [eat healthily] so it was kind of a self-care thing as well" [P10].

Three participants reminded themselves that healthier choices did not mean deprivation, that this was not their last opportunity to eat delicious foods and that pleasurable foods were still available to them, if in moderation, for example, "I'd think 'No, that's hardly the last piece of delicious chocolate you'll ever have in your life'" [P1].

P11 spoke of changing her mindset to recognize that by restricting treats, she was not depriving herself of tasty experiences, but instead was actually allowing herself greater overall pleasure because foods tasted better when eaten less often. Many participants mentioned relishing delicious healthy foods as well as small portions of rich foods as part of successful diet strategies. This appears to affirm the existence of reward and pleasure, even during the restrictive process of weight loss.

### Social Support

There was great individual variation in terms of preferred levels of social engagement in weight loss and the degree to which support from others was helpful for motivation (see Maitland [18] for previous work on social factors relevant for weight loss). Participants differed in how much they cared about having a social network involved in their weight loss efforts and whether it consisted of strangers, acquaintances, or friends. While some embraced the opportunity to feel a sense of community and having others involved with their weight management efforts, many were also less interested. This ranged from some participants who were ambivalent, to others who were adamant that they were not interested in other people's diets at all.

About half of the participants mentioned using social support to motivate weight loss. This included using friends, support groups, partners, and nutritionists: "My hubby, I always rush back to tell him if I've lost some weight, and he'll be very encouraging" [P5] and

> *(My girlfriend) was very supportive, very helpful. She's super thin by genetics. But when we'd go out she'd order very little food like I would, just so she wouldn't be eating a giant pile of food while I was restricting myself. Later on, she'd eat more only when I wasn't around.* [P8]

Several participants said they derived a sense of connection from others in similar situations: “It is really useful, when you read other people’s stories and what inspired them…and those stories always do keep you going” [P4] and “Who cares that I ate a sandwich with carrots in it…these people do! Guess what I had at lunch, a carrot sandwich. It’s nice to share the journey” [P5].

P6 spoke of the strength she gained from having group support: “this group, we are all people with the same anguish…and this is what makes the group strong, we have the same goal, we have same problem” [P6].

In contrast, some participants were also very uninterested in sharing their weight loss journey with others. They felt that weight management was a private issue and that it did not matter what others were doing. When asked whether they were hearing about other people’s weight management stories, P7 said: “Not really…I’m not interested in that trivial aspect of people’s life. I find it intrusive”. When asked if it would help to know other people are struggling too, P7 replied “Totally irrelevant”.

Several participants mentioned that seeing others’ progress could inspire a sense of motivating competition: “It was amazing how competitive I got with my cousin in this game…if I saw her losing 2 pounds I would be desperate to one up her” [P7].

On the other hand, others distinctly disliked the idea of competing with others about weight loss and felt it would hinder them: “It would hinder me. I would feel demoralized, I’m the kind of person whom if I feel like if I’m competition, I refuse to compete” [P3].

#### Encouraging Messages

Similarly, there were divergent opinions on how helpful motivating messages were, both from other people and from technology applications. While the majority of participants felt motivating messages either from friends or devices would not hurt and could possibly help (ie, be rewarding), others felt messages could be a serious annoyance (ie, costly). In particular, 3 participants explicitly mentioned feelings of annoyance at receiving general motivational feedback and messages. For example, when P8 was asked how he would feel about receiving general motivational messages through an application, he replied:

> *I think I’d be open to it if they were funny, or just light. It can be kind of annoying, there’s a fine line between being fun and inspirational and being just…annoying. If someone is too encouraging to you, then I feel like it starts to become a negative…when I feel the motivation starts to become someone else trying to impose their schedule on me, or their goals on me then I become resistant to it.* [P8]

Similarly, P3 spoke of the annoyance of having his motivation externalized and of receiving undeserved congratulations:

> *It’s just annoying because they are valuing my pathetic (attempts towards goals), it’s patronizing. It’s like you’re not actually seeing when I have done a great job or not. And I also don’t like people externalizing my reward…it makes me feel like I’m jumping through hoops like a trained dog.* [P3]

P13 expressed annoyance at receiving generic messages from her mobile application that she felt did not address her personal struggles:

> *A computer telling me, “gain 15 lose 10…Good job I met my goals at the end of the day”—I couldn’t care less. I need it to be personal on some level, and if it’s not, and the computer says “good job”, I’m like “f*** off, who are you to tell me that? You’re just a machine, I don’t appreciate it”.* [P13]

Thus, while encouragement is usually perceived as a positive motivating factor, our results show that motivational messages can have the opposite effect.

## Quantitative Study Results

### Summary

We consolidated the themes from our qualitative study into statements in a Web-based questionnaire and asked 100 respondents to rate on a 7-point scale their agreement with each of our statements. Of our respondents, 56 were trying to lose weight (median BMI 26.6), 20 were trying to maintain weight with a focus on not gaining (median BMI 23.5), 5 were trying to maintain weight with a focus on not losing (median BMI 21.6), 8 were trying to maintain weight with a focus on not gaining or losing (median BMI 20.7), 5 were trying to gain weight (median BMI 21), and 6 did not think about their weight (median BMI 21.6). For those who were trying to lose weight, the median reported target weight loss was 30 pounds. We limit analysis to the responses from those who reported wanting to either lose or maintain weight with a focus on not gaining as they are the population relevant for our study, leaving us with 76 participants for our analysis. Of the 56 participants who reported wanting to lose weight, 27 were female. Of the 20 participants who reported wanting to maintain weight with a focus on not gaining, 9 were female.

We assessed the degree of agreement over perspectives and experiences by segmenting our participants into those who agreed (reported slightly, moderately, or strongly agreeing with the statements), the proportion of participants who were neutral (reported neither agreeing nor disagreeing) and the proportion who disagreed (reported slightly, moderately, or strongly disagreed). We arrange our presentation of results into constructs that discouraged and encouraged weight management.

### Discouraging Constructs

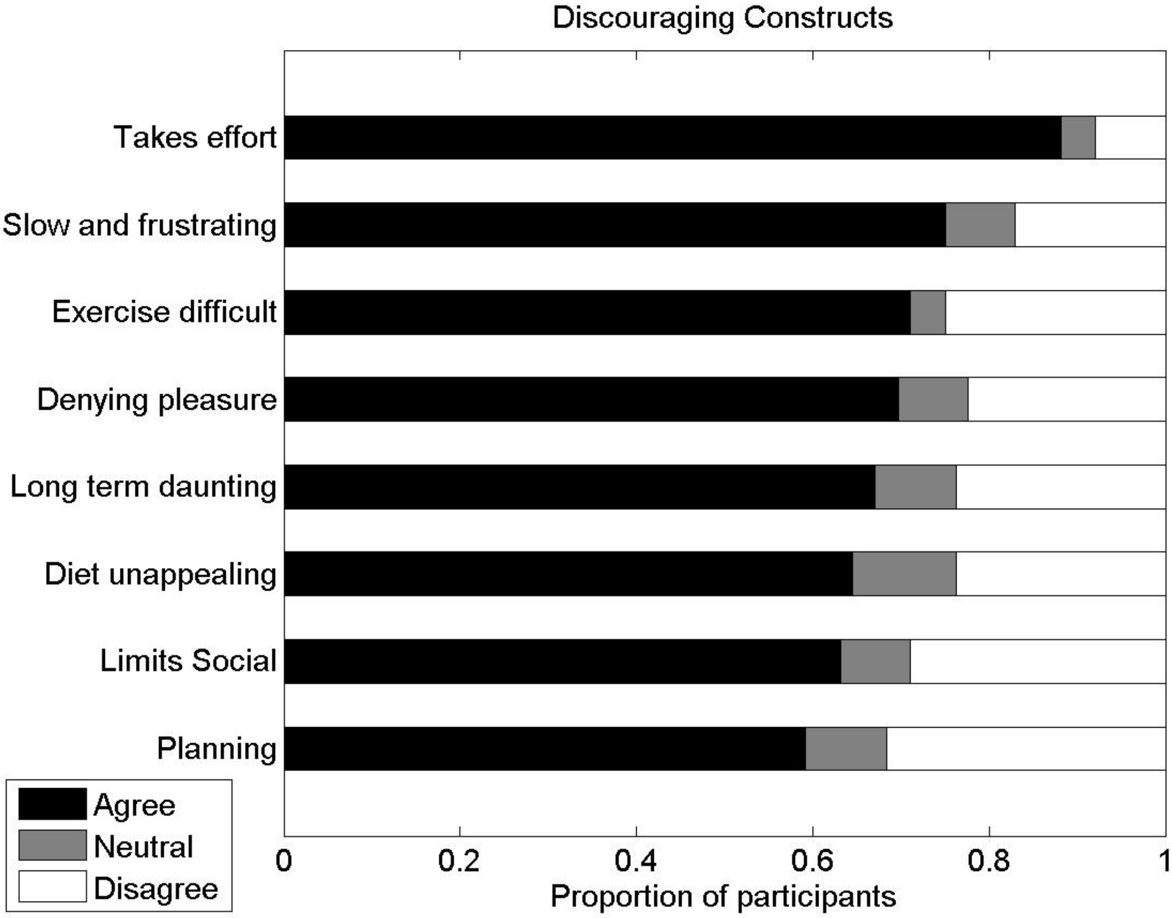
We assessed agreement with the following statements that represented constructs that we found in our qualitative study to be discouraging for weight management efforts:

- I find weight management requires a lot of effort.
- I find the process of denying myself foods I find pleasurable a difficult aspect of weight management.
- It is difficult to keep to my diet in social situations because I want to be able to eat and drink like everyone else.
- I find planning ahead for weight management difficult.
- I find the long-term commitment required for successful weight management daunting.

- I find the process of trying to lose weight a slow and frustrating process.
- I find the notion of being on a diet unappealing.
- I find maintaining a regular exercise routine is difficult.

For all discouraging constructs, there was high agreement among participants and all constructs had reported agreement of at least 59% (45/76). The idea that weight management takes a lot of effort was the most agreed upon construct (see Figure 1).

**Figure 1.** The proportion of respondents who agreed, were neutral, or disagreed with statements reflecting constructs that discouraged successful weight management.



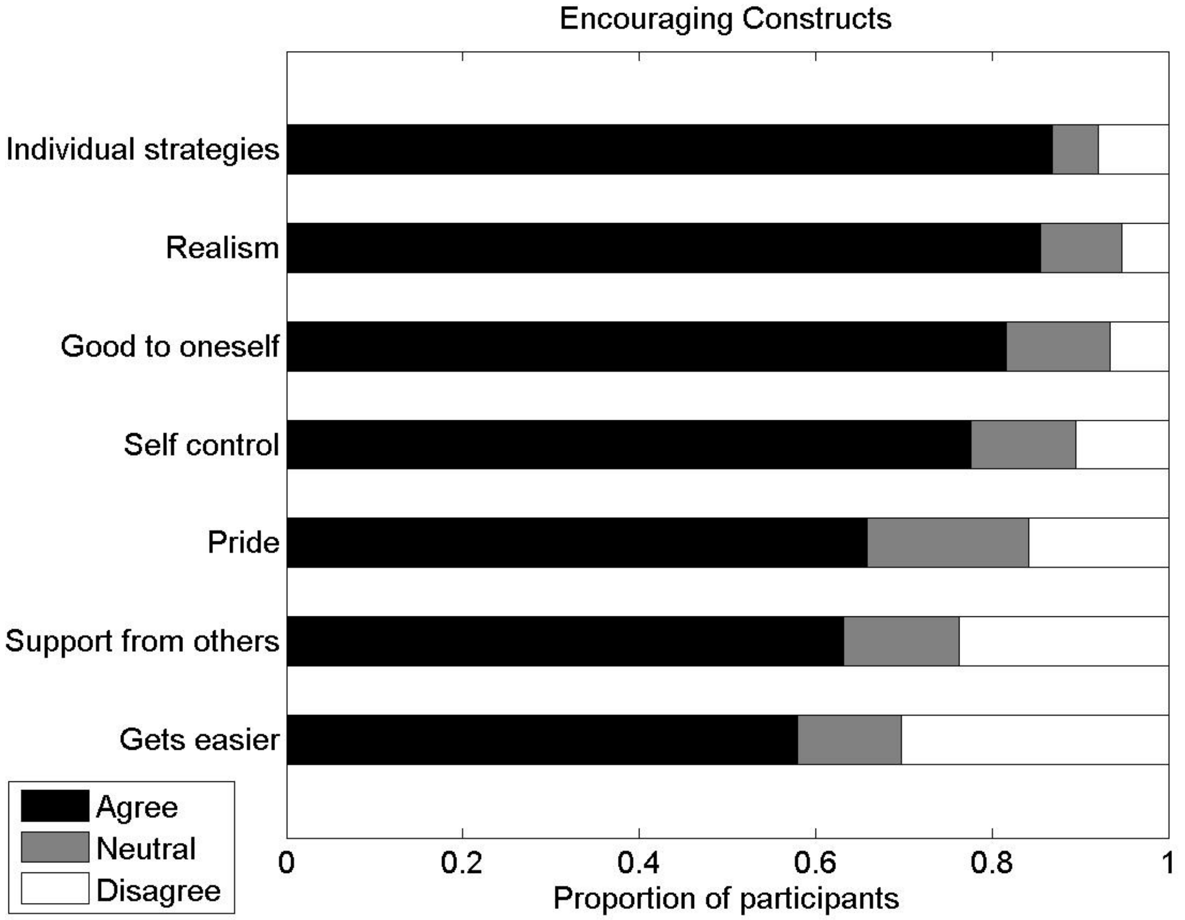

### *Encouraging Constructs*

We assessed agreement with the following statements that represented constructs that our qualitative study found were encouraging for weight management efforts:

- I find weight management becomes easier with time.
- I experience feelings of pride surrounding my weight management efforts.
- I enjoy feeling in control when I make choices that are positive for managing my weight.
- I find that it was important to find a weight management strategy that is specifically suited to my individual tastes and lifestyle preferences.
- Being realistic is a useful concept for my weight management.
- Being good to oneself is a useful concept for my weight management.
- Support from other people helps me a lot in my weight management.

For all encouraging constructs, there was over 58% (44/76) agreement. The most agreed upon constructs were that finding individually tailored strategies was important, the importance of realism, being good to oneself, and the enjoyment of being in control. The most disagreed upon constructs were that it gets easier with time and support from others was helpful (see Figure 2).

**Figure 2.** The proportion of respondents who agreed, were neutral, or disagreed with statements reflecting constructs that encouraged successful weight management.



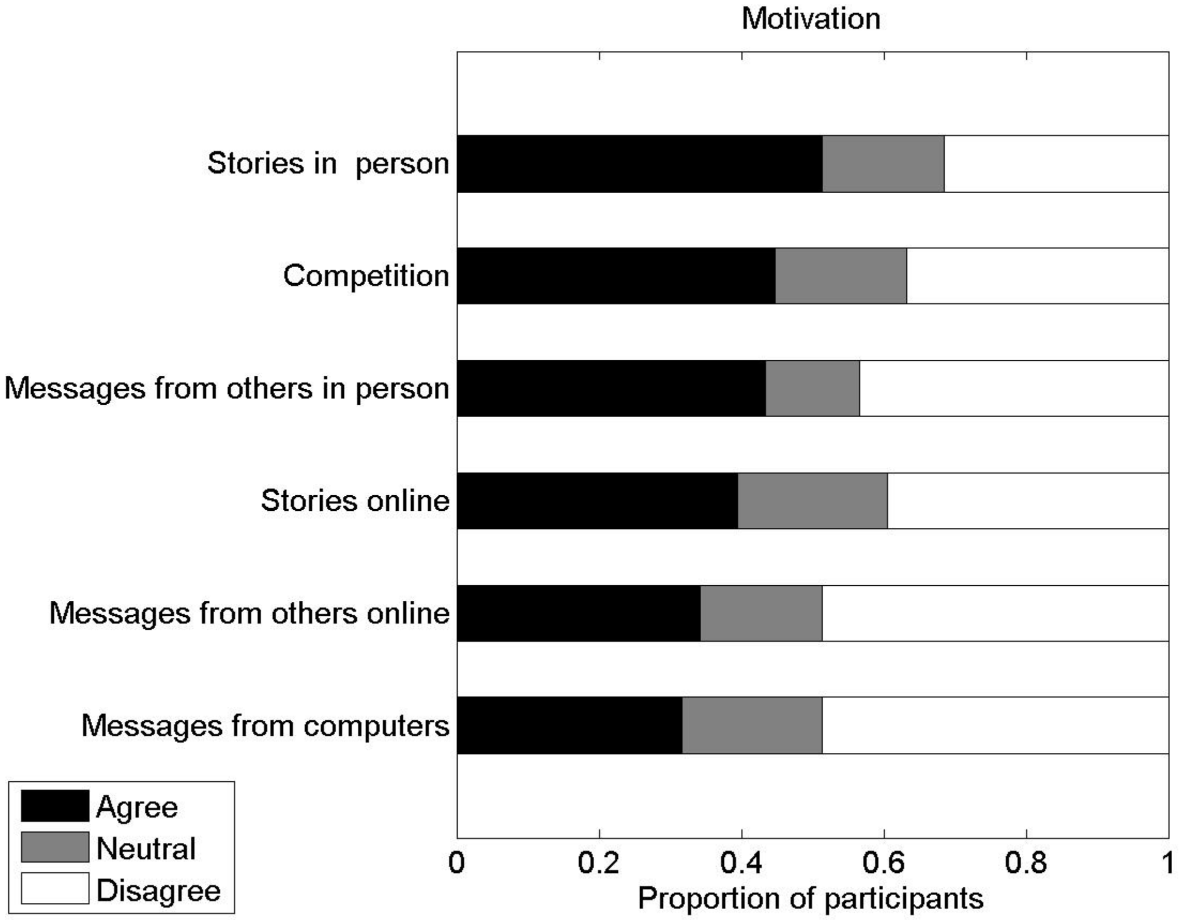

### *Social Motivation*

We had noticed a greater range of disagreement from our qualitative interviews over how much motivation from others was helpful. Thus we probed this in greater detail. We asked whether people enjoyed hearing others' stories in person and online, whether people enjoyed receiving motivational messages either in person or online, and whether people benefited from a sense of competition. We asked participants to rate agreement with the following statements:

- I would enjoy reading about other people's weight management stories *via the Internet*.
- I would enjoy hearing about other people's weight management stories *in person*.
- I would enjoy receiving motivational messages from others *via the Internet* to help encourage my weight management efforts.
- I would enjoy receiving motivational messages from a computer-based program to help encourage my weight management efforts.
- I would enjoy receiving motivational messages from others *in person* to help encourage my weight management efforts.
- I find a feeling of competition motivating for weight management.

For factors of external social motivation, we found there was substantially greater disagreement, especially in comparison to the relatively high agreement we had in response to other statements. None of the detailed statements about external social motivation received greater than 51% (39/76) agreement (see Figure 3). Motivational messages and stories received via the Internet were perceived as less helpful than those received in person. Only 32% (24/76) of respondents said they would enjoy motivational messages delivered from a computer, and 49% (37/76) of respondents reported that they would not enjoy this. These results correspond to the variability in attitudes that we found in our qualitative study results regarding motivational messages from others, and also dislike for computer-based motivational messages.

**Figure 3.** The proportion of respondents who agreed, were neutral, or disagreed with statements reflecting different ways and modes by which one could be motivated by others for weight management.



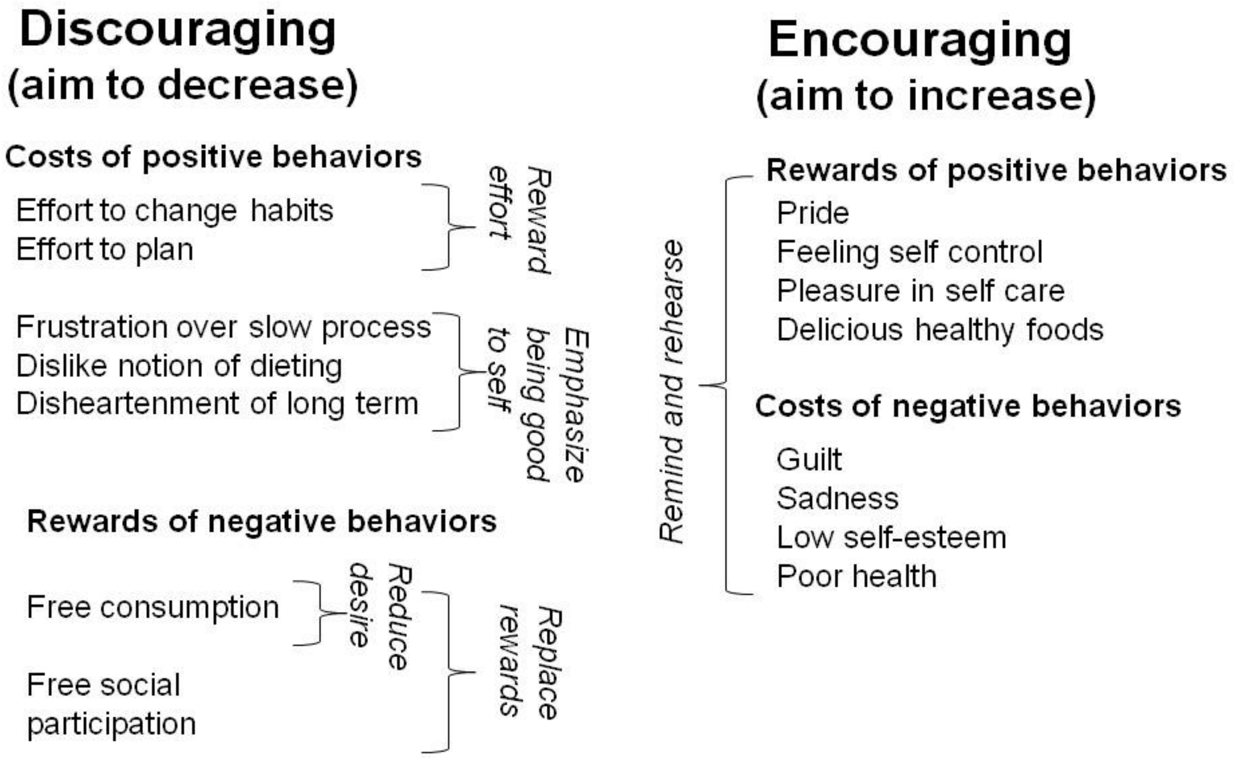

## Discussion

### Principal Results: Rewards, Costs, and Strategies

The themes from our study highlight the many rewards and costs that influence both positive and negative weight management behavior. Our studies found that a key difficulty of weight management was the loss of rewards associated with unhealthy behaviors, such as uninhibited consumption and ability to participate freely in social situations. There were also directly experienced costs associated with weight management. A central cost was the effort required to restrict consumption, change habits, and overcome social pressures. Other costs included negative feelings such as dislike for the concept of dieting, disheartenment at the idea that efforts need to be sustained long term, and frustration when weight loss was slow and there was no perceptible progress. On the other hand, our interviews showed that there are a variety of rewards associated with positive weight management behaviors. These included feelings of pride, self-control, pleasure in taking care of oneself, and enjoying delicious healthy foods. There were also costs associated with unhealthy behaviors such as feelings of guilt, sadness, and low self-esteem. In addition to relevant rewards and costs, our study also revealed commonly used strategies to motivate weight loss efforts. Most universally, participants mentioned finding ways to reduce the cost of weight loss efforts by seeking personalized strategies that addressed individual lifestyles and preferences, and some also felt that weight management gets easier with time. Participants also mentioned the benefits of using social support, and receiving encouraging messages (although as mentioned above, there were significant individual differences in responses to support and encouragement, which is consistent with previous work [18,40]). Finally, participants motivated weight management through emphasizing awareness and realism and reminding themselves of the negative consequences of unhealthy behavior.

The psychological constructs identified in our study are summarized in Figure 4. They are organized into those that encourage weight management, which need to be increased (the rewards of positive behaviors and the costs of negative ones), and those that discourage weight management, which need to be lessened (the costs of positive behaviors and the rewards of negative ones). On the side, in italics, are shown general design principles that can be used to increase/decrease the rewards and costs in the appropriate direction to effect positive behavior change.

**Figure 4.** A summary of psychological constructs relevant to weight management.




## Design Guidelines

### *Overview*

The themes uncovered in our study reveal a variety of costs and rewards associated with weight management behaviors as well as a range of strategies people used to manage their behavior. As mentioned above, decision theory suggests that healthy behaviors can be encouraged by enhancing the associated rewards and decreasing the associated costs. Similarly, unhealthy behaviors can be discouraged by decreasing the associated rewards and increasing associated costs. We apply these principles to our study results to produce design guidelines for weight management systems, summarized in Figure 4. Below we discuss these principles in more detail. We review how they have been implemented in current technologies, and point out where there are gaps that leave open future design opportunities. We also discuss how the constructs in our study can be used for personalization of weight management technology.

### *Decreasing the Costs of Healthy: Reward Effort and Focus on Being Good to Self*

Our findings reveal that effort (eg, planning, restricting food, changing habits and exercise) was the main cost that served as an obstacle to weight loss. One way to address this is for technologies to acknowledge the cost of effort by delivering rewards that offset the cost. Mobile technologies have the advantage of being able to act in the moment of need [21]. This provides an opportunity to design systems that can identify moments of unpleasant effort and then understand the types of rewards that will be appropriate to offset the costs and thus encourage effortful behavior. While there has been a significant rise in the development of systems for sensing user states [22], the accuracy of these systems for identifying user-relevant mental states, such as those found in our study, is yet to be verified. Furthermore, there is relatively little work on how to deliver the appropriate intervention once a "costly moment" has been identified. Systems can offset costs by administering rewards directly, or prompting users to seek appropriate rewards through reminders and suggestions. For example, our study found that planning was considered a significant challenge in weight management. A system can support the difficulty of planning, by acknowledging that planning is difficult, and offering rewards such as encouraging messages or virtual points when a user enters weight loss activities into their calendar.

Other costs found in our study were negative feelings such as dislike of the notion of dieting, frustrations over the slowness of weight loss, and disheartenment by the long-term lifestyle change required. One possibility for reducing these costs is to create systems that focus on being good to oneself and self-care (another theme from our study) rather than focus on the goal of losing weight. Indeed, studies on health messages found that those messages that promoted healthy behavior changes without reference to body weight were most effective and well received [41]. Thus, there is reason to believe that it may be useful to create weight management technologies that frame healthy choices as a process of positive self-care rather than a process of trying to lose weight.

### Decreasing Rewards of Unhealthy: Replace Lost Rewards and Reduce Desire

Another type of “cost” of weight management is the loss of rewards associated with unhealthy behavior. Two strategies for alleviating this are to find healthy replacement rewards and reduce the salience of the unhealthy reward. Our study found, unsurprisingly, that a key loss was the pleasure of unrestricted eating. A very common weight loss strategy is to seek replacement rewards, and this has indeed been implemented in current systems. However, a less explored avenue is to attempt to lessen the perceived reward. Laboratory studies have shown that operant conditioning can reduce people’s interest in unhealthy but tempting foods [42]. It is possible that an application devoted to reducing the desirability of one’s favorite unhealthy foods may be useful. Also, as mentioned above, laboratory research has found methods of reducing food cravings through imagery tasks [32]. While effectiveness has been suggested in laboratory studies, methods for reducing the desirability of unhealthy foods have been little explored in system designs. A second reward associated with unhealthy behavior was the ability to participate freely in social situations. Our participants reported that group meals were challenging for weight control because they felt pressure both from themselves and others to belong by partaking in the same types of (often unhealthy) consumption as others. Our participants also spoke of the importance of not feeling deprived during weight loss. This understanding of rewards and costs leads to a possible role technology can play to alleviate the challenge of not wanting to feel social alienation: When a social activity is scheduled in the calendar, technology can suggest alternative strategies for maintaining social connection even when not sharing consumption, such as a reminder to “focus on finding out something new about someone”, or “ask someone about a hobby they are interested in”.

### Enhancing Rewards of Healthy: Remind and Rehearse

Participants reported a variety of rewards associated with weight loss. This begs the question of how persuasive systems can be designed to emphasize and enhance these rewards. This is a particularly promising route because research has found that users tend to respond better to systems that persuade through positive rather than negative feedback [16]. Furthermore, laboratory research has found that emphasizing rewards can promote healthier food preferences. Remembering enjoyment of healthy foods results in these foods being chosen more often in later meals [31], and rehearsing memories of a meal reduces later snack consumption [43]. Despite these promising laboratory results, there have been few systems designed specifically to enhance memories of healthy experiences. Technology has the capacity to strengthen memory of rewards through reminders and also prompting users to mentally rehearse positive past experiences. This can be implemented through e-journals, using voice, pictures, or text, and structured to encourage individuals to remember/take note of the good feelings (eg, pride and self-control) associated with healthy choices. These platforms can also encourage people to relish their appreciation of healthy foods. While there have been the beginnings of technologies designed specifically to encourage reflection and awareness [16,17], there is much room for further developments in this area. In particular, to our knowledge, there have been no platforms devoted specifically to celebrating the pleasures associated with healthy choices and little research into how to design systems that best enhance the rewards of healthy choices. This presents open design challenges and opportunities.

### Enhancing the Costs of Unhealthy: Remind and Rehearse

In additional to acknowledging the long-term consequences for health, many participants also described immediate costs of unhealthy behaviors, including feelings of sadness, guilt, and anger. We found that some participants tried to remind themselves of these negative consequences to dissuade themselves from unhealthy choices. Furthermore, most participants said that in talking through their past experiences during the interview, they achieved new awareness of the negative experiences that resulted from unhealthy choices. This suggests that technologies can be designed to support further awareness and encourage reflection about the costs involved in weight management. Traditional calorie monitors already achieve this at the level of dietary intake [9,11-14]. However, just as systems may enhance awareness of the rewards of weight management, there is also scope for new technologies to be designed to increase awareness of the costs of unhealthy choices. The delivery of health-warning messages has been found to be effective for smoking cessation [44], although it has been studied less in the domain for weight loss. In addition to warnings about health, systems can be designed to help people remember the bad feelings they experienced after the last time they made unhealthy choices. To our knowledge, no such systems have been studied. Here methods similar to those used to enhance the rewards of healthy behaviors (reminding and prompting mental rehearsals) can be used to enhance the costs of unhealthy behaviors. Note that a system designed to promote awareness of costs is different from a system that punishes and delivers negative feedback, which has been found to put off users [16]. Instead, encouraging awareness of costs is consistent with research showing that there are individual differences in motivational preferences: some tend to be motivated by seeking positive gains (promotion focused) and others by avoiding negative consequences (prevention focused) [45-47]. This suggests there is room in the design space for systems that help users increase awareness and memory of negative feelings, as well as the long-term negative consequences that they may experience as a result of unhealthy choices.

### Personalized Solutions

When it comes to behavioral change, clearly one size does not fit all. The importance of individual preferences was one of the most highly agreed upon constructs in our survey study. Systems should be designed both to contain personalizable features and also to encourage users to seek personalized solutions. The overwhelming majority of our participants who had successfully lost weight spoke of the importance of individually tailored strategies. The effectiveness of personalization has been supported by research on health-messaging where a meta-analysis has found that individual tailoring of information delivered via the Internet improved effectiveness of nutrition interventions [48]. Also, simple text message-based weight loss intervention personalized to individual participants has been shown to be effective [49]. Personalized e-feedback has also been found to increase program adherence [50]. By highlighting the rewards and costs surrounding weight management, we offer further opportunities for personalization. These can serve as a catalogue of psychological constructs used to identify individual differences in weight management and thus guide personalization. Because there are limits to how many changes people are able to focus on at once, one possibility is to characterize an individual by having them indicate a few rewards and costs, which they find to be most salient (eg, someone who especially finds planning difficult or does not like the idea of dieting). A personalizable system can then suggest interventions that focus on these salient factors. Additionally, a catalogue of psychological factors can be used as a method for characterizing the features of existing weight loss technologies, which can be used to help individuals choose systems that support their specific needs.

Finally, personalization is important for features that involve motivation from others. Our study found significant variation as to whether individuals found social support and encouraging messages motivating or seriously annoying. Thus, motivating messages should be administered with caution because they can be hindering as well as helpful.

### Limitations

The themes of our study were based on interviews with relatively well-educated participants from the United Kingdom and United States. While our themes are not obviously related to education or economic status, it is possible that less educated populations or those from different socioeconomic backgrounds or cultures may have different considerations for weight management. For example, recent studies have found links between traits of self control and educational attainment and wealth [46,51]. Thus, it is possible that lower income and less educated populations may need greater self control aids than those from our study.

Finally, our study is based on self-reports and studies have shown that people are not always accurate at making choices that would be best for themselves [52]. Our studies are based on people's reflections of past experiences, and there may be discrepancies between what people report to be motivating and discouraging factors versus what factors actually are influential in the moment of experience [53]. For example, half our survey respondents reported they would not like to receive motivational messages from a computer. However, previous research has found that computer-based motivational messages during a computer-based task improved people's positive affect, enjoyment, willingness to work, and self-perceived performance by a factor of 1.5-2 [54]. Remarkably, this improvement occurred even though people knew that these messages were not contingent on their actual performance. While the study [54] was not in the domain of weight loss, this unintuitive result suggests the possibility that computer-based motivation might be more effective than people assume it to be.

### Conclusions

We have shown how a reward-cost driven inquiry is useful for understanding the psychological constructs in a given behavior change context and for informing persuasive systems design. We applied this framework to understanding the psychological constructs that surrounded individuals' weight management efforts. Our study identifies a variety of rewarding and costly factors that surround individuals' positive and negative weight management choices. In a follow-up questionnaire study, we found these factors to be experienced by the majority across a wider population. We applied decision theory to these factors to produce suggested design principles for persuasive systems and discuss where these point to open design opportunities that warrant further exploration.

## Acknowledgments

We thank Vicky Cullen for helping us with practice interviews and all participants for their contributions to the study. This research has been partly supported by EPSRC Grant GR/G004560/1.

## Conflicts of Interest

None declared.

## Multimedia Appendix 1

Qualitative interview survey materials.

[PDF File (Adobe PDF File), 30KB - jmir_v16i6e138_app1.pdf ]

## References

1. Finkelstein EA, Trogdon JG, Cohen JW, Dietz W. Annual medical spending attributable to obesity: payer-and service-specific estimates. Health Aff (Millwood) 2009;28(5):w822-w831 [FREE Full text] [doi: 10.1377/hlthaff.28.5.w822] [Medline: 19635784]

2. Fogg B. Persuasive Technology: Using Computers to Change What We Think and Do. San Francisco: Morgan Kaufmann; 2003.
3. Fogg BJ. A behavior model for persuasive design. 2009 Presented at: 4th International Conference on Persuasive Technology; 2009; Claremont, California. [doi: 10.1145/1541948.1541999]
4. Oinas-Kukkonen H, Harjumaa M. Persuasive systems design: Key issues, process model, and system features. Communications of the Association for Information Systems 2009:28. [doi: 10.1145/1541948.1541989]
5. Oinas-Kukkonen H. A foundation for the study of behavior change support systems. Pers Ubiquit Comput 2012 Jul 19;17(6):1223-1235. [doi: 10.1007/s00779-012-0591-5]
6. Locke EA, Latham GP. Building a practically useful theory of goal setting and task motivation. A 35-year odyssey. Am Psychol 2002 Sep;57(9):705-717. [Medline: 12237980]
7. Prochaska JO, DiClemente CC, Norcross JC. In search of how people change. Applications to addictive behaviors. Am Psychol 1992 Sep;47(9):1102-1114. [Medline: 1329589]
8. Bandura A. Social Foundations of Thought and Action: A Social Cognitive Theory. New Jersey: Prentice Hall; 1986.
9. Consolvo S, McDonald D, Landay J. Theory-Driven Design Strategies for Technologies that Support Behavior Change in Everyday Life. In: Proceedings of CHI. 2009 Presented at: CHI; April 4-9, 2009; Boston p. 405-414. [doi: 10.1145/1518701.1518766]
10. Fehr E, Rangel A. Neuroeconomic Foundations of Economic Choice—Recent Advances. Journal of Economic Perspectives 2011 Nov;25(4):3-30. [doi: 10.1257/jep.25.4.3]
11. Torning K, Kukkonen H. Persuasive system design: state of the art and future directions. In: Proceedings of the 4th International Conference on Persuasive Technology. 2009 Presented at: International Conference on Persuasive Technology; April 26-29, 2009; Claremont. [doi: 10.1145/1541948.1541989]
12. Consolvo S, Everitt K, Smith I, Landay JA. Design requirements for technologies that encourage physical activity. In: Proceedings of the SIGCHI conference on Human Factors in computing systems. 2006 Presented at: CHI; April 22-27, 2006; Montreal p. 457-466. [doi: 10.1145/1124772.1124840]
13. Lin J, Mamykina L, Lindtner S, Delajoux G, Strub H. Fish 'n' Steps: Encouraging physical activity with an interactive computer game. Ubiquitous Computing 2006:261-278. [doi: 10.1007/11853565_16]
14. Brown B, Chetty M, Grimes A, Harmon E. Reflecting on health: a system for students to monitor diet and exercise. CHI 2006 extended abstracts on Human factors in computing systems 2006:1807. [doi: 10.1145/1125451.1125794]
15. Patrick K, Raab F, Adams MA, Dillon L, Zabinski M, Rock CL, et al. A text message-based intervention for weight loss: randomized controlled trial. J Med Internet Res 2009;11(1):e1 [FREE Full text] [doi: 10.2196/jmir.1100] [Medline: 19141433]
16. Consolvo S, klasnja P, McDonald D, Avrahami DF. Flowers or a robot army? encouraging awareness and activity with personal, mobile displays. Ubicomp 2008:54-63. [doi: 10.1145/1409635.1409644]
17. Baumer EP, Katz SJ, Freeman JE, Adams P, Gonzales AL, Pllak JP, et al. Proceedings of CHI. In: Prescriptive Persuasion and Open-Ended Social Awareness: Expanding the Design Space of Mobile Health. 2012 Presented at: CHI; May 5, 2012; Austin, TX p. 476-484. [doi: 10.1145/2145204.2145279]
18. Maitland C. Designing for Peer Involvement in Weight Management. In: Proceedings of CHI. 2011 Presented at: CHI; May 7, 2011; Vancouver p. 315-324. [doi: 10.1145/1978942.1978988]
19. Lee M, Keisler S, Forlizzi J. Mining Behavioral Economics to Design Persuasive Technology for Healthy Choices. In: Proceedings of CHI. 2011 Presented at: CHI; May 5, 2011; Vancouver p. 325-334. [doi: 10.1145/1978942.1978989]
20. Maitland J. Towards negotiation as a framework for health promoting technology. SIGHIT Rec 2011 Mar 01;1(1):10. [doi: 10.1145/1971706.1971710]
21. Fogg BJ, Eckles D, Bogost I, Consolvo S, Holmen E, Spasojevic M, et al. Mobile Persuasion: 20 Perspectives of the Future of Behavior Change. Stanford, CA: Stanford Captology Media; 2007:978-09795.
22. Rachuri K, Musolesi M, Mascolo C, Rentfrow P, Longworth C, Aucinas A. EmotionSense: A Mobile Phones based Adaptive Platform for Experimental Social Psychology Research. In: Ubiquitous Computing. 2010 Presented at: 12th ACM International Conference on Ubiquitous Computing; Sept 28, 2010; Copenhagen. [doi: 10.1145/1864349.1864393]
23. Gilovich T, Griffin DK. Heuristics and Biases: The Psychology of Intuitive Judgment. Cambridge: Cambridge University Press; 2002:874.
24. Vlaev I, Chater N, Stewart N, Brown GD. Does the brain calculate value? Trends Cogn Sci 2011 Nov;15(11):546-554. [doi: 10.1016/j.tics.2011.09.008] [Medline: 21983149]
25. Peters J, Büchel C. Neural representations of subjective reward value. Behav Brain Res 2010 Dec 1;213(2):135-141. [doi: 10.1016/j.bbr.2010.04.031] [Medline: 20420859]
26. Peters J, Büchel C. Episodic future thinking reduces reward delay discounting through an enhancement of prefrontal-mediotemporal interactions. Neuron 2010 Apr 15;66(1):138-148. [doi: 10.1016/j.neuron.2010.03.026] [Medline: 20399735]
27. Hare TA, Malmaud J, Rangel A. Focusing attention on the health aspects of foods changes value signals in vmPFC and improves dietary choice. J Neurosci 2011 Jul 27;31(30):11077-11087 [FREE Full text] [doi: 10.1523/JNEUROSCI.6383-10.2011] [Medline: 21795556]

28. Gottlieb J, Balan P. Attention as a decision in information space. Trends in Cognitive Science 2010:240.
29. Killeen PR. An additive-utility model of delay discounting. Psychol Rev 2009 Jul;116(3):602-619. [doi: 10.1037/a0016414] [Medline: 19618989]
30. Voh KD, Baumeister RF. Handbook of self-regulation: Research, theory, and applications. New York: Guilford Press; 2010.
31. Robinson E, Blissett J, Higgs S. Changing memory of food enjoyment to increase food liking, choice and intake. Br J Nutr 2012 Oct 28;108(8):1505-1510. [doi: 10.1017/S0007114511007021] [Medline: 22214529]
32. May J, Andrade J, Batey H, Berry LM, Kavanagh DJ. Less food for thought. Impact of attentional instructions on intrusive thoughts about snack foods. Appetite 2010 Oct;55(2):279-287. [doi: 10.1016/j.appet.2010.06.014] [Medline: 20600411]
33. Ajzen I. The theory of planned behavior. Organizational Behavior and Human Decision Processes 1991 Dec;50(2):179-211. [doi: 10.1016/0749-5978(91)90020-T]
34. Triandis H. Interpersonal behavior. Monterey, CA: Brooks/Cole Pub. Co; 1977.
35. Darnton A. GSR Behaviour Change Knowledge Review.: University of Westminster; 2008. Reference Report: An overview of behaviour change models and their uses URL: http://www.civilservice.gov.uk/wp-content/uploads/2011/09/Behaviour_change_reference_report_tcm6-9697.pdf [accessed 2014-05-26] [WebCite Cache ID 6PrEpyqIW]
36. Braun V, Clarke V. Using thematic analysis in psychology. Qualitative Research in Psychology 2006 Jan;3(2):77-101. [doi: 10.1191/1478088706qp063oa]
37. Tice DM, Bratslavsky E, Baumeister RF. Emotional distress regulation takes precedence over impulse control: if you feel bad, do it!. J Pers Soc Psychol 2001 Jan;80(1):53-67. [Medline: 11195891]
38. Bouchard C, Sarzynski MA, Rice TK, Kraus WE, Church TS, Sung YJ, et al. Genomic predictors of the maximal $O_2$ uptake response to standardized exercise training programs. J Appl Physiol 2011 May;110(5):1160-1170 [FREE Full text] [doi: 10.1152/japplphysiol.00973.2010] [Medline: 21183627]
39. Minot S, Sinha R, Chen J, Li H, Keilbaugh SA, Wu GD, et al. The human gut virome: inter-individual variation and dynamic response to diet. Genome Res 2011 Oct;21(10):1616-1625 [FREE Full text] [doi: 10.1101/gr.122705.111] [Medline: 21880779]
40. Newman MW, Lauterbach D, Munson SA, Resnick P, Morris ME. It's not that I don't have problems, I'm just not putting them on Facebook: challenges and opportunities in using online social networks for health. In: Proceedings of the ACM 2011 Conference on Computer supported cooperative work. 2011 Presented at: ACM 2011 Conference on Computer supported cooperative work; March 19-23, 2011; Hangzhou, China p. 341-350. [doi: 10.1145/1958824.1958876]
41. Puhl R, Peterson JL, Luedicke J. Fighting obesity or obese persons? Public perceptions of obesity-related health messages. Int J Obes (Lond) 2013 Jun;37(6):774-782. [doi: 10.1038/ijo.2012.156] [Medline: 22964792]
42. Dwyer DM, Jarratt F, Dick K. Evaluative conditioning with foods as CSs and body shapes as USs: No evidence for sex differences, extinction, or overshadowing. Cognition & Emotion 2007 Feb;21(2):281-299. [doi: 10.1080/02699930600551592]
43. Higgs S, Donohoe JE. Focusing on food during lunch enhances lunch memory and decreases later snack intake. Appetite 2011 Aug;57(1):202-206. [doi: 10.1016/j.appet.2011.04.016] [Medline: 21569808]
44. Hammond D. Health warning messages on tobacco products: a review. Tob Control 2011 Sep;20(5):327-337. [doi: 10.1136/tc.2010.037630] [Medline: 21606180]
45. Cesario J, Grant H, Higgins ET. Regulatory fit and persuasion: transfer from "Feeling Right.". J Pers Soc Psychol 2004 Mar;86(3):388-404. [doi: 10.1037/0022-3514.86.3.388] [Medline: 15008644]
46. Moffitt TE, Arseneault L, Belsky D, Dickson N, Hancox RJ, Harrington H, et al. A gradient of childhood self-control predicts health, wealth, and public safety. Proc Natl Acad Sci U S A 2011 Feb 15;108(7):2693-2698 [FREE Full text] [doi: 10.1073/pnas.1010076108] [Medline: 21262822]
47. Higgins ET. Making a good decision: value from fit. Am Psychol 2000 Nov;55(11):1217-1230. [Medline: 11280936]
48. Enwald HP, Huotari ML. Preventing the obesity epidemic by second generation tailored health communication: an interdisciplinary review. J Med Internet Res 2010;12(2):e24 [FREE Full text] [doi: 10.2196/jmir.1409] [Medline: 20584698]
49. Patrick K, Raab F, Adams MA, Dillon L, Zabinski M, Rock CL, et al. A text message-based intervention for weight loss: randomized controlled trial. J Med Internet Res 2009;11(1):e1 [FREE Full text] [doi: 10.2196/jmir.1100] [Medline: 19141433]
50. Enwald HP, Huotari ML. Preventing the obesity epidemic by second generation tailored health communication: an interdisciplinary review. J Med Internet Res 2010;12(2):e24 [FREE Full text] [doi: 10.2196/jmir.1409] [Medline: 20584698]
51. Duckworth AL, Seligman ME. Self-discipline outdoes IQ in predicting academic performance of adolescents. Psychol Sci 2005 Dec;16(12):939-944. [doi: 10.1111/j.1467-9280.2005.01641.x] [Medline: 16313657]
52. Hsee CK, Hastie R. Decision and experience: why don't we choose what makes us happy? Trends Cogn Sci 2006 Jan;10(1):31-37. [doi: 10.1016/j.tics.2005.11.007] [Medline: 16318925]
53. Robinson MD, Clore GL. Belief and feeling: evidence for an accessibility model of emotional self-report. Psychol Bull 2002 Nov;128(6):934-960. [Medline: 12405138]
54. Fogg B, Nass C. Silicon sycophants: the effects of computers that flatter. International Journal of Human-Computer Studies 1997 May;46(5):551-561. [doi: 10.1006/ijhc.1996.0104]

*Edited by G Eysenbach; submitted 08.10.13; peer-reviewed by J May, L van Velsen; comments to author 30.10.13; revised version received 15.11.13; accepted 21.12.13; published 26.06.14.*

*Please cite as:*
*Hsu A, Blandford A*
*Designing for Psychological Change: Individuals' Reward and Cost Valuations in Weight Management*
*J Med Internet Res 2014;16(6):e138*
*URL: http://www.jmir.org/2014/6/e138/*
*doi:10.2196/jmir.3009*
*PMID:24972304*

Original Paper

# Online Dietary Intake Estimation: The Food4Me Food Frequency Questionnaire

Hannah Forster[1], BSc (Hons); Rosalind Fallaize[2], BSc (Hons); Caroline Gallagher[1], BSc (Hons); Clare B O'Donovan[1], MSc; Clara Woolhead[1], MSc; Marianne C Walsh[1], PhD; Anna L Macready[2], PhD; Julie A Lovegrove[2], PhD; John C Mathers[3], PhD; Michael J Gibney[1], PhD; Lorraine Brennan[1], PhD; Eileen R Gibney[1], PhD

[1]UCD Institute of Food and Health, University College Dublin, Dublin, Ireland

[2]Hugh Sinclair Unit of Human Nutrition and Institute for Cardiovascular and Metabolic Research, University of Reading, Reading, United Kingdom

[3]Human Nutrition Research Centre, Institute for Ageing and Health, Newcastle University, Newcastle, United Kingdom

**Corresponding Author:**
Eileen R Gibney, PhD
UCD Institute of Food and Health
University College Dublin
Science Centre South,
Belfield,
Dublin,
Ireland
Phone: 353 1 716 2819
Fax: 353 1 716 1147
Email: eileen.gibney@ucd.ie

## *Abstract*

**Background:** Dietary assessment methods are important tools for nutrition research. Online dietary assessment tools have the potential to become invaluable methods of assessing dietary intake because, compared with traditional methods, they have many advantages including the automatic storage of input data and the immediate generation of nutritional outputs.

**Objective:** The aim of this study was to develop an online food frequency questionnaire (FFQ) for dietary data collection in the "Food4Me" study and to compare this with the validated European Prospective Investigation of Cancer (EPIC) Norfolk printed FFQ.

**Methods:** The Food4Me FFQ used in this analysis was developed to consist of 157 food items. Standardized color photographs were incorporated in the development of the Food4Me FFQ to facilitate accurate quantification of the portion size of each food item. Participants were recruited in two centers (Dublin, Ireland and Reading, United Kingdom) and each received the online Food4Me FFQ and the printed EPIC-Norfolk FFQ in random order. Participants completed the Food4Me FFQ online and, for most food items, participants were requested to choose their usual serving size among seven possibilities from a range of portion size pictures. The level of agreement between the two methods was evaluated for both nutrient and food group intakes using the Bland and Altman method and classification into quartiles of daily intake. Correlations were calculated for nutrient and food group intakes.

**Results:** A total of 113 participants were recruited with a mean age of 30 (SD 10) years (40.7% male, 46/113; 59.3%, 67/113 female). Cross-classification into exact plus adjacent quartiles ranged from 77% to 97% at the nutrient level and 77% to 99% at the food group level. Agreement at the nutrient level was highest for alcohol (97%) and lowest for percent energy from polyunsaturated fatty acids (77%). Crude unadjusted correlations for nutrients ranged between .43 and .86. Agreement at the food group level was highest for "other fruits" (eg, apples, pears, oranges) and lowest for "cakes, pastries, and buns". For food groups, correlations ranged between .41 and .90.

**Conclusions:** The results demonstrate that the online Food4Me FFQ has good agreement with the validated printed EPIC-Norfolk FFQ for assessing both nutrient and food group intakes, rendering it a useful tool for ranking individuals based on nutrient and food group intakes.

***(J Med Internet Res 2014;16(6):e150)*** doi:10.2196/jmir.3105

**KEYWORDS**

food frequency questionnaire; online dietary assessment tool; Food4Me; dietary assessment; Web-based

## Introduction

Associations between dietary behaviors and chronic health risks have been established on numerous occasions [1,2], making the ability to measure dietary intake crucial for researchers and public health practitioners to improve health outcomes [3,4]. Dietary assessment methods are used for quantification of both short- and long-term (habitual) dietary intakes, and are essential tools in epidemiological investigations and intervention studies assessing relationships between diet and health in both population and clinical settings [3,5].

Food records (or diaries), 24-hour recalls, and food frequency questionnaires (FFQ) are the three principle assessment methods that are used traditionally to measure dietary intake [6,7]. Food records require respondents to record all foods and beverages consumed over a specified period of time, generally between 3 and 7 days prospectively [8-10]. The 24-hour recalls are interviewer led and entail asking the respondent to remember and record all foods consumed in the preceding 24-hour period [7,10,11]. FFQs are also retrospective assessment tools and require respondents to report the frequency of consumption of a predefined list of foods over a prolonged period of time, typically the previous 6 or 12 months [7].

Internet availability and usage has increased globally over the past decade and, as a result, traditional methods of dietary assessment have been modified for online and electronic use in both research and industry [12]. Compared with traditional methods of dietary assessment, online methods allow for the automatic storage of input data and the automatic generation of nutritional outputs [13]. While traditional methods of dietary assessment can be supplemented with food photograph atlases to aid portion size recognition and estimation [14], online methods of dietary assessment can be designed to incorporate food photographs, making them more convenient for users to complete [15-17]. Furthermore, compared with traditional methods, online dietary assessment methods can be used to target specific geographical population groups, can be accessed remotely, and can be designed to be easy to complete.

The strengths and weaknesses of traditional dietary assessment methods are well documented [8,18-21]. The quality of data from any dietary assessment method, traditional or online, will depend ultimately on the respondent's accuracy in recording the required details [22]. As a result, online food diaries may have greater use commercially or for small dietary studies as they require respondents to be highly motivated to record data [22].

FFQs and 24-hour recalls are the most commonly used approaches for assessing dietary intake for large population studies [22]. Although Web-based 24-hour recalls have been demonstrated to show good agreement with traditional methods on numerous occasions [23-25,26], they are largely limited by the day-to-day variability in dietary intake and may not accurately assess intakes of foods that are eaten infrequently (eg, oily fish). As a result, multiple 24-hour recalls over several non-consecutive days are required to reflect usual dietary intake [22]. Unlike food records and 24-hour recalls, FFQs can capture long-term dietary intake in a single administration and are less cumbersome to complete [27-29]. Although FFQs have often been reported to bear the greatest amount of measurement error, not only when considering under-reporting but also over-estimation of dietary intakes [30], they have been shown to have good validity for ranking nutrient intakes on numerous occasions [20-22,31]. As a result, they can be used to categorize nutrient intakes as "low", "recommended", or "high" compared with recommended intakes, rendering them invaluable tools for assessing nutritional intake status [20-21].

In recent years, many well-established FFQs have been developed into Web-based versions and there is a growing body of evidence demonstrating that data from Web-based FFQs are comparable with data from printed versions and/or have good validity with reference methods such as 24-hour recalls and food diaries [15-17,32]. Web-based FFQs possess many benefits over printed questionnaires: they are more cost-effective, they can be pre-programmed to ensure all questions are answered, and photographs can be incorporated to enhance food recognition and portion size estimation [15,17,32].

The present study was conducted as part of the EU 7th European Framework Programme "Food4Me" project [33]. The Food4Me project aims to investigate the potential of, and public attitudes toward, personalized nutrition and is the first study of its kind designed to emulate an entirely Web-based, personalized nutrition service [34].

The objectives of the present study were to develop an online FFQ for dietary data collection in the Food4Me study and to compare estimates of intakes obtained using this tool with those obtained from the validated European Prospective Investigation of Cancer (EPIC) Norfolk printed FFQ [35].

## Methods

### Development of the Online Food4Me Food Frequency Questionnaire

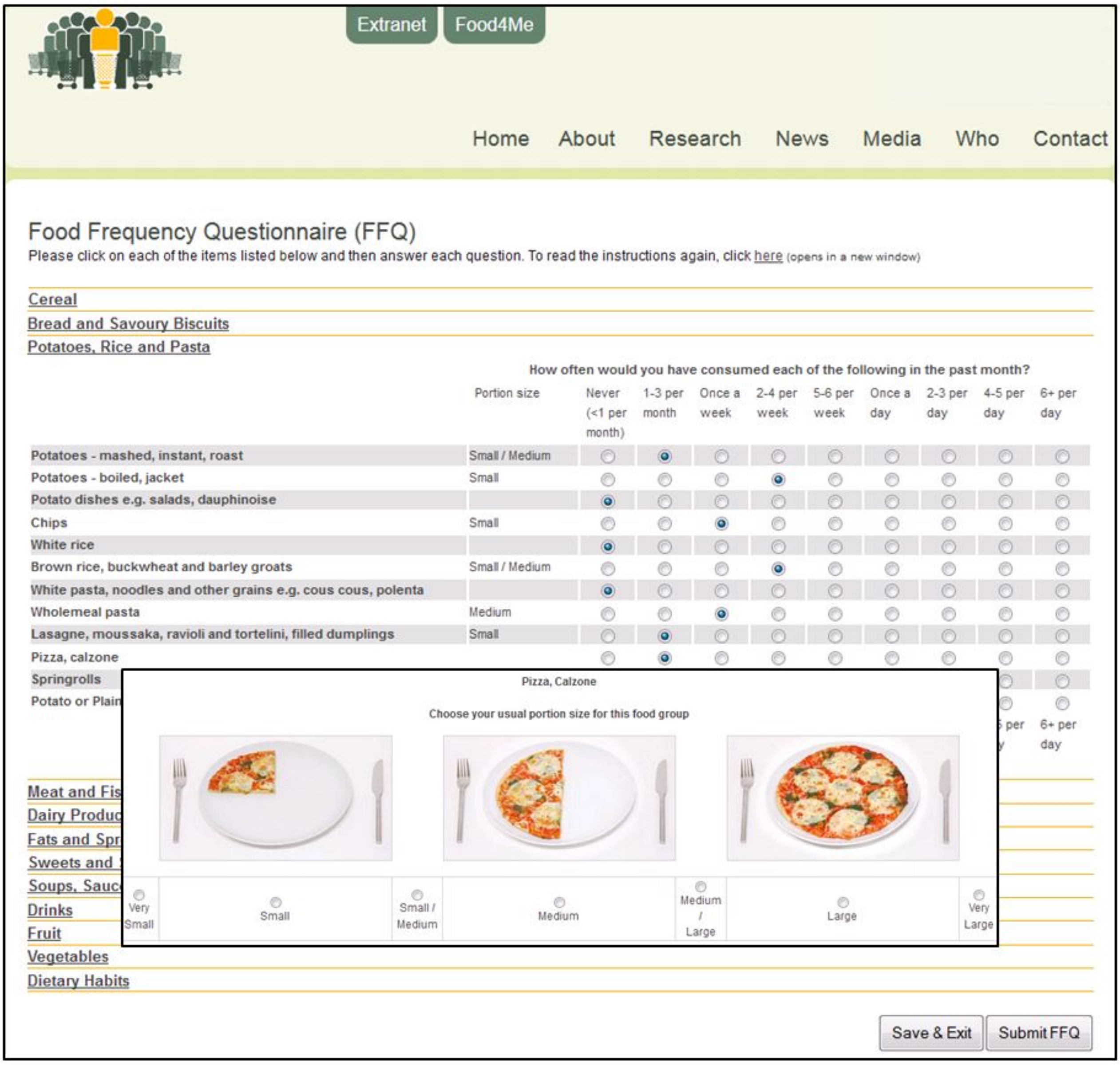
#### Overview

The online Food4Me FFQ was designed to assess food and nutritional intake across seven centers in Europe, as part of a dietary intervention study within the Food4Me project [33]. The design and development of the novel online Food4Me FFQ was led by researchers at University College Dublin and software company Creme Global (Dublin, Ireland).

The well-validated EPIC-Norfolk FFQ (version CAMB/PQ/6/1205) [35] was used as a guide for food items and food group categories. In developing the Food4Me FFQ, the original 130 food items presented in the EPIC-Norfolk FFQ were expanded upon to incorporate an additional 27 commonly consumed food items that were considered nutritionally important across the seven EU countries in the Food4me study. In expanding the food list, some food items were added (eg, tortillas, wraps) to existing food categories; some new foods were added to existing food items (eg, “noodles and cous cous” were added to “white pasta or green pasta”), and, in some cases, existing food items were split into more defined types (eg, “oily fish, fresh or canned” was split into “non-smoked oily fish, canned” and “non-smoked oily fish, fresh”). Standardized color photographs were incorporated into the online Food4Me FFQ to facilitate accurate portion size estimation. As in the printed EPIC-Norfolk FFQ, the 157 food items were divided into 11 categories viz, “cereal”, “bread and savory biscuits”, “potatoes, rice, and pasta”, “meat and fish”, “dairy products”, “fats and spreads”, “sweets and snacks”, “soups, sauces, and spreads”, “drinks”, “fruit”, and last, “vegetables”. In addition, the Food4Me FFQ included an additional section on dietary habits with further questions relating to additional foods consumed, the addition of salt to foods, consumption of fried foods, and supplement use (as in the EPIC-Norfolk FFQ).

Frequency of intake was estimated by asking, “How often would you have consumed each of the following in the past month?” and participants could select their frequency from nine categories of intake ranging from “never (<1 per month)” to “6+ per day”. After selecting their frequency of consumption, participants were asked to choose their usual serving size from a range of portion size pictures for each food item (see Figure 1). The online Food4Me FFQ was pre-programmed to ensure that a frequency of consumption was reported for every food item before the participant could submit the FFQ and was designed so that participants could check and/or modify previous responses before submitting the FFQ. Illustrations of the Food4Me FFQ are shown in Figure 1 and Multimedia Appendix 1.

**Figure 1.** Screenshot of the online Food4Me Food Frequency Questionnaire.



### Nutritional Composition and Portion Sizes

Nutritional composition and portion sizes were calculated from the 2008-2010 National Adult Nutrition Survey (NANS) database, which consists of detailed dietary intake data for 1500 Irish adults [36].

The nutritional composition of the 157 food items, listed in the Food4Me FFQ, was derived from the wider list of corresponding foods within the NANS database. From these, the most frequently consumed foods were identified and used to calculate the composition of the list of foods in the Food4Me FFQ. For example, for all pizzas consumed in the NANS dataset, the nutritional composition per 100g was computed for the three most frequently consumed and the mean of these was then calculated to give a single nutritional composition for pizza. The nutritional composition for the NANS dataset was analyzed using WISP (Tinuviel Software, Anglesey, UK). WISP uses the 5thand 6theditions of McCance and Widdowson's *The Composition of Foods*, plus all nine supplemental volumes to generate nutrient intake data [37,38]. In addition, the nutritional composition dataset was modified previously and updated to include recipes of composite dishes, generic commercial foods, new foods on the market, and current manufacturers' information. For additional foods unique to a specific European country in the Food4Me study, such as Greek baklava, the relevant national food composition database was used.

For the calculation of portion sizes, the food codes for each of the frequently consumed foods identified from the NANS database were merged and recoded into a single food code for each food item listed in the FFQ. Using the newly assigned food code, PASW Statistics version 18 (SPSS Inc Chicago, IL, USA) was used to calculate the 25th, 50th, and 75thpercentiles of daily intake, which represent small, medium, and large portion sizes of these foods when consumed in the free living population. Options for portion sizes above, below, and in between these percentiles were also provided to accommodate the wide variability in portion size across populations.

### Photographs

Foods were purchased from local supermarkets and bakeries in Dublin. All foods were prepared and photographs taken in the Institute of Food and Health, University College Dublin. Food photographs were taken by a professional photographer over 5 days/sessions. A standard dining set of plates and cutlery, positioned uniformly with the same lighting, was used for each session. The calculated NANS portion sizes were used as a guideline and all foods were weighed out using calibrated portable food scales (Tanita, Japan).

## Study Sample and Study Design

### Overview

The comparison of the online Food4Me FFQ with the printed EPIC-Norfolk FFQ was conducted in two centers involved in the Food4Me study (University College Dublin and University of Reading) using the English language version of the questionnaire (consisting of 157 food items). The study received approval from the ethical committees at both universities and was carried out between March and October 2012 (LS-11-118-Gibney-Walsh and 01/12-Lovegrove respectively). Participants (n=177) aged ≥18yrs were recruited at both centers. Participants were provided with an information sheet explaining the study, signed a consent form, and completed a brief screening questionnaire either in person or by post. Weight and height were self-reported. Individuals with self-reported/diagnosed food intolerances/allergies or those receiving dietary advice were ineligible to participate.

Eligible participants completed both the online Food4Me FFQ and the printed EPIC-Norfolk FFQ in random order. The printed EPIC-Norfolk FFQ was modified to ask participants' about their food intake over the past month rather than over the past year. To minimize possible effects of temporal changes in dietary intake, participants with more than 4 weeks between completing both FFQs were excluded from analyses. The printed EPIC-Norfolk FFQ was delivered to the participant in person or by post. The Food4Me FFQ was accessed via a hyperlink to the website sent in an email containing the participant's individual username and password.

### Under-Reporters

The Henry equation was used to calculate basal metabolic rate (BMR) and BMR was multiplied by 1.1 to calculate the lowest possible estimated energy requirements (EER) for each participant [39]. Participants reporting energy intakes lower than their EER were classified as under-reporters.

## Dietary Intake Analysis

Printed EPIC-Norfolk questionnaires were coded using the specified template format and cross-checked before sending to Strangeways Research Laboratory (University of Cambridge) for processing using FETA software [40]. The nutritional composition database used in the EPIC-Norfolk FFQ is based on the revised and extended 5thedition of McCance and Widdowson's *The Composition of Foods* plus supplemental volumes [41]. The Food4Me FFQ nutritional intake data was generated automatically by the online Food4Me programmed system, as described above. For the purpose of the current study, consumption of dietary supplements was not included in the analyses.

Data were imported into SPSS for analysis and descriptive statistics were computed to describe the general characteristics of participants. Mean nutrient intakes and standard deviations were determined for both FFQs. General linear model analysis controlling for energy was used to compare nutrient intakes between the FFQs. Correlation coefficients were computed to assess the association between the two methods. The relative agreement between the two FFQs was assessed using cross-classification of nutrient intakes to estimate the percentage of participants who were classified by the two methods into quartiles of "exact agreement", "exact agreement plus adjacent", "disagreement", and "extreme disagreement". Bland and Altman analysis was performed for the macronutrients to assess the limits of agreement between the two FFQs. For each macronutrient, the differences of the mean between the two methods (EPIC−Food4Me) were plotted against the average of the two methods ([EPIC+Food4Me]/2). Methods were considered comparable if greater than 95% of data plots lay within the limits of agreement (mean ± 2SD).

Differences in food group intakes between the two methods were examined. To do this, the food items in the EPIC-Norfolk and Food4Me FFQs were arranged into 35 food groups. Independent samples *t* tests were used to compare daily food group intakes between the two FFQs. Bland and Altman analysis was performed for the food groups to assess the limits of agreement between the two FFQs. Spearman's correlation coefficients (SCC) were computed to assess the associations between the two methods for the daily intake of each of the 35 food groups. To assess the relative agreement between the two methods for daily food group intake, food group intakes were cross-classified to estimate the percentage of participants classified by the two methods into quartiles of "exact agreement", "exact plus adjacent agreement", and "disagreement". All data were analyzed using PASW Statistics version 18 (SPSS Inc Chicago, IL, USA). $P<.05$ was considered statistically significant. GraphPad PRISM version 6 was used to produce the Bland and Altman plots (GraphPad Software, Inc California, USA).

## Results

### Overview of the Study Population

A total of 177 participants were screened to participate in the study with 159 eligible for inclusion. Following initiation of the study, 27 participants dropped out, as shown in Figure 2. Reasons for dropouts included external commitments, for example, holidays and technical issues. A further 19 participants were excluded from the analysis: 16 had >4 weeks between completion of the two FFQs and 3 reported energy intakes >4500 kcal per day with the Food4Me FFQ (considered to be unrealistically high) [42]. The final data set, therefore, consisted of 113 participants as illustrated in Figure 2. The results presented here are for the dietary assessment of 67 females (59.3%) and 46 males (40.7%) who completed both the printed EPIC-Norfolk FFQ and online Food4Me FFQ in random order.

Demographic characteristics of the study population are presented in Table 1. Overall, for all participants, there were no significant differences in age for males and females; however, self-reported body mass index (BMI) was significantly lower for females compared with males. As shown in Table 1, significant differences in age, weight, and BMI were observed across the two centers. The participants recruited in Dublin were significantly older ($P<.005$), were significantly heavier ($P<.005$), and had higher BMI ($P<.05$) than those recruited in Reading.

**Table 1.** Demographic characteristics of the study population in total and across centers, by gender.

| Participants | | Demographic characteristics, mean (SD) | | | |
|---|---|---|---|---|---|
| | | n | Age (y) | Weight (kg) | BMI ($kg/m^2$)[a] |
| **All Participants** | | | | | |
| | Male | 46 | 32.0 (12.6) | 77.3 (11.3) | 24.3 (3.0) |
| | Female | 67 | 29.0 (8.0) | 62.2 (9.4) | 22.6 (2.6)[d] |
| | All | 113 | 30.0 (10.2) | 68.4 (12.6) | 23.3 (2.9) |
| **Dublin Participants** | | | | | |
| | Male | 32 | 35.1 (13.0) | 78.6 (10.6) | 24.8 (2.8) |
| | Female | 32 | 30.2 (7.2) | 64.3 (8.9) | 23.1 (2.5)[e] |
| | All | 64 | 32.6 (10.7) | 71.5 (12.1) | 24.0 (2.8) |
| **Reading Participants** | | | | | |
| | Male | 14 | 24.2 (7.6)[b] | 74.3 (12.4) | 23.1 (3.2) |
| | Female | 35 | 27.9 (8.6) | 60.3 (9.4) | 22.2 (2.6) |
| | All | 49 | 26.9 (8.4)[b] | 64.3 (12.1)[b] | 22.5 (2.8)[c] |

[a]Body mass index (BMI) based on self-reported weight and height.

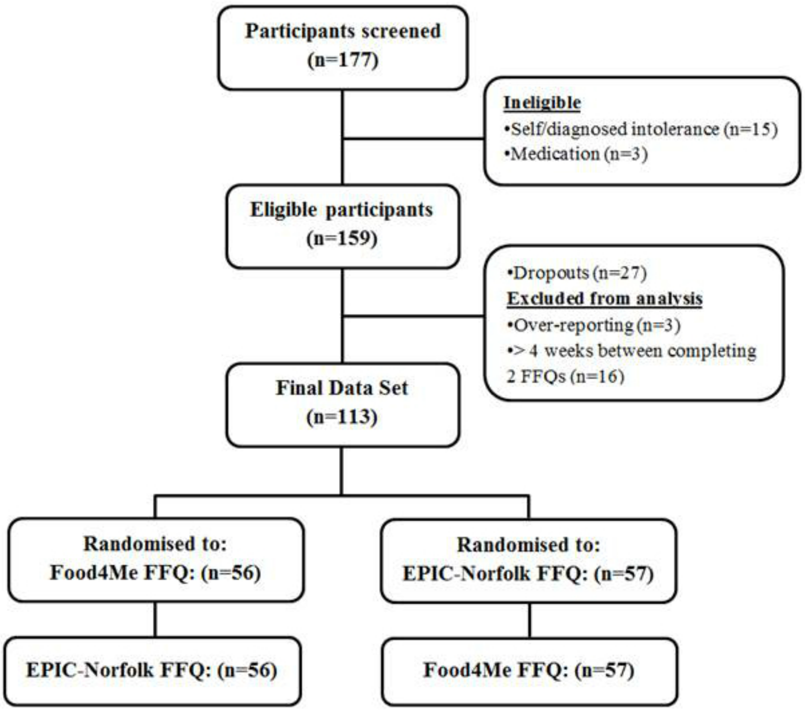
[b]Significantly different between centers, $P<.005$.

[c]Significantly different between centers, $P<.05$.

[d]Significantly different from males, $P<.005$.

[e]Significantly different from males, $P<.05$.

**Figure 2.** Flow of participants through the study. FFQ: food frequency questionnaire.




### Comparison of Nutrient Intakes Between the Two Questionnaires

Mean energy and nutrient intakes estimated from the two FFQs are presented in Table 2. Energy intakes were significantly higher for the Food4Me FFQ in comparison with the EPIC-Norfolk FFQ (*P*<.001). However, when the occurrence of under-reporting was examined, 58 participants were classified as under-reporters with the EPIC-Norfolk FFQ compared with only 20 participants for the Food4Me FFQ. Of the 20 participants' under-reporting in the Food4me FFQ, 18 also under-reported using the EPIC-Norfolk FFQ (90%).

After controlling for energy, intakes of macronutrients showed relatively good agreement with no significant differences in energy derived from total fat, saturated fatty acids (SFA), monounsaturated fatty acids (MUFA), or carbohydrates. Significant differences were observed in both total polyunsaturated fatty acid intake and % energy derived from polyunsaturated fatty acids (PUFA), at *P*<.001. Examination of differences at a micronutrient level demonstrated no significant differences between the two FFQs for intakes of calcium, vitamin B12, and vitamin D. Significant differences were observed for intakes of folate, iron, carotene, riboflavin, thiamin, vitamin B6, vitamin C, vitamin A (RE), retinol, vitamin E, and sodium (Table 2). However, after controlling for energy and, where appropriate, center, randomization group and/or gender, vitamin C and vitamin A (RE) were no longer significantly different (Table 2). The removal of under-reporters reduced the agreement between the two FFQs for total fat (% total energy [TE]), but improved the agreement for protein (% TE) showing no significant difference when controlling for energy, center, and gender (both alone and in combination), as shown in Table 3.

Bland and Altman plots for mean daily energy, total fat, protein, and carbohydrate intakes are presented in Figure 3. The Bland and Altman plot for energy indicated broad limits of agreement. The mean difference in estimated energy intake between FFQs was relatively high (676 kcal/d) with greater energy intakes recorded using the Food4Me FFQ compared with the EPIC-Norfolk FFQ. In addition, the difference in estimates of energy intakes between FFQs became progressively greater with higher mean intakes (Figure 3). Despite this, less than 5% of cases fell outside the limits of agreement for energy (n=5), confirming an acceptable level of agreement between the two methods.

As illustrated in Figure 3, similar to energy, the difference in estimates of total fat (g) and protein (g) intakes between the two FFQs became progressively greater with higher mean intakes. Poor levels of agreement between the methods were observed for the macronutrients, with greater than 5% of cases falling outside the limits of agreement for protein (g) (n=8), carbohydrate (g) (n=6), and total fat (g) (n=6). After adjusting for energy, the agreement between the two methods improved, as less than 5% of cases fell outside the limits of agreement for both carbohydrate (% TE) (n=4) and total fat (% TE) (n=4) (Figure 3). Although energy adjustment improved the distribution of cases for protein, more than 5% of cases (n=7) remained outside the limits of agreement [43], indicating a poorer level of agreement between the methods for protein (% TE). Correlation coefficients for estimates of nutrient intakes between the two FFQs are presented in Table 4. The mean correlation coefficient for nutrient intake between the two FFQs was .60. Correlations varied from .43 (polyunsaturated fatty acids % TE) to .86 (alcohol). For micronutrients, correlation coefficients were lowest for thiamin (.46) and highest for vitamin C (.69). The cross-classification of mean daily intakes between the two FFQs are also shown in Table 4. The percentage of participants classified into quartiles of "exact agreement" varied from 37% (polyunsaturated fatty acids %TE) to 63% (alcohol). The percentage of participants cross-classified into quartiles of "exact agreement plus adjacent" was lowest for polyunsaturated fatty acids (77%) and highest for alcohol (97%). Although the mean percentage of participants classified into quartiles of "disagreement" (opposite plus extreme quartiles) was 15%, the mean percentage categorized into quartiles of "extreme disagreement" was 2.5%.

**Table 2.** Mean daily nutrient intakes estimated by printed EPIC-Norfolk FFQ[a]and online Food4Me FFQ (n=113).

| Nutrient | EPIC-Norfolk FFQ,mean (SD) | Food4Me FFQ,mean (SD) | *P* value[b] | *P* value[c] |
|---|---|---|---|---|
| Energy (kcal) | 1684.62 (483.41) | 2356.08 (809.36) | - | - |
| Total Fat (g) | 66.10 (24.27) | 89.48 (38.23) | .001 | .001 |
| Total Fat (% TE[d]) | 34.88 (6.18) | 33.50 (5.31) | .07 | .03 |
| SFA[e] (g) | 24.91 (10.50) | 36.03 (16.52) | .29 | .29 |
| SFA (% TE) | 13.13 (3.40) | 13.39 (2.78) | .52 | .73 |
| MUFA[f](g) | 23.26 (8.75) | 32.82 (14.84) | .09 | .09 |
| MUFA (% TE) | 12.26 (2.35) | 12.27 (2.54) | .99 | .99 |
| PUFA[g](g) | 12.18 (6.33) | 14.33 (5.97) | <.001 | <.001 |
| PUFA (% TE) | 6.44 (2.63) | 5.46 (1.15) | <.001 | <.001 |
| Protein (g) | 75.53 (21.82) | 96.92 (36.87) | .26 | .91 |
| Protein (% TE) | 18.33 (4.24) | 16.56 (3.35) | .001 | .001 |
| Carbohydrate (g) | 197.09 (69.81) | 281.89 (96.48) | .09 | .12 |
| Carbohydrate(% TE) | 46.82 (8.14) | 48.41 (6.91) | .11 | .06 |
| Total sugars (g) | 103.92 (45.78) | 130.00 (48.61) | .04 | .001 |
| Alcohol (g) | 7.21 (9.10) | 13.61 (15.72) | .18 | .18 |
| Calcium (mg) | 835.03 (255.85) | 1159.12 (459.22) | .17 | .17 |
| Total folate (µg) | 250.16 (68.70) | 375.16 (136.40) | <.001 | <.001 |
| Iron (mg) | 9.70 (2.74) | 15.91 (5.97) | <.001 | <.001 |
| Total carotene (µg) | 3512.61 (2004.14) | 5811.99 (4180.17) | .001 | .02 |
| Riboflavin (mg) | 1.74 (0.47) | 2.42 (0.92) | .02 | .02 |
| Thiamin (mg) | 1.34 (0.37) | 2.42 (1.66) | <.001 | <.001 |
| Vitamin B6 (mg) | 2.03 (0.52) | 2.84 (1.08) | .03 | .01 |
| Vitamin B12 (µg) | 5.93 (2.79) | 7.22 (3.24) | .49 | .49 |
| Vitamin C (mg) | 107.12 (55.87) | 164.50 (87.85) | .003 | .11 |
| Vitamin A (RE) (µg) | 984.94 (470.95) | 1735.23 (3712.62) | .04 | .95 |
| Retinol (µg) | 385.73 (300.15) | 445.73 (277.59) | .02 | .02 |
| Vitamin D (µg) | 2.96 (1.90) | 3.67 (2.15) | .44 | .48 |
| Vitamin E (mg) | 10.64 (4.63) | 10.71 (4.32) | <.001 | <.001 |
| Sodium (mg) | 2442.27 (772.86) | 2597.38 (1070.53) | <.001 | <.001 |
| Salt (g) | 6.11 (1.93) | 6.49 (2.68) | <.001 | <.001 |

[a]FFQ: food frequency questionnaire.

[b]All *P* values were derived by controlling for energy using general linear model analysis.

[c]Controlled for energy and, where appropriate, center, gender, and randomization group using general linear model analysis. No significant interactions were observed between method and gender, center and randomization group.

[d]TE: total energy.

[e]SFA: saturated fatty acids.

[f]MUFA: monounsaturated fatty acids.

[g]PUFA: polyunsaturated fatty acids.

**Table 3.** Mean daily nutrient intakes estimated by printed EPIC FFQ[a](n=55) and online Food4Me FFQ (n=93) with under-reporters removed.

| Nutrient | EPIC (n=55),mean (SD) | Food4Me (n=93),mean (SD) | *P* value[b] | *P* value[c] |
|---|---|---|---|---|
| Energy (kcal) | 2023.79 (402.71) | 2573.63 (714.10) | - | - |
| Total Fat (g) | 80.68 (20.15) | 98.82 (35.18) | .01 | .01 |
| Total Fat (% TE [d]) | 35.84 (4.72) | 34.11 (5.08) | .04 | .04 |
| SFA[e](g) | 30.43 (9.44) | 39.88 (15.46) | .60 | .60 |
| SFA (% TE) | 13.54 (3.02) | 13.68 (2.71) | .76 | .76 |
| MUFA[f](g) | 28.51 (7.58) | 36.33 (13.82) | .30 | .30 |
| MUFA (% TE) | 12.65 (1.97) | 12.55 (2.47) | .78 | .78 |
| PUFA[g](g) | 14.80 (5.29) | 15.72 (5.57) | <.001 | <.001 |
| PUFA (% TE) | 6.57 (1.97) | 5.50 (1.13) | <.001 | <.001 |
| Protein (g) | 85.69 (17.42) | 105.73 (33.99) | .85 | .30 |
| Protein (% TE) | 17.21 (3.29) | 16.53 (3.26) | .22 | .22 |
| Carbohydrate (g) | 239.40 (70.54) | 306.18 (87.44) | .48 | .48 |
| Carbohydrate (% TE) | 47.04 (7.61) | 47.97 (6.94) | .45 | .36 |
| Total sugars (g) | 131.41 (47.46) | 141.51 (44.27) | .009 | .001 |
| Alcohol (g) | 8.50 (11.60) | 14.80 (16.84) | .33 | .33 |
| Calcium (mg) | 956.48 (226.18) | 1256.82 (442.11) | .14 | .14 |
| Total folate (µg) | 285.67 (63.38) | 403.13 (125.66) | <.001 | <.001 |
| Iron (mg) | 10.91 (2.58) | 17.18 (5.61) | <.001 | <.001 |
| Total carotene (µg) | 4078.51 (2051.75) | 6280.68 (4311.00) | .004 | .004 |
| Riboflavin (mg) | 1.97 (0.41) | 2.60 (0.90) | .03 | .03 |
| Thiamin (mg) | 1.55 (0.35) | 2.48 (1.48) | .001 | .001 |
| Vitamin B6 (mg) | 2.32 (0.47) | 3.09 (1.01) | .02 | .01 |
| Vitamin B12 (µg) | 6.88 (2.93) | 7.82 (3.20) | .72 | .72 |
| Vitamin C (mg) | 126.64 (57.42) | 178.47 (87.62) | .01 | .11 |
| Vitamin A (RE) (µg) | 1190.08 (471.67) | 1917.85 (4067.44) | .53 | .53 |
| Retinol (µg) | 490.82 (323.56) | 481.24 (287.30) | .01 | .01 |
| Vitamin D (µg) | 3.48 (2.03) | 3.98 (2.21) | .58 | .58 |
| Vitamin E (mg) | 13.06 (4.56) | 11.65 (4.07) | <.001 | <.001 |
| Sodium (mg) | 2879.23 (712.59) | 2841.48 (1009.77) | <.001 | <.001 |
| Salt (g) | 7.20 (1.78) | 7.10 (2.52) | <.001 | <.001 |

[a]FFQ: food frequency questionnaire.

[b]All *P* values were derived by controlling for energy using general linear model analysis.

[c]Controlled for energy and, where appropriate, center and/or gender using general linear model analysis. No significant interactions were observed between method and gender or center.

[d]TE: total energy.

[e]SFA: saturated fatty acids.

[f]MUFA: monounsaturated fatty acids.

[g]PUFA: polyunsaturated fatty acids.

**Table 4.** Unadjusted correlation coefficients and cross-classification of quartiles of mean energy and nutrient intakes derived from the online Food4Me FFQ[a] and printed EPIC-Norfolk FFQ.

| | Correlation[b] | Exact agreement[d], (%) | Exact agreement + adjacent[e], (%) | Disagreement[f], (%) | Extreme disagreement[g], (%) |
|---|---|---|---|---|---|
| Energy (kcal) | .68 | 52 | 88 | 12 | 1 |
| Total Fat (g) | .70 | 46 | 90 | 10 | 1 |
| Total Fat (% TE[h]) | .54[c] | 39 | 78 | 22 | 4 |
| SFA[i] (g) | .71 | 46 | 91 | 9 | 1 |
| SFA (% TE) | .63[c] | 38 | 84 | 16 | 2 |
| MUFA[j](g) | .70 | 47 | 93 | 7 | 2 |
| MUFA (% TE) | .57[c] | 39 | 81 | 19 | 2 |
| PUFA[k](g) | .56 | 39 | 86 | 14 | 4 |
| PUFA (% TE) | .43 | 37 | 77 | 23 | 1 |
| Protein (g) | .63 | 46 | 86 | 14 | 1 |
| Protein (% TE) | .63 | 50 | 85 | 15 | 2 |
| Carbohydrate (g) | .63 | 55 | 84 | 16 | 3 |
| Carbohydrate (% TE) | .72[c] | 53 | 88 | 12 | 0 |
| Total sugars (g) | .74 | 57 | 94 | 6 | 2 |
| Alcohol (g) | .86 | 63 | 97 | 3 | 0 |
| Calcium (mg) | .51 | 45 | 81 | 19 | 3 |
| Total folate (µg) | .53[c] | 49 | 81 | 19 | 3 |
| Iron (mg) | .48 | 44 | 79 | 21 | 5 |
| Total carotene (µg) | .58 | 44 | 80 | 20 | 2 |
| Riboflavin (mg) | .52 | 38 | 82 | 18 | 4 |
| Thiamin (mg) | .46 | 40 | 84 | 16 | 5 |
| Vitamin B6 (mg) | .56 | 49 | 85 | 15 | 4 |
| Vitamin B12 (µg) | .49 | 39 | 81 | 19 | 4 |
| Vitamin C (mg) | .69 | 52 | 89 | 11 | 2 |
| Vitamin A (RE) (µg) | .55 | 42 | 82 | 18 | 3 |
| Retinol (µg) | .65 | 48 | 91 | 9 | 3 |
| Vitamin D (µg) | .57 | 42 | 87 | 13 | 4 |
| Vitamin E (mg) | .57 | 43 | 81 | 19 | 4 |
| Sodium (mg) | .58 | 50 | 84 | 16 | 1 |

[a]FFQ: food frequency questionnaire.

[b]Correlation is significant at the .01 level (2-tailed) for all nutrients analyzed.

[c]Pearson’s correlation.

[d]Exact agreement: % of cases cross-classified into the same quartile.

[e]Exact + adjacent agreement: % of cases cross-classified into the same or adjacent quartile.

[f]Disagreement: % of cases cross-classified 2 quartiles apart.

[g]Extreme quartiles: % of cases cross-classified into extreme quartiles.

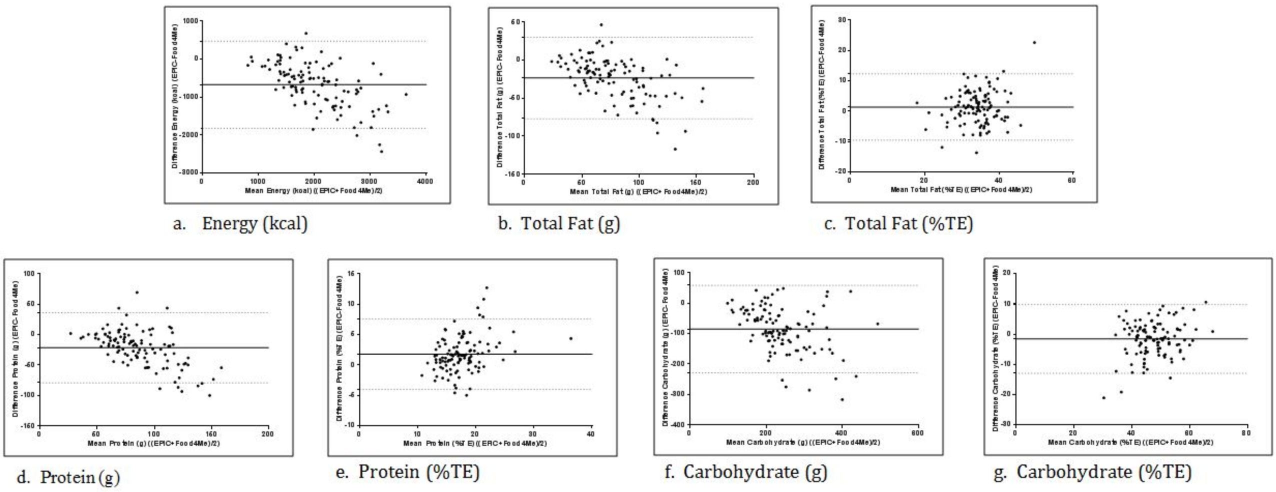
[h]TE: total energy.

[i]SFA: saturated fatty acids.

[j]MUFA: monounsaturated fatty acids.

[k]PUFA: polyunsaturated fatty acids.

**Figure 3.** Bland and Altman plots with mean difference and limits of agreement (solid line represents mean difference and dotted lines represent limits of agreement). TE: total energy.




## Comparison of Food Group Intakes Between the Two Questionnaires

To examine differences in food group intakes between the two FFQs, the food items in the EPIC-Norfolk FFQ and Food4Me FFQ were aggregated into 35 food groups. Mean daily intakes estimated from the two FFQs for the 35 food groups are presented in Table 5. Mean daily intakes for 17 of the 35 food groups analyzed were significantly higher for the online Food4Me FFQ in comparison with the printed EPIC-Norfolk FFQ.

Bland and Altman analysis for daily food group intake was performed to examine the agreement between both methods. Overall, acceptable levels of agreement were observed for 15 of the 35 food groups, with less than 5% of cases (n<6) falling outside the limits of agreement. The Bland and Altman plots for mean daily intakes for six of the 35 food groups (“rice, pasta, grains, and starches”, “yoghurts”, “eggs and egg dishes”, “other vegetables”, “fish and fish products”, “red meat”) are presented in Figure 4. The mean difference between the methods (bias) was small for all six food groups. Overall, these plots indicate good agreement between the two methods for the assessment of “rice, pasta, grains, and starches”, “yoghurts”, “eggs and egg dishes”, and “red meat”. Poorer agreement was observed for “other vegetables” and “fish and fish products/dishes”, with more than 5% of cases (n=7) outside the limits of agreement for both food groups [43].

SCC and cross-classification of mean daily food group intakes are presented in Table 6. The mean SCC for food group intake between the two FFQs was .68 and SCCs ranged from .41 for “savories” (lasagna, pizza) to .90 for “other fruits” (apples, pears, citrus fruits). High correlations (SCCs≥.5) were observed for 32 of the 35 food groups. Overall, ranking participants into quartiles of “exact agreement” was lowest for “cakes, buns, and pastries” (35%) and highest for “bananas” (73%). The percentage of participants cross-classified into quartiles of “exact agreement plus adjacent” was lowest for “cakes, buns, and pastries” (77%) and highest for “other fruits” (apples, pears, citrus fruits) (99%). The mean percentage misclassified for all food groups was 12%.

**Table 5.** Mean daily food group intakes estimated by printed EPIC-Norfolk FFQ[a] and online Food4Me FFQ (n=113).

| Food group | EPIC (grams), mean (SD) | Food4Me (grams), mean (SD) | *P* value[b] |
|---|---|---|---|
| Rice, pasta, grains, and starches | 87.26 (74.30) | 99.03 (87.54) | .28 |
| Savories (lasagna, pizza) | 17.69 (17.40) | 34.85 (29.75) | <.001 |
| White bread (rolls, tortillas, crackers) | 13.65 (19.69) | 43.93 (69.54) | <.001 |
| Wholemeal and brown breads and rolls | 28.20 (37.76) | 54.28 (67.59) | <.001 |
| Breakfast cereals and porridge | 50.51 (50.67) | 93.91 (91.64) | <.001 |
| Biscuits | 6.43 (10.56) | 18.94 (25.06) | <.001 |
| Cakes, pastries, and buns | 17.76 (24.47) | 19.70 (18.55) | .50 |
| Milk | 280.97 (166.19) | 240.53 (178.04) | .08 |
| Cheeses | 17.36 (22.68) | 24.38 (29.29) | .045 |
| Yoghurts | 29.20 (38.112) | 60.98 (99.82) | .002 |
| Ice cream, creams, and desserts | 16.60 (28.48) | 12.61 (17.44) | .21 |
| Eggs and egg dishes | 18.63 (19.62) | 34.92 (36.39) | <.001 |
| Fats and oils (eg, butter, low-fat spreads, hard cooking fats) | 10.34 (10.38) | 14.75 (13.00) | .005 |
| Potatoes and potato dishes | 47.39 (35.00) | 68.18 (63.48) | .003 |
| Chipped, fried, and roasted potatoes | 11.51 (15.43) | 14.13 (17.30) | .23 |
| Peas, beans, and lentils and vegetable and pulse dishes | 25.46 (23.91) | 30.13 (31.56) | .21 |
| Green vegetables | 26.31 (27.96) | 28.06 (35.97) | .68 |
| Carrots | 18.93 (20.84) | 23.83 (23.43) | .10 |
| Salad vegetables (eg, lettuce) | 13.00 (14.45) | 10.28 (10.97) | .11 |
| Other vegetables (eg, onions) | 96.05 (53.06) | 111.62 (96.73) | .14 |
| Tinned fruit or vegetables | 15.30 (19.10) | 18.84 (26.22) | .25 |
| Bananas | 52.00 (55.01) | 61.54 (70.20) | .26 |
| Other fruits (eg, apples, pears, oranges) | 156.69 (140.10) | 218.90 (206.63) | .01 |
| Nuts and seeds, herbs and spices | 3.54 (6.67) | 2.48 (5.79) | .19 |
| Fish and fish products/dishes | 29.99 (31.68) | 48.29 (48.70) | .001 |
| Bacon and ham | 12.76 (16.81) | 12.11 (14.33) | .75 |
| Red meat (eg, beef, veal, lamb, pork) | 26.87 (31.75) | 41.31 (39.25) | .003 |
| Poultry (chicken and turkey) | 31.47 (37.20) | 42.79 (53.92) | .07 |
| Meat products (eg, burgers, sausages, pies, processed meats) | 9.15 (10.18) | 19.76 (23.18) | <.001 |
| Alcoholic beverages | 104.80 (182.33) | 200.32 (261.08) | .002 |
| Sugars, syrups, preserves, and sweeteners | 8.15 (10.21) | 7.04 (9.53) | .40 |
| Confectionary and savory snacks | 23.87 (32.88) | 25.31 (24.53) | .71 |
| Soups, sauces, and miscellaneous foods | 51.83 (52.32) | 83.76 (84.80) | .001 |
| Teas and coffees | 533.78 (398.43) | 472.08 (403.98) | .25 |
| Other beverages (eg, fruit juices, carbonated beverages, squash) | 109.73 (123.90) | 213.66 (204.12) | <.001 |

[a]FFQ: food frequency questionnaire.

[b]All *P* values were derived using independent samples *t* tests.

**Table 6.** Spearman's correlation coefficients (SCC) and cross-classification of quartiles of food group intake.

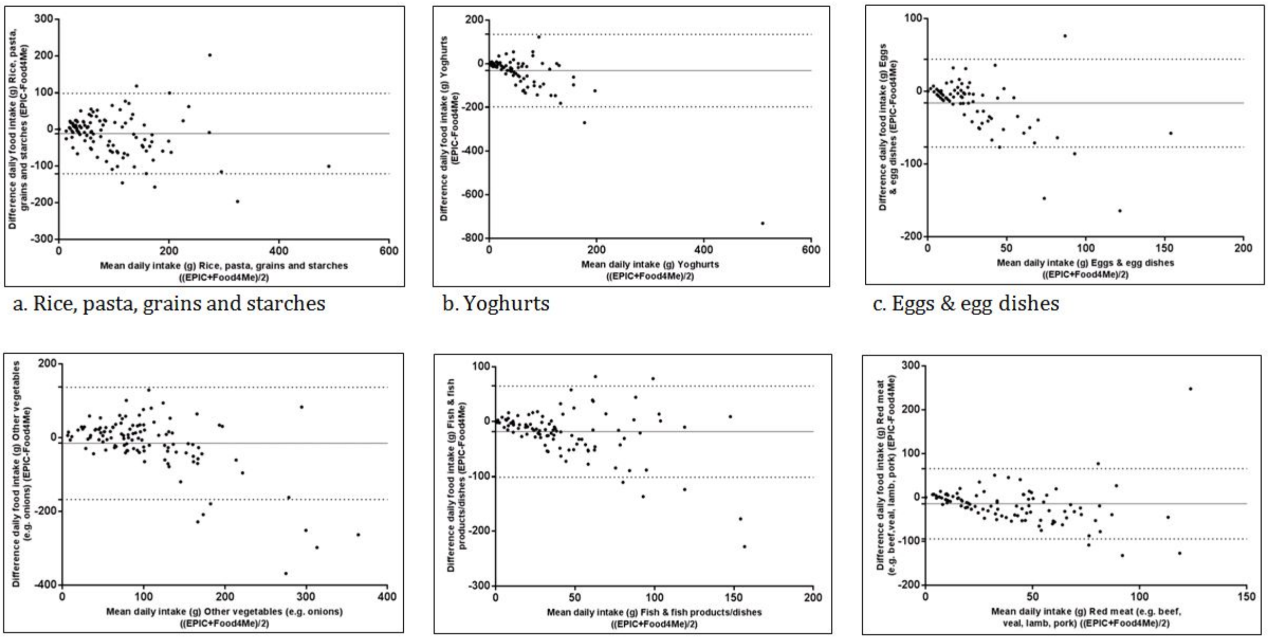
| Food group | SCC | Exact agreement[a](%) | Exact agreement + adjacent[b](%) | Disagreement[c](%) |
|---|---|---|---|---|
| Rice, pasta, grains, and starches | .76 | 55 | 94 | 6 |
| Savories (lasagna, pizza) | .41 | 36 | 79 | 21 |
| White bread (rolls, tortillas, crackers) | .55 | 42 | 83 | 17 |
| Wholemeal and brown breads and rolls | .74 | 54 | 92 | 8 |
| Breakfast cereals and porridge | .76 | 62 | 93 | 7 |
| Biscuits | .67 | 45 | 90 | 13 |
| Cakes, pastries, and buns | .48 | 35 | 77 | 23 |
| Milk | .55 | 49 | 80 | 20 |
| Cheeses | .66 | 50 | 85 | 15 |
| Yoghurts | .70 | 58 | 89 | 11 |
| Ice cream, creams, and desserts | .49 | 43 | 81 | 19 |
| Eggs and egg dishes | .59 | 43 | 83 | 17 |
| Fats and oils (eg, butter, low-fat spreads, hard cooking fats) | .64 | 43 | 86 | 14 |
| Potatoes and potato dishes | .61 | 44 | 83 | 17 |
| Chipped, fried, and roasted potatoes | .63 | 45 | 88 | 12 |
| Peas, beans, and lentils and vegetable and pulse dishes | .66 | 49 | 83 | 17 |
| Green vegetables | .76 | 56 | 91 | 9 |
| Carrots | .65 | 51 | 85 | 15 |
| Salad vegetables (eg, lettuce) | .58 | 50 | 84 | 16 |
| Other vegetables (eg, onions) | .67 | 47 | 90 | 10 |
| Tinned fruit or vegetables | .72 | 53 | 90 | 10 |
| Bananas | .88 | 73 | 96 | 4 |
| Other fruits (eg, apples, pears, oranges) | .90 | 70 | 99 | 1 |
| Nuts and seeds, herbs and spices | .68 | 56 | 83 | 17 |
| Fish and fish products/dishes | .73 | 51 | 90 | 10 |
| Bacon and ham | .75 | 50 | 91 | 9 |
| Red meat (eg, beef, veal, lamb, pork) | .69 | 50 | 93 | 7 |
| Poultry (chicken and turkey) | .69 | 48 | 83 | 17 |
| Meat products (eg, burgers, sausages, pies, processed meats) | .67 | 53 | 87 | 13 |
| Alcoholic beverages | .87 | 66 | 95 | 5 |
| Sugars, syrups, preserves, and sweeteners | .79 | 62 | 92 | 8 |
| Confectionary and savory snacks | .66 | 53 | 88 | 12 |
| Soups, sauces, and miscellaneous foods | .53 | 43 | 82 | 18 |
| Teas and coffees | .77 | 59 | 93 | 7 |
| Other beverages (eg, fruit juices, carbonated beverages, squash) | .79 | 60 | 92 | 8 |

[a]Exact agreement: % of cases cross-classified into the same quartile.

[b]Exact + adjacent agreement: % of cases cross-classified into the same or adjacent quartile.

[c]Disagreement: % of cases cross-classified 2 quartiles apart.

**Figure 4.** Bland and Altman plots for selected food groups with mean difference and limits of agreement (solid line represents mean difference and dotted lines represent the limits of agreement).



a. Rice, pasta, grains and starches b. Yoghurts c. Eggs & egg dishes d. Other vegetables e. Fish & fish products/dishes f. Red meat

## Discussion

### Principal Results and Comparisons With Other Work

The present study demonstrates the development of a novel online FFQ and its comparison with the validated printed EPIC-Norfolk FFQ [35]. The Food4Me FFQ was developed to capture dietary intake in an online fashion. It was designed to include a range of portion size options and incorporated food photographs to aid food recognition and portion size estimation.

Overall, the current results demonstrate good agreement between the online Food4Me FFQ and the printed EPIC-Norfolk FFQ for both nutrient and food group intakes. Cross-classification of daily energy and nutrient intakes showed good agreement between the two FFQs indicating that the online Food4Me FFQ generates ranks of dietary intakes that are highly comparable with the previously validated printed EPIC-Norfolk FFQ. Similar to many previous published studies, classification into exact plus adjacent quartiles ranged from 77% to 97% and exact disagreement/misclassification ranged between 0% and 5% [21,28,44,45]. Furthermore, Bland and Altman plots demonstrated an acceptable level of agreement between the two methods for energy and total fat and carbohydrate intakes as a percentage of total energy.

In the present study, there were moderate to high correlation coefficients, ranging from .43 to .86, between the methods for individual nutrients. For the majority of nutrients analyzed, the correlation coefficients were within the ranges recommended by Willet et al [46] and Masson et al [47]; 25 out of 29 of the nutrients had a correlation ≥.50 of which four had a correlation >.70, indicating that estimates of intake obtained using the Food4Me FFQ are strongly correlated with those from the printed EPIC-Norfolk FFQ. The mean correlation coefficient was .60, which is within the range of those reported in the literature [16,32]. Furthermore, the ranges of correlation coefficients obtained in the present study are similar to those reported by Kristiansen et al [48]. The latter authors compared estimates of nutrient intake obtained at two time points by a semi-quantitative FFQ that had undergone slight modifications and obtained correlations ranging from .43 to .75.

Analyses at the food group level also showed good agreement between the EPIC-Norfolk and Food4Me FFQs. Validation studies of FFQs examining food group intakes have reported SCC ranging from .46 to .87 [49] and .14 to .90 [50]. In the current study, correlation coefficients >.50 were obtained for the majority of food groups showing that the Food4Me FFQ has reasonable ranking ability for food group intake estimates, and is comparable with the EPIC-Norfolk FFQ. Good agreement between the two methods for quartile classification of food group intakes was also observed with more than 75% of participants correctly classified into the same or adjacent quartiles for each of the food groups analyzed.

While we have demonstrated that the online Food4Me FFQ shows good agreement with the printed EPIC-Norfolk FFQ overall, some disagreement was observed between the two FFQs, particularly in relation to energy intakes. Similar to findings by Beasley et al [32], in the current study, the online FFQ yielded higher estimates for mean nutrient intakes in comparison to the printed FFQ. However, the percentage of participants classified as under-reporters was 33.6% higher with the printed EPIC-Norfolk FFQ compared with the online Food4Me FFQ, indicating that the Food4Me FFQ may have a greater ability to capture usual dietary intake than the EPIC-Norfolk FFQ.

Multiple factors could have contributed to the discrepancies observed in mean daily intakes and the occurrence of under-reporting between the two methods. First, numerous differences in food group consumption were observed between the two FFQs. For 17 of the 35 food groups (49%), mean daily intakes were significantly higher with the online Food4Me FFQ compared with the printed EPIC-Norfolk FFQ. In addition, Bland and Altman plots demonstrated a poor level of agreement between the methods for 20 of the 35 food groups (57%). The low level of agreement for food group consumption between the two methods is most likely attributable to differences in reported food intake between both FFQs. The Food4Me FFQ included an additional 27 food items not present in the printed EPIC-Norfolk FFQ and as a result several of the 35 food groups analyzed in the current study did not contain equal numbers of food items for both methods. For example, the food group "fish and fish products/dishes" consisted of 10 food items for the Food4Me FFQ compared with six food items from the EPIC-Norfolk FFQ. Such variances in the number of food items aggregated into food groups (for both FFQs) could partly explain the differences observed in mean daily food group intakes between the two methods.

The additional 27 food items listed in the Food4Me FFQ would have offered participants a greater selection of food items and, as a result, both food group consumption and subsequent nutrient intakes may be more reflective of true dietary intake. However, it is also possible that the additional food items included in the Food4Me FFQ may have resulted in an overestimation of consumption frequency for particular nutrients and food groups. This can occur when several food items of a single food group are listed in a questionnaire [50]. Furthermore, despite both FFQs being conducted within 4 weeks (to minimize temporal changes in dietary intakes), there is also the potential that the consumption of a particular food item/group was recalled/reported with one FFQ and not the other (impacting on nutrient and energy intakes).

A second factor potentially contributing to the differences observed between the two FFQs is portion size estimation. The online Food4Me FFQ incorporates a selection of portion sizes for the majority of food items, as opposed to applying a standard one to each food item. Presuming all participants consume standard portion sizes is a generalization and the use of standard portion sizes in heterogeneous population groups is likely to result in additional inaccuracies [51]. Printed questionnaires are limited in their ability to collect complex information (eg, portion size consumption) due to practical restrictions in-built in the questionnaire format [52]. It is more feasible to obtain complex information with online questionnaires, which can be designed to embed multiple photographs to aid with portion size estimation. However, questionnaires with multiple portion size options will exhibit more variability compared to those without variable portion sizes (which may be a truer estimate of actual intakes) [50]. When examining food group intakes, Ocke et al [53] found that the use of photographs for dairy desserts resulted in an overestimation of milk and milk products. Other studies have reported that photographs have a positive effect on the respondents' ability to accurately estimate portion sizes [14,32] and further investigation is needed to determine whether the use of photographs in the Food4Me FFQ aids portion size estimation and food recognition.

Third, the differences we observed between the two methods in relation to daily nutrient intakes may have been related to variances in the nutritional composition databases utilized in both methods, as the nutritional composition database used to calculate daily nutrient intakes is more up to date than that used for analysis of the printed EPIC-Norfolk FFQ [41]. The nutritional composition database used in the EPIC-Norfolk FFQ is based on the revised and extended 5th edition of McCance and Widdowson's *The Composition of Foods* plus supplemental volumes, while the nutritional composition data for the Food4Me FFQ is based on the 6th and 5th editions of McCance and Widdowson's *The Composition of Foods* plus all nine supplemental volumes [38,41].

## Strengths and Limitations

The strengths of the current study include the cross-over design and adequate sample size [46,54]. In addition, all participants included in the analyses completed both questionnaires within 1 month, minimizing the likelihood of changes in dietary intake. Limitations of the current study include the use of self-reported weight and height measurements for all participants. BMR was estimated using the Henry equations and therefore any errors in these self-reported measurements could have impacted on the frequency of under-reporting that we observed in the results. Another limitation of the current study is that the majority of participants involved were recruited from within the universities and are therefore representative of a convenient sample rather than a nationally representative sample. As the accuracy of any dietary assessment method using self-report depends ultimately on the cooperation and motivation of the participants, further testing of the Food4Me FFQ will be necessary to establish its wider utility.

## Conclusions

In conclusion, the online Food4Me FFQ has good agreement with the previously validated printed EPIC-Norfolk FFQ for assessing both nutrient and food group intakes of healthy young adults. While some differences were observed between the methods, particularly in relation to mean daily nutrient and food group intakes, good agreement was observed at both the nutrient and food group level using a variety of analyses. The most common use of an FFQ is not to measure absolute intake but to rank individuals by their food and nutrient intakes [21]. In the current study, the Food4Me FFQ was able to generate ranks of nutrient and food group intakes that were highly comparable with the validated EPIC-Norfolk FFQ, with levels of agreement from quartile cross-classification similar to many previous published studies. Therefore, the good agreement with the printed EPIC-Norfolk FFQ combined with its ease of use make the online Food4Me FFQ a useful tool for ranking individuals based on their nutrient intake and could be potentially valuable for use in other epidemiological studies.

## Acknowledgments

This work was funded by Food4Me (KBBE.2010.2.3-02, Project no. 265494). The authors would like to thank Creme Global (Dublin, Ireland) for their considerable involvement in the development of the online Food4Me FFQ and the participants for their time and dedication throughout the study.


## Authors' Contributions

All authors participated in the design of the study. HF, RF, CG, and ALM carried out the data collection. HF, MCW, LB, and ERG carried out the statistical analyses and drafted the manuscript. All authors critically reviewed and approved the final manuscript submitted for publication.

## Conflicts of Interest

None declared.

## Multimedia Appendix 1

Food4Me Food Frequency Questionnaire screenshots.

[PDF File (Adobe PDF File), 240KB - jmir_v16i6e150_app1.pdf ]

## References


1. Roberts CK, Barnard RJ. Effects of exercise and diet on chronic disease. J Appl Physiol (1985) 2005 Jan;98(1):3-30 [FREE Full text] [doi: 10.1152/japplphysiol.00852.2004] [Medline: 15591300]
2. Kant AK. Dietary patterns: biomarkers and chronic disease risk. Appl Physiol Nutr Metab 2010 Apr;35(2):199-206. [doi: 10.1139/H10-005] [Medline: 20383233]
3. Fialkowski MK, McCrory MA, Roberts SM, Tracy JK, Grattan LM, Boushey CJ. Evaluation of dietary assessment tools used to assess the diet of adults participating in the Communities Advancing the Studies of Tribal Nations Across the Lifespan cohort. J Am Diet Assoc 2010 Jan;110(1):65-73 [FREE Full text] [doi: 10.1016/j.jada.2009.10.012] [Medline: 20102829]
4. Beechy L, Galpern J, Petrone A, Das SK. Assessment tools in obesity - psychological measures, diet, activity, and body composition. Physiol Behav 2012 Aug 20;107(1):154-171. [doi: 10.1016/j.physbeh.2012.04.013] [Medline: 22548766]
5. Jain M, Howe GR, Rohan T. Dietary assessment in epidemiology: comparison on food frequency and a diet history questionnaire with a 7-day food record. Am J Epidemiol 1996 May 1;143(9):953-960 [FREE Full text] [Medline: 8610709]
6. Biró G, Hulshof KF, Ovesen L, Amorim Cruz JA, EFCOSUM Group. Selection of methodology to assess food intake. Eur J Clin Nutr 2002 May;56 Suppl 2:S25-S32 [FREE Full text] [doi: 10.1038/sj.ejcn.1601426] [Medline: 12082515]
7. Thompson FE, Subar AF, Loria CM, Reedy JL, Baranowski T. Need for technological innovation in dietary assessment. J Am Diet Assoc 2010 Jan;110(1):48-51 [FREE Full text] [doi: 10.1016/j.jada.2009.10.008] [Medline: 20102826]
8. Wrieden W, Peace H, Armstrong J, Barton K. A short review of dietary assessment methods used in National and Scottish Research Studies. 2003. URL: http://multimedia.food.gov.uk/multimedia/pdfs/scotdietassessmethods.pdf [accessed 2014-03-05] [WebCite Cache ID 6NqPw2A1a]
9. Rutishauser IH. Dietary intake measurements. Public Health Nutr 2005 Oct;8(7A):1100-1107. [Medline: 16277822]
10. Tucker KL. Assessment of usual dietary intake in population studies of gene-diet interaction. Nutr Metab Cardiovasc Dis 2007 Feb;17(2):74-81. [doi: 10.1016/j.numecd.2006.07.010] [Medline: 17046222]
11. Johnson RK. Dietary intake--how do we measure what people are really eating? Obes Res 2002 Nov;10 Suppl 1:63S-68S. [doi: 10.1038/oby.2002.192] [Medline: 12446861]
12. Falomir Z, Arregui M, Madueño F, Corella D, Coltell Ó. Automation of food qestionnaires in medical studies: a state-of-the-art review and future prospects. Comput Biol Med 2012 Oct;42(10):964-974. [doi: 10.1016/j.compbiomed.2012.07.008] [Medline: 22898338]
13. Ngo J, Engelen A, Molag M, Roesle J, García-Segovia P, Serra-Majem L. A review of the use of information and communication technologies for dietary assessment. Br J Nutr 2009 Jul;101 Suppl 2:S102-S112. [doi: 10.1017/S0007114509990638] [Medline: 19594959]
14. Foster E, Matthews JN, Nelson M, Harris JM, Mathers JC, Adamson AJ. Accuracy of estimates of food portion size using food photographs--the importance of using age-appropriate tools. Public Health Nutr 2006 Jun;9(4):509-514. [Medline: 16870024]
15. Matthys C, Pynaert I, De Keyzer W, De Henauw S. Validity and reproducibility of an adolescent web-based food frequency questionnaire. J Am Diet Assoc 2007 Apr;107(4):605-610. [doi: 10.1016/j.jada.2007.01.005] [Medline: 17383266]
16. González Carrascosa R, García Segovia P, Martínez Monzó J. Paper and pencil vs online self-administered food frequency questionnaire (FFQ) applied to university population: a pilot study. Nutr Hosp 2011 Dec;26(6):1378-1384 [FREE Full text] [doi: 10.1590/S0212-16112011000600027] [Medline: 22411386]

17. Labonté M, Cyr A, Baril-Gravel L, Royer MM, Lamarche B. Validity and reproducibility of a web-based, self-administered food frequency questionnaire. Eur J Clin Nutr 2012 Feb;66(2):166-173. [doi: 10.1038/ejcn.2011.163] [Medline: 21934698]
18. Thompson FE, Byers T. Dietary assessment resource manual. J Nutr 1994 Nov;124(11 Suppl):2245S-2317S [FREE Full text] [Medline: 7965210]
19. Segovia-Siapco G, Singh P, Jaceldo-Siegl K, Sabaté J. Validation of a food-frequency questionnaire for measurement of nutrient intake in a dietary intervention study. Public Health Nutr 2007 Feb;10(2):177-184. [doi: 10.1017/S1368980007226047] [Medline: 17261227]
20. Araujo MC, Yokoo EM, Pereira RA. Validation and calibration of a semiquantitative food frequency questionnaire designed for adolescents. J Am Diet Assoc 2010 Aug;110(8):1170-1177. [doi: 10.1016/j.jada.2010.05.008] [Medline: 20656092]
21. Dehghan M, del Cerro S, Zhang X, Cuneo JM, Linetzky B, Diaz R, et al. Validation of a semi-quantitative Food Frequency Questionnaire for Argentinean adults. PLoS One 2012;7(5):e37958 [FREE Full text] [doi: 10.1371/journal.pone.0037958] [Medline: 22662256]
22. Tucker KL, Smith CE, Lai CQ, Ordovas JM. Quantifying diet for nutrigenomic studies. Annu Rev Nutr 2013 Jul;33:349-371. [doi: 10.1146/annurev-nutr-072610-145203] [Medline: 23642200]
23. Vereecken CA, Covents M, Sichert-Hellert W, Alvira JM, Le Donne C, De Henauw S, HELENA Study Group. Development and evaluation of a self-administered computerized 24-h dietary recall method for adolescents in Europe. Int J Obes (Lond) 2008 Nov;32 Suppl 5:S26-S34. [doi: 10.1038/ijo.2008.180] [Medline: 19011650]
24. Arab L, Tseng CH, Ang A, Jardack P. Validity of a multipass, web-based, 24-hour self-administered recall for assessment of total energy intake in blacks and whites. Am J Epidemiol 2011 Dec 1;174(11):1256-1265 [FREE Full text] [doi: 10.1093/aje/kwr224] [Medline: 22021561]
25. Touvier M, Kesse-Guyot E, Méjean C, Pollet C, Malon A, Castetbon K, et al. Comparison between an interactive web-based self-administered 24 h dietary record and an interview by a dietitian for large-scale epidemiological studies. Br J Nutr 2011 Apr;105(7):1055-1064. [doi: 10.1017/S0007114510004617] [Medline: 21080983]
26. Liu B, Young H, Crowe FL, Benson VS, Spencer EA, Key TJ, et al. Development and evaluation of the Oxford WebQ, a low-cost, web-based method for assessment of previous 24 h dietary intakes in large-scale prospective studies. Public Health Nutr 2011 Nov;14(11):1998-2005. [doi: 10.1017/S1368980011000942] [Medline: 21729481]
27. Kroke A, Klipstein-Grobusch K, Voss S, Möseneder J, Thielecke F, Noack R, et al. Validation of a self-administered food-frequency questionnaire administered in the European Prospective Investigation into Cancer and Nutrition (EPIC) Study: comparison of energy, protein, and macronutrient intakes estimated with the doubly labeled water, urinary nitrogen, and repeated 24-h dietary recall methods. Am J Clin Nutr 1999 Oct;70(4):439-447 [FREE Full text] [Medline: 10500011]
28. Goulet J, Nadeau G, Lapointe A, Lamarche B, Lemieux S. Validity and reproducibility of an interviewer-administered food frequency questionnaire for healthy French-Canadian men and women. Nutr J 2004 Sep 13;3:13 [FREE Full text] [doi: 10.1186/1475-2891-3-13] [Medline: 15363100]
29. Christensen SE, Möller E, Bonn SE, Ploner A, Wright A, Sjölander A, et al. Two new meal- and web-based interactive food frequency questionnaires: validation of energy and macronutrient intake. J Med Internet Res 2013;15(6):e109 [FREE Full text] [doi: 10.2196/jmir.2458] [Medline: 23739995]
30. Adamson AJ, Collerton J, Davies K, Foster E, Jagger C, Stamp E, Newcastle 85+ Study Core Team. Nutrition in advanced age: dietary assessment in the Newcastle 85+ study. Eur J Clin Nutr 2009 Feb;63 Suppl 1:S6-18. [doi: 10.1038/ejcn.2008.60] [Medline: 19190647]
31. Liu L, Wang PP, Roebothan B, Ryan A, Tucker CS, Colbourne J, et al. Assessing the validity of a self-administered food-frequency questionnaire (FFQ) in the adult population of Newfoundland and Labrador, Canada. Nutr J 2013 Apr;12:49 [FREE Full text] [doi: 10.1186/1475-2891-12-49] [Medline: 23590645]
32. Beasley JM, Davis A, Riley WT. Evaluation of a web-based, pictorial diet history questionnaire. Public Health Nutr 2009 May;12(5):651-659 [FREE Full text] [doi: 10.1017/S1368980008002668] [Medline: 18547450]
33. Food4Me. 2011. URL: http://www.food4me.org/ [accessed 2013-08-23] [WebCite Cache ID 6J5McFpZv]
34. Walsh M, Kuhn S. Developments in personalised nutrition. Nutrition Bulletin 2012 Nov 08;37(4):380-383. [doi: 10.1111/j.1467-3010.2012.01998.x]
35. Bingham SA, Gill C, Welch A, Cassidy A, Runswick SA, Oakes S, et al. Validation of dietary assessment methods in the UK arm of EPIC using weighed records, and 24-hour urinary nitrogen and potassium and serum vitamin C and carotenoids as biomarkers. Int J Epidemiol 1997;26 Suppl 1:S137-S151 [FREE Full text] [Medline: 9126542]
36. IUNA. National Adult Nutrition Survey. 2011. URL: http://www.iuna.net/?P=106 [accessed 2013-08-23] [WebCite Cache ID 6J5N8UBfD]
37. Tinuviel Software. Food Composition Databank. 2003. URL: http://www.tinuvielsoftware.com/wisp41.htm [accessed 2013-08-23] [WebCite Cache ID 6J5NOm32z]
38. IUNA. National Adults Nutrition Survey (NANS) methodology. 2011. URL: http://www.iuna.net/wp-content/uploads/2011/04/methods.pdf [accessed 2013-08-23] [WebCite Cache ID 6J5NY9c1w]
39. Goldberg GR, Black AE, Jebb SA, Cole TJ, Murgatroyd PR, Coward WA, et al. Critical evaluation of energy intake data using fundamental principles of energy physiology: 1. Derivation of cut-off limits to identify under-recording. Eur J Clin Nutr 1991 Dec;45(12):569-581. [Medline: 1810719]

40. European Prospective Investigation of Cancer. EPIC-Norfolk food frequency questionnaire (FFQ) entry and processing documentation. 2013. URL: http://www.srl.cam.ac.uk/epic/epicffq/websitedocumentation_2111.html [accessed 2013-10-09] [WebCite Cache ID 6KEvSnenG]
41. Welch AA, Luben R, Khaw KT, Bingham SA. The CAFE computer program for nutritional analysis of the EPIC-Norfolk food frequency questionnaire and identification of extreme nutrient values. J Hum Nutr Diet 2005 Apr;18(2):99-116. [doi: 10.1111/j.1365-277X.2005.00593.x] [Medline: 15788019]
42. Hébert JR, Peterson KE, Hurley TG, Stoddard AM, Cohen N, Field AE, et al. The effect of social desirability trait on self-reported dietary measures among multi-ethnic female health center employees. Ann Epidemiol 2001 Aug;11(6):417-427. [Medline: 11454501]
43. Bland JM, Altman DG. Statistical methods for assessing agreement between two methods of clinical measurement. Lancet 1986 Feb 8;1(8476):307-310. [Medline: 2868172]
44. Torheim LE, Barikmo I, Hatløy A, Diakité M, Solvoll K, Diarra MM, et al. Validation of a quantitative food-frequency questionnaire for use in Western Mali. Public Health Nutr 2001 Dec;4(6):1267-1277. [Medline: 11796090]
45. Chiu TH, Huang HY, Chen KJ, Wu YR, Chiu JP, Li YH, et al. Relative validity and reproducibility of a quantitative FFQ for assessing nutrient intakes of vegetarians in Taiwan. Public Health Nutr 2013 Jun 20:1-8. [doi: 10.1017/S1368980013001560] [Medline: 23782894]
46. Willett W. Nutritional epidemiology. New York: Oxford University Press; 1998.
47. Masson LF, McNeill G, Tomany JO, Simpson JA, Peace HS, Wei L, et al. Statistical approaches for assessing the relative validity of a food-frequency questionnaire: use of correlation coefficients and the kappa statistic. Public Health Nutr 2003 May;6(3):313-321. [doi: 10.1079/PHN2002429] [Medline: 12740081]
48. Kristiansen AL, Lillegaard IT, Lande B, Andersen LF. Effect of changes in an FFQ: comparing data from two national dietary survey instruments among 2-year-olds. Br J Nutr 2013 Jan 28;109(2):363-369. [doi: 10.1017/S0007114512001109] [Medline: 22716945]
49. Wong JE, Parnell WR, Black KE, Skidmore PM. Reliability and relative validity of a food frequency questionnaire to assess food group intakes in New Zealand adolescents. Nutr J 2012;11:65 [FREE Full text] [doi: 10.1186/1475-2891-11-65] [Medline: 22950540]
50. Bohlscheid-Thomas S, Hoting I, Boeing H, Wahrendorf J. Reproducibility and relative validity of food group intake in a food frequency questionnaire developed for the German part of the EPIC project. European Prospective Investigation into Cancer and Nutrition. Int J Epidemiol 1997;26 Suppl 1:S59-S70 [FREE Full text] [Medline: 9126534]
51. Subar AF, Thompson FE, Kipnis V, Midthune D, Hurwitz P, McNutt S, et al. Comparative validation of the Block, Willett, and National Cancer Institute food frequency questionnaires: the Eating at America's Table Study. Am J Epidemiol 2001 Dec 15;154(12):1089-1099 [FREE Full text] [Medline: 11744511]
52. Kristal AR, Peters U, Potter JD. Is it time to abandon the food frequency questionnaire? Cancer Epidemiol Biomarkers Prev 2005 Dec;14(12):2826-2828 [FREE Full text] [doi: 10.1158/1055-9965.EPI-12-ED1] [Medline: 16364996]
53. Ocké MC, Bueno-de-Mesquita HB, Goddijn HE, Jansen A, Pols MA, van Staveren WA, et al. The Dutch EPIC food frequency questionnaire. I. Description of the questionnaire, and relative validity and reproducibility for food groups. Int J Epidemiol 1997;26 Suppl 1:S37-S48 [FREE Full text] [Medline: 9126532]
54. Cade J, Thompson R, Burley V, Warm D. Development, validation and utilisation of food-frequency questionnaires - a review. Public Health Nutr 2002 Aug;5(4):567-587. [doi: 10.1079/PHN2001318] [Medline: 12186666]

## Abbreviations

**BMI:** body mass index
**BMR:** basal metabolic rate
**EER:** estimated energy requirements
**EPIC:** European Prospective Investigation of Cancer
**FFQ:** food frequency questionnaire
**MUFA:** monounsaturated fatty acids
**NANS:** National Adult Nutrition Survey
**PUFA:** polyunsaturated fatty acids
**SCC:** Spearman's correlation coefficient
**SFA:** saturated fatty acids
**TE:** total energy
**Vitamin A (RE):** vitamin A retinol equivalents

*Edited by G Eysenbach; submitted 19.11.13; peer-reviewed by P Stumbo, L Korkalo; comments to author 11.02.14; revised version received 07.03.14; accepted 05.05.14; published 09.06.14.*

*Please cite as:*
*Forster H, Fallaize R, Gallagher C, O'Donovan CB, Woolhead C, Walsh MC, Macready AL, Lovegrove JA, Mathers JC, Gibney MJ, Brennan L, Gibney ER*
*Online Dietary Intake Estimation: The Food4Me Food Frequency Questionnaire*
*J Med Internet Res 2014;16(6):e150*
*URL: http://www.jmir.org/2014/6/e150/*
*doi:10.2196/jmir.3105*
*PMID:24911957*

Original Paper

# Exploring the Value of Technology to Stimulate Interprofessional Discussion and Education: A Needs Assessment of Emergency Medicine Professionals

Jennifer Riley[1,2*], MD; Melissa McGowan[1*], MHK; Linda Rozmovits[3*], DPhil

[1]St Michael's Hospital, Department of Emergency Medicine, Toronto, ON, Canada

[2]Division of Emergency Medicine, Department of Medicine, University of Toronto, Toronto, ON, Canada

[3]Independent Qualitative Researcher, Toronto, ON, Canada

[*]all authors contributed equally

**Corresponding Author:**
Jennifer Riley, MD
St Michael's Hospital
Department of Emergency Medicine
Shuter 1-008
30 Bond Street
Toronto, ON, M5B 1W8
Canada
Phone: 1 416 864 5095
Fax: 1 416 864 5431
Email: jennifer.riley@utoronto.ca

## Abstract

**Background:** The emergency department (ED) is an environment fraught with increasing patient volumes, competing priorities, fluctuating information, and ad hoc interprofessional clinical teams. Limited time is available to reflect on and discuss clinical experiences, policies, or research with others on the involved team. Online resources, such as webcasts and blogs, offer an accessible platform for emergency shift workers to engage in interprofessional discussion and education.

**Objective:** Our objective was to explore the current opportunities for shared learning and discussion and to discover the potential of online resources to foster and facilitate interprofessional education within an academic tertiary emergency department community.

**Methods:** A qualitative study using semistructured interviews was conducted to solicit participants' views of the current culture of IPE in the ED, the potential value of introducing new online resources and technology in support of IPE, and possible barriers to uptake. Participation was voluntary and participants provided verbal informed consent.

**Results:** Online resources discussed included webcasts, interactive discussion forums, websites, and dashboard with links to central repositories. Identified barriers to uptake of new online resources were an unwillingness to "work" off-shift, a dislike of static one-directional communication, concerns with confidentiality, and the suggestion that new resources would be used by only a select few.

**Conclusions:** Owing to the sensitive dynamics of emergency medicine—and the preference among its professional staff to foster interprofessional discussion and education through personal engagement, in an unhurried, non-stressful environment—introducing and investing in online resources should be undertaken with caution.

***(J Med Internet Res 2014;16(6):e162)*** doi:10.2196/jmir.3482

**KEYWORDS**

qualitative research; interprofessional education; technology; emergency medicine

## Introduction

The emergency department (ED) is an unpredictable environment characterized by competing priorities, frequent interruptions [1], and constant demands on resources, personnel, and time. The external demands from ED crowding limit educational opportunities during clinical shifts where there is little or no downtime for detailed discussion [2]. Emergency physicians, nurses, and allied health practitioners within this environment work in shifts, often of varying durations with different start times, resulting in a constantly changing landscape of staff, interprofessional clinical teams, and patients [3]. Owing to these dynamics, there is limited opportunity while working clinically in the ED to collectively discuss or debrief clinical practice and experiences. Moreover, the inherent culture of emergency medicine and the nature of shift work further limit face-to-face interactions and attendance at scheduled events. With these constraints on interprofessional education (IPE), potential gains to communication, team behaviors, and collaborative practice are lost [4,5].

One potential way to overcome the lack of time and space for shared learning in the ED is through the use of online resources. The increased connectedness that results from information and communication technologies (ICT) has overcome geographic barriers of rural or widely dispersed health practitioners, with variable access to peers, specialists, and information resources in other disciplines [6-8]. These tools can facilitate the evolution of virtual "communities of practice" (VCoP) [9], groups of individuals who share interests and expertise through online collaboration. For example, discussion forums can facilitate access to information, such as case management [10] and practice issues [11], foster communication through a collaborative and reflective environment [12-14], and serve as a repository for educational content [11] and archived discussion histories [10]. Such an online platform for knowledge management using Web 2.0 technologies was evaluated for ED physicians, nurses, and trainees and found to be a useable option for collaboration [15]. Similarly, wikis (collaboratively managed, information-based websites) have been explored as possible knowledge translation tools designed to improve patient care in trauma through access to evidence-based information and standardized protocols and leading to information sharing and teamwork [16]. However, while incorporating emerging technologies into IPE programing may address the obstacles to shared learning that exist in the ED environment, for ED staff, the introduction of any new online resources should be associated with a perceived usefulness and benefit to clinical practice [17,18]. We sought to explore the perspectives, attitudes, and receptivity of health professionals (HP) in the ED community to inform the development of online platforms for future IPE.

## Methods

### Aims

The aim of this study was to explore and describe (1) current opportunities for shared learning and discussion among emergency health care professionals, and (2) the potential value and interest in online resources to foster and improve IPE within the ED community.

### Design

This qualitative study was conducted from July to September 2012 and used semistructured interviews to solicit participants' views of the current culture of IPE in the ED, the potential value of introducing new online resources and technology in support of IPE, and possible barriers to uptake. Participation was voluntary and participants provided verbal informed consent. Ethical approval was received from the Institutional Research Ethics Board.

### Setting

St Michael's Hospital Emergency Department is an urban, academic, tertiary care center that serves over 72,000 patient visits and approximately 650 trauma team activations annually.

### Sampling and Recruitment

All current emergency department physicians, nurses, and allied health professionals (25 medical doctors, 77 full-time registered nurses, and 1 social worker) were invited to participate via email by the study coordinator. Purposive sampling supplemented by snowball sampling was used to capture a range of professions, years in practice, and gender.

### Qualitative Data Collection

Semistructured, one-to-one interviews were conducted by an experienced, independent qualitative researcher not associated with the emergency department. All interviews were digitally audio-recorded for verbatim transcription. Interviews took place either in person or by telephone at the convenience of the participant.

### Qualitative Analysis

All transcripts were checked against sound files for accuracy and corrected where necessary. Data were then entered into HyperResearch software for qualitative data analysis. A coding structure was developed in discussion with the research team. For the analysis, the method of constant comparison was used [19] including searches for disconfirming evidence.

## Results

### Summary

Twelve semistructured one-to-one interviews were conducted over a 6-week period between August and September 2012 with a range of years of practice and professions (6 registered nurses, 5 medical doctors, and 1 social worker) represented (Table 1). Interviews lasted between 17 and 34 minutes with an average length of 27 minutes. Three were conducted in person, and the remainder were conducted by telephone.

**Table 1.** Demographics of ED participants.

| | | n |
|---|---|---|
| **Sex** | | |
| | Male | 4 |
| | Female | 8 |
| **Age** | | |
| | 20-29 | 1 |
| | 30-39 | 5 |
| | 40-49 | 5 |
| | 50-59 | 1 |
| **Years in emergency medicine** | | |
| | <1-5 | 3 |
| | 6-10 | 4 |
| | 11-15 | 3 |
| | 16-20 | 1 |
| | >20 | 1 |
| **Years at study institution** | | |
| | <1-5 | 4 |
| | 6-10 | 3 |
| | 11-15 | 4 |
| | 16-20 | 0 |
| | >20 | 1 |

## Current Culture of Shared Learning

Although participants reported good working relationships within and between professions, this did not necessarily translate into a culture of shared learning. Discussion was described as occurring within rather than between professional groups and tended to be informal, brief, and accessed on an ad hoc basis, leaving little if any time for substantive debriefing or unhurried reflection. For example, “I would say, for the most part...the culture is you tend to bounce things off of another physician, maybe because they’re sort of in the same position as you and have the same role, I guess in the same way like nurses tend to talk to each other” [ED 12].

In addition, time pressure and increasingly demanding workloads engendered a sense of apathy among many emergency providers and affected staff willingness to attend education and/or debriefing sessions on days when they were not working:

> *I think there’s workload issues…Sometimes the department is busier…doing anything else when you leave here, like, you’re just totally fried. And then coming in on your day off to, like, go and do something is also a bit of a challenge, right? So I think there’s a lot of barriers.* [ED 07]

## Perceived Potential Benefits of New Interprofessional Education Opportunities

Overall, participants recognized that IPE held the potential to enhance team dynamics and patient care and safety by providing the chance to learn from errors and by improving understanding of other HP roles and perspectives: “any time you share an experience with the people that you work with it only makes your cohesion, your communication, the way you work, better together” [ED 07].

In addition, some participants felt that IPE could address inequity in learning opportunities because current formal meetings and rounds were predominantly physician-driven due to scheduling and historical culture. More importantly, many participants felt that improving discussion across the ED would foster engagement, lead to higher levels of job satisfaction and mutual support, and help thwart burnout: “I just think the burnout is kind of there and it potentially could prevent some of it, and just lead to more job satisfaction which, of course, would improve patient care” [ED 06].

## Acknowledging Emergency Department Culture

Although some participants attached little value to proposed IPE opportunities—believing that the current culture was adequate to meet their needs—others saw merit in the idea but doubted they would participate in new initiatives because they were so habituated to the current culture. In order to engage staff, participants felt that any new learning opportunities should be substantially “value-added”, should address compelling subject matter, and directly affect clinical practice. Many also argued emphatically that new resources should consolidate and replace those currently in existence to encourage uptake in already overburdened ED staff. Finally, skepticism about the value and effectiveness of IPE due to inherent professional and hierarchical differences among emergency professionals must be acknowledged:

> *So interprofessional learning is hot and it's going to be hot for two or three more years until we find the new interprofessional learning...I'm not closing my mind to it, I just don't know what the value is in me learning from other people downstream or upstream of me. I don't know what I'm supposed to do with that.* [ED 05]

### Enhancing Interprofessional Education With Technology

#### *Overview*

The potential utility of online resources and technology to address the limitations of shared learning in the ED environment was explored. Participants commented on a variety of possible online resources including webcasts, discussion forums, and a knowledge archive.

#### *Webcasts*

Participants' responses to the proposed use of webcasts were mixed. Although many saw value in the flexibility enabled by webcasting (such as adding value in the workplace during downtime and eliminating the issues and cost associated with commuting and/or childcare), they also expressed doubt about ever accessing such a resource because of its impersonal and unidirectional nature and the limited access to computers in the workplace.

#### *Discussion Forums*

A range of views was expressed about the value of an online discussion forum as a vehicle for enabling discussion and shared learning. Although discussion forums were preferred over webcasting because of their interactive nature, asynchronous features, and potential for sharing ideas and questions about evolving clinical practice and new research, many felt such interfaces would be adopted by only a few individuals because participation during personal time was a critical factor for success, interaction, and sustainability. Significant concerns about confidentiality and the protection of patient information were also raised: "the problem is how private can you be, because you can just screenshot anything in your computer and send that around…it really becomes a bit tricky" [ED 02].

In order for a discussion forum to be genuinely beneficial in the eyes of the emergency health care professionals, it would have to be secure and well moderated with clearly defined goals for particular types of exchange.

#### *Knowledge Archive*

A technology-based resource that held the greatest appeal for participants was a departmental website that would serve as a centralized repository for information and documents critical to patient flow in an emergency department, such as clinic forms, policies, protocols, and important and frequently accessed contact numbers. This kind of centralized "hub" would potentially consolidate information of value to all team members and improve on the current, rather haphazard system that was not easily, consistently or universally accessible:

> *Taking these 58 fragments of how we're supposed to do things, whether it's on a piece of paper stuck to the wall, an old email, on a print-out that's in the doctors' office, what somebody said this week…one common base for all of it. That would be my ideal.* [ED 05]

Once established, it was suggested that additional, interactive components, such as a blog or discussion forum, could then evolve: "if the website had other things that we need for work…different policies or things we might have to look up, or the clinic referral forms…it'd be convenient enough that we would use it during work, then you could probably tag on, say, a blog there" [ED 12].

#### *Consideration for Investment in Interprofessional Education With Technology*

Engaging in work during off hours was viewed as undesirable by most participants, despite the value attached to enhancing practice and patient care through participation in technology-assisted IPE. The nature and culture of emergency medicine with long shifts and fast-paced, unpredictable clinical volumes and patient acuities reinforced the notion that time away from work was a precious commodity: "people I think work so hard here that it's...they give so much that they just...they're done" [ED 01].

Moreover, many participants were concerned about continued investment in tools and resources that did not fill a need and did not consolidate or replace what was currently available. In response to suggestions that investing in technology would foster new and greater IPE opportunities, many felt that face-to-face interaction was preferable. This was partly owing to the sensitive nature of some discussions and partly because they valued the opportunity to interact directly with colleagues in an unhurried, non-stressful manner:

> *We're human beings…no matter the way the world is changing, we communicate face-to-face and it's important to be able to read facial expressions, body language when we're sharing things. I just think having the warm body in the room makes the experience that much more valuable. I can type my feelings out in a discussion board but I'm certain that it wouldn't have as much value for me.* [ED 03]

## Discussion

### Principal Findings

The findings of this study revealed a culture of collegial working relationships between professions in the ED and the recognition that interprofessional collaboration fosters communication, positively impacts team dynamics, and in turn improves patient care and safety. However, similar to the findings of Creswick et al [20], shared learning occurrences in the ED were found to be "siloed" within professions. This was evident both in the clinical arena and in educational rounds, which are more readily offered and accessible to physicians. New IPE ventures must address these current inequities and build upon the natural rapport between professions in the clinical emergency setting [3] to benefit all.

Important considerations in the development and implementation of technology-based IPE opportunities for emergency HPs were identified. To facilitate maximal uptake, new resources must consolidate and unambiguously replace previously existing resources and, more importantly, make processes easier and more efficient rather than becoming an additional burden. Creating new online resources that overlap with current, partially abandoned resources is more likely to engender skepticism than engagement among emergency HPs and to exacerbate "change fatigue". Demonstrable enhancement of practice in the ED before implementation must be considered. As Ayatollahi et al [17] showed, the perceived usefulness of technology was a more powerful predictor of positive attitude than actual ease of use. Likewise, usability and trust in information and communication technology have been shown to be critical factors for the success of virtual communities of practice [21].

The most well-received proposal to enhance shared learning and discussion through the use of technology was for a departmental website, initially serving as a knowledge archive for frequently needed clinical resources. Online repositories are not novel and have been successfully deployed as platforms for knowledge management [22], including among emergency medicine staff and trainees as an alternative portal to traditional lectures and rounds [15]. Given the potential of the website to add value to the emergency HP shift experience and flow, successful implementation and uptake may enable the addition of future, interactive components beyond its initial purpose as demonstrated by Reid et al [23]. They described an intervention initially established to enhance communication with an online discussion board that evolved into a repository of documents, presentations, and images, in addition to a value-added tool to improve operations with group emails, scheduling, and portfolios.

The findings of our study suggest that introduction of technology to create more space for discussion and shared learning among emergency HPs should be undertaken with caution. The importance of face-to-face interaction among emergency staff cannot be discounted because many topics are sensitive in nature, and non-verbal cues are important to the dynamics of interaction, discussion, and ultimately shared learning [21]. Platforms such as webcasts and discussion forums, which also create potential space for shared learning and discussion were largely considered impersonal and unlikely to be used by the collective. This caution should be heeded as Tse and Wise [24] found that while most participants in an online discussion forum logged into the resource, two-thirds did not post any comments because of self-consciousness about posts and a lack of time due to competing demands—considerations translatable to the ED.

A critical factor for the success of virtual communities of practice (VCoP) is highly relevant or "value-added" content. However, this alone may still not be enough to encourage uptake of online resources. Dube found that despite including highly relevant topics, VCoP have failed because members did not see value in moving from the informal network to one that is online [18], another consideration when planning online IPE.

Moreover, in an era of heightened privacy and increasing legislative protection of information, many emergency HPs were concerned about the challenge of maintaining confidentiality [25]. The process for discussing case management or practice in an online setting, where anything posted on the Web can be reproduced and circulated without restriction with a simple screenshot, is a serious matter that must be addressed in advance of any implementation. Foong and McGrouther [11] discuss this and suggest limiting access to a selected group of users, but recognize that this is insufficient protection. Reid et al [23] also emphasize that information posted online must be considered to be in the public domain, and patient confidentiality must be preserved. These are important aspects to consider in relation to an initial knowledge archive to share and learn from experiential information and to any subsequent interactive discussion forum.

Finally, difficulties with sustaining the technologies were raised, including updating and moderating the resource. Curran-Smith and Best [12] identified skilled facilitators as pivotal to sustaining and promoting meaningful discussion with Web-based continuing education, while Archambault et al [16], when developing an online wiki for trauma, were faced with the frequency of changing information and the potential difficulties with keeping the site updated. These considerations have clear resource implications, which may pose further challenges to implementation.

## Limitations

Our study was conducted within a single emergency department. Variations in culture between institutions, departments, and HPs could yield differing perceptions of current opportunities for technology-enhanced IPE and perceived barriers to participation. As this was a small-scale exploratory study intended primarily to inform proposals for possible technology-based IPE initiatives in the ED, indications of data saturation were beginning to emerge but were not fully consolidated after 12 interviews.

## Conclusions

Introducing online resources in the ED to support IPE and discussion should be viewed with caution. New opportunities must fill a clearly defined need, be value-added, and enhance clinical practice through consolidating and simplifying existing resources. Creating a collaborative website to improve process and function may lead to a future interactive resource for shared learning across professions.

## Acknowledgments

The authors thank all the emergency health care providers who gave their time to be interviewed for the study, the Clinical Leader Manager who facilitated interviewing the nurses while on shift, editorial guidance of Andrea Meeson, and the mentorship afforded by Dr Glen Bandiera.

This work was presented at the 2013 Collaborating across Borders IV Conference, Vancouver, British Columbia, June 13, 2013.

This work was supported by funds from the Department of Emergency Medicine Trust Fund, St Michael's Hospital.

## Conflicts of Interest

None declared.

## References

1. Westbrook JI, Coiera E, Dunsmuir WT, Brown BM, Kelk N, Paoloni R, et al. The impact of interruptions on clinical task completion. Qual Saf Health Care 2010 Aug;19(4):284-289. [doi: 10.1136/qshc.2009.039255] [Medline: 20463369]
2. Atzema C, Bandiera G, Schull MJ. Emergency department crowding: the effect on resident education. Ann Emerg Med 2005 Mar;45(3):276-281. [doi: 10.1016/j.annemergmed.2004.12.011] [Medline: 15726050]
3. Collin KM, Valleala UM, Herranen S, Paloniemi S. Ways of interprofessional collaboration and learning in emergency work. Ways of Interprofessional Collaboration and Learning in Emergency Work Studies in Continuing Education 2012 Nov;34(3):281-300. [doi: 10.1080/0158037X.2011.617364]
4. Reeves S, Perrier L, Goldman J, Freeth D, Zwarenstein M. Interprofessional education: effects on professional practice and healthcare outcomes (update). Cochrane Database Syst Rev 2013;3:CD002213. [doi: 10.1002/14651858.CD002213.pub3] [Medline: 23543515]
5. World Health Organization (WHO). Framework for action on interprofessional education and collaborative practice. Geneva: World Health Organization; 2010.
6. Cassidy L. Online communities of practice to support collaborative mental health practice in rural areas. Issues Ment Health Nurs 2011;32(2):98-107. [doi: 10.3109/01612840.2010.535648] [Medline: 21247275]
7. Hills DJ, Robinson T, Kelly B, Heathcote S. Outcomes from the trial implementation of a multidisciplinary online learning program in rural mental health emergency care. Educ Health (Abingdon) 2010 Apr;23(1):351. [Medline: 20589605]
8. Valaitis RK, Akhtar-Danesh N, Brooks F, Binks S, Semogas D. Online communities of practice as a communication resource for community health nurses working with homeless persons. J Adv Nurs 2011 Jun;67(6):1273-1284. [doi: 10.1111/j.1365-2648.2010.05582.x] [Medline: 21306424]
9. Wenger EC, Snyder WM. Communities of practice: the organizational frontier. In: Harvard Business Review. Boston, MA: Harvard Business Publishing; 2000:139-145.
10. Ramsey DJ, Schmidt ML, Anderson-Shaw L. Online ethics discussion forum facilitates medical center clinical ethics case reviews. JONAS Healthc Law Ethics Regul 2010 Mar;12(1):15-20. [doi: 10.1097/NHL.0b013e3181d2a5a2] [Medline: 20195081]
11. Foong DP, McGrouther DA. An Internet-based discussion forum as a useful resource for the discussion of clinical cases and an educational tool. Indian J Plast Surg 2010 Jul;43(2):195-197 [FREE Full text] [doi: 10.4103/0970-0358.73448] [Medline: 21217980]
12. Curran-Smith J, Best S. An experience with an online learning environment to support a change in practice in an emergency department. Comput Inform Nurs 2004 Apr;22(2):107-110. [Medline: 15520575]
13. Santy J, Beadle M, Needham Y. Using an online case conference to facilitate interprofessional learning. Nurse Educ Pract 2009 Nov;9(6):383-387. [doi: 10.1016/j.nepr.2008.11.004] [Medline: 19155192]
14. Clouder DL, Goodman S, Bluteau P, Jackson A, Davies B, Merriman L. An investigation of agreement in the context of interprofessional discussion online: a netiquette of interprofessional learning? J Interprof Care 2011 Mar;25(2):112-118. [doi: 10.3109/13561820.2010.500445] [Medline: 21182443]
15. Dinh M, Tan T, Bein K, Hayman J, Wong YK, Dinh D. Emergency department knowledge management in the age of Web 2.0: evaluation of a new concept. Emerg Med Australas 2011 Feb;23(1):46-53. [doi: 10.1111/j.1742-6723.2010.01373.x] [Medline: 21284813]
16. Archambault PM, Bilodeau A, Gagnon MP, Aubin K, Lavoie A, Lapointe J, et al. Health care professionals' beliefs about using wiki-based reminders to promote best practices in trauma care. J Med Internet Res 2012;14(2):e49 [FREE Full text] [doi: 10.2196/jmir.1983] [Medline: 22515985]
17. Ayatollahi H, Bath PA, Goodacre S, Lo SY, Draegebo M, Khan FA. What factors influence emergency department staff attitudes towards using information technology? Emerg Med J 2013 Apr;30(4):303-307. [doi: 10.1136/emermed-2011-200446] [Medline: 22544876]
18. Dubé L, Bourhis A, Jacob R. The impact of structuring characteristics on the launching of virtual communities of practice. Journal of Organizational Change Management 2005;18(2):145-166. [doi: 10.1108/09534810510589570]
19. Kvale S. InterViews: an introduction to qualitative research interviewing. Thousand Oaks, CA: Sage Publications; 1996.

20. Creswick N, Westbrook JI, Braithwaite J. Understanding communication networks in the emergency department. BMC Health Serv Res 2009;9:247 [FREE Full text] [doi: 10.1186/1472-6963-9-247] [Medline: 20043845]
21. Gannon-Leary P, Fontainha E. Communities of Practice and virtual learning communities: benefits, barriers and success factors. eLearning Papers 2007;5:1-13 [FREE Full text]
22. Pouliquen B, Le Duff F, Delamarre D, Cuggia M, Mougin F, Le Beux P. Managing educational resource in medicine: system design and integration. Int J Med Inform 2005 Mar;74(2-4):201-207. [doi: 10.1016/j.ijmedinf.2004.04.020] [Medline: 15694625]
23. Reid C, Harper S, Tzannes A, Habig K, Coombes S, Hayes S, et al. Google governance: increasing the effectiveness of critical care physicians through the use of an online usergroup. Emerg Med J 2010 Jan;27(1):50-51. [doi: 10.1136/emj.2009.075713] [Medline: 20029008]
24. Tse J, Wise L. Peer learning, lectures and online learning--putting it all together. Aust Fam Physician 2005 Dec;34 Suppl 1:27-30 [FREE Full text] [Medline: 16369678]
25. Government of Ontario. 1990. FIPPA - Freedom of Information and Protection of Privacy Act URL: http://www.e-laws.gov.on.ca/html/statutes/english/elaws_statutes_90f31_e.htm [accessed 2014-04-15] [WebCite Cache ID 6Or5r2Uoy]

## Abbreviations

**ED:** emergency department
**HP:** health professionals
**ICT:** information and communication technologies
**IPE:** interprofessional education
**VCoP:** virtual communities of practice

*Edited by G Eysenbach; submitted 22.04.14; peer-reviewed by K Devon, J Heilman, K Ho; comments to author 15.05.14; revised version received 29.05.14; accepted 12.06.14; published 30.06.14.*

*Please cite as:*
*Riley J, McGowan M, Rozmovits L*
*Exploring the Value of Technology to Stimulate Interprofessional Discussion and Education: A Needs Assessment of Emergency Medicine Professionals*
*J Med Internet Res 2014;16(6):e162*
*URL: http://www.jmir.org/2014/6/e162/*
*doi:10.2196/jmir.3482*
*PMID:24981597*

Original Paper

# Exploring Design Requirements for Repurposing Dental Virtual Patients From the Web to Second Life: A Focus Group Study

Panagiotis E Antoniou[1], MSc, PhD; Christina A Athanasopoulou[1], PhDEng; Eleni Dafli[1], MSc; Panagiotis D Bamidis[1], PhD

Medical School, Faculty of Health Sciences, Aritstotle University of Thessaloniki, Thessaloniki, Greece

**Corresponding Author:**
Panagiotis D Bamidis, PhD
Medical School
Faculty of Health Sciences
Aritstotle University of Thessaloniki
PO Box 376
Thessaloniki, 54124
Greece
Phone: 30 2310 999310
Fax: 30 2310 999702
Email: bamidis@med.auth.gr

## Abstract

**Background:** Since their inception, virtual patients have provided health care educators with a way to engage learners in an experience simulating the clinician's environment without danger to learners and patients. This has led this learning modality to be accepted as an essential component of medical education. With the advent of the visually and audio-rich 3-dimensional multi-user virtual environment (MUVE), a new deployment platform has emerged for educational content. Immersive, highly interactive, multimedia-rich, MUVEs that seamlessly foster collaboration provide a new hotbed for the deployment of medical education content.

**Objective:** This work aims to assess the suitability of the Second Life MUVE as a virtual patient deployment platform for undergraduate dental education, and to explore the requirements and specifications needed to meaningfully repurpose Web-based virtual patients in MUVEs.

**Methods:** Through the scripting capabilities and available art assets in Second Life, we repurposed an existing Web-based periodontology virtual patient into Second Life. Through a series of point-and-click interactions and multiple-choice queries, the user experienced a specific periodontology case and was asked to provide the optimal responses for each of the challenges of the case. A focus group of 9 undergraduate dentistry students experienced both the Web-based and the Second Life version of this virtual patient. The group convened 3 times and discussed relevant issues such as the group's computer literacy, the assessment of Second Life as a virtual patient deployment platform, and compared the Web-based and MUVE-deployed virtual patients.

**Results:** A comparison between the Web-based and the Second Life virtual patient revealed the inherent advantages of the more experiential and immersive Second Life virtual environment. However, several challenges for the successful repurposing of virtual patients from the Web to the MUVE were identified. The identified challenges for repurposing of Web virtual patients to the MUVE platform from the focus group study were (1) increased case complexity to facilitate the user's gaming preconception in a MUVE, (2) necessity to decrease textual narration and provide the pertinent information in a more immersive sensory way, and (3) requirement to allow the user to actuate the solutions of problems instead of describing them through narration.

**Conclusions:** For a successful systematic repurposing effort of virtual patients to MUVEs such as Second Life, the best practices of experiential and immersive game design should be organically incorporated in the repurposing workflow (automated or not). These findings are pivotal in an era in which open educational content is transferred to and shared among users, learners, and educators of various open repositories/environments.

***(J Med Internet Res 2014;16(6):e151)*** doi:10.2196/jmir.3343

**KEYWORDS**

education; medical; dental; focus groups; patient simulation; problem-based learning; video games

## Introduction

### Virtual Patients

From as early as the 1980s, the amount of available medical information has doubled every couple of years [1]. This has led to the implementation of computer-assisted learning in many aspects of health care education. From simple indexed medical data repositories to full-fledged online virtual medical education institutions [2], nothing showed more promise for health care professionals' education than virtual patient educational cases. Virtual patients have been defined as "interactive computer simulations of real-life clinical scenarios for the purpose of medical training, education, or assessment" by the MedBiquitous Consortium for the development of health care technology standards [3]. The need for streamlining the virtual patient creation process became apparent and standardization solutions were offered [4] with a formal MedBiquitous virtual patient initiative for the smooth exchange of virtual patients across systems and institutions being finalized in a formal International Standard form since 2010 [5,6]. Virtual patients, with current Web-based rapid development and deployment cycles, can be ubiquitously present in the curriculum (lectures, exams, project-problem-based learning, synchronous or asynchronous e-learning sessions) [7]. This proliferation of virtual patients has led to attempts of highly specialized, context-specific virtual patient design models for catering to specific medical specialties [8], or the use of virtual environments' immersiveness by deploying virtual patients in environments such as Second Life [9].

### Serious Games and Multi-User Virtual Environments

The evolution of computer games and massively multiplayer online role-playing games (MMORPGs), specifically, has led to an interesting spin-off, the multi-user virtual environment (MUVE). A MUVE has been defined as a synchronous, persistent network of people, represented as avatars, facilitated by networked computers [10]. The characteristics of this definition also describe the inherent advantages of this platform for educational purposes. The synchronous and persistent networking of users seamlessly facilitates collaboration between them in pursuit of a common goal, be it the defeat of a powerful monster in a game environment or the treatment of a virtual patient in a health care educational environment. Additionally, the avatar representation, the graphical depiction of the user in a human likeness of her/his choice, implicitly facilitates the immersion of the user in the virtual environment. This immersion enables the user to participate in the online events with an invaluable experiential intensity [11].

Second Life is one of the oldest MUVEs. As such, it is quite mature in resources and stability. It has spun off an open source, multiplatform, multi-user, 3-dimensional (3D) application server, OpenSim [12], from which many more contemporary MUVE grids have spawned. In fact, grids such as Kitely [13] or Avination [14] are already mature MUVEs with graphics creation and scripting capabilities. However, Second Life, as the pioneer in the market, is the most recognizable of the MUVEs. The multitude of health care resources, studies, and locations in it [15-52] creates a precedent of a de facto recognizable platform for deploying educational content for health care. Although we aim to leverage new MUVEs for the deployment of future cases, in our first repurposing effort in the MUVE space we chose the most recognizable, standardized, and stable—albeit dated—platform, which is Second Life. It provides a persistent online environment where users connect to it from their computers utilizing a viewer program through which they interact with the environment (Linden Labs) provides a default viewer, but also has provided the means for the community to develop its own versions of it with different capabilities). The user controls her/his avatar by mouse and keyboard; communication modes include text chat, an email-like instant message system, and built-in voice chat with distance-based volume control. Users in this MUVE can purchase land and use it to create their own objects consisting of primitive objects (prims). Applying a simple scripting language (Linden Scripting Language; LSL), these objects can be programmed to respond to environmental- or user-initiated events to create custom interactive audiovisual experiences [53].

### Health Care Content in Second Life

Despite the criticism regarding the barriers that MUVEs and Second Life impose on the educational settings [54,55], health care content is abundant in Second Life. First of all, Second Life has been used as a treatment aid in several situations in which patient immersion in a virtual environment seemed beneficial. Such situations include addiction studies [15], weight maintenance studies [16], and building sexual health awareness [17]. Several health care resources in Second Life deal with mental health care, specifically for social anxiety disorder [18,19], delineating delusional beliefs [20], or even the study of the psychodynamics of transference [21].

Regarding the topics encountered in Second Life medical education material, one can find many and diverse aspects of the medical curriculum from the foundations of it, such as anatomy [22], to specialty material, such as pediatric primary care [23], pneumology [24], cardiopulmonary resuscitation [25,26], and emergency medicine and care [27,28]. Other efforts include such diverse topics as disability health care [29], or pharmacy student training in communication skills [30] or in the general aspects of their specialty [31].

There are a significant number of pure simulations in Second Life, such as a human immunodeficiency virus (HIV) epidemic simulator [32] and a transfusion operation simulator [33], but the bulk of the focus in the Metaverse is on building awareness through serious games and experiential learning tools, both for students (eg, Ohio State Medical Center, a virtual place for educational purposes [34]) and for postgraduate continuing medical education (eg, Wiecha et al [35]).

Simulations of dangerous or potentially dangerous activities have been implemented as scenarios in Second Life [36,37]. Nursing training has a strong presence in the Second Life virtual environment. The literature is teeming with studies and reviews about Second Life and nursing education [38-43], from general facilitation of nurse education with facilitated journal clubs [44], improving interpersonal interview skills [45], and cultivating decision-making capabilities [46], to specific subjects, such as mental health nursing [47], or meta-education, such as the education of faculty about the methods of teaching nursing [48]. This could be attributed to the combination of the necessity in nursing education for hands-on experience in an environment where no human life will be put at risk in conjunction with the lack of specialized hardware and software to simulate nursing work and the ease of development of Second Life resources through a simple scripting language.

In contrast, in the field of dentistry—an equally demanding, hands-on health care profession—only a limited number of resources have been created in Second Life in the last few years [49-52], whereas there are a large number of standalone full-fledged virtual reality simulators regarding specific dentistry applications [56-59].

This is only a cursory glance of the material available in the Metaverse. For more details, the reader is directed to Kamel Boulos et al [11] and HealthCyberMap [60] for a more comprehensive catalog of medical education resources in Second Life.

Nevertheless, even from this simple excursion in the Second Life medical education space, there is a great deal of content available and a significant research interest exists for both the creation of new and the migration of existing educational content in this virtual environment.

### Educational Content Repurposing and Standards

The idea of educational content repurposing (ie, transferring and reusing resources originally created for a certain educational context into another context) has matured in the past years [61]. However, interest in that direction goes further back. As early as 2002, a standard for metadata (physical or digital information about an object) suitable to describe every learning resource was established as the learning object metadata (LOM) standard [62]. A couple of years later, with the imminent explosion of Web-based e-learning platforms, the need for reusability and interoperability of content and platforms led to the establishment of the Sharable Content Object Reference Model (SCORM), which consisted of a collection of standards and specifications aiming to facilitate standardized content packaging, delivery, and consumption of content [63]. In 2008, the MedBiquitous Consortium for health care technology standards established the Health Care LOM scheme to address the specific needs for medical education content [64]. As this infrastructure became mainstream, an effort was initiated, in the form of the mEducator project, "to critically evaluate existing standards and models in the field of e-learning in order to enable state-of-the-art medical educational content to be discovered, retrieved, shared, repurposed, and re-used across European higher academic institutions" [61]. Both Web 2.0 mash-up technologies and federated, semantic, Web-based learning content management systems were explored as possible avenues of standardizing the repurposing of medical education content [65]. In the virtual patient section of this research, a Web-based platform (Linked Labyrinth+) [66] managed to integrate the standardized repurposing metadata scheme into the already existing virtual patient metadata scheme, thereby enabling the publication of virtual patients in the semantic Web and their subsequent consumption from all compatible semantically enabled platforms [67].

### Repurposing Virtual Patients From the Web to the Multi-User Virtual Environment

The next logical step appears to be repurposing (in a standardized manner) existing virtual patients from the Web to the virtual environment. However, this is not a straightforward issue. Some years ago, inspired by a critical review of the then current state of e-learning [68], a discourse was initiated into the intricacies of the virtual environments as an educational medium and the nuances that would be required for a truly successful deployment/repurposing of Web-based content (virtual patients or otherwise) to them [69]. It was postulated that the unique features of the virtual environment (seamless collaboration, sensory immersion, etc) should lead content creators to apply different principles when authoring for the virtual environment than when authoring for the Web. In the authors' own words: "It would be more useful to investigate the 2 modalities (3D and 2D) in this context, as different but complementary and synergistic media rather than as competing media trying to replace one another" [68,69].

Regarding the transfer of virtual patients from the Web to the Second Life MUVE, what design principles will optimally leverage the advantages of it as a virtual patient deployment platform? A multitude of virtual patient content exists in Second Life (eg, [23-30,34-37,39,46,49-52]) and there are efforts to assess the effectiveness of Second Life as a medical education platform [35], but no attempt has been made so far to document user feedback regarding the strengths and weaknesses of the repurposing process for virtual patient content from a Web-based virtual patient player to the Second Life MUVE.

### The Focus Group

In the investigation of these experiential and immediate educational modalities, the initial assessment method of choice emerges to be the focus group study. In a detailed review of the focus group methodology in medical education, Barbour [70] demonstrated the advantages of this assessment type in experiential forms prevalent in medical teaching, such as case-based and problem-based learning, and their technological evolution, the virtual patient. Fast and effective, focus group studies have the significant advantage of allowing changes to occur on the educational episode (eg, change the content of a course during a semester instead of waiting for a time consuming statistical study) far quicker than other more traditional methods, such as the survey or the personal interview, which usually require the ending of the educational effort to provide results. Additionally, focus group assessment has the distinct advantage of diluting the power imbalance between the student and the teacher, a very important fact when trying to get an immediate feel for experiential and student-centered learning modalities. Furthermore, the ability of the focus group methodology to capture the ambience and the atmosphere of a group regarding the whole of a subject matter can lead to insights that are difficult to explore through the traditional avenues of assessment [70]. Despite the significant challenges regarding correct group composition and good facilitation during focus group meetings, the significant goal that can be achieved through a focus group study if it is well designed and executed is "theoretical generalizability" [71]. In brief, focus group studies facilitate the rapid deduction of theoretical insights into a subject matter, which later can be used to both affect change in the aforementioned subject matter or to become the trigger for further quantitative studies [70].

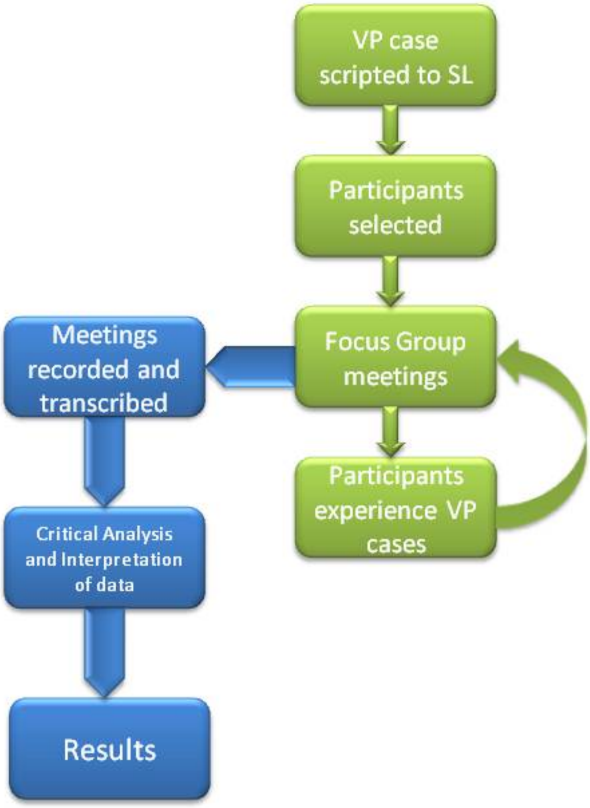
It is the aim of this work to use a dentistry virtual patient as a pilot case for a first exploration (via a student focus group) of the design modifications that need to be implemented when repurposing virtual patient content from the traditional Web-based virtual patient player to the Second Life MUVE deployment platform.

## Methods

### Overview

A periodontology virtual patient case deployed on the Web was transferred in every detail to the Second Life MUVE. A group of dental students were asked to run both the Web-based and the Second Life cases. These students were organized into a focus group to provide their feedback regarding their experience and possible avenues for improvement. A flowchart of the process is demonstrated in Figure 1.

**Figure 1.** Flow diagram demonstrating this study's overall methodology. The green area demonstrates the collection of data and the blue area demonstrates analyzing and extracting meaningful results from these data. VP: virtual patient; SL: Second Life.




### Virtual Patient Case in OpenLabyrinth

The virtual patient case used for our study was a periodontology patient suffering from drug-induced gingival hyperplasia. The optimal learner course followed the correct sequence of treatment, resorting to surgery after attempting the prerequisite alternatives, while adhering to the correct procedures for the patient's care. The case explores the knowledge of the correct surgical procedures, but does not include training in the manual techniques required in surgery.

The Web-based virtual patient was deployed using the OpenLabyrinth open source virtual patient authoring platform [72]. The case was authored as a branching scenario with multiple-choice user responses guiding the path of the case. The user interface was a standard Web browser window in which a small description of the situation was given along with any relevant images (Figure 2). The user navigated the case through multiple-choice responses available at the bottom of the Web page. A 10-minute time limit was imposed for each learner to finish the case; the case ended in a failure if the learner exceeded this time limit.

**Figure 2.** Characteristic screenshot from the OpenLabyrinth case. From the image, the learner is asked if the patient has starting periodontitis, chronic advanced periodontitis, or gingivitis.


## Virtual Patient Case in Second Life

The case in Second Life was created in the form of a point-and-click adventure (Figure 3). The user is introduced to the case by a presentation. Then the user is guided by chat messages through the adventure and interaction with the environment through multiple-choice menu cards. The case aimed to evaluate and teach the learner, with the adventure proceeding according to her/his choices. This virtual case was designed with focus on the imparting and establishment of knowledge; therefore, there were fail states. But, most of the player's choices were evaluated by the narrator with the option of retrying, which significantly narrowed down the end states of the adventure. This was intentional to give the player the opportunity to learn without the added frustration from unnecessarily repeating all the adventure after each failed step. Because this was a prototype virtual patient case in Second Life and because we did not have any means of assessing the time limit for negotiating the case in the virtual environment, no time limit was imposed on the users in the Second Life virtual case. Additionally, it was felt that imposing a time limit in the context of an interactive adventure that "spanned" several weeks would be detrimental to the user's immersion in the assigned role in the case. The Second Life virtual case was developed in the privately owned island of the Lab of Medical Physics of the Medical School of Aristotle University of Thessaloniki. On that island, an indoors environment (office) of sufficient space was modified to emulate a dentist's office. All graphical assets were either bought from other users in the Second Life Marketplace or they were modified from simple prims.

All the functionality of the virtual patient simulation was coded using LSL and the necessary Web resources (eg, images) were archived for retrieval on one of the lab's servers. LSL is an event/state-based language. The script utilizes events, such as clicking on (touching) objects, the presence (listening) of chat messages, or the creation (rezzing) of items in the environment. These events can be used as triggers within the LSL script to trigger a specific response from the script or to change the script's state thereby enabling it to respond to a different set of events. Through these small building blocks, complex interactive behavior can be created in the simulator. Through the scripting environment, each node of the virtual patient was coded as a specific state that the case script entered when the appropriate situation occurred. The activities of the case were coded as events that triggered as the user interacted with the environment by touching pieces of it and receiving challenges in the form of multiple-choice questions. The user's response triggered additional events that led the case to move to the next relevant state/node. Additionally, all the patient data, narrative, values, or external media references were stored in the case script as global variables. Each in-world object contained its own script that communicated with the main simulator scripts to facilitate interaction through clicking on objects. To create interactive surfaces in parts of objects, a number of invisible, interaction objects were drawn in front of the visible geometry. The transfer of the case to Second Life took approximately 10 person-hours. Our scripting methodology is demonstrated in Figure 4.

**Figure 3.** Second Life case screenshots. The user is introduced through a presentation (top image), then proceeds to the case taking cues from chat messages (second top image), and making choices through multiple-choice cards (second bottom image). The simulation involves the user interacting with the patient both in the office environment and on the dental chair (bottom image).

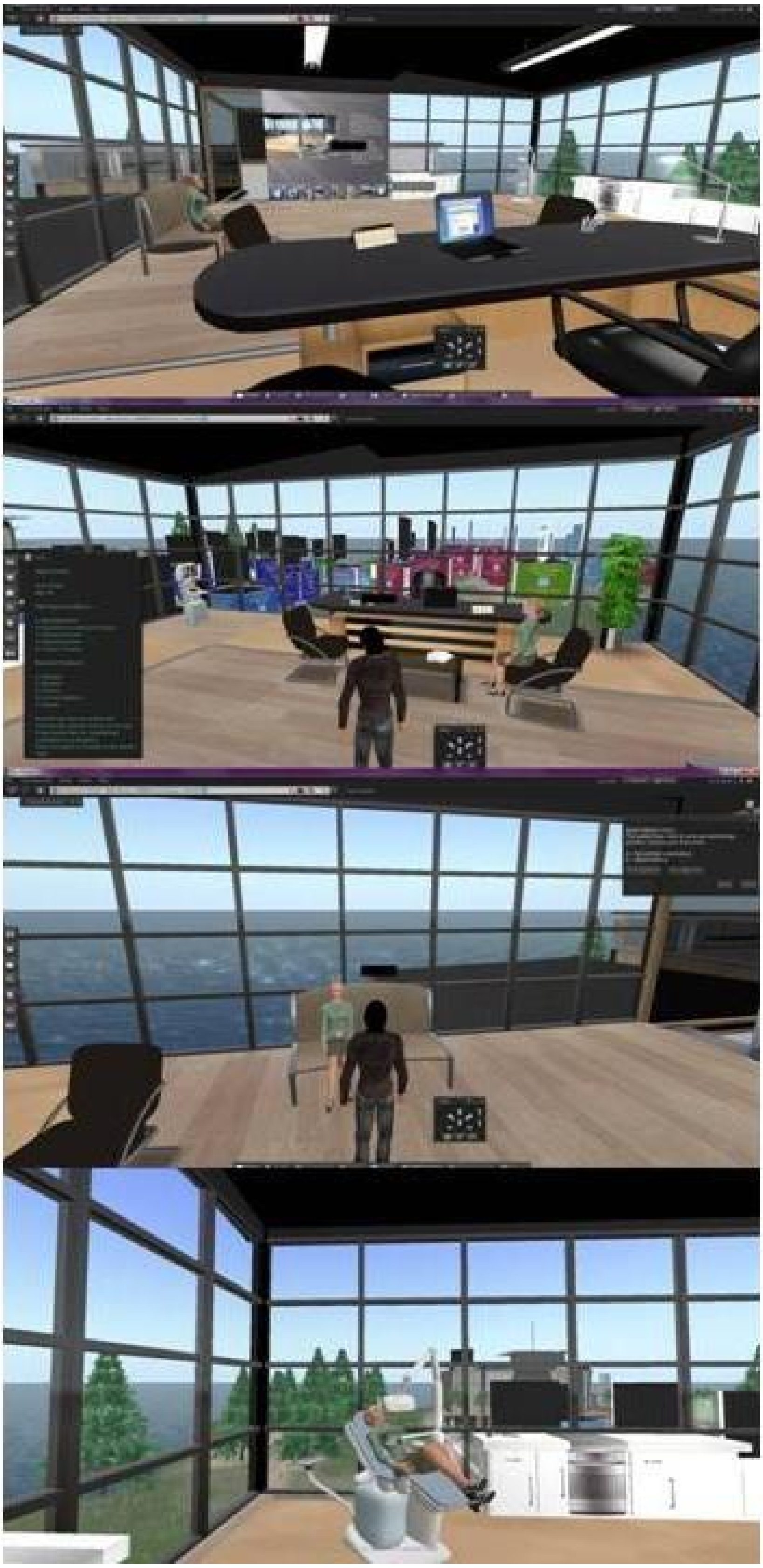
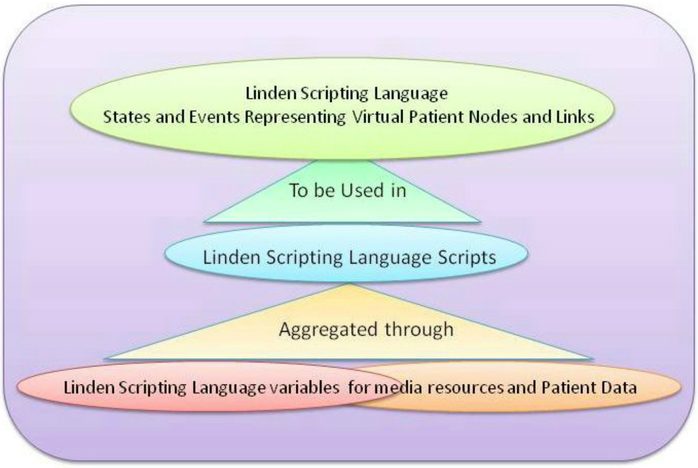


**Figure 4.** Second Life virtual patient development methodology.

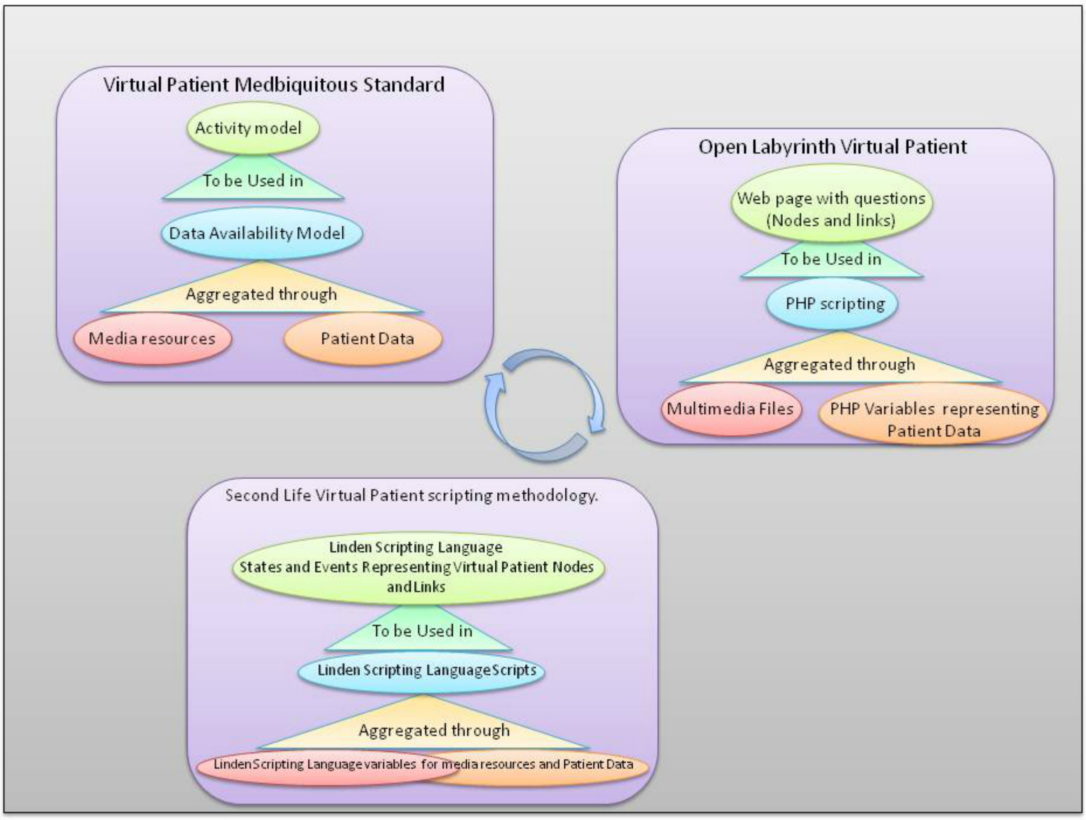



## Second Life Scripting Methodology

Technically, this approach facilitated a streamlining of the Web-based virtual patient data from the OpenLabyrinth platform. In OpenLabyrinth, a virtual patient is represented through a branching Web page tree, whereas each node is a specific Web page containing the narrative and the relevant data along with multiple buttons to allow for the different choices. Additionally, in OpenLabyrinth, all image files and other similar patient data are stored in bulk and referenced in each node as needed to facilitate reusability of assets [73].

This design approach was used to allow the OpenLabyrinth platform to conform as a virtual patient player to the MedBiquitous Virtual Patient Standard. In that standard, media resources and patient data are aggregated to a data availability model that is used to create a structured activity model of nodes and choices that provide the desired educational outcome [3]. Mimicking, in scripting methodology, the OpenLabyrinth virtual patient deployment strategy led to analogies with the MedBiquitous Virtual Patient Standard. These design analogies between the Second Life virtual patient scripting methodology, the OpenLabyrinth virtual patient deployment platform, and the MedBiquitous Virtual Patient Standard are demonstrated in Figure 5.

**Figure 5.** Design analogies: Second Life (SL) scripting paradigm, OpenLabyrinth deployment paradigm, MedBiquitous Virtual Patient Standard. PHP: Hypertext Preprocessor.



### Student Group Composition and Selection Process

A group of dentistry students experienced both the Second Life adventure and the Web-based virtual case. The group consisted of 9 members, 6 male and 3 female, all dentistry students in the latter half of their studies. An open call for participants was made in an optional undergraduate course of dental informatics at the local dentistry school to participate in the project. A brief explanation of the tasks required by the participants was given and invitation was extended in a completely volunteer fashion. The focus group met 3 times in total: once before and twice after the participants had experienced the virtual case. This simple process ensured that the participants' pool would be both thematically interested, but also engaged in providing relevant and meaningful feedback.

### Focus Group Methodology

All participants were organized into a single focus group. Feedback was received from a series of 3 meetings. Each meeting was between 25 and 45 minutes in duration and covered one of each of the major topics summarized in Textbox 1. The first group meeting took place before the participants experienced the virtual patient cases and served as an introduction and orientation session.

**Textbox 1.** Focus group meeting agenda.

1. Computer and gaming literacy: Are you familiar with any educational computer game? If yes, which one(s)?

2. Usability of the Second Life as a virtual patient deployment platform: Have you felt that you needed personal human assistance with the interface while playing the Second Life virtual case?

3. Comparisons between the Web and Second Life deployed case: Did you feel that the tasks required of you in the Web-based/Second Life virtual case were adequately challenging? Do you think the level of difficulty differed?

In all meetings, one of the authors was appointed as a facilitator for the focus group. For the group's meetings, a question pool was developed to initiate and facilitate the discussion. Because the goal was to allow the group members as much freedom of expression as possible, the facilitator intervened with further exploratory questions only when the discussion reached a dead end. During the discussion, the facilitator diverged many times from the question pool to explore emergent themes and opinions that came up through the discussion.

The participants were provided with the URL addresses of both the Web-deployed and the MUVE-deployed cases and were asked to complete both before the second focus group session. No specific order of case completion was asked of them. The participants used their own personal computers, laptops, or desktops to experience the 2 cases. Discussed briefly in the beginning of the second focus group session, the technical specifications of the participants' hardware were split. Although no specifics were recorded, nongaming participants had hardware near to the medium-low performance spectrum of contemporary hardware configurations, whereas gaming enthusiasts had hardware close to the high end of the performance spectrum. One of the weaknesses of the approach that was used on exposing the users to both cases was the evoked competitive comparison of the 2 platforms in the discussions of the focus group sessions. Because all users encountered the same case across different platforms with primarily esthetic changes between them, any kind of merit or flaw of the MUVE as a virtual patient deployment platform was viewed comparatively to similar aspects of the Web-deployment platform. This comparative approach that emerged from the discussions was not suppressed by the facilitators to maintain the openness of the discussion. Instead, it was used as means for elaborating on the repurposing needs of the MUVE deployment platform.

All focus group meetings were audiotaped and transcribed with notes kept during the sessions to capture the nonverbal "mood of the moment" that could not be documented through the recordings.

The analysis of the recorded data was a process of dissecting the discussion transcripts, discovering common themes across the participants' opinions, and noting tone, context, and mood at each stage. Then these were coded to assess possible unifying or dividing causal themes that might emerge from the discussion exploiting the immersion of the researcher to facilitate both analysis and interpretation of the data [74].

All participants were informed about the study before their appointment and a signed informed consent was obtained from each of them before the focus group meeting. The study was approved by the Bioethics Committee of the Aristotle University of Thessaloniki Medical School.

## Results

### Summary

Although all members of the focus group were at a relevantly similar stage in their dentistry studies, there was a diversification in computer literacy as shown in Table 1. Some users were significantly less experienced in computer games (reported playing games at least 8 hours per week) or professional computer use. From the first focus group session, it became apparent that all users that considered themselves familiar with gaming were intimately familiar with noncasual games, such as real-time strategy games, adventures, first-person shooters, and MMORPGs.

The interpretation of the focus group sessions led to 7 categories of issues concerning the migration and repurposing of a Web-deployed virtual patient to the Second Life MUVE. These results are summarized in Table 2.

**Table 1.** Breakdown of the group members' computer, gaming, and educational gaming familiarity.

| Computer literacy (gaming and otherwise) of focus group members | Members | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | #1 | #2 | #3 | #4 | #5 | #6 | #7 | #8 | #9 |
| Average weekly hours of professional computer use | 6 | 5 | 1 | 9 | 1 | 3 | 3 | 5 | 4 |
| Average weekly hours of gaming | 12 | 3 | 8 | 18 | 9 | 0 | 5 | 3 | 14 |
| # of other educational computer games played | 4 | 0 | 0 | 1 | 0 | 2 | 1 | 0 | 3 |

**Table 2.** -Focus group's results at-a-glance.

| Category | Comments |
|---|---|
| Second Life as an educational MUVE in general | Navigation in Second Life difficult to people unfamiliar with games |
| | Second Life graphics engine unoptimized for its capabilities |
| Interactivity and its educational value | Second Life more interactive than the Web-based case |
| | Simple Web-to-Second Life transfer is an underutilization of the MUVEs capabilities |
| | Users familiar with games trapped in gaming mindset implicit from the environment |
| | Users frustrated by disappointment of expectations because of limited interactivity |
| Immersiveness and its educational capacity | Users expected more immersive content from Second Life because of the nature of the platform |
| Clarity of educational purpose and content | In Second Life, the visual representation of the case provided significant implicit feedback and direction regarding the next step |
| Challenge level | Visual representation and action implied correct procedures |
| | Apparent decrease of challenge in Second Life |
| Scope of educational use | Useful as an asynchronous teaching tool |
| Suggestions | More complex case would better leverage Second Life's capabilities |
| | Increased feedback required |
| | Increased interactivity and immersiveness requested |
| | Introduction of a human factor in the case requested |

### Category 1: Second Life as an Educational Multi-User Virtual Environment

The focus group reported no issues with either registering or accessing the Web-based virtual patient. The consensus of the group was that the Web-based interface was easy to use. On the contrary, accessing the virtual patient in the Second Life proved to be a challenge for some members of the focus group. To people unfamiliar with gaming conventions, the navigation in the virtual environment seemed difficult. On the other hand, there were cases of gaming veterans reporting equal difficulties because they expected game-like challenges where none existed.

The strong points of a mature multi-user environment such as Second Life emerged through a consensus of simplicity, ease of use, and overall stability. As expected, the users most familiar with computer games had a markedly easier time interacting with the environment, another strong point of MUVEs given the pervasiveness of massive multiplayer online games (MMOG). Because this was a test case of transferring a Web-based virtual patient to the simulator, it was not a polished system, but the group considered its features as complete for the purpose it was built.

Finally, some concerns were raised about the unoptimized graphics engine; although not state of the art, it did tax the capacity of nongaming-focused computer systems:

> *The frame rate was very low which was tiring after some time using the system.*
>
> *Yeah, and it's odd! The graphics are really simple so I don't understand why it was so slow.*

### Category 2: Interactivity and Its Educational Value

People with a lot of experience with computer games but not with professional computer use became trapped in the gaming mindset and had preconceptions about challenges of the simulator which did not exist in it:

> *I flew around the building and saw the venue of the case but did not search for the entrance because I thought that there might be a puzzle to solve in order to gain access to the office.*

It was clear from the instructions that the only problem to be tackled was the medical one and that no environmental barriers or hazards were present in the simulation environment. In addition, all group members (including the one offering the previous quote) were adamant that the instructions given to them were adequate and that they understood them perfectly.

Another opinion expressed, which also bears upon interactivity, was that the linear design, with primarily multiple-choice questions, constituted a disservice to the simulator's capabilities. Participants suggested that a more nonlinear, user-driven experience would be more appropriate:

> *...I was forced to do what you've designed for me to do. I could either click to the patient to do something, or to the notepad that you had over there to take something or to the x-ray or something...I could not do anything else. I have played adventure games before, those mystery games, where I was in control of what to do. For example, I could pick up a pencil and do this, or that, or even choose not to pick up the pencil at all.*

The unanimous feeling of the group was that the Second Life virtual patient case was significantly more interactive than the Web-based one:

> *Second Life is more immediate, you have the patient sit in the dental chair, you see him, every step, you know he will come again, it is demonstrated that what you will do requires time, it doesn't end in a day. In the Web-based case you make choices and the patient go back and forth but it doesn't show.*

However, some members considered that the Second Life platform could facilitate a much higher level of interactivity and a much more complex virtual case:

> *While the environment was pleasant, the case was too linear and without enough branches to take advantage of the environment.*

Moreover, the simple transfer of the case from the Web to the simulator, a fact that led to underutilization of the MUVEs capabilities, appeared to create strong feelings of frustration that were counterproductive in the negotiation of the case:

> *The Web case was more acceptable than Second Life because in Second Life you have more demands. In the Web it is like you are filling out a test. I had no more expectations from that...*

> *As if it was not bad enough that it is studying, which is boring by definition (laugh), there were no good graphics to support it...forget about it! Students will want to fire up another game and play instead.*

Some members of the group regarded the feedback of the case as too straightforward and provided information that they would prefer to have gathered through more steps in the case:

> *...It asks me if I want to take the patients history. I do and it presents me with the history record. It does not allow me to choose what to ask, how to follow up on a question, a thing that is common in an adventure where you ask a person and he replies to you and then you reply back and you lead the discussion where you want and if you lead the discussion poorly you will not get the information that you need to solve the mystery...*

### Category 3: Immersiveness and Its Educational Capacity

Most of the focus group considered the Second Life virtual patient case significantly more immersive than the Web-based case:

> *In Second Life, there was the environment of a dental office, you imagine how it would be and it is nice to see it. Seeing the patient, it helps to create a spirit of immersion even although graphics are not state of the art.*

However, the aforementioned critique regarding interactivity was transferred almost verbatim to the discussion about immersion:

> *...when you have to examine the patient with some tools it just lists choices a, b ,c. Why don't you present me with the tools on a plate to look and choose a tool? After all it has the visual capability...to allow me to experience it myself...*

Additionally, there were suggestions about more immersive, more stimulating feedback:

> *I think they could have put more medical details that would make it more realistic. I mean, I do something and it says that the patient did not respond. It would be better to tell me what was the response and if I could do something else to follow up.*

### Category 4: Clarity of Educational Purpose and Content

In discussion about clarity of purpose and content, the group was unanimous that in both the Web-based and the Second Life cases there was always a clearly described medical situation that a prepared student could negotiate according to her/his knowledge without doubt about the medical problem at hand. Small differences in opinion were formed in the group regarding some issues of translating terminology in English (all students were nonnative English speakers) because of some of the members' poor technical language skills, but these were mentioned only as minor nuisances. What was mentioned unanimously was the fact that the visual representation of the case's progress was a kind of feedback that facilitated clarity of purpose and provided direction regarding the next step in the simulator:

*Seeing the patient in the dental chair was a significant boost to the feedback I took from the Second Life virtual patient compared to the Web-based* one.

> *Seeing the patient in the dental chair, it prompted you to think that it is time for some intervention and so it focused your mind more on the case.*

### Category 5: Challenge Level

Regarding the challenge level, the group was divided with members considering the challenge level of the case adequate but a bit on the easy side, whereas others considered it adequate to challenging. An interesting point was that the perceived challenge was less in the Second Life case because of the visual props that prompted them toward the correct course of action at some points of the virtual case. Members who reported feeling challenged by the case and being facilitated by the props of Second Life did indeed finish the case on the first try, whereas the users that considered the case challenging and finished it on the second try after reaching a fail state in the first try were those who had extensive gaming experience but very little professional computer experience. Table 3 summarizes the duration of both the Web case and the Second Life one. There was a slight difference in the finish times. All participants took between 10 and 20 minutes to finish it (mean 15.1, SD 4.7 minutes); however, these times were sufficiently short that the difference can be attributed to attention differences between the participants.

**Table 3.** Comparison of time to finish the virtual cases on Second Life and the Web.

| Completion time for the Second Life and Web-based virtual patient | Members (minutes) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | #1 | #2 | #3 | #4 | #5 | #6 | #7 | #8 | #9 |
| Time to complete the Second Life case | 10 | 20 | 20 | 13 | 20 | 120[a] | 8 | 15 | 15 |
| Time to complete the Web case | 8 | 5 | 9 | 7 | 5 | 3 | 3 | 10 | 10 |

[a]This time includes bibliographical referencing and study time so actual time interacting with the environment should be assessed as being much lower. This was considered an outlier and was not included in the calculation of the mean time for completing the case.

### Category 6: Scope of Educational Use

Most of the group thought that Second Life would be a very useful tool as a teaching aid, primarily used asynchronously:

> *...If there was such an application I would buy it for me to do it at home as training, it would be fun, to be relaxed at home and to ask the patient stuff and take responses or to do what I want in the cases...*

It was suggested that it would be an invaluable tool in the training of preclinical students to familiarize them with practical matters in a safe environment before actual practice begins. Learning from errors was identified by participants as a pivotal educational/pedagogical issue, and this was properly incorporated in the Second Life MUVE:

> *It is good that it tells you that you made a mistake and it lets you learn from it by leading you and letting you retry. Retrying and learning from mistakes is very good for digesting the material.*

### Category 7: Suggestions

Many of the suggestions of the focus group's members were regarding the need for the cases to be more interactive and immersive:

> *...it would only be interesting if it had more choices, more depth of choice and interaction, less limitation in options...*
>
> *I would really like to be allowed to continue down a fail path and explore the consequences of my mistake in order to understand why this was the wrong choice.*
>
> *And also about feedback that would be more explanatory as opposed to just expositional of the techniques.*
>
> *...it did not say why we do that, or why we will not do the other. I would like it to provide the "why," not just the "how" of the treatment.*
>
> *Exactly! It would be nice to continue, even after a failed step, in order for us to see why our choice was wrong.*

From the discussion, it became clear that the group would prioritize the improvement of the case itself regarding depth and meaning of choice. A close second priority was the ability to be able to vividly see and do things in the simulator. The introduction of a human factor in the case was suggested. Some of the participants suggested multiple branching dialog options, history-taking questions, and a better exploration of the patient factor in treatment (ie, offering an effective but intrusive treatment and the patient refusing it), along with the needed management options:

> *...in medicine/dentistry, the patient is a human being, and, therefore, it is not a yes/no thing, "yes he is ill/ no he is not;" there are gray situations...*
>
> *...A realistic patient would have objected and asked for clarifications regarding the practices that were applied.*

Another suggestion was one touching on interactivity, namely the ability of the user to utilize the simulator's capabilities for a more hands-on experience with the practical techniques of the case:

> *...Surgery could be simulated, not the manual practice, but by a graphical drawing of the incisions by the player on a photo and be graded by the margin by which you were off the optimal ones.*

## Discussion

### Principal Results

From the focus group discussions, some interesting insights emerged. The most straightforward was the realization that the Web-based case was a direct "by the book" implementation of this virtual patient case. The focus group's verdict was that this was indeed a platform where cases such as the one they experienced would thrive. The case's level of interactivity and data were appropriate for the Web. The Web platform itself was the most ubiquitous in the world; thus, this simple and easy-to-use implementation of a virtual case seems the standard by which other implementations can be assessed. Although not a direct substitute for face-to-face experiential forms of learning, the Web-deployed virtual patient is established as standard learning material [75] with literature covering detailed aspects, such as the conceptual concerns of connecting specific clinical guidelines in the design of virtual patients [76] or quality control metrics for assessing them [77]. However, repurposing from the Web to the MUVE requires much more than a simple transfer of the data across the 2 platforms. The MUVE's increased interactivity potential and rich immersive nature supports but also requires significant changes to the content of a virtual patient package to meaningfully adapt the Web-based case to the MUVE platform. The deployment of virtual patients in a 3D MUVE is far less explored than the Web-based one where there have even been attempts to facilitate the deployment of such virtual patients directly from the staff of health care institutions, to facilitate a more rapid development of virtual patient content and increase awareness of the virtual patient educational medium [78]. First, the Second Life platform, with its 3D environment and its references to both real-world verisimilitude and increasingly pervasive MMOGs, prepares the user to expect a significantly increased level of interactivity from anything deployed in it. In fact, many users, specifically the avid gamers, expected so much more from a 3D MUVE that the simple transfer of the less interactive and nonexperiential Web-based case harmed the educational effort by frustrating them and caused aversion to the poorly implemented (for the platform's capabilities) case.

Second, for a virtual case to be relevant in a MUVE it should have a significant amount of complexity. A basic tree structure with some short branches to a couple of fail states or to some retry nodes does indeed work on the Web where its ubiquitous pervasiveness and ease of use provides a rapid way for learners to confirm or reinforce their knowledge with no mediating learning or computational overhead. The proliferation of virtual patients as a learning resource [7] has led to exploration of their usability as assessment tools, but only in the Web-deployment platform [79,80]. Things change drastically when considering the 3D MUVE deployment platform. When a user has to invest a serious amount of time to enter a specific virtual environment with its own conventions, control schemes, and system requirements, then that user expects a rich branching case, similar to a real minigame, that will engage both sensorially and intellectually to keep the user focused and present. This kind of experience could be a knowledge confirmation tool but also a significant, even the primary, disseminator of knowledge regarding the subject matter that the case is negotiating. Additionally, interesting contemporary evolutions could be leveraged to increase interactivity and spontaneity in the users' reactions. For example, interactions through nonscripted, natural language processing [81] with the simulator would greatly enhance the sense of presence of the user, especially if the simulator's response came from a nonscripted artificial cognition process, or the medical challenges came not prescripted, but emerged from full-fledged vital signs simulation engines (eg, [82-84]). However, as was revealed by the discussions of the focus group, for the system to play that role, the case itself should consist of a complex tree with several branches that lead to interesting and meaningful consequences after each user choice providing an experience more akin to one that would happen in a real-world environment and less like one in a controlled test-like environment with artificially imposed barriers.

Third, in order for a Second Life deployed virtual case to be an effective learning tool, the quantity of interactivity should be great and so should its quality. The sensory capacity for immersion in a MUVE is both a blessing and a curse. A blessing for the user in a fully developed case who can meaningfully interact with the environment moving through and freely manipulating the objects present there and using manual practices that she will be called to apply in a real-world environment. For example, in the 3D virtual environment it seemed odd to the focus group members to be asked to identify medical tools by name when they could be modeled in front of a tray and picked up and used by the user. However, this is also the curse for the author and developer of the case in the MUVE. One must resort as little as possible to narration through text and utilize the sensory immersive potential of the MUVE by creating rich and immersive audiovisual content to present the user with all the pertinent information. In every other case, she risks alienating the user base who, trained from the all-pervasive MMORPGs, have very strongly established preconceptions of what to expect from any environment that is presented in 3D and where they interact through their avatar. Almost all the members of our focus group praised the interactivity of the MUVE compared to the Web, but they found it heavily lacking considering the potential that the MUVE platform has and the expectations that this created for them. It is not unrelated that all the suggestions offered for improving the case were toward that goal either through more realistic manipulation of the in-world objects or the more hands-on manipulation in the manual procedures applied to the case (eg, surgery).

### Context

This work was triggered by the repurposing efforts applied to the mEducator program [61]. In that program funded by the European Commission, the main goal was the identification of the prerequisites, the development of infrastructures, and the piloting of a streamlined process for repurposing medical educational content across European academic institutions [61]. For this reason, a specific architecture and a dedicated schema was developed for federating and semantically enriching content across learning content management systems (LCMS) [67]. The overarching purpose was to make educational content discoverable and context-naïve to facilitate its reusability and repurposing for different educational goals and across different educational environments [61].

A significant part of the aforementioned project was the semantic enrichment of Web-based virtual patients for them to be discoverable and reusable across different contexts and purposes [85]. However, virtual patients can be repurposed pedagogically, but also technologically. Repurposing virtual patients to Second Life could provide a new platform for implementing the results of the Linked Labyrinth+ mEducator project [85,67].

The Linked Labyrinth+ semantic enrichment of virtual cases was a first important step in making the virtual patient content discoverable and repurposable across learning objectives and academic institutions [85,67]. However, establishing sound repurposing principles to the Second Life platform would be the important missing link that would allow the use of existing content as the basis for creating custom virtual patients from existing material, or even incorporating procedural methods [86] of game design to create dynamic virtual patient content. At this point, the Second Life MUVE is rather dated. Because of its age, unoptimized graphics engine, and cumbersome user interface (UI), the experience is rather difficult at times. However, these drawbacks, along with the maturity of the platform and the multitude of existing health care content, were the reasons that led to the choice of this platform for exploring repurposing of virtual patients from the Web to the MUVE. By conducting our test in a rather cumbersome and dated platform and subsequently deducing repurposing guidelines in this "difficult" environment, it is ensured that future deployments in more current MUVE platforms will provide an even smoother experience. Moving beyond the limitations, the repurposing guidelines that emerge from this study could facilitate the use of even more open-ended virtual patients and eventually lead to procedural virtual patients. Additionally, such semantic enrichment in the context of a highly interactive 3D virtual environment could facilitate the game feedback in the form of artificial intelligence (AI) avatars that can provide meaningful challenge or assistance to a user by tapping into resources linked through semantic enrichment [87-89]. That kind of sophisticated user interaction and automated content creation in 3D environments would greatly enhance both the utility and the impact of the MUVE-deployed virtual patient. However exploring such options requires a clear vision of what works and what does not in repurposing virtual patients from the Web to the MUVE.

Efforts for content generation in 3D environments are not novel. Especially in the field of cultural heritage, there are several efforts for migrating real-world cultural content (eg, monuments, depictions of works of art) to 3D environments (eg, [90,91]). There are even successful attempts at utilizing semantic enrichment of such content to automate the transfer from the real world to the virtual [92]. By embedding metadata from wikis and established semantic namespaces along with geospace information, there have been successful attempts to provide real-time automated updating of 3D environments to real-world cultural heritage sites [93].

Thus, an effort to put together the aforementioned 2 axes of research, the virtual patient repurposing from the Web to the 3D virtual environment and the automation by semantification of content generated in 3D virtual environments, one very important prerequisite must be met. That is the identification of the guidelines and best practices regarding the pedagogically correct repurposing of the virtual patient content from the Web to a 3D virtual environment.

This makes the current study unique, original, and valuable. Before engaging the academic teams and structures (eg, Health Sciences Education Office) in such an endeavor, one needs to investigate the suitability of the decision for undergraduate (dental) education. It is certain that the incorporation of virtual patients in medical curricula is not a novelty; there are studies of their impact and effectiveness as course materials in general medical training [94] and in dentistry [73]. However, the transition from the Web to the virtual environment is not a pedagogically straightforward one. To explore the necessities of the MUVE platform, user feedback is required.

By transferring the virtual patient from the Web to the MUVE verbatim, we have provided a single-user learning experience; that is, we have not facilitated the collaboration of multiple users for resolving the case's challenges. The advantages of collaborative learning in medical education are well documented [95,96]; however, at this point we were focused on uncovering the differences between deployment platforms and the details of exploiting the different deployment media than to explore the multi-user dynamics of a collaborative virtual patient educational episode. It is one of the future goals of this line of research to investigate the optimal multi-user modes of interaction in a MUVE-deployed virtual patient.

This study is a first overview of the challenges that must be overcome in repurposing virtual patients to a 3D MUVE. It consists of only 1 focus group, which is not enough to provide a detailed relief of the requirements for repurposing in the MUVE. However, this was a conscious choice. This first attempt in repurposing virtual patients across platforms could only be explored in broad strokes when dealing with simple transfer between platforms. To be able to explore more details in true repurposing and no transference, a need exists to deconstruct the virtual patient down to its learning objectives and to its expected teaching outcomes to be able to repurpose either to specific topics or to specific outcomes. As mentioned in the literature [69], the 2 media should not be considered as competitive, but as complementary of one another. Thus, a repurposing effort should focus in the strong points of each platform and reinforce the teaching outcomes that can be conveyed in the most impactful way by the specific platform. For example, in a Web-based patient, the theoretical breadth of knowledge in periodontology is the area in which the platform thrives, whereas in a 3D MUVE-based patient, manual practice on incision techniques is where its graphics-rich environment can really help the learner acquire a different and complementary skill set to what the Web-based virtual patient can offer. Further qualitative study (eg, with additional focus groups) can come only after the redesigning of the MUVE-deployed virtual patient. However, to successfully achieve this task, there must be adherence to both the guidelines that emerged from the present study, but also from the aforementioned conceptual considerations. Only after such an effort has been the subject of rigorous qualitative study can a formal quantitative assessment be attempted. It becomes clear that this study, with only 1 focus group should be considered the required first step in meaningfully utilizing the MUVE as a virtual patient deployment and repurposing platform beyond the mere transference of resources.

Students, as the immediate consumers of this educational content, are the best group to provide feedback. Additionally, student input was important for discovering feedback from users familiar with the gaming culture in general. Their opinion should be considered more "expert" regarding gaming than, for example, senior faculty members. For these reasons, the authors engaged into a straightforward but rather strict process to facilitate such an exploration in this focus group study. The participants of this study were all volunteers from a relevant optional course of dental informatics in the undergraduate curriculum of a dentistry school. The fact that the student pool from which the participants' were chosen was that of a relevant optional course ensured that only those actively interested in the subject were chosen for the study. Additionally, the voluntary character of the participation meant that even those interested in the subject, only students with active commitment for engaging with the subject would participate. These 2 factors ensured that the participants' feedback in the focus group discussions would be both on topic and thorough.

Focus group studies can uncover subtle context, whereas survey or interview studies are best suited at quantifying established truths [70]. Our goal to explore the guidelines for the pedagogically successful repurposing of Web-deployed virtual patients to the 3D MUVE platform seemed best suited for the focus group approach. The differences of the 2 deployment platforms are subtle. Both are computer based, both have been used for game deployment in a recreational context, and both have also been used as learning facilitators. Exploring the best practices for platform repurposing in the deployment of the virtual patients requires the investigation of the user experience not only by concrete metrics of user satisfaction and system usability, but also by assessing contextually the user experience. Subtleties such as the user extrapolating from previous experiences in 3D MUVEs through serious or even recreational gaming need to be established first before being quantified.

The goal of this study was not to quantify the usability or the satisfaction of a user base regarding an information technology (IT) system in medical education, but to establish qualitative guidelines that will evolve to best practices through further study.

### Conclusions and Direction for Future Work

These insights lead to some interesting conclusions regarding the design requirements in the effort of repurposing Web-based virtual cases for MUVEs:

1. Show, don't tell. When repurposing an existing virtual case to a MUVE, text narrative should be kept to a minimum. Instead, audiovisual assets should replace the narration to immerse the user into the narration and provide an increased sense of presence into the case.
2. Call for action, don't call for answers. The nature of the MUVE is such that many of the challenges presented during a case can be simulated by avatar actions. When the opportunity appears then provisions should be made, even if that means additional development overhead, for the user to be able to actuate the requested solution instead of just choosing it from a multiple-choice questionnaire.
3. Consequences, not barriers. This is probably useful in all virtual case deployment platforms, but its effects are outlined with stark clarity in a MUVE because of the immediacy with which the user encounters all enforced barriers and artificial preventions of her actions. Instead, all actions of the user should provide useful feedback and lead to plausible evolution of the case instead of abrupt fail states or returns to previous choices.

These are straightforward and simple principles, but it is important to be clear that they are not optional embellishments. In the continuing effort for a systematic repurposing of Web-based virtual cases to MUVEs, the aforementioned required design practices that emerged from this focus group study are not just going to be adhered to as rough guidelines, but incorporated in the core of the workflow (automated or not) of the repurposing effort.

These guidelines should be seen as first steps in a wider context. Current trends point to open education as a method for acquiring skills and knowledge on demand. Internet technologies facilitate that kind of student-directed learning in 2 significant ways [97]. One axis of Internet technologies concerns the remote use of expensive equipment through online time-sharing and collaboration with established professionals in relevant fields, for example, by initiating a telescope observation with the help of experts through a network of remote observatories [98]. The other axis concerns the availability of specific knowledge online and on demand for "learn-at-your-own-pace" episodes [97]. This and social learning (ie, learning by asking questions and doing things relevant to the field [99]) are a perfect match for a virtual environment that contains meaningful interaction with realistic challenges. Finding the correct parameters for streamlining virtual patient repurposing from the Web to Second Life becomes more than just an interesting research niche. Instead, it is important for meaningfully combining the impact of the immersive 3D MUVE experience with the mature and growing virtual patient effort. This combination could lead to new aspects of open social learning [97] by facilitating the mass migration of the growing virtual patient content in a form that each and every learner can absorb at her own pace, but also can engage in such an experiential way as to be able to affect that "learning to be" [97] part that is missing from the Web-based virtual patients. For this future goal, the guidelines that have emerged from this work are an important first step.

## Authors' Contributions

PE Antoniou: concept, creation of the virtual patient in Second Life, literature review, focus group facilitator, Introduction, Methods, Results, and Discussion writing contribution; C Athanasopoulou: focus group recruiter, organizer and principal facilitator, Results writing contribution; E Dafli: creation of the Web-based virtual patient, literature review, focus group results transcript taking, Results writing contribution; PD Bamidis: concept, coordination, editing, literature review, Introduction, Discussion, and Conclusions writing contribution.

## References

1. Schittek M, Mattheos N, Lyon HC, Attström R. Computer assisted learning. A review. Eur J Dent Educ 2001 Aug;5(3):93-100. [Medline: 11520331]
2. Beux PL, Fieschi M. Virtual biomedical universities and e-learning. Int J Med Inform 2007 Jun;76(5-6):331-335. [doi: 10.1016/S1386-5056(07)00060-3] [Medline: 17407747]
3. Ellaway R, Candler C, Greene P, Smothers V. MedBiquitous. 2006. An Architectural Model for MedBiquitous Virtual Patients URL: http://groups.medbiq.org/medbiq/display/VPWG/MedBiquitous+Virtual+Patient+Architecture [accessed 2014-06-03] [WebCite Cache ID 6Q3YH8IMB]
4. Ellaway R, Poulton T, Fors U, McGee JB, Albright S. Building a virtual patient commons. Med Teach 2008 Jan;30(2):170-174. [doi: 10.1080/01421590701874074] [Medline: 18464142]
5. MedBiquitous. Standards URL: http://www.medbiq.org/std_specs/standards/index.html [accessed 2014-02-21] [WebCite Cache ID 6NYOmCCAO]
6. MedBiquitous Virtual Patient Summary. 2010. URL: http://www.medbiq.org/working_groups/virtual_patient/MedBiquitousVirtualPatientSummary.pdf [accessed 2014-02-21] [WebCite Cache ID 6NYOwDoh7]
7. Poulton T, Balasubramaniam C. Virtual patients: a year of change. Med Teach 2011;33(11):933-937. [doi: 10.3109/0142159X.2011.613501] [Medline: 22022903]
8. Salminen H, Zary N, Björklund K, Toth-Pal E, Leanderson C. Virtual patients in primary care: developing a reusable model that fosters reflective practice and clinical reasoning. J Med Internet Res 2014;16(1):e3 [FREE Full text] [doi: 10.2196/jmir.2616] [Medline: 24394603]
9. Papadopoulos L, Pentzou AE, Louloudiadis K, Tsiatsos TK. Design and evaluation of a simulation for pediatric dentistry in virtual worlds. J Med Internet Res 2013;15(10):e240 (forthcoming). [doi: 10.2196/jmir.2651]
10. Bell M. Toward a definition of vrtual worlds. JVW 2008;1(1):2-5 [FREE Full text]
11. Boulos MN, Hetherington L, Wheeler S. Second Life: an overview of the potential of 3-D virtual worlds in medical and health education. Health Info Libr J 2007 Dec;24(4):233-245. [doi: 10.1111/j.1471-1842.2007.00733.x] [Medline: 18005298]
12. OpenSimulator. What is OpenSimulator URL: http://opensimulator.org/wiki/Main_Page [accessed 2014-04-14] [WebCite Cache ID 6OpPhr7CP]
13. Kitely. URL: http://www.kitely.com/ [accessed 2014-04-18] [WebCite Cache ID 6Ovop155d]
14. Avination. URL: https://www.avination.com/ [accessed 2014-04-18] [WebCite Cache ID 6Ovp1ZgPa]
15. Culbertson C, Nicolas S, Zaharovits I, London ED, De La Garza R, Brody AL, et al. Methamphetamine craving induced in an online virtual reality environment. Pharmacol Biochem Behav 2010 Oct;96(4):454-460 [FREE Full text] [doi: 10.1016/j.pbb.2010.07.005] [Medline: 20643158]
16. Sullivan DK, Goetz JR, Gibson CA, Washburn RA, Smith BK, Lee J, et al. Improving weight maintenance using virtual reality (Second Life). J Nutr Educ Behav 2013 Jun;45(3):264-268. [doi: 10.1016/j.jneb.2012.10.007] [Medline: 23622351]
17. Kamel Boulos MN, Toth-Cohen S. The University of Plymouth Sexual Health SIM experience in Second Life: evaluation and reflections after 1 year. Health Info Libr J 2009 Dec;26(4):279-288. [doi: 10.1111/j.1471-1842.2008.00831.x] [Medline: 19930475]
18. Yuen EK, Herbert JD, Forman EM, Goetter EM, Comer R, Bradley JC. Treatment of social anxiety disorder using online virtual environments in second life. Behav Ther 2013 Mar;44(1):51-61. [doi: 10.1016/j.beth.2012.06.001] [Medline: 23312426]
19. Lisetti C, Pozzo E, Lucas M, Hernandez F, Silverman W, Kurtines B, et al. Second life, bio-sensors, and exposure therapy for anxiety disorders. Stud Health Technol Inform 2009;144:19-21. [Medline: 19592722]
20. Freeman D, Pugh K, Vorontsova N, Antley A, Slater M. Testing the continuum of delusional beliefs: an experimental study using virtual reality. J Abnorm Psychol 2010 Feb;119(1):83-92 [FREE Full text] [doi: 10.1037/a0017514] [Medline: 20141245]
21. Gorrindo T, Groves JE. The psychodynamics of transference--a virtual reality model. Am J Psychother 2012;66(2):151-163. [Medline: 22876527]
22. Richardson A, Hazzard M, Challman SD, Morgenstein AM, Brueckner JK. A "Second Life" for gross anatomy: applications for multiuser virtual environments in teaching the anatomical sciences. Anat Sci Educ 2011 Feb;4(1):39-43. [doi: 10.1002/ase.195] [Medline: 21265036]
23. Jane Cook M. Design and initial evaluation of a virtual pediatric primary care clinic in Second Life(®). J Am Acad Nurse Pract 2012 Sep;24(9):521-527. [doi: 10.1111/j.1745-7599.2012.00729.x] [Medline: 22931477]
24. Second Life. Second Life maps URL: http://maps.secondlife.com/secondlife/Imperial%20College%20London/150/86/27 [accessed 2014-02-21] [WebCite Cache ID 6NYPeZhyS]
25. Creutzfeldt J, Hedman L, Medin C, Heinrichs WL, Felländer-Tsai L. Exploring virtual worlds for scenario-based repeated team training of cardiopulmonary resuscitation in medical students. J Med Internet Res 2010;12(3):e38 [FREE Full text] [doi: 10.2196/jmir.1426] [Medline: 20813717]
26. Creutzfeldt J, Hedman L, Heinrichs L, Youngblood P, Felländer-Tsai L. Cardiopulmonary resuscitation training in high school using avatars in virtual worlds: an international feasibility study. J Med Internet Res 2013;15(1):e9 [FREE Full text] [doi: 10.2196/jmir.1715] [Medline: 23318253]

27. Diener S, Windsor J, Bodily D. Design and development of clinical simulations in Second Life. 2009 Presented at: EDUCAUSE Australasia Conference; May 2009; Perth Australia p. 3-6 URL: https://researchspace.auckland.ac.nz/handle/2292/4305
28. Schwaab J, Kman N, Nagel R, Bahner D, Martin DR, Khandelwal S, et al. Using second life virtual simulation environment for mock oral emergency medicine examination. Acad Emerg Med 2011 May;18(5):559-562. [doi: 10.1111/j.1553-2712.2011.01064.x] [Medline: 21521404]
29. Hall V, Conboy-Hill S, Taylor D. Using virtual reality to provide health care information to people with intellectual disabilities: acceptability, usability, and potential utility. J Med Internet Res 2011;13(4):e91 [FREE Full text] [doi: 10.2196/jmir.1917] [Medline: 22082765]
30. Hussainy SY, Styles K, Duncan G. A virtual practice environment to develop communication skills in pharmacy students. Am J Pharm Educ 2012 Dec 12;76(10):202 [FREE Full text] [doi: 10.5688/ajpe7610202] [Medline: 23275667]
31. Veronin MA, Daniels L, Demps E. Pharmacy cases in Second Life: an elective course. Adv Med Educ Pract 2012;3:105-112 [FREE Full text] [doi: 10.2147/AMEP.S35358] [Medline: 23762008]
32. Gordon R, Björklund NK, Smith RJ, Blyden ER. Halting HIV/AIDS with avatars and havatars: a virtual world approach to modelling epidemics. BMC Public Health 2009;9 Suppl 1:S13 [FREE Full text] [doi: 10.1186/1471-2458-9-S1-S13] [Medline: 19922683]
33. Patel V, Lee H, Taylor D, Aggarwal R, Kinross J, Darzi A. Virtual worlds are an innovative tool for medical device training in a simulated environment. Stud Health Technol Inform 2012;173:338-343. [Medline: 22357014]
34. SLurl. Ohio State University Medical Center in Second Life URL: http://slurl.com/secondlife/OSU%20Medicine/83/98/302 [accessed 2014-02-21] [WebCite Cache ID 6NYPlkZx2]
35. Wiecha J, Heyden R, Sternthal E, Merialdi M. Learning in a virtual world: experience with using second life for medical education. J Med Internet Res 2010;12(1):e1 [FREE Full text] [doi: 10.2196/jmir.1337] [Medline: 20097652]
36. Cohen D, Sevdalis N, Taylor D, Kerr K, Heys M, Willett K, et al. Emergency preparedness in the 21st century: training and preparation modules in virtual environments. Resuscitation 2013 Jan;84(1):78-84. [doi: 10.1016/j.resuscitation.2012.05.014] [Medline: 22659598]
37. Conradi E, Kavia S, Burden D, Rice A, Woodham L, Beaumont C, et al. Virtual patients in a virtual world: Training paramedic students for practice. Med Teach 2009 Aug;31(8):713-720. [Medline: 19811207]
38. Hansen MM, Murray PJ, Erdley WS. The potential of 3-D virtual worlds in professional nursing education. Stud Health Technol Inform 2009;146:582-586. [Medline: 19592909]
39. Wood A, McPhee C. Establishing a virtual learning environment: a nursing experience. J Contin Educ Nurs 2011 Nov;42(11):510-515. [doi: 10.3928/00220124-20110715-01] [Medline: 21780735]
40. Ahern N, Wink DM. Virtual learning environments: second life. Nurse Educ 2010 Dec;35(6):225-227. [doi: 10.1097/NNE.0b013e3181f7e943] [Medline: 20975400]
41. Warren JJ, Brixey JJ. Second life: not your conventional simulation. Stud Health Technol Inform 2009;146:843. [Medline: 19593012]
42. Schmidt B, Stewart S. Implementing the virtual world of Second Life into community nursing theory and clinical courses. Nurse Educ 2010 Apr;35(2):74-78. [doi: 10.1097/NNE.0b013e3181ced999] [Medline: 20173592]
43. Trangenstein PA, Weiner EE, Gordon JS, McNew R. An analysis of nursing education's immersion into Second Life, a multi-user virtual environment (MUVE). Stud Health Technol Inform 2010;160(Pt 1):644-647. [Medline: 20841766]
44. Billingsley L, Rice K, Bennett M, Thibeau S. Using a multiuser virtual environment to facilitate nursing journal clubs: a mixed-methods study. Clin Nurse Spec 2013 Jun;27(3):146-154. [doi: 10.1097/NUR.0b013e31828c8408] [Medline: 23575171]
45. Sweigart L, Hodson-Carlton K. Improving student interview skills: the virtual avatar as client. Nurse Educ 2013 Feb;38(1):11-15. [doi: 10.1097/NNE.0b013e318276df2d] [Medline: 23222623]
46. McCallum J, Ness V, Price T. Exploring nursing students' decision-making skills whilst in a Second Life clinical simulation laboratory. Nurse Educ Today 2011 Oct;31(7):699-704. [doi: 10.1016/j.nedt.2010.03.010] [Medline: 20807671]
47. Kidd LI, Knisley SJ, Morgan KI. Effectiveness of a second life(®) simulation as a teaching strategy for undergraduate mental health nursing students. J Psychosoc Nurs Ment Health Serv 2012 Jul;50(7):28-37. [doi: 10.3928/02793695-20120605-04] [Medline: 22694785]
48. Weiner E, McNew R, Trangenstein P, Gordon J. Using the virtual reality world of second life to teach nursing faculty simulation management. Stud Health Technol Inform 2010;160(Pt 1):615-619. [Medline: 20841760]
49. Phillips J, Berge ZL. Second life for dental education. J Dent Educ 2009 Nov;73(11):1260-1264 [FREE Full text] [Medline: 19910474]
50. SLurl. Maryland Dental School in Second Life URL: http://slurl.com/secondlife/UMaryland%20Dental%20School/122/103/45 [accessed 2014-02-21] [WebCite Cache ID 6NYPrIJ8X]
51. UMDS Virtual Dental School Insider. 2009. Virtual skull practical URL: http://dspub.umaryland.edu/vi/ [accessed 2014-02-21] [WebCite Cache ID 6NYPwKYuF]

52. Griffith S. Case Western Reserve University. 2008 Jul 28. A virtual toothache helps student dentists learn patient-side communications URL: http://blog.case.edu/case-news/2008/07/28/virtualdentistry [accessed 2014-02-21] [WebCite Cache ID 6NYQ11nfz]
53. Second Life. Welcome to the Second Life® Wiki URL: http://wiki.secondlife.com/wiki/Main_Page [accessed 2014-04-17] [WebCite Cache ID 6OtlTcw04]
54. Warburton S. Second Life in higher education: Assessing the potential for and the barriers to deploying virtual worlds in learning and teaching. British Journal of Educational Technology 2009;40(3):414-426.
55. Gorman P. Ariadne. 2012. Has Second Life lived up to expectations? URL: http://www.ariadne.ac.uk/issue68/gorman [accessed 2014-06-03] [WebCite Cache ID 6Q3Z9iFM0]
56. Buchanan JA. Experience with virtual reality-based technology in teaching restorative dental procedures. J Dent Educ 2004 Dec;68(12):1258-1265 [FREE Full text] [Medline: 15576814]
57. Rodrigues MAF, Silva WB, Barbosa Neto ME, Gillies DF, Ribeiro IM. An interactive simulation system for training and treatment planning in orthodontics. Computers & Graphics 2007 Oct;31(5):688-697 [FREE Full text] [doi: 10.1016/j.cag.2007.04.010]
58. Marras I, Nikolaidis N, Mikrogeorgis G, Lyroudia K, Pitas I. A virtual system for cavity preparation in endodontics. J Dent Educ 2008 Apr;72(4):494-502 [FREE Full text] [Medline: 18381855]
59. Papadopoulos L. Virtual reality simulators in dental training. Hel Stom Rev 2010;54(3):263-276.
60. HealthCyberMap. Social Web ("Web 2.0") and the 3D Web (Virtual Worlds and Second Life) URL: http://healthcybermap.org/sl.htm [accessed 2014-02-21] [WebCite Cache ID 6NYQ6S3Kz]
61. Bamidis P, Kaldoudi E, Pattichis C. mEducator: A best practice network for repurposing sharing medical educational multi-type content leveraging knowledge for innovation. In: Camarinha-Matos LM, Paraskakis I, Afsarmanesh H, editors. Leveraging Knowledge for Innovation in Collaborative Networks. Berlin Heidelberg: Springer; 2009:769-779.
62. Hodgins W, Duval E. Draft Standard for Learning Object Metadata. 2002. URL: http://ltsc.ieee.org/wg12/files/LOM_1484_12_1_v1_Final_Draft.pdf [accessed 2014-02-21] [WebCite Cache ID 6NYQCtnfg]
63. Rustici Software. SCORM URL: http://scorm.com/scorm-explained/technical-scorm/ [accessed 2014-02-21] [WebCite Cache ID 6NYQGngy1]
64. Smothers V. MedBiquitous Consortium. 2009. ANSI/MEDBIQ Healthcare Learning Object Metadata Specifications and Description Document URL: http://www.medbiq.org/working_groups/learning_objects/HealthcareLOMSpecification.pdf [accessed 2014-02-21] [WebCite Cache ID 6NYQLXG6S]
65. Nicolaidou I, Giordano D, Spampinato C, Pattichis C, Bamidis P, Antoniades A. Evaluation of educational content sharing solutions: Challenges of the mEducator best practice network. In: Bastiaens T, Ebner M, editors. Proceedings of World Conference on Educational Multimedia, Hypermedia and Telecommunications. Chesapeake, VA: Association for the Advancement of Computing in Education; 2011.
66. mEducator 3.0. LinkedLabyrinth+ URL: http://www.meducator3.net/llplus/ [accessed 2014-02-21] [WebCite Cache ID 6NYQPan7x]
67. Nikolaidou M, Bamidis P. D.9.13 mEducator Final Report. 2012 Jul 06. URL: http://www.meducator.net/sites/default/files/D9.13_mEducator_Final_Report_v.3.pdf [accessed 2014-06-03] [WebCite Cache ID 6Q3bPlLS7]
68. Cook DA. The failure of e-learning research to inform educational practice, and what we can do about it. Med Teach 2009 Feb;31(2):158-162. [doi: 10.1080/01421590802691393] [Medline: 19330674]
69. Kamel Boulos MN, Maramba I. Pitfalls in 3-D virtual worlds health project evaluations: The trap of drug-trial-style. Journal For Virtual Worlds Research, North America 2009 Aug;2:4-6 [FREE Full text]
70. Barbour RS. Making sense of focus groups. Med Educ 2005 Jul;39(7):742-750. [doi: 10.1111/j.1365-2929.2005.02200.x] [Medline: 15960795]
71. Sim J. Collecting and analysing qualitative data: issues raised by the focus group. J Adv Nurs 1998 Aug;28(2):345-352. [doi: 10.1046/j.1365-2648.1998.00692.x]
72. Ellaway R. OpenLabyrinth: An abstract pathway-based serious game engine for professional education. In: Proceedings of the Fifth International Conference on Digital Information Management (ICDIM). 2010 Jul 05 Presented at: Fifth International Conference on Digital Information Management (ICDIM); July 5-8, 2010; Thunder Bay, ON.
73. Zary N, Johnson G, Fors U. Web-based virtual patients in dentistry: factors influencing the use of cases in the Web-SP system. Eur J Dent Educ 2009 Feb;13(1):2-9. [doi: 10.1111/j.1600-0579.2007.00470.x] [Medline: 19196286]
74. Kitzinger J. Qualitative research. Introducing focus groups. BMJ 1995 Jul 29;311(7000):299-302 [FREE Full text] [Medline: 7633241]
75. Poulton T, Conradi E, Kavia S, Round J, Hilton S. The replacement of 'paper' cases by interactive online virtual patients in problem-based learning. Med Teach 2009 Aug;31(8):752-758. [Medline: 19811214]
76. Kononowicz AA, Hege I, Krawczyk P, Zary N. New approaches to linking clinical guidelines to virtual patients. Stud Health Technol Inform 2012;180:958-962. [Medline: 22874335]
77. Hege I, Zary N, Kononowicz AA. Criteria to assess the quality of virtual patients. Stud Health Technol Inform 2012;180:954-957. [Medline: 22874334]

78. Round J, Conradi E, Poulton T. Training staff to create simple interactive virtual patients: the impact on a medical and healthcare institution. Med Teach 2009 Aug;31(8):764-769. [Medline: 19811216]
79. Round J, Conradi E, Poulton T. Improving assessment with virtual patients. Med Teach 2009 Aug;31(8):759-763. [Medline: 19811215]
80. Williams K, Wryobeck J, Edinger W, McGrady A, Fors U, Zary N. Assessment of competencies by use of virtual patient technology. Acad Psychiatry 2011;35(5):328-330. [doi: 10.1176/appi.ap.35.5.328] [Medline: 22007093]
81. Liddy ED. Natural language processing. In: Encyclopedia of Library Information Science, 2nd Ed. New York: Marcel Decker, Inc; 2001.
82. Ryan M, Hill D, McGrath D. Simulation interoperability with a commercial game engine. 2005 Jun 27 Presented at: European Simulation Interoperability Workshop; June 27-30, 2005; Toulouse, France.
83. Schwid HA, Rooke GA, Michalowski P, Ross BK. Screen-based anesthesia simulation with debriefing improves performance in a mannequin-based anesthesia simulator. Teach Learn Med 2001;13(2):92-96. [doi: 10.1207/S15328015TLM1302_4] [Medline: 11302037]
84. Kononowicz AA, Narracott AJ, Manini S, Bayley MJ, Lawford PV, McCormack K, et al. A framework for different levels of integration of computational models into web-based virtual patients. J Med Internet Res 2014;16(1):e23 [FREE Full text] [doi: 10.2196/jmir.2593] [Medline: 24463466]
85. Laka C, Dafli E. Virtual patients on the Semantic Web: the mEducator3.0/Linked Labyrinth Plus approach. 2012 Apr 06 Presented at: Proceedings of 1st intenational Conference on Medical Education Informatics; April 6-7, 2012; Thessaloniki, Greece.
86. Nitsche M, Ashmore C, Hankinson W, Fitzpatrick R, Kelly J, Margenau K. Designing procedural game spaces: A case study. 2006 Presented at: FuturePlay; 2006; London, ON p. 10-12.
87. Conde T, Thalmann D. An artificial life environment for autonomous virtual agents with multi-sensorial and multi-perceptive features. Comp. Anim. Virtual Worlds 2004 Jun 16;15(34):311-318. [doi: 10.1002/cav.34]
88. Donikian S, Rutten E. Reactivity, concurrency, data-flow and hierarchical preemption for behavioural animation. In: Proceedings of the Eurographics Workshop. 1995 Sep 02 Presented at: Eurographics Workshop; September 2-3, 1995; Maastricht, The Netherlands p. 137-153.
89. Sanchez S, Luga H, Duthen Y, Balet O. Bringing autonomy to virtual characters. In: Ramos FF, Unger H, Larios V, editors. Advanced Distributed Systems. Berlin Heidelberg: Springer; 2004:137.
90. Meli M. Knowledge Management: a new challenge for science museums. Cultivate Interactive 2003 Feb 07(9):2003.
91. Marcos G, Eskudero H, Lamsfus C, Linaza MT. Data retrieval from a cultural knowledge database. 2005 Presented at: Workshop on Image Analysis for Multimedia Interactive Services; April 13-15, 2005; Montreux, Switzerland.
92. Mrissa M, Dietze S, Thiran P, Ghedira C, Benslimane D, Maamar Z. Context-based semantic mediation. In: King I, Baeza-Yates R, editors. Weaving Services and People on the World Wide Web. Berlin Heidelberg: Springer; 2009:49-66.
93. Dunwell I, Petridis P, Protopsaltis A, de Freitas S, Panzoli D, Samuels P. Automating content generation for large-scale virtual learning environments using semantic Web services. In: Proceedings of the 5th Workshop on Semantic Wikis (SemWiki-2010). 2010 May 31 Presented at: 5th Workshop on Semantic Wikis (SemWiki-2010); May 31, 2010; Heraklion, Greece.
94. Edelbring S, Broström O, Henriksson P, Vassiliou D, Spaak J, Dahlgren LO, et al. Integrating virtual patients into courses: follow-up seminars and perceived benefit. Med Educ 2012 Apr;46(4):417-425. [doi: 10.1111/j.1365-2923.2012.04219.x] [Medline: 22429178]
95. Arrow H, Cook J. Configuring and reconfiguring groups as complex learning systems. In: Work Group Learning: Understanding, Improving & Assessing How Groups Learn in Organizations. London: Lawrence Erlbaum Associates, Taylor & Francis Group; 2008:45-71.
96. Bleakley A. Working and learning in "teams" in a new era of health-care. In: Patient-Centred Medicine in Transition. Cham (ZG) Switzerland: Springer International Publishing; 2014:129-138.
97. Brown JS, Adler RP. Open education, the long tail, and learning 2.0. Educause Review 2008;43(1):16-20 [FREE Full text]
98. Faulkes Telescope Project. URL: http://www.faulkes-telescope.com/ [accessed 2014-02-21] [WebCite Cache ID 6NYQYBU2w]
99. Brown JS, Collins A, Duguid P. Situated cognition and the culture of learning. Educational Researcher 1989 Jan 01;18(1):32-42. [doi: 10.3102/0013189X018001032]

## Abbreviations

**LCMS:** Learning Content Management System
**LOM:** Learning Object Metadata
**LSL:** Linden Scripting Language
**MMOG:** massive multiplayer online game
**MMORPG:** massive multiplayer online role-playing game
**MUVE:** multi-user virtual environment

**SCORM:** Sharable Content Object Reference Model

*Edited by N Zary; submitted 23.02.14; peer-reviewed by M Hendrix, A Kononowicz, P Rhienmora, M Hendrix; comments to author 25.03.14; revised version received 01.05.14; accepted 13.05.14; published 13.06.14.*

*Please cite as:*
*Antoniou PE, Athanasopoulou CA, Dafli E, Bamidis PD*
*Exploring Design Requirements for Repurposing Dental Virtual Patients From the Web to Second Life: A Focus Group Study*
*J Med Internet Res 2014;16(6):e151*
*URL: http://www.jmir.org/2014/6/e151/*
*doi:10.2196/jmir.3343*
*PMID:24927470*

Original Paper

# What Explains Usage of Mobile Physician-Rating Apps? Results From a Web-Based Questionnaire

Sonja Bidmon[1], PhD; Ralf Terlutter[1], PhD; Johanna Röttl[1], MSc

Department of Marketing and International Management, Alpen-Adria Universitaet Klagenfurt, Klagenfurt am Woerthersee, Austria

**Corresponding Author:**
Sonja Bidmon, PhD
Department of Marketing and International Management
Alpen-Adria Universitaet Klagenfurt
Universitaetsstrasse 65-67
Klagenfurt am Woerthersee, 9020
Austria
Phone: 43 463 2700 ext 4048
Fax: 43 463 2700 994048
Email: sonja.bidmon@aau.at

## Abstract

**Background:** Consumers are increasingly accessing health-related information via mobile devices. Recently, several apps to rate and locate physicians have been released in the United States and Germany. However, knowledge about what kinds of variables explain usage of mobile physician-rating apps is still lacking.

**Objective:** This study analyzes factors influencing the adoption of and willingness to pay for mobile physician-rating apps. A structural equation model was developed based on the Technology Acceptance Model and the literature on health-related information searches and usage of mobile apps. Relationships in the model were analyzed for moderating effects of physician-rating website (PRW) usage.

**Methods:** A total of 1006 randomly selected German patients who had visited a general practitioner at least once in the 3 months before the beginning of the survey were randomly selected and surveyed. A total of 958 usable questionnaires were analyzed by partial least squares path modeling and moderator analyses.

**Results:** The suggested model yielded a high model fit. We found that perceived ease of use (PEOU) of the Internet to gain health-related information, the sociodemographic variables age and gender, and the psychographic variables digital literacy, feelings about the Internet and other Web-based applications in general, patients' value of health-related knowledgeability, as well as the information-seeking behavior variables regarding the amount of daily private Internet use for health-related information, frequency of using apps for health-related information in the past, and attitude toward PRWs significantly affected the adoption of mobile physician-rating apps. The sociodemographic variable age, but not gender, and the psychographic variables feelings about the Internet and other Web-based applications in general and patients' value of health-related knowledgeability, but not digital literacy, were significant predictors of willingness to pay. Frequency of using apps for health-related information in the past and attitude toward PRWs, but not the amount of daily Internet use for health-related information, were significant predictors of willingness to pay. The perceived usefulness of the Internet to gain health-related information and the amount of daily Internet use in general did not have any significant effect on both of the endogenous variables. The moderation analysis with the group comparisons for users and nonusers of PRWs revealed that the attitude toward PRWs had significantly more impact on the adoption and willingness to pay for mobile physician-rating apps in the nonuser group.

**Conclusions:** Important variables that contribute to the adoption of a mobile physician-rating app and the willingness to pay for it were identified. The results of this study are important for researchers because they can provide important insights about the variables that influence the acceptance of apps that allow for ratings of physicians. They are also useful for creators of mobile physician-rating apps because they can help tailor mobile physician-rating apps to the consumers' characteristics and needs.

***(J Med Internet Res 2014;16(6):e148)*** doi:10.2196/jmir.3122

**KEYWORDS**

physician-rating apps; physician-rating websites; sociodemographic variables; psychographic variables; digital literacy; TAM

## Introduction

### Background

Technological advances have always had major impacts on medicine [1]. Many leading companies in the computer and Internet industries have entered the mobile marketplace, such as Google with the Android Mobile Operating System and Apple with the iPhone being the 2 dominant operating systems [2]. The smartphone is one of the fastest growing sectors in the technology industry and also has significant impact on medicine [1]. The number of people who use smartphones and mobile tablet computers is expanding rapidly. More than 95% of young US adults between the ages of 18 and 29 years own a mobile phone, and almost 30% of those use their mobile phone to look for health or medical information. In the United States, more than half of the adults aged 65 and older own a mobile phone [3]. Younger people are more likely than older people to own and use a smartphone. Regarding apps, recent studies show that there has been an enormous increase in the number of smartphone and tablet apps downloaded over the past years [4]. More than 300 million apps were downloaded in 2009 and more than 5 billion apps were downloaded in 2010 [5]. Patients use mobile devices and apps to manage and control their health, and 1 in 5 smartphone owners has at least 1 health app (eg, for diet, weight, and exercise) [5,6]. Hence, similar to developments in most consumer markets, consumers increasingly access health-related information via mobile devices. Mobile media devices are popular tools in the area of medicine because they allow for immediate information [7]. Smartphones and mobile tablet computers offer many advantages for patients in comparison to other technologies, such as mobility, capability, portability, intuitive and tactile graphical user interface, permanent connection to the Internet, and storage capacity [4,5,7-9].

An *app* is defined as “a software program for a computer or phone operating system” [9]. In this paper, we use the term *mobile apps* to describe “Internet applications that run on smartphones and other mobile devices” [9]. Apple offers the highest number of health-related apps of any platform. In 2010, Apple’s App Store offered more than 7136 health-related apps; 1296 health-related apps were offered by Google Android and 333 by BlackBerry [5]. In October 2013, the IMS Institute for Healthcare Informatics released a report on mobile health apps (all apps categorized as “health or wellness” or “medical” were reviewed) showing that 43,689 health care apps were currently available on the US iTunes Store [10]. The health application market is booming [11]. The Global Mobile Health Market Report estimates that by 2015 more than one-third of all 1.4 billion smartphone users will utilize a mobile health care app [11]. In Europe, Germany is one of the biggest app markets with average growth rates of 183% over the past 4 years [12].

Several recently released mobile apps allow consumers to rate and locate physicians , such as Vitals [13], Rate MDs [14], ZocDoc [15], and Healthgrades [16] in the United States, or Jameda [17], DocInsider [18], and Imedo [19] in Germany. However, there is practically no research on factors that contribute to the adoption of such mobile physician-rating apps.

Physician-rating websites (PRWs) provide patients with information on the quality of health care system participants, such as physicians or hospitals [20]. On the Internet, they are a source of peer-to-peer information about individual physicians [21], an opportunity to review a physician in an anonymous and self-driven way [22], and another way to find health information and make health-related decisions [23] in addition to the usually preferred sources of recommendation from friends, colleagues, and family members, or from other physicians (eg, finding a new general practitioner) [24]. The structure of PRWs is similar to the well-known rating systems on the Internet for travel websites, hotels, or restaurants [20]. There is an increasing number of PRWs throughout the world [25-27]. A controversial discussion about the utility and the impact of PRWs in several health systems has been ongoing [21]. A cross-sectional study by Emmert et al in 2013 [28] showed that approximately one-third of an online sample in Germany was aware of the existence of German PRWs and approximately one-quarter had searched for a physician on a PRW at least once in the past. Compared to a study in the United States conducted in 2010 [29] in which 16% of Internet users and 19% of people who were looking for health-related information on the Internet had used a PRW, a slight increase of usage can be seen, but usage is still at a relatively low level. According to Emmert et al [28], people who have already posted a rating on a German PRW belong to the minority. Poor usage goes hand in hand with a small number of patient satisfaction/experience ratings per physician [20,30,31]. A study conducted by Terlutter et al in 2012 [32] found that younger, male, more highly educated people and those people with a chronic disease were more inclined to use PRWs. Users also differed psychographically from nonusers of PRWs because they revealed more positive feelings about the Internet and other Web-based applications in general and had a higher digital literacy rate than nonusers. Users ascribed higher usefulness to PRWs than nonusers, trusted information on PRWs to a greater degree, and were more likely to rate a physician on a PRW in the future as well as to use them in the future [32]. The study further showed that sociodemographic variables and health status alone did not satisfactorily predict usage or nonusage of PRWs, but that psychographic variables and variables of information-seeking behavior were needed to predict usage of PRWs [32].

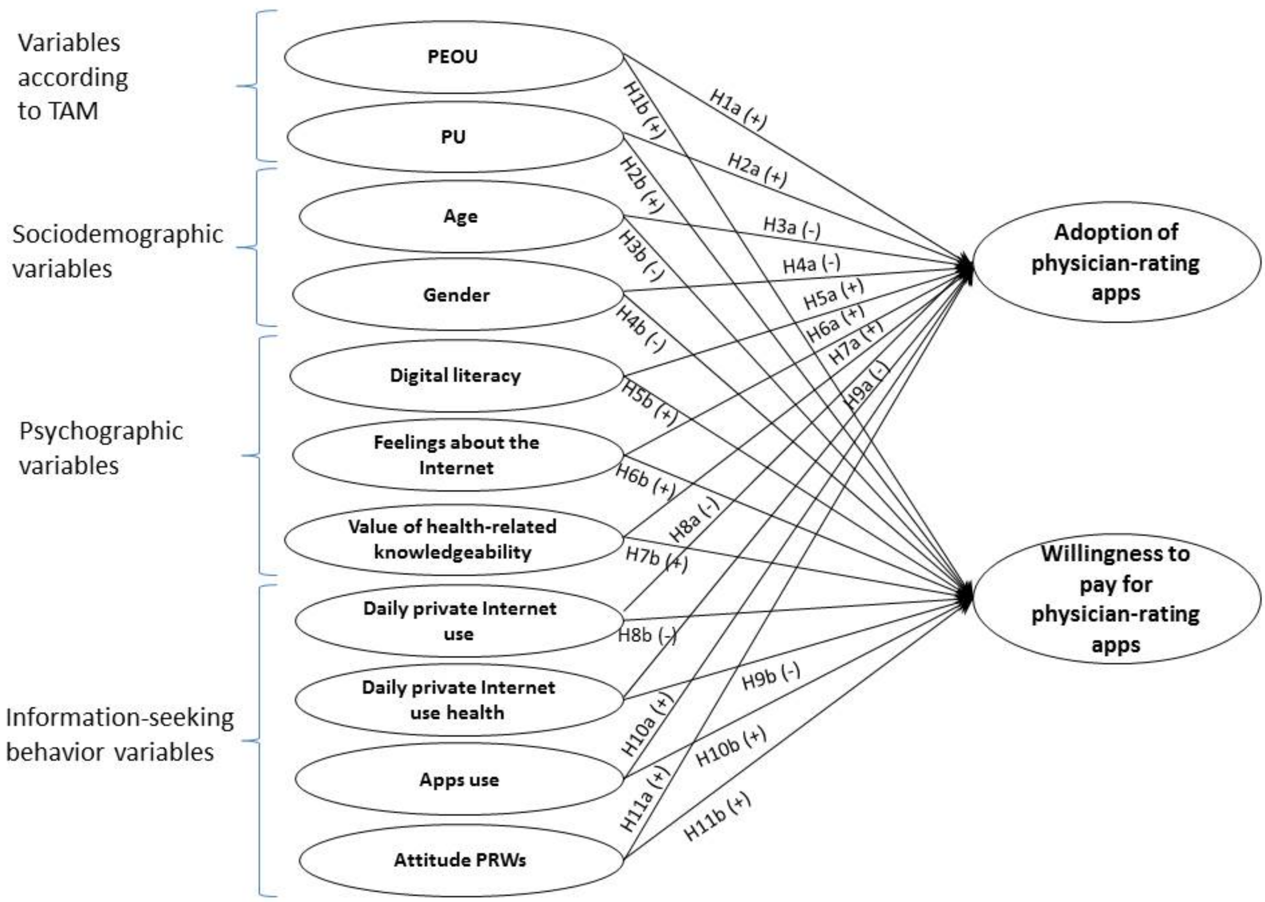
Applying PRWs through mobile apps could be a way to boost usage of PRWs in general. A mobile physician-rating app transfers existing functionality of PRWs to the mobile realm, possibly making it easier and more flexible for patients to both access information and provide information (rate a physician). Consequently, this paper aims at delivering important insights into the usage of mobile physician-rating apps by looking at what kind of variables explain adoption of mobile physician-rating apps. With this knowledge, creators of mobile physician-rating apps could better tailor them to the consumers’ characteristics and needs.

Because some of the apps are available free of charge, whereas others are only available at a cost (typically a relatively small fee), we are also interested in patients’ willingness to pay for mobile physician-rating apps.

## Conceptual Model

This study proposes a causal model consisting of different antecedents of adoption of mobile physician-rating apps and willingness to pay for them (Figure 1). A plus sign or minus sign signifies an increase or decrease, respectively, in the dependent variable evoked by an increase in the independent variable (ceteris paribus). The relationships and expected directions of influence are described in detail subsequently.

**Figure 1.** Theoretical model of adoption of physician-rating (PR) apps and willingness to pay for them showing various hypothesized (H) relationships. A plus or minus sign signifies an increase or decrease, respectively, in the dependent variable evoked by an increase in the independent variable (ceteris paribus). PEOU: perceived ease of use; PRW: physician-rating website; PU: perceived usefulness; TAM: Technology Acceptance Model.




## Technology Acceptance Model

The Technology Acceptance Model (TAM) [33,34], based on the Theory of Reasoned Action, is an applied and widely used model to describe and predict the acceptance and use of new information technology. The model focuses on what attributes of a certain technology increase the acceptance of a technology. According to TAM, acceptance of a technology depends on how the technology is perceived. TAM identified perceived usefulness and perceived ease of use (PEOU) as 2 central beliefs about a new technology which influence the attitude toward and the use of that technology [35-38]. The perceived usefulness is defined as "the user's perception of the degree to which using a particular system will improve her/his performance" [38]. The PEOU is defined as the "user's perception of the extent to which using a particular system will be free of effort" [38]. The TAM has been supported by many studies and has been applied in different contexts of online consumer behavior [39,40], including the area of health information websites [41] or mobile health services [42]. According to Kim and Chang [41], perceived usefulness and PEOU are "key factors in accepting information technology like health information service on the Internet." Given the broad support of PEOU and perceived usefulness for understanding acceptance of new technologies, the 2 constructs from TAM have been included in our model. In our study, we conceptualize perceived usefulness as the usefulness of the Internet to gain health-related information and PEOU as the perceived ease of use of the Internet to gain health-related information, and we expect both variables to have a significant impact on the adoption and willingness to pay for a mobile physician-rating app. It is hypothesized that:

H1a: Individuals ascribing higher ease of use (PEOU) to the Internet to gain health-related information are more likely to adopt a mobile physician-rating app.

H1b: Individuals ascribing higher ease of use (PEOU) to the Internet to gain health-related information are more willing to pay for a mobile physician-rating app.

H2a: Individuals ascribing higher usefulness to the Internet to gain health-related information are more likely to adopt a mobile physician-rating app.

H2b: Individuals ascribing higher usefulness to the Internet to gain health-related information are more likely to pay for a mobile physician-rating app.

In addition, we extended the model with variables related to health information search that were identified in an extensive literature review. Sociodemographic variables (eg, age, gender), psychographic variables (eg, digital literacy, feelings about the Internet and other Web-based applications in general, patients' value of health-related knowledgeability), and information-seeking behavior variables (eg, daily private Internet use and daily private Internet use for health-related information, frequency of using apps for health-related information in the past, attitude toward PRWs) were included in the final model.

## Sociodemographic Variables

### *Age*

Age is likely to be an important predictor of evaluation of and behavior toward mobile physician-rating apps. Similar to the use of the Internet in general [3,43-49], mobile Internet use also declines with increasing age. The German Digitalbarometer I/2012 reported that 44% of people in the age range of 14-29 years, 28% in the age range of 30-49 years, and 10% of people older than 50 years used apps [50]. In 2013, another German online study showed that the use of apps decreases continuously with rising age: 70% of people aged between 14 and 29 years used apps, 46% aged between 30 and 49 years, 24% aged between 50 and 69 years, and only 12% age 70 years and older [51]. Charness and Boot [52] identified attitudinal barriers, cognitive barriers (eg, fluid and crystallized intelligence, computer anxiety), as well as age-related changes (eg, in perceptual, cognitive, and motor systems) affecting technology use and greater privacy concerns that lead to the lag of older adults in technology adoption. Therefore, it can be suggested that:

H3a: Younger people are more likely to adopt a mobile physician-rating app than older people.

H3b: Younger people are more willing to pay for a mobile physician-rating app than older people.

### *Gender*

Even though women are typically more inclined to use the Internet for health-related information [2,53-59], when it comes to mobile usage of the Internet, men are more likely to use the Internet on their mobile phone than women, as reported in an European eHealth survey by Kummervold et al [60], for example. According to the German ARD/ZDF online study in 2013, 46% of men, but only 36% of women, were mobile users of the Internet [51]. Another German study in 2013 revealed that 58.7% of mobile Internet users were male and 41.3% were female [61]. The German Digitalbarometer I/2012 reported that 36% of men and 18% of women used apps [50]. One explanation for the higher usage of mobile devices and apps by men than by women may be lower levels of computer anxiety and higher perceived behavioral control by men than by women [62]. In summary, men consistently show higher levels of mobile Internet and app usage than women do. Therefore, we hypothesize that:

H4a: Men are more likely to adopt a mobile physician-rating app than women are.

H4b: Men are more likely to pay for a mobile physician-rating app than women are.

## Psychographic Variables

### *Digital Literacy*

Digital literacy describes the ability to effectively and critically use a range of digital technologies. High levels of digital literacy enable individuals to make responsible choices and to access information and ideas in the digital world and share them with others and it is deemed an important prerequisite in today's digital world [63]. High levels of literacy in the digital domain are seen as leading to many social and psychological benefits across the life span [64]. However, low levels of literacy can pose barriers to the access and use of health information and eHealth tools, especially if paired with low health literacy [65]. A digitally literate individual is able to make use of different technical devices and use these to his or her advantage. Therefore, we expect that a higher level of digital literacy likely leads to a higher affinity for new digital offers, especially when designed to facilitate the use of digital content, such as an app. In addition, it has been demonstrated that people with higher digital literacy show less computer anxiety [66], which also likely leads to greater openness toward new offers. Therefore, the following hypotheses can be assumed:

H5a: Individuals with a higher digital literacy are more likely to adopt a mobile physician-rating app.

H5b: Individuals with a higher digital literacy are more willing to pay for a mobile physician-rating app.

### *Feelings About the Internet and Other Web-Based Applications*

Whereas digital literacy primarily concerns the ability to make use of digital technologies and information, people also hold more or less positive or negative affective evaluations or feelings toward the Internet or other Web-based applications [39,67]. If they hold more favorable feelings, they are more likely willing to adopt new technologies. Thus, it can be suggested that:

H6a: Individuals with more positive feelings about the Internet and other Web-based applications in general are more likely to adopt a mobile physician-rating app.

H6b: Individuals with more positive feelings about the Internet and other Web-based applications in general are more willing to pay for a mobile physician-rating app.

### *Patients' Value of Health-Related Knowledgeability*

Literature has shown that the amount of information a person is seeking and the amount of cognitive effort and elaboration a person is willing to devote to a specific task may vary substantially based on the personality of the individual [40,68]. Whereas some patients are inclined to prepare themselves for visiting a doctor and search for health-related information, others search for health-related information to a lesser extent. Patients who value health-related knowledgeability more highly (eg, believe being well informed leads to better patient-physician communication or that the physician offers more time to well-informed patients) are inclined to make significant health decisions on the basis of health-related information found on the Internet [39,68]. They even decide whether professional medical care is needed; alternatively, they decide whether to rely on self-treatment based on their online findings [69]. Patients with a high value of health-related knowledgeability are used to searching for health-related information on the Internet to a greater extent than individuals who have a lower value of health-related knowledgeability. Therefore, these patients may evaluate a mobile physician-rating app to be a useful amendment to a health-related information search. This leads us to the following hypothesis:

H7a: Patients with a higher value of health-related knowledgeability are more likely to adopt a mobile physician-rating app.

H7b: Patients with a higher value of health-related knowledgeability are more willing to pay for a mobile physician-rating app.

### Information-Seeking Behavior Variables

#### *Daily Private Internet Use and Use for Health-Related Information*

According to a recent study conducted in Germany, 1 of the 2 main motivations for people to own a tablet personal computer or a smartphone that enables mobile access to the Internet is saving time [70]. Between 2011 and 2013, the number of respondents who used mobile Internet over their smartphone or mobile phone because they wanted to save time rose from 51.9% to 57.6% [71]. Because mobile access allows for fast and flexible access to the Internet, it can be assumed that people who have a strong motivation to save time spend less time on private Internet use in general and also on searching for health-related information on the Internet. In turn, we expect that people who spend less time on private Internet use in general and on searching for health-related information should be more interested in a physician-rating app because they may be under more time pressure and may be looking for fast alternatives to a health-related information search. This leads us to the following hypotheses:

H8a: Individuals with a higher amount of daily private Internet use in general are less likely to adopt a mobile physician-rating app.

H8b: Individuals with higher amount of daily private Internet use in general are less willing to pay for a mobile physician-rating app.

H9a: Individuals with a higher amount of daily private Internet use for health-related information search are less likely to adopt a mobile physician-rating app.

H9b: Individuals with higher amount of daily private Internet use for health-related information search are less likely to pay for a mobile physician-rating app.

#### *Past Use of Apps for Health-Related Information*

Patients can make use of different devices to search the Internet for health-related information, the most prominent being personal computer, laptop, smartphone, or mobile tablet computer. Apps are designed primarily for use with smartphones or mobile tablet computers, and along with the massive expansion of these mobile devices, usage of apps for different purposes has increased significantly. According to a study conducted in Germany in November 2012, there were 43.7 apps on average installed on an iPhone, 28 apps on an Android Smartphone, 32.9 apps on an iPad, and 36.1 apps on an Android Tablet [72], including apps for health and fitness issues. More than half of the apps installed were actually used by the consumer [72]. A systematic review investigating patient acceptance of consumer health information technology found out that prior experience or exposure to computer and/or health technology increases its acceptance [62]. Of the 20 studies investigating the effects of different dimensions of prior experience to computer/health technology, 15 confirmed that prior experience was associated with increased acceptance [62]. We can assume that individuals who already make use of health-related apps more frequently are probably more open toward a mobile physician-rating app. So we conclude from the usage of health-related apps to the likely usage of a mobile physician-rating app:

H10a: Individuals who use apps more frequently for health-related information in the past are more likely to adopt a mobile physician-rating app.

H10b: Individuals who use apps more frequently for health-related information in the past are more willing to pay for a mobile physician-rating app.

#### *Attitude Toward Physican Rating Websites*

We also assume a positive influence of the patients' attitude toward PRWs in general on patients' perception of physician-rating apps. If patients' overall attitude toward PRWs is positive, patients are likely to be more positive toward apps that facilitate access to the PRW. This leads us to the final hypotheses:

H11a: Individuals who have a better attitude toward PRWs are more likely to adopt a mobile physician-rating app.

H11b: Individuals who have a better attitude toward PRWs are more willing to pay for a mobile physician-rating app.

#### *Moderator Analysis: Users vs Nonusers of Physician-Rating Websites*

It might be expected that respondents who have already used PRWs on some technological (nonmobile) device in the past behave differently with regards to the adoption of mobile physician-rating apps than those who have no experience. Hence, we explore whether the usage of PRWs moderates the relationships in the conceptual model. According to Baron and Kenney [73], a moderator is a "qualitative (eg, sex, race, class) or quantitative (eg, level of reward) variable that affects the direction and/or strength of the relation between the independent or predictor variable and a dependent or criterion variable."

## Methods

### Participant Recruitment

An online survey of 1006 German patients was conducted in September 2012. The sample was drawn from an e-panel maintained by GfK HealthCare, a leading survey research company in Nuremberg, Germany. It was based on a randomly generated set of users who had visited a general practitioner at least once in the 3 months before the beginning of the survey. In all, 1561 people were contacted; 555 people could not participate because they had not visited a general practitioner within the past 3 months. The recruitment rate was 64.4% [74]. Another 20 participants were excluded from the analysis because of an extremely short response time and inconsistent answer patterns (eg, flatliners, contradictions). Another 28 respondents were excluded because their number of missing values exceeded the limit of 30% [75] in scale items. The final sample consisted of 958 participants. Small monetary incentives were offered for survey completion.

### Questionnaire

The survey was designed by the researchers based on the existing literature. All items (except categorizing variables) were measured with 7-point rating scales. For construct measures used in the final partial least squares (PLS) model and sociodemographic measures see Multimedia Appendix 1. Existing scales from the literature were used where applicable. The data were checked and missing values were imputed with SPSS version 20 (IBM Corp, Armonk, NY, USA). The data were analyzed by PLS path modeling with the software SmartPLS.

### Measurement Model

#### *Overview*

The PEOU and perceived usefulness of the Internet to gain health-related information were measured by existing multi-item scales derived and adapted from Venkatesh and Davis [36]; PEOU was entered into SmartPLS with 2 items, PU was entered with 3 items. Age and gender were measured by a single item (year of birth and gender, respectively). Digital literacy was measured with an item based on Norman and Skinner [76] (1=not literate at all, 7=very literate). Feelings about the Internet and other Web-based applications in general were measured by an item derived from Porter and Donthu [35] (1=very negative, 7=very positive). Patients' value of health-related knowledgeability was measured with a scale of 9 items, which was developed by the researchers. Some items were adapted from the health information orientation scale by Dutta-Bergman [77]. Exploratory factor analysis revealed a single factor solution, explaining 53.88% of variance. Factor loadings ranged from .639 to .807; Cronbach alpha was .892. Items were reduced for modeling. The 3 items with the highest outer weights were included in the final model. Total daily private Internet use in general and total daily Internet use for health-related information searches were measured in hours per day (or alternatively per week or per month) with 2 separate questions. Measures were subsequently recoded into the average measure of hours per day in general and hours per day for health-related information searches. The frequency of using apps for health-related information in the past was measured with the item "How often do you use apps for health-related information searching on the Internet?" (1=daily, 2=weekly, 3=less often than weekly, 4=monthly, 5=less often than monthly, 6=never). This variable was coded inversely; therefore, the variable was recoded before entering the SmartPLS model. Attitude toward PRWs was measured by 3 items representing trust in PRWs, utility of PRWs, and intention to use them in the future. All these questions had a "no answer" category as an alternative.

#### *Moderator Variable: Usage vs Nonusage of PRWs*

The moderator variable "experience with PRWs" was measured dichotomously with the following wording: "Have you ever gathered information about a physician on a physician-rating site?" (1=yes, 2=no, 3=no answer). A total of 15 respondents chose the no answer category and were excluded from the subsequent group comparisons.

#### *Endogenous Variables: Adoption of Physician-Rating Apps and Willingness to Pay for Them*

Respondents were asked to think of a mobile physician-rating app and decide how much they would appreciate it and how much they would pay for it. We asked respondents to imagine a physician-rating app for several reasons. First, as outlined by Emmert et al [28], PRW use is relatively low in general and usage would be even lower when we focused on mobile usage. Secondly, we wanted to avoid asking participants about a specific physician-rating app only because such apps differ in their quality and distribution and are not yet widespread. By describing a physician-rating app and asking participants to imagine it, we were able to realize a substantial number of evaluations and could base them on comparable stimuli. The following text was used as introduction: "Imagine that there exists an app for smartphones to search for physicians. The user could fill in a symptom of a condition and as a result all physicians in the surrounding area were listed, including the ratings of these physicians according to the satisfaction of the rating patients with him/her, with the atmosphere of the waiting room, waiting time, the treatment, et cetera."

Adoption of physician-rating apps was measured by asking respondents to indicate their agreement with the following 2 items on a 7-point rating scale (1=strongly disagree; 7=strongly agree): (1) I appreciate such an app, and (2) I am willing to use such an app.

Willingness to pay for physician-rating apps was measured by the item "I am willing to pay for such an app." Again, participants could indicate their agreement on a 7-point rating scale (1=strongly disagree; 7=strongly agree).

### Analytical Procedure

The causal relationships between the constructs were analyzed through structural equation modeling using the PLS approach, as implemented in the free software environment of SmartPLS [78]. PLS has found prevalent usage in the area of technology adoption and information systems literature [79], particularly because it is also well suited for research in its early stages when the focus is on saturated prediction-oriented models [80].

Bootstrapping with 5000 bootstrap samples to receive inference statistics was applied. To assess PLS path models, the results were evaluated in a 2-step process. First, the measurement models were analyzed, evaluating the reliability and validity of the estimates for the latent variables. Second, the structural (inner) model was assessed [81,82].

We calculated a PLS analysis for the total sample (N=958) and in a second step for the 2 groups of users (n=254) and nonusers (n=689) of PRWs. The quality of the fit of the measurement model was evaluated extensively and was based on the criteria formulated by Ringle et al [79]. Fit measures were calculated for the total sample and for both subsamples. Factor loadings, composite reliability, and average variance extracted were used to evaluate local fit of the constructs. The internal consistency reliability was evaluated using Cronbach alpha. Convergent validity was evaluated based on the average variance extracted. For assessing discriminant validity, the Fornell-Larcker criterion was applied [83]. Finally, multicollinearity was checked.

## Results

### Sample Characteristics

A comparison of the sample of the current study and the 2012 German Internet users (the German online population) [84] reveals that the sample represents the German online population quite well concerning the sociodemographic variables (Table 1). With regard to gender, the sample mirrors the German online population well. Regarding age, participants in our sample were slightly older than those in the German online population. The reason for this deviation lies probably in the selection criterion for participation; to qualify for our study, participants must have visited a general practitioner at least once in the previous 3 months. With regard to education, the percentage of respondents with higher education was larger in our sample than in the German online population. There were no comparable data in the German online population regarding marital status or household size.

**Table 1.** Overview of study sample in comparison with German Internet population (2012).

| Variable and category | Study sample data N=958 | German Internet users (rounded to 1000 people) N=57,045,000 |
|---|---|---|
| **Gender, n (%)** | | |
| Men | 517 (54.0) | 29,553,000 (51.8) |
| Women | 441 (46.0) | 27,492,000 (48.2) |
| **Age (years), mean (SD)** | 43.73 (13.0) | |
| Age limits (years) | 18-70 | >10 |
| **Age dichotomized, n (%)** | | |
| <44 years | 471 (49.2) | 32,896,000 (57.7) |
| 45-70 years | 487 (50.8) | 24,147,000 (42.3) |
| **Age categories (years), n (%)** | | |
| <24 | 81 (8.5) | 12,552,000 (22.0) |
| 25-44 | 390 (40.7) | 20,344,000 (35.6) |
| 45-64 | 431 (45.0) | 18,799,000 (33.0) |
| >65 | 56 (5.8) | 5,348,000 (9.4) |
| **Education, n (%)** | 951 (100.0) | 52,589,000 (100.0) |
| Without school qualification | 4 (0.4) | Low education: 9,487,000 (18.0) |
| Secondary general school | 13 (1.4) | |
| Polytechnic secondary school | 120 (12.5) | Medium education: 29,467,000 (56.0) |
| Intermediate secondary school | 269 (28.1) | |
| Matura examination or higher | 545 (57.0) | High education: 13,635,000 (26.0) |
| **Household, n (%)** | 956 (100) | |
| 1 | 207 (21.6) | |
| 2 | 363 (37.9) | |
| 3-4 | 355 (37.1) | |
| >4 | 31 (3.2) | |
| **Marital status, n (%)** | 948 (100.0) | |
| Single | 200 (20.9) | |
| Close-partnered | 215 (22.4) | |
| Married | 460 (48.0) | |
| Divorced | 64 (6.7) | |
| Widowed | 9 (0.9) | |

## Evaluation of the Measurement Model

The measurement models yielded adequate fit for the total sample and for users of PRWs and nonusers of PRWs groups (Tables 2 and 3). None of the local fit indicators of the measurement models, such as factor loading, composite reliability (CR), average variance extracted (AVE), were violated and values of Cronbach alpha were relatively high.

The Fornell-Larcker criterion [83] revealed that discriminant validity of the constructs is also supported. Each given construct is clearly different from the measures of other constructs [85]. The square roots of AVE values were all well above the values in the appropriate rows and columns of the correlation matrix of latent variables (Table 4). Further, cross loadings show that all items had the highest loadings on their respective construct and every construct loaded highest with its own items. Discriminant validity was also supported for the 2 subsamples.

**Table 2.** Fit of measurement model including factor loading, composite reliability (CR), average variance extracted (AVE), and Cronbach alpha of endogenous constructs for the final model in the total sample (N=958).

| Composite and item[a] | Mean (SD) | Loading | AVE | CR | Cronbach alpha |
|---|---|---|---|---|---|
| **PEOU** | | | | | |
| F11_1 | 6.26 (1.16) | 0.95 | 0.90 | 0.95 | .89 |
| F11_2 | 6.14 (1.17) | 0.95 | | | |
| **PU** | | | | | |
| F11_11 | 4.37 (1.97) | 0.85 | 0.74 | 0.89 | .82 |
| F11_12 | 4.10 (1.98) | 0.88 | | | |
| F11_15 | 3.85 (1.94) | 0.85 | | | |
| Age (S2_1) | 43.73 (13.04) | 1.00 | — | — | — |
| Gender (D1) | — | 1.00 | — | — | — |
| Digital literacy (F2_1) | 5.87 (1.06) | 1.00 | — | — | — |
| Feelings about the Internet (F1_1) | 5.78 (1.11) | 1.00 | — | — | — |
| **Value of health-related knowledgeability** | | | | | |
| F20_5 | 4.71 (1.71) | 0.78 | 0.74 | 0.89 | .82 |
| F20_8 | 3.37 (1.89) | 0.89 | | | |
| F20_9 | 3.61 (1.93) | 0.90 | | | |
| Daily private Internet use (F3_per day) | 3.10 (2.29) | 1.00 | — | — | — |
| Daily private Internet use health (F4_per day) | 0.43 (1.53) | 1.00 | — | — | — |
| Apps use (F7_10recoded) | — | 1.00 | — | — | — |
| **Attitude toward PRWs** | | | | | |
| F25_1 | 4.18 (2.00) | 0.93 | 0.87 | 0.95 | .93 |
| F26_1 | 4.27 (1.92) | 0.94 | | | |
| F27_1 | 3.59 (1.63) | 0.94 | | | |

[a] PEOU: perceived ease of use; PU: perceived usefulness. The denomination of measurement variables corresponds to the denomination of the items in Multimedia Appendix 1.

**Table 3.** Fit of measurement model including factor loading, composite reliability (CR), average variance extracted (AVE), and Cronbach alpha of endogenous constructs for the final model in the subsample of users of PRWs (n=254) and the subsample of nonusers of PRWs (n=689).

| Composite and item[a] | Mean (SD) | | Loading | | AVE | | CR | | Cronbach alpha | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Users | Nonusers | Users | Nonusers | Users | Nonusers | Users | Nonusers | Users | Nonusers |
| **PEOU** | | | | | | | | | | |
| F11_1 | 6.45 (0.95) | 6.21 (1.20) | 0.94 | 0.95 | 0.90 | 0.90 | 0.95 | 0.95 | .90 | .89 |
| F11_2 | 6.36 (0.91) | 6.07 (1.23) | 0.96 | 0.95 | | | | | | |
| **PU** | | | | | | | | | | |
| F11_11 | 4.48 (1.88) | 4.32 (2.01) | 0.81 | 0.86 | 0.71 | 0.75 | 0.88 | 0.90 | .80 | .83 |
| F11_12 | 4.21 (1.96) | 4.06 (1.99) | 0.87 | 0.88 | | | | | | |
| F11_15 | 4.03 (1.85) | 3.78 (1.98) | 0.85 | 0.84 | | | | | | |
| Age (S2_1) | 42.39 (12.92) | 44.37 (13.00) | 1.00 | 1.00 | — | — | — | — | — | — |
| Gender (D1) | — | — | 1.00 | 1.00 | — | — | — | — | — | — |
| Digital literacy (F2_1) | 6.09 (0.95) | 5.78 (1.09) | 1.00 | 1.00 | — | — | — | — | — | — |
| Feelings about the Internet (F1_1) | 5.97 (1.01) | 5.73 (1.12) | 1.00 | 1.00 | — | — | — | — | — | — |
| **Value of health-related knowledgeability** | | | | | | | | | | |
| F20_5 | 5.07 (1.57) | 4.58 (1.74) | 0.72 | 0.79 | 0.71 | 0.74 | 0.88 | 0.90 | .80 | .82 |
| F20_8 | 3.76 (1.87) | 3.21 (1.88) | 0.90 | 0.88 | | | | | | |
| F20_9 | 4.01 (1.93) | 3.45 (1.92) | 0.89 | 0.90 | | | | | | |
| Daily private Internet use (F3_per day) | 3.17 (2.04) | 3.05 (2.36) | 1.00 | 1.00 | — | — | — | — | — | — |
| Daily private Internet use health (F4_per day) | 0.55 (1.78) | 0.39 (1.44) | 1.00 | 1.00 | — | — | — | — | — | — |
| Apps use (F7_10recoded) | — | — | 1.00 | 1.00 | — | — | — | — | — | — |
| **Attitude toward PRWs** | | | | | | | | | | |
| F25_1 | 5.47 (1.44) | 3.71 (1.98) | 0.85 | 0.93 | 0.78 | 0.88 | 0.91 | 0.96 | .86 | .93 |
| F26_1 | 5.24 (1.45) | 3.91 (1.95) | 0.91 | 0.94 | | | | | | |
| F27_1 | 4.43 (1.32) | 3.28 (1.64) | 0.90 | 0.94 | | | | | | |

[a] PEOU: perceived ease of use; PU: perceived usefulness. The denomination of measurement variables corresponds to the denomination of the items in Multimedia Appendix 1.

**Table 4.** Correlation matrix of the latent constructs with square root of average variance extracted (AVE) in the diagonal (total sample).

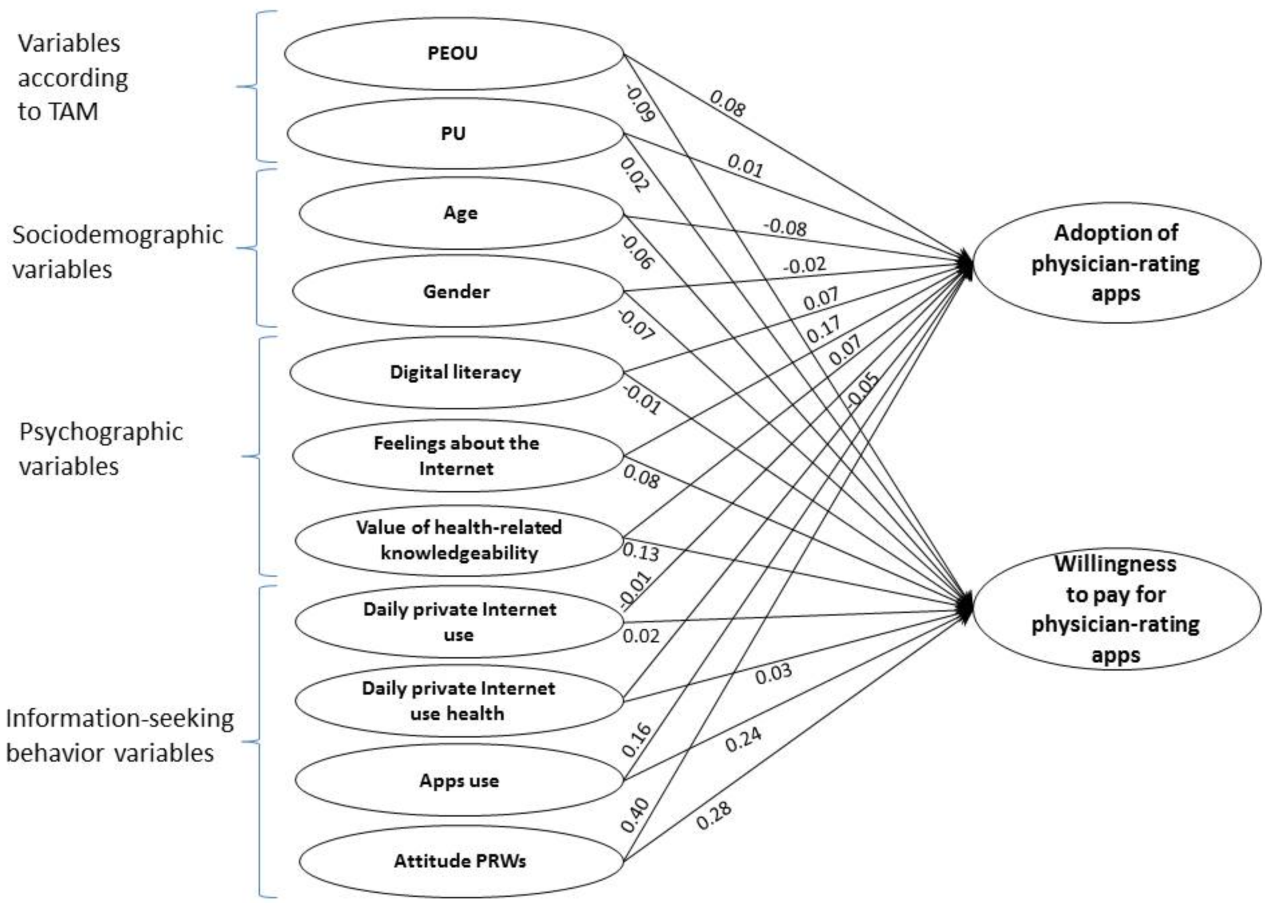
| | Construct[a] | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | PEOU | 0.94 | | | | | | | | | | | | |
| 2 | PU | 0.22 | 0.86 | | | | | | | | | | | |
| 3 | Age | 0.07 | –0.09 | — | | | | | | | | | | |
| 4 | Gender | 0.06 | 0.04 | –0.18 | — | | | | | | | | | |
| 5 | Digital literacy | 0.19 | 0.17 | –0.15 | –0.13 | — | | | | | | | | |
| 6 | Feelings about the Internet | 0.25 | 0.19 | –0.11 | –0.02 | 0.49 | — | | | | | | | |
| 7 | Value of health-related knowledgeability | 0.14 | 0.32 | 0.01 | 0.01 | 0.20 | 0.16 | 0.86 | | | | | | |
| 8 | Daily private Internet use | –0.01 | 0.20 | –0.19 | 0.03 | 0.18 | 0.18 | 0.16 | — | | | | | |
| 9 | Daily private Internet use health | –0.07 | 0.09 | –0.05 | 0.06 | 0.03 | 0.05 | 0.09 | 0.21 | — | | | | |
| 10 | Apps use | 0.29 | –0.11 | –0.27 | –0.05 | 0.21 | 0.24 | 0.23 | 0.15 | 0.17 | — | | | |
| 11 | Attitude toward PRWs | 0.26 | 0.34 | –0.07 | 0.06 | 0.18 | 0.20 | 0.46 | 0.10 | 0.16 | 0.19 | 0.93 | | |
| 12 | Adoption of physician-rating apps | 0.23 | 0.28 | –0.17 | –0.04 | 0.30 | 0.36 | 0.34 | 0.13 | 0.03 | 0.31 | 0.53 | — | |
| 13 | Willingness to pay for physician-rating apps | –0.01 | 0.24 | –0.16 | 0.03 | 0.16 | 0.20 | 0.33 | 0.15 | 0.13 | 0.37 | 0.39 | 0.53 | 0.97 |

[a] PEOU: perceived ease of use; PU: perceived usefulness.

## Evaluation of the Structural Model

Given that the measurement model yielded an acceptable fit, the structural model could be evaluated. The factors included in the conceptual model explained 40% of variance for adoption of physician-rating apps ($R^2$=.40) and 28% for willingness to pay for physician-rating apps ($R^2$=.28). Bootstrapping with 5000 samples revealed that 14 of 22 path coefficients of the conceptual model were significant. Figure 2 shows the results for model estimation of the total sample.

**Figure 2.** Structural model for the total sample. PEOU: perceived ease of use; PRW: physician-rating website; PU: perceived usefulness; TAM: Technology Acceptance Model.




## Evaluation of the Hypotheses

Hypotheses testing results are reported in Table 5. As can be seen from the standardized beta coefficients (B), the hypotheses H1a, H3a + b, H4a, H5a, H6a + b, H7a + b, H9a, H10a + b, H11a + b are supported. The results for the total sample reveals that the present attitude toward PRWs is the most important factor to predict adoption of physician-rating apps and willingness to pay for a physician-rating app. In addition, the frequency of the use of apps for health-related information in the past also predicts adoption of physician-rating apps and willingness to pay to a high degree. Feelings toward the Internet and other Web-based applications also have a significant influence on adoption of physician-rating apps and they also predict willingness to pay for physician-rating apps. The patients' value of health-related knowledgeability has a significant impact on adoption of physician-rating apps and an even stronger influence on willingness to pay for physician-rating apps. There is a significant positive influence of PEOU of the Internet to gain health-related information on adoption of mobile physician-rating apps and, in contrast to our initial predictions, a significantly negative influence on willingness to pay for physician-rating apps. As expected, age influences adoption and willingness to pay in a negative way (increasing age impedes willingness to adopt and to pay for physician-rating apps). Digital literacy has a significant, although weak, impact on the adoption of mobile physician-rating apps and no impact on willingness to pay. The daily Internet use for health-related information searches has significant impact on adoption of physician-rating apps, but not on willingness to pay for them. Gender influences adoption of a mobile physician-rating app and appears to affect willingness to pay for it although this was nonsignificant. As was expected, men were more prone to adopt physician-rating apps. In contrast to our initial predictions, perceived usefulness of the Internet to gain health-related information and the amount of daily private Internet use in general did not exert significant influence on the endogenous variables.

**Table 5.** Summary of partial least squares (PLS) estimation from the total sample (N=958).

| Hypothesis | Path[a] | B | $t_{941}$ | *P* (1-sided) | Hypothesis testing results |
|---|---|---|---|---|---|
| H1a | PEOU → adoption (+) | 0.08 | 3.26 | .001 | Supported |
| H1b | PEOU → willingness to pay (+) | –0.08 | 2.72 | .003 | Rejected |
| H2a | PU → adoption (+) | 0.01 | 0.33 | .37 | Rejected |
| H2b | PU → willingness to pay (+) | 0.03 | 0.83 | .30 | Rejected |
| H3a | Age → adoption (-) | –0.10 | 3.48 | <.001 | Supported |
| H3b | Age → willingness to pay (-) | –0.07 | 2.33 | .01 | Supported |
| H4a | Gender → adoption (-) | –0.07 | 2.58 | .01 | Supported |
| H4b | Gender → willingness to pay (-) | –0.05 | 1.59 | .06 | Rejected |
| H5a | Digital literacy → adoption (+) | 0.05 | 1.79 | .04 | Supported |
| H5b | Digital literacy → willingness to pay (+) | –0.02 | 0.50 | .31 | Rejected |
| H6a | Feelings → adoption (+) | 0.18 | 5.69 | <.001 | Supported |
| H6b | Feelings → willingness to pay (+) | 0.08 | 2.41 | .01 | Supported |
| H7a | Patients' value of health-related knowledgeability → adoption (+) | 0.07 | 2.09 | .02 | Supported |
| H7b | Patients' value of health-related knowledgeability → willingness to pay (+) | 0.13 | 3.70 | <.001 | Supported |
| H8a | Internet use → adoption (-) | 0.01 | 0.49 | .31 | Rejected |
| H8b | Internet use → willingness to pay (-) | 0.02 | 0.50 | .31 | Rejected |
| H9a | Internet use health → adoption (-) | –0.04 | 1.99 | .02 | Supported |
| H9b | Internet use health → willingness to pay (-) | 0.03 | 1.10 | .14 | Rejected |
| H10a | Apps use → adoption (+) | 0.15 | 5.19 | <.001 | Supported |
| H10b | Apps use → willingness to pay (+) | 0.23 | 6.16 | <.001 | Supported |
| H11a | Attitude PRWs → adoption (+) | 0.41 | 12.57 | <.001 | Supported |
| H11b | Attitude PRWs → willingness to pay (+) | 0.28 | 7.77 | <.001 | Supported |

[a] PEOU: perceived ease of use; PU: perceived usefulness. A plus sign or minus sign signifies an increase or decrease, respectively, in the dependent variable evoked by an increase in the independent variable (ceteris paribus).

## Group Comparisons: Usage vs Nonusage of Physician-Rating Websites

As outlined previously, a moderation analysis of usage of PRWs was carried out and the structural model was estimated for the 2 groups of users and nonusers of PRWs to explore whether the relationships in the model varied depending on the moderator variable. The model for users of PRWs explained 33% of variance for adoption of physician-rating apps ($R^2$=.33) and 27% for willingness to pay for physician-rating apps ($R^2$=.27), and the model for nonusers of PRWs explained 42% of variance for adoption of physician-rating apps ($R^2$=.42) and 28% for willingness to pay for physician-rating apps ($R^2$=.28).

A permutation test [86] was applied to examine the significance of group differences in path coefficients between the 2 subsamples. The path differences were tested running 1000 permutation samples for each model comparison [87]. The results can be seen in Table 6. The *P* value indicates the percentage of how many sampled path differences are greater or less than the observed path differences (2-sided test). The group comparison between users and nonusers of PRWs reveals that there was only one significant difference between the 2 groups demonstrating that the attitude toward PRWs has a stronger influence on adoption of a mobile physician-rating app and on willingness to pay for it, if the respondent had no experience with PRWs in the past. All other differences in the path coefficients were not significant.

**Table 6.** Model results including group comparisons of users and nonusers of physician-rating websites (PRWs).

| Hypothesis | Path description[a] | Users of PRW (n=254) | | Nonusers of PRWs (n=689) | | Differences (permutation test) | |
|---|---|---|---|---|---|---|---|
| | | B | *P* (1 sided) | B | *P* (1 sided) | B | *P* (2 sided) |
| H1a | PEOU → adoption (+) | 0.03 | .24 | 0.11 | <.001 | –0.08 | .19 |
| H1b | PEOU → willingness to pay (+) | –0.11 | .04 | –0.05 | .07 | –0.06 | .39 |
| H2a | PU → adoption (+) | 0.08 | .11 | –0.2 | .30 | 0.09 | .18 |
| H2b | PU → willingness to pay (+) | 0.08 | .11 | –0.01 | .38 | 0.09 | .22 |
| H3a | Age → adoption (-) | –0.17 | <.001 | –0.07 | .02 | –0.10 | .13 |
| H3b | Age → willingness to pay (-) | –0.12 | .01 | –0.04 | .10 | –0.08 | .23 |
| H4a | Gender → adoption (-) | –0.02 | .36 | –0.08 | .01 | 0.06 | .35 |
| H4b | Gender → willingness to pay (-) | –0.07 | .14 | –0.03 | .17 | –0.03 | .62 |
| H5a | Digital literacy → adoption (+) | 0.10 | .07 | 0.05 | .10 | 0.05 | .47 |
| H5b | Digital literacy → willingness to pay (+) | 0.03 | .33 | –0.03 | .23 | 0.06 | .42 |
| H6a | Feelings → adoption (+) | 0.21 | <.001 | 0.17 | <.001 | 0.04 | .61 |
| H6b | Feelings → willingness to pay (+) | 0.09 | .13 | 0.09 | .01 | 0.00 | .99 |
| H7a | Patients' value of health-related knowledgeability → adoption (+) | 0.08 | .09 | 0.06 | .06 | 0.02 | .81 |
| H7b | Patients' value of health-related knowledgeability → willingness to pay (+) | 0.22 | <.001 | 0.09 | .02 | 0.13 | .11 |
| H8a | Internet use → adoption (-) | 0.01 | .46 | –0.01 | .34 | 0.02 | .76 |
| H8b | Internet use → willingness to pay (-) | 0.02 | .39 | 0.02 | .27 | 0.00 | .97 |
| H9a | Internet use health → adoption (-) | –0.06 | .08 | –0.04 | .07 | –0.02 | .67 |
| H9b | Internet use health → willingness to pay (-) | 0.05 | .28 | 0.03 | .15 | 0.02 | .81 |
| H10a | Apps use → adoption (+) | 0.07 | .09 | 0.17 | <.001 | –0.10 | .12 |
| H10b | Apps use → willingness to pay (+) | 0.18 | .01 | 0.24 | <.001 | –0.06 | .49 |
| H11a | Attitude PRWs → adoption (+) | 0.27 | <.001 | 0.43 | <.001 | –0.16 | .03 |
| H11b | Attitude PRWs → willingness to pay (+) | 0.15 | .01 | 0.32 | <.001 | –0.17 | .04 |

[a] PEOU: perceived ease of use; PU: perceived usefulness. A plus sign or minus sign signifies an increase or decrease, respectively, in the dependent variable evoked by an increase in the independent variable (ceteris paribus).

## Discussion

### Principal Findings

The result of the current study and the empirical testing of the conceptual model using structural equation modeling yield some interesting results. First, the results indicate that the most important factors that predict adoption of physician-rating apps and willingness to pay for physician-rating apps are present attitudes toward PRWs in general as well as frequency of apps use for health-related information in the past. Hence, if individuals have a positive attitude toward PRWs, then they are also open to apps that enable mobile access to these PRWs, and they might even be willing to pay for such apps. Similarly, if individuals already make use of other health-related apps, then they are prone to make use of physician-rating apps too, and would even accept to be charged for them.

Secondly, according to TAM, it was hypothesized that perceived usefulness of the Internet to gain health-related information and PEOU of the Internet to gain health-related information exert an influence on adoption of physician-rating apps and on willingness to pay for physician-rating apps. As expected, PEOU had a significant positive impact on adoption of physician-rating apps, but a negative impact on willingness to pay for it, in contrast to our expectations. This means that ascribing higher PEOU to the Internet to gain health-related information leads to a higher willingness to adopt physician-rating apps, but to a diminished willingness to pay for them. A possible explanation for these findings might be that there is a trade-off between Internet accessed via laptop or personal computer and Internet accessed via smartphones or tablet computers. If someone judges the Internet to be easy to use for gaining health-related information, he/she may not be willing to pay extra for the same information delivered by another sort of technological device. Additionally, these findings might also be related to the fact that a higher amount of daily private Internet use for health-related information exerted a significant negative impact on adoption of a mobile physician-rating app (see H9a). Therefore, if someone is under time pressure he/she may find it more attractive to use a PRW app instead of looking at a PRW through Internet accessed via laptop or personal computer. On the other hand, someone who currently spends more time with convenient Internet access may be less interested in a physician-rating app because the quick and ubiquitous availability, which is offered only by the mobile solution of PRW usage, may be less important for him/her.

The path coefficients from perceived usefulness to both endogenous variables were not significant (H2a+b). The results indicate that when it comes to adoption of mobile physician-rating apps, PEOU of the Internet to gain health-related information search plays a more important role than perceived usefulness of the Internet to gain health-related information. Apps are typically designed for convenient use; hence, higher PEOU of the Internet to gain health-related information leads to higher propensity to adopt physician-rating apps.

Furthermore, in-line with prior studies on the influence of age and gender on the use of the Internet concerning health-related information, the results of our study demonstrate that younger patients are more willing to adopt physician-rating apps and to pay for them. Male patients were also more willing to pay for physician-rating apps, but these differences did not meet criteria for significance.

In addition, both digital literacy and positive (affective) feelings toward the Internet proved to exert influence on physician-rating apps adoption. As was expected, individuals with higher digital literacy may see more advantages with applying the new technology of apps for PRWs and therefore are more prone to use them. However, with regard to willingness to pay for the physician-rating apps, only positive feelings toward the Internet exerts a positive influence, whereas digital literacy does not.

Another interesting finding of the current study is that patients' value of health-related knowledgeability has a positive impact on adoption and willingness to pay. Physician-rating apps are probably perceived as devices that enable individuals to increase their knowledgeability about the physician. If patients think that being well informed is important to strengthen the communicative dimension of the relationship with the physician, mobile access to physician-related information via apps is appreciated. Interestingly, the influence of patients' knowledgeability on willingness to pay for physician-rating apps is even stronger.

The current study reveals that the amount of daily private Internet use in general does not predict adoption and willingness to pay for physician-rating apps. The amount of daily private Internet use for health-related information search proved to be a significant predictor for the adoption of mobile physician-rating apps, but not for willingness to pay. It may be assumed that people who spend a lot of time on the Internet for health-related information searches are less interested in fast access to PRWs via apps because they may perceive a less considerable time pressure. Apps are typically designed to allow for fast access so that less time would be needed for information searching and people under time pressure are more inclined to appreciate them. But time pressure may not necessarily lead to higher willingness to pay because PRWs are accessible via normal distribution channels (laptop, personal computer) without extra costs.

Finally, group comparisons between users and nonusers of PRWs demonstrate that there is only one moderating effect of PRW usage on one of the relationships. The influence of attitude toward PRWs on adoption of mobile physician-rating apps and willingness to pay for them is moderated by usage of PRWs. Among the group of nonusers, attitude toward PRWs has a higher influence on the 2 variables than among the group of users. This may be explained by the fact that users normally have a more positive attitude toward PRWs and a smaller variability in attitude than nonusers because of their experiential background. Therefore, the predictive power of attitude toward PRWs may be lower for adoption of physician-rating apps and willingness to pay for them in the group of users than in the group of nonusers.

### Limitations and Directions for Future Research

Some limitations to the study should be noted. There is the possibility of selection bias among respondents, although random selection out of the database is held to minimize its likelihood. The recruitment rate of 64% for this online panel sample also indicates that selection bias among respondents is probably low. A demographic comparison of our sample showed that there were slightly more men and older people as well as more higher educated respondents in the sample than in the average online population of Germany. Although the number of respondents was quite high, a larger randomized sample of the average online population would be desirable.

There are also limitations concerning the survey instrument. We asked about the intended use of a hypothetical mobile physician-rating app rather than use of an existing mobile physician-rating app. Asking for an existing mobile physician-rating app was not an option for us because usage of existing mobile physician-rating apps has been scarce; therefore, only a small number of people would have been able to answer our questions. In addition, by describing a physician-rating app and asking participants to imagine it, we avoided asking participants about one specific physician-rating app because such apps differ in their quality and distribution. To draw conclusions from hypothetical variables (eg, buying intentions) to real variables (buying of products) is a common phenomenon in many social sciences. Nevertheless, some uncertainty remains about transferring the results to existing mobile physician-rating apps. Future studies might focus on existing physician-rating apps once more of these apps are available and used to a larger extent.

### Conclusion and Practical Implications

This paper analyzes the use of PRWs through mobile apps in the future. More specifically, the study identifies antecedents of physician-rating apps adoption and of willingness to pay for such apps. A mobile physician-rating app allows for flexible access to PRWs, irrespective of the individual's location, and it may also be useful in certain circumstances (eg, when a patient is on a journey or a physician's practice is unexpectedly closed). Several sociodemographic, psychographic, and behavioral variables of Internet use contribute to the adoption of mobile physician-rating apps and willingness to pay for mobile physician-rating apps. With regard to sociodemographic variables, male and younger patients are more prone to adopt physician-rating apps. Therefore, these target groups of mobile physician-rating apps could be used as testimonials and promoters. The first step of enhancing awareness and adoption of physician-rating apps could be to promote the physician-rating apps through social media (eg, Facebook) and other Web-based communication channels that are often used by male and younger patients. Some psychographic variables (eg, digital literacy, feelings about the Internet and Web-based applications, and value of health-related knowledgeability) support proneness of future physician-rating apps adoption. Therefore, the communication concepts for the promotors and testimonials of physician-rating apps could be tailored more specifically. In a second step of innovation diffusion of physician-rating apps the results of this study are additionally useful for creators of mobile physician-rating apps and of PRWs in general. The results have shown that the PEOU of the Internet of health-related information is a valuable antecedent of physician-rating apps adoption. Therefore, the design of physician-rating apps as well as the accessibility, usability, and user-generated content should meet the users' requirements for further usage of physician-rating apps. The search functions should be kept simple for people who look for a physician via mobile physician-rating apps (eg, on smartphones) [88,89]. The results of this paper also reveal that an improvement of the attitude toward PRWs is also likely to lead to increased mobile physician-rating apps adoption; hence, enhancing trust in PRWs and increasing the usefulness of PRWs are critical factors for mobile physician-rating apps adoption. It might also be assumed that usage of physician-rating apps could boost the usage of PRWs in general so that PRWs could ultimately be more interesting for the populace. Additionally, higher awareness of PRWs would also lead to an even greater number of ratings per physician and the representativeness of PRWs could be enhanced. Therefore, the (nonmobile) usage of PRWs and physician-rating apps adoption are interdependent and are likely to benefit from each other.

## Acknowledgments

The authors are grateful to Martina Moick for her contribution in developing the questionnaire, and to GfK HealthCare Nuremberg, Germany, in particular Dr Susanna Meyer and Norbert Schell, for their contributions and for collecting the data for this analysis.

## Conflicts of Interest

None declared.

## Multimedia Appendix 1

Construct measures used in the final PLS model and sociodemographic measures of the study.

[PDF File (Adobe PDF File), 81KB - jmir_v16i6e148_app1.pdf ]

## References

1. Ozdalga E, Ozdalga A, Ahuja N. The smartphone in medicine: a review of current and potential use among physicians and students. J Med Internet Res 2012;14(5):e128 [FREE Full text] [doi: 10.2196/jmir.1994] [Medline: 23017375]
2. Sechrest RC. The internet and the physician-patient relationship. Clin Orthop Relat Res 2010 Oct;468(10):2566-2571 [FREE Full text] [doi: 10.1007/s11999-010-1440-3] [Medline: 20574803]
3. Fox S. The social life of health information. Washington, DC: Pew Internet & American Life Project; 2011 May 12. URL: http://www.pewinternet.org/~/media//Files/Reports/2011/PIP_Social_Life_of_Health_Info.pdf [accessed 2013-11-20] [WebCite Cache ID 6LGpMcwCG]
4. Free C, Phillips G, Felix L, Galli L, Patel V, Edwards P. The effectiveness of M-health technologies for improving health and health services: a systematic review protocol. BMC Res Notes 2010;3:250 [FREE Full text] [doi: 10.1186/1756-0500-3-250] [Medline: 20925916]
5. Boulos MNK, Wheeler S, Tavares C, Jones R. How smartphones are changing the face of mobile and participatory healthcare: an overview, with example from eCAALYX. Biomed Eng Online 2011 Apr 05;10:24 [FREE Full text] [doi: 10.1186/1475-925X-10-24] [Medline: 21466669]
6. Fox S, Duggan M. Mobile Health 2012. Washington, DC: Pew Internet & American Life Project; 2012 Nov 08. URL: http://www.pewinternet.org/files/old-media//Files/Reports/2012/PIP_MobileHealth2012_FINAL.pdf [accessed 2014-03-28] [WebCite Cache ID 6OPKPEoit]
7. Franko OI, Bhola S. iPad apps for orthopedic surgeons. Orthopedics 2011 Dec;34(12):978-981. [doi: 10.3928/01477447-20111021-37] [Medline: 22147214]
8. Perera C. The Evolution of E-Health – Mobile Technology and mHealth. Journal of Mobile Technology in Medicine 2012 Mar;1(1):1-2 [FREE Full text] [doi: 10.7309/jmtm.1]
9. Chun SG, Chung D, Shin YB. Issues in Information Systems. 2013. Are students satisfied with the use of smartphone apps? URL: http://iacis.org/iis/2013/247_iis_2013_23-33.pdf [accessed 2013-11-21] [WebCite Cache ID 6LHW33z8b]

10. Aitken M. Patient Apps for Improved Healthcare From Novelty to Mainstream. Parsippany, NJ: IMS Institute for Healthcare Infomatics; 2013. URL: http://www.imshealth.com/deployedfiles/imshealth/Global/Content/Corporate/IMS%20Health%20Institute/Reports/Patient_Apps/IIHI_Patient_Apps_Report.pdf [accessed 2013-11-19] [WebCite Cache ID 6LFPFCudB]
11. Leijdekkers P, Gay V. Mobile apps for chronic disease management: lessons learned from myFitnessCompanion®. Health and Technology 2013 Feb 15;3(2):111-118. [doi: 10.1007/s12553-013-0044-9]
12. research2guidance. Smartphone App Market Monitor: Germany. 2012 Oct. URL: http://www.research2guidance.com/shop/index.php/downloadable/download/sample/sample_id/234/ [accessed 2013-11-21] [WebCite Cache ID 6LHWthaFk]
13. Vitals. URL: http://www.vitals.com/ [accessed 2014-03-10] [WebCite Cache ID 6NyIlRbi2]
14. RateMDs. URL: http://www.ratemds.com [accessed 2014-03-10] [WebCite Cache ID 6NyIeuW8u]
15. Zocdoc. URL: http://www.zocdoc.com/ [accessed 2014-03-10] [WebCite Cache ID 6NyIwWYr8]
16. Healthgrades. URL: http://www.healthgrades.com/ [accessed 2014-03-10] [WebCite Cache ID 6NyJMG3C4]
17. Jameda. URL: http://www.jameda.de/ [accessed 2014-03-10] [WebCite Cache ID 6NyKNIw8f]
18. Docinsider. URL: http://www.docinsider.de/ [accessed 2014-03-28] [WebCite Cache ID 6OPLEioAB]
19. Imedo. URL: http://www.imedo.de/ [accessed 2014-03-28] [WebCite Cache ID 6OPLPEvn0]
20. Lagu T, Hannon NS, Rothberg MB, Lindenauer PK. Patients' evaluations of health care providers in the era of social networking: an analysis of physician-rating websites. J Gen Intern Med 2010 Sep;25(9):942-946 [FREE Full text] [doi: 10.1007/s11606-010-1383-0] [Medline: 20464523]
21. Reimann S, Strech D. The representation of patient experience and satisfaction in physician rating sites. A criteria-based analysis of English- and German-language sites. BMC Health Serv Res 2010 Jan;10(1):332 [FREE Full text] [doi: 10.1186/1472-6963-10-332] [Medline: 21138579]
22. López A, Detz A, Ratanawongsa N, Sarkar U. What patients say about their doctors online: a qualitative content analysis. J Gen Intern Med 2012 Jun;27(6):685-692 [FREE Full text] [doi: 10.1007/s11606-011-1958-4] [Medline: 22215270]
23. Skiba DJ. Nursing practice 2.0: the wisdom of crowds. Nurs Educ Perspect 2009 ;30(3):191-192. [Medline: 19606664]
24. Kofahl C, Nickel S, Trojan A. Arztsuche im Internet. In: Böcken J, Braun B, editors. Gesundheitsmonitor 2009. Gesundheitsversorgung und Gestaltungsoptionen aus der Perspektive der Bevölkerung. Gütersloh: Verlag Bertelsmann Stiftung; 2009:38-58.
25. Emmert M, Sander U, Esslinger AS, Maryschok M, Schöffski O. Public Reporting in Germany: the Content of Physician Rating Websites. Methods Inf Med 2012;51(2):112-120. [doi: 10.3414/ME11-01-0045] [Medline: 22101427]
26. Greaves F, Millett C. Consistently increasing numbers of online ratings of healthcare in England. J Med Internet Res 2012 Jun 29;14(3):e94 [FREE Full text] [doi: 10.2196/jmir.2157] [Medline: 22742977]
27. Strech D. Arztbewertungsportale aus ethischer Perspektive. Eine orientierende Analyse. [Physician rating sites from an ethical viewpoint: a roadmap]. Z Evid Fortbild Qual Gesundhwes 2010;104(8-9):674-681. [doi: 10.1016/j.zefq.2010.09.019] [Medline: 21129706]
28. Emmert M, Meier F, Pisch F, Sander U. Physician choice making and characteristics associated with using physician-rating websites: cross-sectional study. J Med Internet Res 2013 Aug 23;15(8):e187 [FREE Full text] [doi: 10.2196/jmir.2702] [Medline: 23985220]
29. Fox S, Purcell K. Chronic Disease and the Internet. Washington, DC: Pew Internet & American Life Project; 2010 Mar 24. URL: http://web.pewinternet.org/~/media/Files/Reports/2010/PIP_Chronic_Disease_with_topline.pdf [accessed 2014-04-10] [WebCite Cache ID 6OizFFwDX]
30. McKinlay J, Marceau L. When there is no doctor: reasons for the disappearance of primary care physicians in the US during the early 21st century. Soc Sci Med 2008 Nov;67(10):1481-1491 [FREE Full text] [doi: 10.1016/j.socscimed.2008.06.034] [Medline: 18701201]
31. McMullan M. Patients using the Internet to obtain health information: how this affects the patient-health professional relationship. Patient Educ Couns 2006 Oct;63(1-2):24-28. [doi: 10.1016/j.pec.2005.10.006] [Medline: 16406474]
32. Terlutter R, Bidmon S, Röttl J. Who uses physician-rating websites? Differences in sociodemographic variables, psychographic variables, and health status of users and nonusers of physician-rating websites. J Med Internet Res 2014 Mar 31;16(3):e97 [FREE Full text] [doi: 10.2196/jmir.3145] [Medline: 24686918]
33. Davis FD, Bagozzi RP, Warshaw PR. User Acceptance of Computer Technology: A Comparison of Two Theoretical Models. Management Science 1989 Aug;35(8):982-1003 [FREE Full text] [doi: 10.1287/mnsc.35.8.982]
34. Davis FD. A technology acceptance model for empirically testing new end-user information systems: theory and results (PhD dissertation). Cambridge, MA: MIT Sloan School of Management; 1986. URL: http://dspace.mit.edu/handle/1721.1/15192 [accessed 2014-05-29] [WebCite Cache ID 6Pvwb5Y2O]
35. Porter CE, Donthu N. Using the technology acceptance model to explain how attitudes determine Internet usage: The role of perceived access barriers and demographics. Journal of Business Research 2006;59(9):999-1007 [FREE Full text] [doi: 10.1016/j.jbusres.2006.06.003]
36. Venkatesh V, Davis FD. A model of the antecedents of perceived ease of use: Development and test. Decision Sciences 1996 Sep;27(3):451-481. [doi: 10.1111/j.1540-5915.1996.tb00860.x]

37. Davis FD, Venkatesh V. A critical assessment of potential measurement biases in the technology acceptance model: three experiments. International Journal of Human-Computer Studies 1996 Jul;45(1):19-45. [doi: 10.1006/ijhc.1996.0040]
38. Subramanian GH. A replication of perceived usefulness and perceived ease of use measurement. Decision Sciences 1994 Sep;25(5-6):863-874. [doi: 10.1111/j.1540-5915.1994.tb01873.x]
39. Moick M, Terlutter R. Physicians' motives for professional internet use and differences in attitudes toward the internet-informed patient, physician-patient communication, and prescribing behavior. Medicine 2.0 2012 Jul 06;1(2):e2 [FREE Full text] [doi: 10.2196/med20.1996]
40. Cacioppo JD, Petty RE. The need for cognition. Journal of Personality and Social Psychology 1982 Jan;42(1):116-131. [doi: 10.1037/0022-3514.42.1.116]
41. Kim D, Chang H. Key functional characteristics in designing and operating health information websites for user satisfaction: an application of the extended technology acceptance model. Int J Med Inform 2007 ;76(11-12):790-800. [doi: 10.1016/j.ijmedinf.2006.09.001] [Medline: 17049917]
42. Sun Y, Wang N, Guo X, Peng Z. Understanding the acceptance of mobile health services: a comparison and integration of alternative models. Journal of Electronic Commerce Research 2013;14(2):183-200 [FREE Full text]
43. Internet Access - Households and Individuals 2012. London, UK: Office for National Statistics; 2012 Aug. URL: http://www.ons.gov.uk/ons/dcp171778_275775.pdf [accessed 2013-11-21] [WebCite Cache ID 6LHYJBezE]
44. Smith-Barbaro PA, Licciardone JC, Clarke HF, Coleridge ST. Factors associated with intended use of a Web site among family practice patients. J Med Internet Res 2001 ;3(2):e17 [FREE Full text] [doi: 10.2196/jmir.3.2.e17] [Medline: 11720959]
45. Iverson SA, Howard KB, Penney BK. Impact of internet use on health-related behaviors and the patient-physician relationship: a survey-based study and review. J Am Osteopath Assoc 2008;108(12):699-711 [FREE Full text] [Medline: 19075034]
46. Houston TK, Allison JJ. Users of Internet health information: differences by health status. J Med Internet Res 2002 ;4(2):e7 [FREE Full text] [doi: 10.2196/jmir.4.2.e7] [Medline: 12554554]
47. Smith RP, Devine P, Jones H, DeNittis A, Whittington R, Metz JM. Internet use by patients with prostate cancer undergoing radiotherapy. Urology 2003 Aug;62(2):273-277. [doi: 10.1016/S0090-4295(03)00251-6] [Medline: 12893334]
48. Campbell RJ, Harris KD, Wabby J. The internet and locus of control in older adults. 2002 Jan Presented at: Annual Symposium AMIA; November 9-13, 2002; San Antonio, TX p. 96-100 URL: http://www.ncbi.nlm.nih.gov/pmc/articles/PMC2244513/pdf/procamiasymp00001-0137.pdf
49. Cutler SJ, Hendricks J, Guyer A. Age differences in home computer availability and use. The Journals of Gerontology Series B: Psychological Sciences and Social Sciences 2003 Sep 01;58(5):271-280. [doi: 10.1093/geronb/58.5.S271]
50. TNS Emnid. DigitalBarometer 1/2012: Mobiles Internet. 2012 Jun. URL: http://www.tns-emnid.com/presse/pdf/presseinformationen/DigitalBarometer2012_TNS_Emnid.pdf [accessed 2013-11-21] [WebCite Cache ID 6LHZWmmMn]
51. van Eimeren B. Media Perspektiven. 2013. "Always on" - Smartphone, Tablet & Co als neue Taktgeber im Netz URL: http://www.media-perspektiven.de/uploads/tx_mppublications/0708-2013_Eimeren_Frees_01.pdf [accessed 2013-11-21] [WebCite Cache ID 6LHZaWeHA]
52. Charness N, Boot WR. Aging and information technology use potential and barriers. Current Directions in Psychological Science 2009 Oct;18(5):253-258 [FREE Full text] [doi: 10.1111/j.1467-8721.2009.01647.x]
53. Eysenbach G. Infodemiology: tracking flu-related searches on the web for syndromic surveillance. AMIA Annual Symposium Conference Proceeding 2006 Jan:244-248 [FREE Full text]
54. Gao GG, McCullough JS, Agarwal R, Jha AK. A changing landscape of physician quality reporting: analysis of patients' online ratings of their physicians over a 5-year period. J Med Internet Res 2012 Feb;14(1):e38 [FREE Full text] [doi: 10.2196/jmir.2003] [Medline: 22366336]
55. Gunter J. OBG Management. 2011 Mar. For better or, maybe, worse, patients are judging your care online URL: http://www.stg.obgmanagement.com/pdf/2303/2303OBG_Gunter.pdf [accessed 2013-11-21] [WebCite Cache ID 6LHaNkefl]
56. Lagu T, Lindenauer PK. Putting the public back in public reporting of health care quality. JAMA 2010 Oct 20;304(15):1711-1712. [doi: 10.1001/jama.2010.1499] [Medline: 20959582]
57. Marton C, Choo CW. A review of theoretical models of health information seeking on the web. Journal of Documentation 2012;68(3):330-352. [doi: 10.1108/00220411211225575]
58. Wicks P, Massagli M, Frost J, Brownstein C, Okun S, Vaughan T, et al. Sharing health data for better outcomes on PatientsLikeMe. J Med Internet Res 2010 ;12(2):e19 [FREE Full text] [doi: 10.2196/jmir.1549] [Medline: 20542858]
59. Kim J, Park HA. Development of a health information technology acceptance model using consumers' health behavior intention. J Med Internet Res 2012 ;14(5):e133 [FREE Full text] [doi: 10.2196/jmir.2143] [Medline: 23026508]
60. Kummervold PE, Chronaki CE, Lausen B, Prokosch HU, Rasmussen J, Santana S, et al. eHealth trends in Europe 2005-2007: a population-based survey. J Med Internet Res 2008 Nov 17;10(4):e42 [FREE Full text] [doi: 10.2196/jmir.1023] [Medline: 19017584]
61. Statista-Dossier zum Thema Mobiles Advertising. 2013. Mobiles Internet - Statista-Dossier 2013 URL: http://de.statista.com/statistik/studie/id/13136/dokument/mobiles-internet--statista-dossier-2013/ [accessed 2014-05-26] [WebCite Cache ID 6Prz3C4C6]
62. Or CKL, Karsh BT. A systematic review of patient acceptance of consumer health information technology. J Am Med Inform Assoc 2009 ;16(4):550-560 [FREE Full text] [doi: 10.1197/jamia.M2888]

63. Hobbs R. Digital and media literacy: A plan of action. Washington, DC: The Aspen Institute; 2010. URL: http://www.knightcomm.org/wp-content/uploads/2010/12/Digital_and_Media_Literacy_A_Plan_of_Action.pdf [accessed 2013-11-19] [WebCite Cache ID 6LFRHQnz3]
64. Poynton TA. Computer literacy across the lifespan: a review with implications for educators. Computers in Human Behavior 2005 Nov;21(6):861-872. [doi: 10.1016/j.chb.2004.03.004]
65. Chang BL, Bakken S, Brown SS, Houston TK, Kreps GL, Kukafka R, et al. Bridging the digital divide: reaching vulnerable populations. J Am Med Inform 2004 ;11:448-457. [doi: 10.1197/jamia.M1535]
66. Beckers J, Schmidt H. The structure of computer anxiety: a six-factor model. Computers in Human Behavior 2001 Jan;17(1):35-49. [doi: 10.1016/S0747-5632(00)00036-4]
67. Durndell A, Haag Z. Computer self efficacy, computer anxiety, attitudes towards the Internet and reported experience with the Internet, by gender, in an East European sample. Computers in Human Behavior 2002 Sep;18(5):521-535. [doi: 10.1016/S0747-5632(02)00006-7]
68. Petty RE, Briñol P, Loersch C, McCaslin MJ. The need for cognition. In: Leary M, Hoyle R, editors. Handbook of Individual Differences in Social Behavior. New York: The Guilford Press; 2009:318-329.
69. Goonawardene N N, Jiang T, Tan SSL, Jiang Z. Pacific Asia Conference on Information Systems. 2013. Online health information seeking and adolescents' intention towards health self-management URL: http://www.pacis-net.org/file/2013/PACIS2013-174.pdf [accessed 2013-11-21] [WebCite Cache ID 6LHbUdhqr]
70. TOMORROW Focus Media. Mobile Effects 2012: Special edition Vol 1. 2012. URL: http://www.tomorrow-focus-media.de/uploads/tx_mjstudien/MobileEffects_2012_SpecialEdition_Vol1.pdf [accessed 2013-11-21] [WebCite Cache ID 6LHbaEIGr]
71. TOMORROW Focus Media. Mobile Effects 2013-1. A part of our lifes: Mobiles Internet begleitet den Alltag. 2013 Feb. URL: http://www.tomorrow-focus-media.de/uploads/tx_mjstudien/TFM_Mobile_Effects_2013-01.pdf [accessed 2013-11-21] [WebCite Cache ID 6LHbeNRdr]
72. Focus - Statista. Focus App Charts - App Monitor Deutschland 2013. 2013 Aug. URL: http://statista-research.com/wp-content/uploads/2013/07/Leseprobe-App-Monitor-Deutschland-2013.pdf [accessed 2013-11-19] [WebCite Cache ID 6LFOlDhII]
73. Baron R, Kenny DA. The moderator-mediator variable distinction in social psychological research: conceptual, strategic, and statistical considerations. Journal of Personality and Social Psychology 1986;51(6):1123-1182 [FREE Full text] [doi: 10.1037/0022-3514.51.6.1173]
74. Eysenbach G. Improving the quality of Web surveys: the Checklist for Reporting Results of Internet E-Surveys (CHERRIES). J Med Internet Res 2004 Sep 29;6(3):e34 [FREE Full text] [doi: 10.2196/jmir.6.3.e34] [Medline: 15471760]
75. Wirtz M. Über das Problem fehlender Werte: Wie der Einfluss fehlender Informatione auf Analyseergebnisse entdeckt und reduziert werden kann. On the problem of missing data: How to identify and reduce the impact of missing data on findings of data analysis. Rehabilitation 2004 Apr;43(2):109-115. [doi: 10.1055/s-2003-814839] [Medline: 15100920]
76. Norman CD, Skinner HA. eHealth Literacy: Essential Skills for Consumer Health in a Networked World. J Med Internet Res 2006 ;8(2):e9 [FREE Full text] [doi: 10.2196/jmir.8.2.e9] [Medline: 16867972]
77. Dutta-Bergman MJ. Health attitudes, health cognitions, and health behaviors among Internet health information seekers: population-based survey. J Med Internet Res 2004 ;6(2):e15 [FREE Full text] [doi: 10.2196/jmir.6.2.e15]
78. Hansmann KW, Ringle CM. SmartPLS manual. Hamburg: University of Hamburg; 2004. URL: http://mis.mju.ac.kr/~servor/notes/adv_research_methods/lectures/3_SmartPLS%20User%20Guide.pdf [accessed 2014-05-27] [WebCite Cache ID 6Ps42aCBs]
79. Ringle CM, Sarstedt M, Straub DW. MIS Quarterly. 2012. A critical look at the use of PLS-SEM in MIS Quarterly URL: http://dl.acm.org/citation.cfm?id=2208956 [accessed 2014-05-26] [WebCite Cache ID 6Ps1pIIPH]
80. Okazaki S, Castañeda JA, Sanz S, Henseler J. Factors affecting mobile diabetes monitoring adoption among physicians: questionnaire study and path model. J Med Internet Res 2012 Jan 21;14(6):e183 [FREE Full text] [doi: 10.2196/jmir.2159] [Medline: 23257115]
81. Henseler J, Ringle CM, Sinkovics RR. The use of partial least squares path modeling in international marketing. Adv Int Mark 2009;20(4):277-319.
82. Chin WW. Handbook of Partial Least Squares: Concepts, Methods and Applications. Berlin: Springer Verlag; 2010. How to write up and report PLS analyses URL: http://www.cob.unt.edu/slides/Paswan/BUSI6280/Handbook%20of%20Partial%20Least%20Squares%20Concepts,%20Methods%20and%20Applications.pdf [accessed 2014-05-27] [WebCite Cache ID 6Ps2LjFOn]
83. Fornell C, Larcker DF. Evaluating structural equation models with unobservable variables and measurement errors. Journal of Marketing Research 1981;18(1):39-50 [FREE Full text]
84. Statistisches Bundesamt. Wirtschaftsrechnungen. Private Haushalte in der Informationsgesellschaft - Nutzung von Informations- und Kommunikationstechnologien. 2012. URL: https://www.destatis.de/DE/Publikationen/Thematisch/EinkommenKonsumLebensbedingungen/PrivateHaushalte/PrivateHaushalteIKT2150400127004.pdf?__blob=publicationFile [accessed 2014-03-28] [WebCite Cache ID 6OPPC4HiD]
85. Hulland J. Use of partial least squares PLS in strategic management research: a review of four recent studies. Strateg Manag J 1999;20(2):195-204. [doi: 10.1002/(SICI)1097-0266(199902)]

86. Wdowiak MA, Schwarz EJ, Breitenecker RJ, Wright RW. Linking the cultural capital of the entrepreneur and early performance of new ventures: A cross-country comparison. Journal for East European Management Studies 2012;17(2):149-183 [FREE Full text]
87. Dibbern J, Chin WW. Using a permutation based approach. In: Bliemel F, Eggert A, Fassott G, Henseler J, editors. Handbuch PLS Pfadmodellierung: Methode, Anwendung, Praxisbeispiele. Stuttgart: Schäffer-Pöschel; 2005:139-159.
88. Layon KD. The Web Designer's Guide to iOS Apps: Create iPhone, iPod touch, and iPad apps with Web Standards (HTML5, CSS3, and JavaScript) (Voices That Matter). Berkeley: New Riders Press; 2010.
89. Pawer V. Web Application Design Patterns. San Diego: Morgan Kaufmann; Feb 2009.

## Abbreviations

**AVE:** average variance extracted
**CR:** composite reliability
**PEOU:** perceived ease of use
**PLS:** partial least squares
**PRW:** physician-rating website
**TAM:** Technology Acceptance Model

*Edited by G Eysenbach; submitted 21.11.13; peer-reviewed by M Emmert, U Sander, J Castañeda; comments to author 11.02.14; revised version received 10.04.14; accepted 27.04.14; published 11.06.14.*

*Please cite as:*
*Bidmon S, Terlutter R, Röttl J*
*What Explains Usage of Mobile Physician-Rating Apps? Results From a Web-Based Questionnaire*
*J Med Internet Res 2014;16(6):e148*
*URL: http://www.jmir.org/2014/6/e148/*
*doi:10.2196/jmir.3122*
*PMID:24918859*

Viewpoint

# The Behavioral Intervention Technology Model: An Integrated Conceptual and Technological Framework for eHealth and mHealth Interventions

David C Mohr[1], PhD; Stephen M Schueller[1], PhD; Enid Montague[2], PhD; Michelle Nicole Burns[1], PhD; Parisa Rashidi[3], PhD

[1]Center for Behavioral Intervention Technologies, Department of Preventive Medicine, Northwestern University, Chicago, IL, United States

[2]Center for Behavioral Intervention Technologies, Department of Medicine, Division of General Internal Medicine, Northwestern University, Chicago, IL, United States

[3]Department of Biomedical Engineering, University of Florida, Gainsville, FL, United States

**Corresponding Author:**
David C Mohr, PhD
Center for Behavioral Intervention Technologies
Department of Preventive Medicine
Northwestern University
680 N Lakeshore Drive, Suite 1400
Chicago, IL, 60611
United States
Phone: 1 312 503 1403
Fax: 1 312 503 0982
Email: d-mohr@northwestern.edu

**Related Article:**

Letter: http://www.jmir.org/2014/8/e188/

## Abstract

A growing number of investigators have commented on the lack of models to inform the design of behavioral intervention technologies (BITs). BITs, which include a subset of mHealth and eHealth interventions, employ a broad range of technologies, such as mobile phones, the Web, and sensors, to support users in changing behaviors and cognitions related to health, mental health, and wellness. We propose a model that conceptually defines BITs, from the clinical aim to the technological delivery framework. The BIT model defines both the conceptual and technological architecture of a BIT. Conceptually, a BIT model should answer the questions why, what, how (conceptual and technical), and when. While BITs generally have a larger treatment goal, such goals generally consist of smaller intervention aims (the "why") such as promotion or reduction of specific behaviors, and behavior change strategies (the conceptual "how"), such as education, goal setting, and monitoring. Behavior change strategies are instantiated with specific intervention components or “elements” (the "what"). The characteristics of intervention elements may be further defined or modified (the technical "how") to meet the needs, capabilities, and preferences of a user. Finally, many BITs require specification of a workflow that defines when an intervention component will be delivered. The BIT model includes a technological framework (BIT-Tech) that can integrate and implement the intervention elements, characteristics, and workflow to deliver the entire BIT to users over time. This implementation may be either predefined or include adaptive systems that can tailor the intervention based on data from the user and the user’s environment. The BIT model provides a step towards formalizing the translation of developer aims into intervention components, larger treatments, and methods of delivery in a manner that supports research and communication between investigators on how to design, develop, and deploy BITs.

***(J Med Internet Res 2014;16(6):e146)*** doi:10.2196/jmir.3077

**KEYWORDS**

mhealth; ehealth; behavioral intervention technology

## Background and Purpose

A growing number of investigators have commented on the lack of models informing the design of behavioral intervention technologies (BITs) [1]. We use the term BITs to refer to behavioral and psychological interventions that use a broad range of technologies, such as mobile phones, the Web, and sensors, aimed at changing behaviors and cognitions related to health, mental health, and wellness [2]. To date, some BITs use psychological models, such as the Theory of Planned Behavior or Social Cognitive Theory, to inform design [3]. While these models are useful in describing the types of behavioral and cognitive changes required of users in their environments to achieve clinical targets, they offer little information on how to design and implement BITs to ensure that they are useful and usable [1]. Specifically, these models are limited in at least two ways. First, they focus on clinical outcomes, which are often more distal to the behavioral targets of specific BIT interventions and are unlikely to change within the timeframe necessary to inform design considerations or to submit BITs to rapid development, evaluation, and iteration [4]. Second, purely psychological models do not include critically important factors that can guide the design and specifications for a BIT.

The purpose of this paper is to describe a BIT model that supports the translation of the clinical aims of a BIT treatment and its intervention components into BIT features. The BIT model proposed here is intended to provide a broad hybrid framework that combines behavioral principles with technological features that can help bridge the fields of behavioral science and technology. Experts from both fields contribute to the development of BITs, but the vastly different training and knowledge backgrounds have led to differences in conceptual models that guide development and evaluation. A framework that integrates behavioral science, design, and engineering can support the definition of systems in terms of testable hypotheses that could then be evaluated. This would help avoid the all-too-common process of developing BITs that ignore psychological or engineering principles or that rely entirely on developer intuition [1,3].

## Review of Existing Models

### Overview

We review here three design models proposed by Ritterband [5], Fogg [6], and Oinas-Kukkonen [7,8] that have informed the development of BITs. This review is intended to provide a context for the proposed BIT model and not as an exhaustive review and critique of theoretical models used to inform the development of BITs. Other sources provide a more exhaustive review of the different models of behavior change used to inform BITs development [3,9].

### Ritterband

Ritterband provided one of the first generalizable models depicting how a Web-based intervention contributes to symptom change [5]. The model posits that website design, human support (eg, a coach or therapists), user characteristics, and environmental factors contribute to website use, which in turn leads to behavior change and ultimately symptom improvement. The model also describes, although does not categorize, attributes of a website including intervention components (eg, media, messaging, assessment) and quality attributes (eg, appearance, difficulty of use, accuracy of information) intended to support behavior change.

The Ritterband model is useful, as it specifies the elements and characteristics to consider when designing an intervention website. Many elements of the model could also be applicable to other technologies, such as mobile devices. However, the Ritterband model does not articulate how technological components might be mapped onto more specific (and proximal) intervention goals, which is important in intervention design. Furthermore, while Ritterband emphasizes that the model is not necessarily linear (eg, components do not necessarily need to be deployed sequentially), the non-linear properties are not articulated. These non-linear properties are increasingly important as technologies are able to receive and react to data obtained from the user, the user's environment, and third parties such as a health care system or coaches.

### Fogg Behavioral Model

The Fogg Behavior Model [6] is a model for understanding behavior change that identifies the factors that control whether a behavior is performed. As it focuses on specific behaviors, it is most applicable to changing small, clearly defined behaviors, which he refers to as "tiny habits". The model does not purport to guide applications focused on changing attitudes or cognitions nor does it guide applications that target more complex treatment goals. Fogg focuses on three constructs: motivation, ability, and triggers. Motivation and ability are inversely related such that simpler behaviors require lower levels of motivation to initiate. Triggers are events in the environment (or from an intervention) that elicit the behavior at a given level of motivation. Fogg does not believe that technologies are particularly effective at teaching new behaviors, rather, he argues that they are best suited to simplifying tasks, thereby increasing ability and providing triggers that might initiate the desired behavior when applied at the appropriate time (ie, when appropriate given the level of ability and motivation). He argues that the best design of BITs is to be responsive to an individual's motivation and to adapt the behavior (through simplification) or the environment (through triggers) appropriately. A key requirement of Fogg's model is that the initial target behavior be small; larger behavioral goals can be achieved through the concatenation of smaller goals.

Fogg's model is elegantly simple and very useful within the constraints he outlines. However, the restricted focus does not fit the goals of many treatment interventions that attempt to address more complex problems such as reducing symptoms of depression or anxiety, treating insomnia, improving self-management of chronic illnesses, coping with addictions, or implementing healthy lifestyle programs. Users may not know what steps to take to attain their goals and may require some education. It may even be difficult for users to identify behavioral goals that are circumscribed enough to be attainable. Motivation may wax and wane and thus can be a focus of BITs. However, Fogg's model may be very useful for small behaviors.

As such, the model could serve as a useful tool in considering and designing individual components of larger intervention programs.

### Persuasive System Design

Oinas-Kukkonan has described comprehensive models, which he refers to as Persuasive System Design and the Behavior Change Support System, which, in spite of the name, also addresses cognitive change and adherence to a BIT [7,8]. Oinas-Kukkonen identifies 3 areas of change: (1) forming a behavior, cognition, or BIT adherence behavior, (2) altering a behavior, cognition, or BIT adherence behavior, and (3) maintaining a behavior, cognition, or BIT adherence behavior. To this we would add stopping or reducing a behavior or cognition, such as unhealthy eating or addictions. Oinas-Kukkonen also identifies four general design features, each of which contains a number of more specific components: (1) primary task support, which includes reducing complex behaviors into simpler ones, tunneling experience, tailoring and personalization, self-monitoring, simulation, and rehearsal, (2) dialogue support, including positive reinforcement, reminders, and suggestions, (3) credibility, by conveying trustworthiness and expertise, and (4) social support, including both social networking components and the provision of social normative information.

A strength of Oinas-Kukkonen's model is that it supports the transfer of design components into software functionality. Its clear articulation also allows the evaluation of the value of these components, as evidenced by a meta-analysis that evaluated both the frequency of the use of these components, as well as their impact on adherence [10]. While this model links intervention aims with a variety of well-articulated intervention elements, it does not discuss how individual intervention elements may be varied or integrated into a larger treatment program.

## BIT Model Description

The BIT model provides a framework for the translation of treatment and intervention aims into an implementable treatment model. For the purposes of clarity, we use the term "intervention" to refer to a single interaction with a single element and the term "treatment" to refer to multiple interactions that unfold over the entire course of interaction with the BIT.

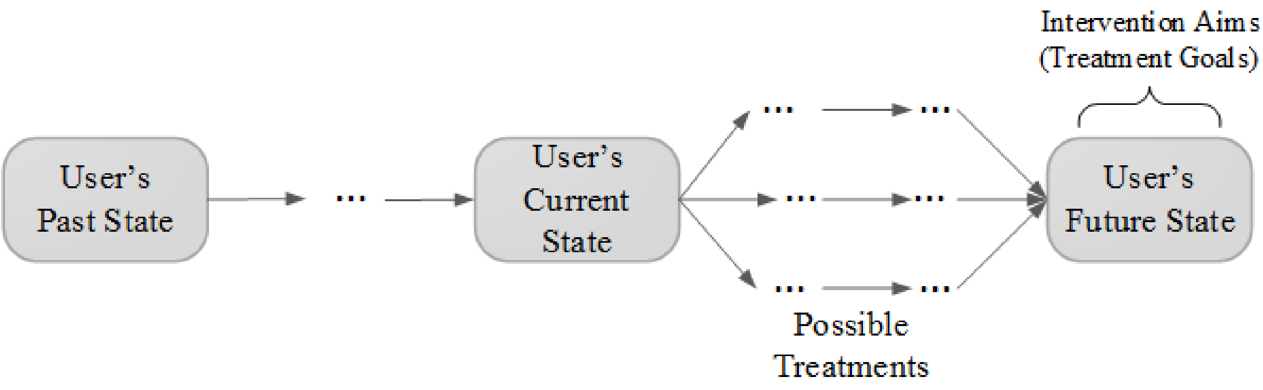
BITs are intended to assist users in achieving a goal related to health, mental health, or wellness. A single BIT intervention enables users to change their current state (the state at the moment of the BIT use) using one or more possible interventions to achieve the intervention aims (desired future states) (see Figure 1). We use the term "Past State" to indicate prior states and events. This time point can be defined depending on the application context (eg, events in the past hour, or before yesterday). The future state can be defined in a similar manner. A BIT treatment can be defined as a concatenation of these BIT interventions over time.

The BIT model displayed in Table 1 displays the "why", "what", "how (both conceptual and technical)", and "when" of BITs. The theoretical level consists of the "why" and conceptual "how", whereas the instantiation level consists of the "what", technical "how", and "when". Most BITs consist of a sequence of intervention steps delivered to the user, each intended to achieve a specific *aim* related to the broader treatment goal, such as monitoring calorie intake for a weight-loss intervention. The aim in Table 1 describes the *why* of any specific intervention and intervention component and reflects the intention of a developer. *How* an aim is achieved is defined by a behavior change strategy, which conceptually defines more proximal aims that support the user in attaining an aim. Each behavior change strategy is instantiated by a BIT element or set of elements, which are more granularly defined intervention components of the overall BIT treatment. Elements are the *what* of the model. *How* an element is displayed is affected by the characteristics, such as the output complexity (difficult, easy) or the medium (video, text, etc). This *how* refers to the technical rather than conceptual considerations. Because a BIT is considered to be a sequence of intervention elements delivered to the user over time, the relative order and rules for progressing through the BIT must be defined. The workflow describes *when* each intervention element will be displayed by determining the precedence of features and conditions under which intervention elements may be delivered. In the following sections, we discuss each of these components in more detail. The overall BIT model consists of these 4 constituent parts (aims, elements, characteristics, and workflow). As "interventions" refer to individual instances or interactions with the user, it includes the elements and their characteristics. "Treatment" refers to how these aspects unfold over time and thus adds workflow.

**Table 1.** Summary of BIT model.

| | | BIT component | Examples |
|---|---|---|---|
| **Theoretical** | | | |
| | Why | Aims | Clinical aims:<br>Weight reduction:<br>Decrease caloric intake<br>Increase physical activity<br>Promote sleep hygiene<br>Decrease depression:<br>Increase positive activities<br>Decrease avoidance behaviors<br>Usage aims:<br>Use of Intervention tools |
| | How (Conceptual) | Behavior change strategies | Education<br>Goal setting<br>Monitoring<br>Feedback<br>Motivation enhancement |
| **Instantiation** | | | |
| | What | Elements | Information delivery<br>Notifications<br>Logs<br>Passive data collection<br>Messaging<br>Reports |
| | How (Technical) | Characteristics | Medium<br>Complexity<br>Aesthetics |
| | When | Workflow | User defined<br>Frequency<br>Conditions:<br>Time-based rules<br>Task completion rules<br>Event-based rules<br>Tunneling |

**Figure 1.** BITs facilitate reaching future changes (ie, intervention aims) through possible interventions.




## "Why": Intervention Aims

The overall goals of a BIT treatment, as well as the aims of any given intervention component, reflect the intentions of the developer [8]. In the context of BITs, these aims can generally be classified into two somewhat overlapping classes: clinical and usage aims. Clinical aims refer to changes in behaviors, cognitions, knowledge, skills, and motivation for treatment-related behaviors. Clinical aims refer to the clinical goals of the intervention or treatment (Table 1 shows examples such as increasing weight reduction, promoting sleep hygiene, or decreasing depression). Often the larger treatment goal also includes hierarchies of sub-aims, each of which supports the attainment of the larger treatment goal. For example, to decrease depression, sub-aims may be to increase positive activities that bring pleasure or a sense of accomplishment, as well as reducing avoidance behaviors that prevent the individual from engaging more fully in life [11]. Similarly, a weight reduction aim may include decreasing caloric intake and increasing physical activity. The hierarchy of aims should be as specific and as clearly defined as possible to facilitate a clear treatment plan.

Usage aims focus on maintaining engagement with the BIT generally and/or with its specific intervention components. Usage aims are often thought to be related to clinical aims, although the relationship between use and outcome has been mixed [12]. Furthermore, in many studies, investigators examine usage outcomes as a proxy for proximal outcomes, although we would caution against that as these are better treated as distinct rather than interchangeable concepts. Usage aims, are more frequently employed in studies conducted by technologists, such as usability testing. These studies use theories, such as the technology acceptance model, that imply that the perceived usefulness and ease of use of the intervention contribute to an individual's motivation to continue using the application [13,14], while psychologists and behavioral scientists tend to focus more on clinical outcomes.

## "How" (conceptual): Behavioral Intervention Strategies

Behavioral change strategies are the methods used to attain clinical and use aims. They are grounded in models and theories of how behavior change occurs and is maintained. Table 1 provides examples of common behavior change strategies, which are described below. This list is drawn from Michie's extensive taxonomy of behavior change strategies [15,16] and is not intended as a comprehensive list. Many of these strategies can relate to either clinical or usage outcomes. For example, education may focus on providing the requisite knowledge to change a behavior related to a clinical aim and/or provide instruction on why and how to use the application to increase its usage. A critical step, however, in selecting which aims to promote is to have a clear rationale for how a given strategy will support the overall goal of treatment.

Education aims to increase the user's understanding of their past and current state and of the steps required to achieve the future state (see Figure 1). Examples include providing information and instruction and may include material about the problem, treatment rationalization, information on consequences of behaviors, modeling, and demonstrating a behavior. In addition, education may include instruction on how to use the application.

Goal setting involves future planning to achieve desired future states. This can include activity scheduling, setting tasks of progressively greater difficulty, anticipation of barriers, or goals with respect to application use.

Monitoring involves recording of past states or current states. Examples include recording of current or past behaviors, cognitions, or events, reviewing previously set goals and identifying barriers, or monitoring intervention and application use.

Feedback provides information on current and past states, or the likelihood of future states, with the goal of increasing insight and understanding regarding the user's condition or actions. Feedback may also overlap with other behavior intervention components, such as motivation enhancement (eg, feedback on goal attainment may provide information about progress and may also increase or decrease motivation).

Motivation enhancements are interventions that increase the likelihood that the user will engage in specific behaviors related to treatment goals or use of the application in the future (motivation to change current state into future state through behavior change or BIT use). These include positive reinforcement, contingent rewards, behavioral contracts, incentives, and social support [10]. Providing opportunities for social comparison and identification with role models are examples of motivational enhancement that utilize social support elements.

### "What": BIT Elements

BIT elements are distinct components or objects of a BIT intended to implement the behavior change strategies, which in turn support the user in achieving the clinical and usage aims required to attain the treatment goal. By BIT elements, we mean the actual technical instantiations present in the BIT. For example, a data entry field created in a food logging application supports the behavior change strategy of monitoring. Thus, the BIT elements are the aspects of the BIT, with which the user actually interacts. Below is a list of commonly used elements of existing BITs, but this list could expand as aims, designs, and technologies continue to advance.

Information delivery typically involves one-way interactions in which the system provides content to the user when the user initiates access. These can include such things as text, video, images, audio, or a combination of media. They are distinct from other similar components in that they commonly remain available after release and are often used didactically.

Notifications are individual messages pushed to the user, such as text messages, emails, or within app notifications.

Logs are a form of data collection that require the user to enter data. Examples include free entry, selection menus, and using a rating scale.

Passive data collection refers to data collected without any user effort, such as phone sensor data collection, data from external devices such as pedometer, and data collected through application programming interfaces (APIs) from other available sources (eg, weather data or prescription refills).

Messaging elements link the user with other individuals including those supporting the interventions (both professionals and paraprofessionals), peers drawn from their social network, or peers using the system. Messaging refers to more than just one-to-one correspondence and can include discussion boards.

Reports are reflections of data collected by the BIT that are provided back to the user (eg, calendars, calorie counts, thought records).

Visualizations may be considered a subset of reports and convey specific information derived from previously collected data and assessments. Data may be aggregated across an individual user or across groups of users.

BIT element(s) are mapped onto behavior change strategies. A specific behavior change strategy can be targeted by more than one BIT element, which may be delivered sequentially or may be embedded in each other. For example, education is often achieved by delivering didactic tools that rely on text-based information. But such learning may be augmented by embedded reports (visualizations or text) derived from data and assessment, thereby providing feedback to illustrate a point and support learning.

### "How" (technical): Characteristics

BIT elements can be further defined and/or refined across a number of dimensions to better fit the user and/or optimize the element to achieve its aim and overall treatment goal of the BIT, commonly by improving the user's comprehension, ability to complete tasks, and engagement. We describe four characteristics (medium, complexity, aesthetics, personalization) that have received attention in BIT research, however, these are intended as examples and are by no means an exhaustive list.

Medium refers to media employed, such as text, video, audio. Variation in the medium can be varied for many of the intervention elements, including information delivery, social networking, or data collection. In considering the medium, it can be useful to apply a framework, such as media richness theory, which can provide information on how media may vary in their suitability for communicating different types of information effectively [17]. The media richness hierarchy is organized from high to low levels of richness based on the capacity of media types to process information or cues. Each cue can be assessed on multiple criteria including (1) speed of feedback (fast, slow, instant), (2) the capacity of the medium to transmit multiple cues simultaneously, (3) the ability to use natural language, and (4) the personal focus of the medium. Richer media are not necessarily better [18]; the aims of any given intervention element are most likely to be effective if the communication channel fits the task and the capabilities of the users [19]. For example, video may be a better media for communicating information to users who have low literacy, while text may be preferable to more educated groups.

Complexity can be varied depending on the user, target population, and the task (eg, providing didactic information, a notification, or data collection). For example, some users may prefer more elaborate content, while others may prefer leaner content [20]. Or, for logging features, some users prefer the control and specificity afforded by free text entry, while others prefer the simplicity of drop-down menus. The complexity of content or tasks may vary by user capabilities and limitations such as educational level or familiarity with device. The complexity of content and tasks may also vary based on the context in which application is used (eg, at home, work, or in transit).

Aesthetics may vary depending on the user characteristics and tastes [21]. Aesthetics can have a substantial impact on user acceptance and usability [22]. There are engineering principles of aesthetics that relate to user acceptance and performance that should be considered [23].

Personalization refers to altering the characteristics or content of a BIT to increase the relevance for an individual user. For example, the content of information may be tailored to fit the user's needs and capabilities by altering language or providing examples that are more likely to be relevant to the user [24]. Personalization has generally relied on predetermined criteria to adapt the form of interventions; however, it is also possible to use machine learning methods that can learn from population and individual user data to automatically adapt the form of interventions to meet the user's needs and capabilities [25-27]. Personalization can impact the characteristics of the medium, complexity, and aesthetics, where these characteristics are made more relevant based on individual user needs and characteristics.

The characteristics in this model are intended to reflect the need to modify BIT elements. Conceptually, the elements could be considered objects, and the characteristics could be considered the potential attributes of those objects. It is beyond the scope of this paper to provide guidance on the methods one might use to decide which attributes best meet the needs of users, as these questions are the subject of entire fields of study such as human factors engineering and human computer interaction (HCI).

### "When": Workflow

Most BITs are designed for repeated interactions over an extended period of time. That is, within our terminology, most BITs are intended as a treatment consisting of a series of interventions. The workflow defines when and under what conditions BIT interventions are delivered and can take into account changes in the aims, elements, and/or characteristics that occur over the course of a treatment. The workflow identifies when an intervention is delivered and potentially also the sequence of interventions. Below we describe common examples of workflows (user defined, frequency, conditions, tunneling).

User defined workflows allow the user access to all intervention elements and content, permitting the user to decide the sequence and timing of their use.

Frequency refers to the frequency with which any intervention is deployed. Some interventions have expectations of the frequency of use.

Conditions use data to determine when an intervention will be delivered. A variety of types of conditions can be employed. (1) Time-based rules define the release of an intervention element based on the passage of time. For example, Web-based treatments modeled on standard face-to-face treatments sometimes release new content on a weekly basis [28]. (2) Task-completion rules define the release of intervention elements based on the user's completion of prescribed intervention tasks, such as the completion of a pre-determined number or set of activities detected by the intervention system. (3) Event-based rules define the release of elements based on the detection of criteria detected by the intervention. Events may be derived from user-entered data (eg, a patient characteristic or change in state), sensor data, or any other data (eg, data from an electronic medical record). An "event" may also be defined as the absence of data (eg, a notification may be provided when no user activity has been detected over a given period of time).

Tunneling uses data to determine which interventions are most like to meet the needs or preferences of an individual at a given time. For example, an intervention for anxiety can use information on comorbidities to provide specific interventions targeting those problems to improve efficacy [29]. As with personalization, adaptive systems, using artificial intelligence and machine learning techniques, can potentially use population-level data along with individual user data to determine the workflow of an intervention, similar to commercial recommendation systems such as Netflix or Amazon [25-27].

Workflows may use and integrate a number of these elements, for example, providing core interventions in a predetermined sequence with a mixture of time-based and task completion rules and then allowing the user to select from a variety of additional interventions that the user believes are most useful [30,31].

## BIT Model: Example Using MyFitnessPal

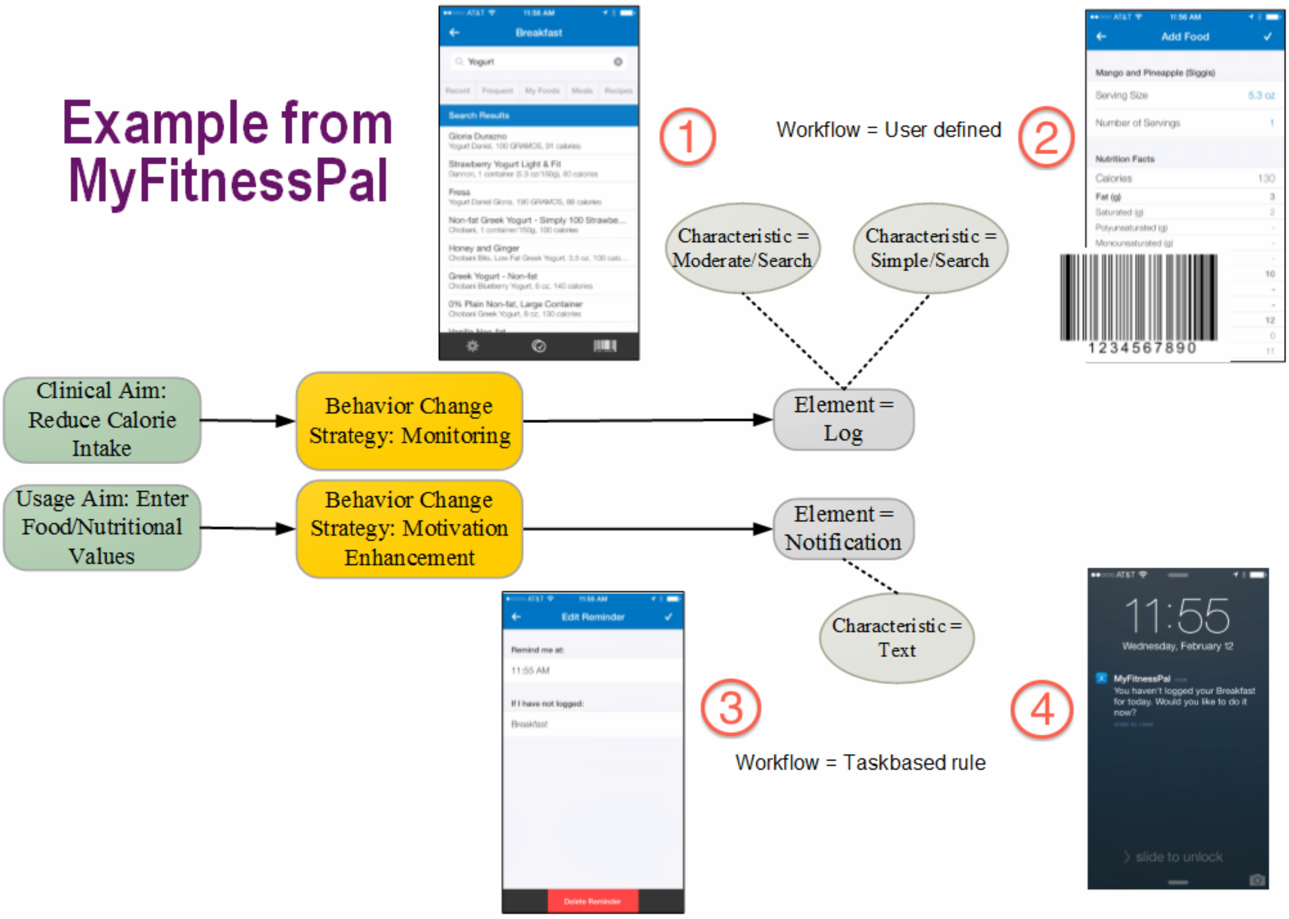
To further explain the BIT model, we provide an example of a portion of a popular fitness app (MyFitnessPal). MyFitnessPal is an Internet website and mobile application designed to help people lose weight. The MyFitnessPal mobile application is freely available for the Android, BlackBerry, iOS, and Windows platforms. The overall clinical aim of MyFitnessPal is to promote weight loss. Two of the sub-aims of the application are to reduce caloric intake and increase physical activity. Although MyFitnessPal makes use of several behavior change strategies (education, feedback, goal setting, motivation enhancement), the major behavior change principle used is monitoring. That is, weight loss is promoted by helping people track what they eat and how much they exercise. Reviewing every feature of MyFitnessPal is beyond the scope of this paper; however, we present aspects of the core functionality of entering food into one's diary to illustrate the BIT model.

Figure 2 displays the BIT model as it applies to a single action, that is, logging one's breakfast into the MyFitnessPal diary. Starting with the clinical aim of reducing caloric intake, the behavior change strategy is monitoring one's food intake. Thus, the behavior change strategy (monitoring) bridges the clinical aim (reduction of caloric intake) and the technological instantiation. The BIT element with which a user initiates the interaction with the application is a food log. The food logging element has a number of potential characteristics (how). A user can enter the nutritional data in free text. To simplify this entry, a user can search for a particular food, in this example yogurt, in order to input that specific nutritional data into one's diary (see element 1 in Figure 2). However, an even simpler form of entry allows the user to scan the barcode of the food item (see element 2 in Figure 2). MyFitnessPal will then use the barcode to search for the item, eliminating the need for the user to search and then correctly select the item from the items within MyFitnessPal's database. The workflow here is user defined.

The use of the food diary requires the user to initiate the interaction, requiring the user to remember and be sufficiently motivated to engage in the task. To mitigate the effects of forgetfulness or low motivation, MyFitnessPal makes use of another behavior change strategy, motivational enhancement, to support the usage aim of entering consumed food into the application. One technological manifestation of a motivation enhancer is through the BIT element of a notification. In MyFitnessPal, these notifications are delivered via text push notifications from the application. These notifications are created from the system using task completion rules. As Figure 2 illustrates, the notification is programmed into the system to be delivered at a specific time if, and only if, the food logging task has not been accomplished (see element 3 in Figure 2). In this example, a notification to log one's breakfast is provided if breakfast has not been logged by 11:55 a.m. (see element 4 in Figure 2). The characteristic of the notification is text (as opposed to audio or visual). In this way, a user can forgo receiving the notification by engaging in the user-defined workflow prior to the programmed event that will initiate the task completion rule leading to the BIT element of the notification.

The MyFitnessPal example is an illustration of how the BIT model maps onto an existing application. High quality applications often contain these elements; however, there is no shortage of poorly designed applications available that do not effectively engage users to accomplish the intended actions or achieve the intended aims. The BIT model is intended to support developers and designers by providing a clear model of how to move from a general clinical aim to a clearly defined and effective application. We now move to a discussion of translating these conceptual design decisions into technological implementations.

**Figure 2.** BIT model example using MyFitnessPal calorie intake monitoring features.




## *From Theory to Application: Technological Implementation of the Model*

The instantiation of a design based on the BIT model requires technological implementation in a system that can actually deliver the BIT to users. In this section, we provide an example of a hybrid model that integrates a general technological framework using the BIT model. We refer to this as BIT Technological, or BIT-Tech. BIT-Tech is an example that can be used by system designers and developers as a conceptual guideline. It shows the relationship among (1) software components developed for supporting BITs, (2) the user, and (3) the environment.

BIT-Tech is defined with respect to the previously defined BIT model concepts, that is, intervention *(I)*, aim *(A)*, element *(E)*, characteristics *(C)*, and workflow *(W)*. Data, denoted by *D*, can be acquired from a variety of sources. We denote user data by *D(U)* and environmental data by *D(E)*. User data include data related to user, such as demographic information, activity data collected by an accelerometer, and entered calories. Environmental data include data from environment (and not the user). Examples include weather data, traffic data, and geo-location information. Again, each intervention *(I)* is a combination of an element and its characteristics I=<E, C>. The benefit of BIT-Tech is that it is not a separate model, but rather an instantiation of the BIT model in technological form. Thus, both aspects of the BIT model (those displayed in Table 1 and the BIT-Tech displayed in Figure 1) are equally important for the model.

We use the superscript notation $A^t$ to refer to the specific *aim* at time *t*. This time step will be defined by the system designers depending on the treatment's needs and may represent a precise moment, for example, a second or a longer block of time, such as an hour, a day, or a week. The same notation is used for other concepts at time *t*: intervention component $(I^t)$, intervention element $(E^t)$, characteristics $(C^t)$, workflow $(W^t)$, and data $(D^t)$. Note that if the system is stationary, that is, it does not change over time, we can simply eliminate the superscripts. It also should be noted that the units for *t* selected may correspond to the application context, computational resources, need for a fine-grained versus coarse-grained intervention, and/or the specific aspect of the BIT model. For example, one might represent *t* in terms of seconds for aspects such as data to create a "just-in-time" intervention, but in terms of weeks for aspects, such as workflow if the designer wants the conditions that trigger interventions to be consistent for the length of the intervention.

Inspired by the robotics paradigm, we will describe our model in terms of *sensing*, *planning*, and *acting* primitives. As described in the literature, in a reactive paradigm (see Figure 3), there are multiple instances of *sense-act* coupling, where each instance processes the sensed data independently and acts independently [32,33]. In a deliberative paradigm, data are sensed from different sensing modules and integrated into a global model, then an action is planned, and next the action is executed. Finally, the hybrid model is a combination of both paradigms, where a direct *sense-act* coupling exists, but the data can also be used by the planning module. The latter allows for inclusion of a planning component, while also providing the flexibility of the reactive models such as layered architectures [34].

The BIT-Tech aspect of the model is composed of several components (Figure 4):

- Profiler: The profiler is responsible for collecting data to define the user and environment at any given point in time. The profiler passes data *(D)* to the intervention-planner component. This corresponds to the sensing module in the hybrid paradigm.
- Intervention Planner: The intervention-planner is responsible for planning interventions at current time *t* by choosing the relevant intervention elements *(E)* with characteristics *(C)*. Exact mapping of intervention (as defined in Equation 1) will depend on the application needs and will be determined by the developer at design time.
- Intervention Repository: The intervention repository stores all the intervention elements developed for the use with the BIT and can be implemented in terms of a database. Once the intervention repository receives the specification of the current intervention step from the intervention-planner at time *t*, the specification will be passed to the "User Interface" component. The Intervention Planner and the Intervention Repository components together comprise the planning module in the hybrid paradigm.
- User Interface: This delivers an intervention *(E+C)* using a user-friendly interface. The user interface corresponds to the acting module in the hybrid paradigm.

The unfolding of these interventions over time is specified by the workflow *(W)* and influenced by the available data *(D)*. As workflow aspects are considered, specific interventions *(I)* combine to create larger treatments intended to achieve the clinical goals.

Note that the selection of aims and elements can be predefined by the BIT based on the developer's expertise, or alternatively can be chosen by the user or may be determined adaptively based on information received during the intervention. A treatment as a sequence of intervention steps is defined in terms: (1) elements *(E)*, (2) characteristics *(C)*, and (3) relative order and transition condition of intervention steps, all determined according to workflow *(W)*. Thus, the intervention-planner's function Φ can be defined according to Equation 1. It uses aims *A*, data *D*, as well as workflow *W*, as the input and provides an intervention step specification $I=< E^t,C^t >$ is the output. The intervention-planner function Φ typically will be designed based on designer's definition of the workflow to determine the transition between intervention steps. Therefore, Equation 1 is as follows: $\Phi\ (A^{1..t}, D^{1..t}, W^t) = I^t = <E^t,C^t>$

More specifically, the workflow *W* is defined in terms of a finite state machine [35]. A finite state machine (FSM) is a graph used in computer science as an abstract model of programs. Each FSM has a finite number of states (graph nodes), and the machine is at one of the states at any given moment (called current state). It can change from current state to another through graph edges (called a transition) when a triggering event happens or a condition is satisfied. In our model, the states represent the intervention steps, and the intervention steps proceed through transitions (see Figure 6 for an example workflow).

The transition among intervention steps is defined by function Φ. In general, a transition depends on the previous intervention steps according to the workflow, as well as previous aims, historical data, and current time, as in Equation 1. It should be noted that depending on the specific needs of the system and the available computational resources, one might store/use all the historical information or use only the most recent data. Note that there also may be self-transitions. For example, if the user does not respond to a notification, then the notification can be repeated (a self-loop). In Figure 5, all intervention steps have self-transitions. The self-transitions determine the frequency of a specific intervention step (ie, how many times it will be repeated). Figure 5 shows another example of a workflow based on our MyFitnessPal.

The transition function might also be designed using partial contextual information. For example, a transition might be triggered simply if a certain amount of time has elapsed (eg, 1 week) or by the completion of specified tasks, regardless of the contextual information about previous interventions, aims, and collected data. However, it is also possible to begin developing adaptive BITs that employ artificial intelligence techniques to adapt the workflow to the user's preferences and/or needs over time. That is, the workflow structure can be modified over time using collective and individual data to provide and sequence specific intervention elements with specific modifications to the characteristics to increase the likelihood of achieving the treatment and intervention aims.

Data gathered through the profiler may be initialized with specific profile data, such as demographic information and clinical status (user data), or specific time and location (environment data), which may determine the BIT tools delivered, any tailoring or refinement of the elements, characteristics, and workflow. The profiler may also gather additional types of data over the course of the treatment, such as updated data on clinical status, information on the patient's use of the application elements, or environmental data such as location or weather (see Figure 4).

After the system is developed and deployed, the system performance and effectiveness can be evaluated using different computational metrics. For example, the interaction aspects of the BIT can be evaluated using HCI measures such as usability, ease of use, and usefulness [36,37]. Other aspects of the system related to software quality, such as reliability, security, maintainability, and efficiency, can be evaluated using software engineering metrics [38-40]. Finally, if the system is using artificial intelligence and machine learning techniques, related metrics such as accuracy and precision of predictions and recommendations can be used [41,42].

**Figure 3.** Three paradigms: Reactive, Deliberative, and Hybrid.

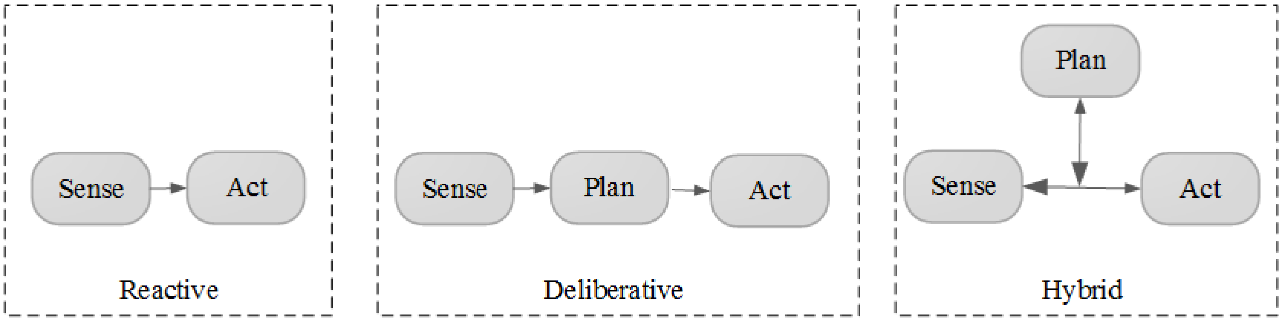



**Figure 4.** BIT-Tech framework: required environment and user data is collected by the Profiler component; collected data is passed to the Intervention Planner, which is responsible for planning intervention at time t; the Intervention Repository component stores all the interventions and passes specific details of the selected intervention to the User interface component, which then delivers the intervention.

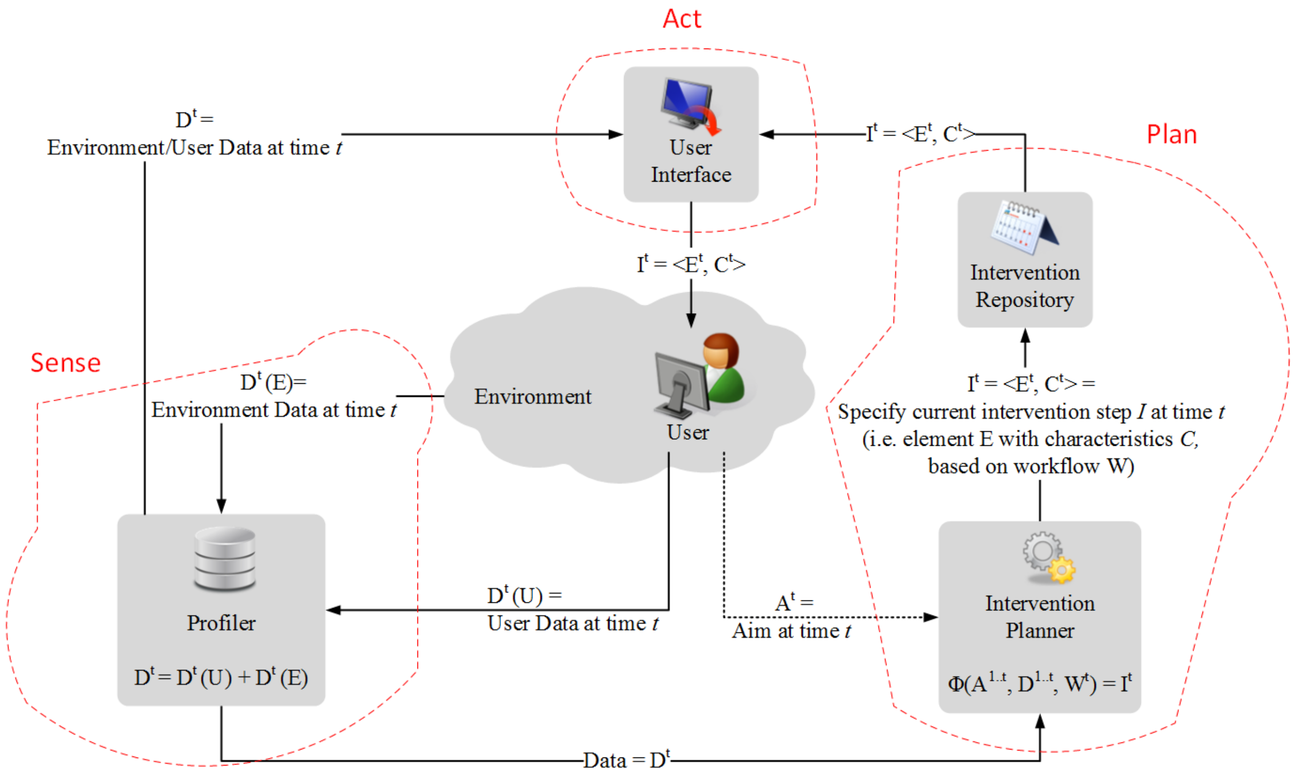


**Figure 5.** Example workflow generated by the workflow-planner specifying the elements (rectangular nodes), element's characteristics (elliptical nodes), as well as order of transitions among elements.

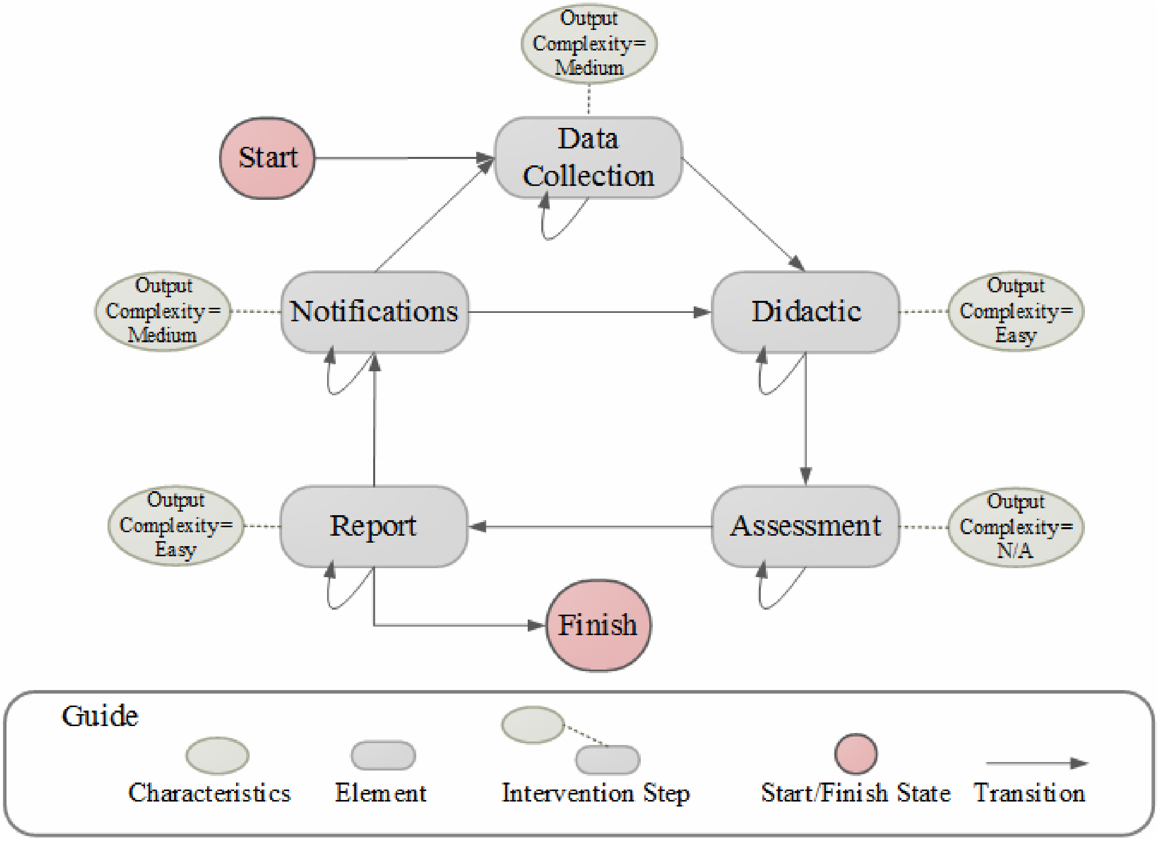
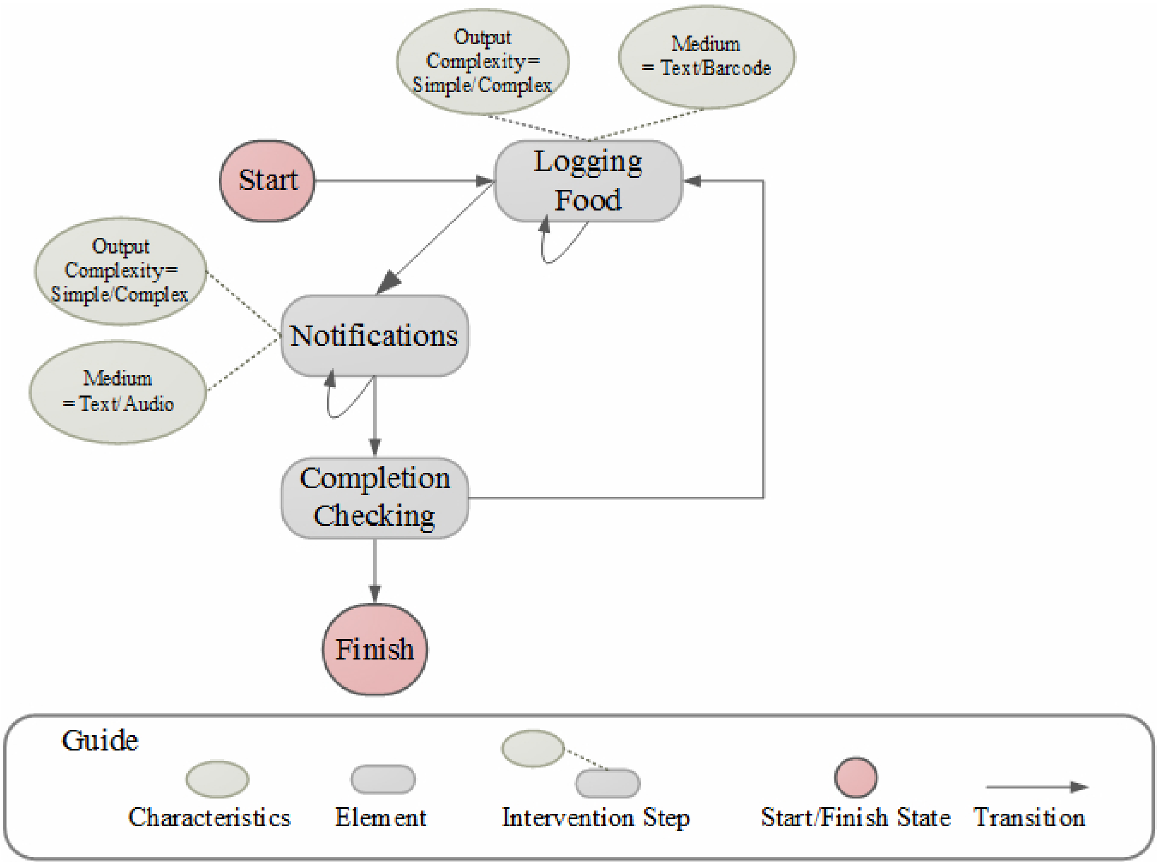



**Figure 6.** Workflow for MyFitnessPal specifying the elements (rectangular nodes), element's characteristics (elliptical nodes), as well as order of transitions among elements.



## Discussion

### Implications

We have described the BIT model, which includes both a framework for articulating the relationship between intervention aims, elements, characteristics, and workflow and its technological counterpart (BIT-Tech). This model has a number of potential uses and implications for BIT research.

The BIT model can help developers formalize their intentions with respect to each design consideration, as well as assist in the clarification of how the intervention aims will be implemented in terms of intervention elements. This formalization can be assisted through the development of checklists and flow diagrams that allow the developer to utilize the general model in the development of a specific intervention. In this way, the BIT model can guide development (particularly those who are new to the area) to think through the various decisions that are critical to the design of a BIT and promote the integration of behavioral and psychological theory with BIT design.

Much of the development of BITs to date has been informed primarily through the application of behavioral and psychological theories and by developer intuition [1]. Behavioral and psychological theories provide guidance regarding the relationship between user behaviors and the attainment of ultimate treatment goals and may be helpful in determining proximal intervention aims, but they are less helpful in guiding the development of elements, characteristics, and workflow. While developer intuition has contributed to the rapid growth of BIT research, the use of clear models that formalize and make developers' intentions transparent will facilitate the communication of those intentions. Clear communication about design intentions will support the exchange of ideas and the growth of the field.

The formalization of the design and development process also supports the translation of the developer's intentions into testable hypotheses regarding the effects of specific intervention elements, characteristics, and workflow decisions, as well as determining the required data outputs to test those hypotheses. Much of the evaluation of BITs has focused on efficacy, which limits the growth in our knowledge regarding the mechanisms by which BITs achieve both their proximal intervention aims as well as the ultimate treatment goals [4]. Attaining some level of consistency in how aims, elements, characteristics, and workflow are defined would facilitate the evaluation of these components across studies [10].

The proposed conceptual framework could be further refined through the development of more detailed ontologies that further define BIT elements, characteristics, and workflows. An ontology is a formal language used to create a map of a domain, which can provide the conceptual framework to facilitate the rapid or automated construction of BIT applications [43]. Ontologies can also allow data to be defined consistently, allowing it to be queried and retrieved in structured ways [44]. A well-defined generally accepted ontology would facilitate interchange of information across diverse systems by describing the data at various levels of detail, independent of the particular names used in any one system [43]. This would facilitate investigations across treatment protocols and potentially across research groups.

### Limitations

There are several caveats and limitations of the present work that should be mentioned. First, the BIT model we present is intended to be generalizable and is therefore a simplification. It is intended as a general framework that should be modified and elaborated to fit the needs of a specific BIT treatment protocol. Second, the proposed model is intended to respond to calls for a framework that integrates developers' intentions, behavioral and psychological theory, the design of BIT treatment protocols, and the implementation in a technology framework. We fully expect and encourage the modification of this framework to take into account the ideas of other investigators, new technological developments, the needs and intentions of other stakeholders such as purveyors and care systems [45,46], and most importantly, the development of data that can be used to modify and refine the model. In short, this is intended as a starting place for the development of more comprehensive models and theories that can guide development and research in BITs. Finally, the BIT model has not integrated design processes, such as user-centered design. This model is intended as a high level model that can be used as the basis to develop an ontology, and not to guide specific instantiations of a BIT. Design processes that integrate information on the needs, desires, and limitations of users into the development process are also critical to ensuring that BITs are usable and useful [47].

### Conclusion

The BIT model builds on existing models. Our BIT model extends the Ritterband model [5] by including the intentions of the developer and by increasing the level of granularity. The Fogg Behavioral Model [6] can be used to explain a user's engagement with any specific intervention element, or set of elements. The BIT model extends the work of Oinas-Kukkonen [7,8] by allowing more granular definition of elements, characteristics, and workflow. The BIT model provides a step towards formalizing a map that can translate clinical aims into behavioral strategies, application specifications, and delivery systems in a manner that supports design, the development of testable hypotheses aimed at improving BIT design, and communication between investigators and across research groups.

### Acknowledgments

This paper was funded by National Institutes of Health (NIH) Grant Nos. P20MH090318, R01MH100482, R01MH095753, and R34MH095907.

## Conflicts of Interest

None declared.

## References

1. Riley WT, Rivera DE, Atienza AA, Nilsen W, Allison SM, Mermelstein R. Health behavior models in the age of mobile interventions: are our theories up to the task? Transl Behav Med 2011 Mar;1(1):53-71 [FREE Full text] [doi: 10.1007/s13142-011-0021-7] [Medline: 21796270]
2. Mohr DC, Burns MN, Schueller SM, Clarke G, Klinkman M. Behavioral intervention technologies: evidence review and recommendations for future research in mental health. Gen Hosp Psychiatry 2013;35(4):332-338. [doi: 10.1016/j.genhosppsych.2013.03.008] [Medline: 23664503]
3. Webb TL, Joseph J, Yardley L, Michie S. Using the internet to promote health behavior change: a systematic review and meta-analysis of the impact of theoretical basis, use of behavior change techniques, and mode of delivery on efficacy. J Med Internet Res 2010;12(1):e4 [FREE Full text] [doi: 10.2196/jmir.1376] [Medline: 20164043]
4. Klasnja P, Consolvo S, Pratt W. How to evaluate technologies for health behavior change in HCI research. 2011 Presented at: SIGCHI Conference on Human Factors in Computing Systems (CHI); 2011; Vancouver, BC.
5. Ritterband LM, Thorndike FP, Cox DJ, Kovatchev BP, Gonder-Frederick LA. A behavior change model for internet interventions. Ann Behav Med 2009 Aug;38(1):18-27 [FREE Full text] [doi: 10.1007/s12160-009-9133-4] [Medline: 19802647]
6. Fogg BJ. A behavior model for persuasive design. 2009 Presented at: Persuasive '09; 2009; Claremont, CA.
7. Oinas-Kukkonen H. A foundation for the study of behavior change support systems. Pers Ubiquit Comput 2012 Jul 19;17(6):1223-1235. [doi: 10.1007/s00779-012-0591-5]
8. Oinas-Kukkonen H, Harjumaa M. Persuasive systems design: Key issues, process model, and system features. Communications of the Association for Information Systems 2009;24:485-500.
9. Lyons EJ, Hatkevich C. Prevalence of behavior changing strategies in fitness video games: theory-based content analysis. J Med Internet Res 2013;15(5):e81 [FREE Full text] [doi: 10.2196/jmir.2403] [Medline: 23651701]
10. Kelders SM, Kok RN, Ossebaard HC, Van Gemert-Pijnen JE. Persuasive system design does matter: a systematic review of adherence to web-based interventions. J Med Internet Res 2012;14(6):e152 [FREE Full text] [doi: 10.2196/jmir.2104] [Medline: 23151820]
11. Martell CR, Dimidjian S, Herman-Dunn R. Behavioral activation for depression: A clinician's guide. New York: Guilford Press; 2010.
12. Donkin L, Christensen H, Naismith SL, Neal B, Hickie IB, Glozier N. A systematic review of the impact of adherence on the effectiveness of e-therapies. J Med Internet Res 2011;13(3):e52 [FREE Full text] [doi: 10.2196/jmir.1772] [Medline: 21821503]
13. Sumak B, Hericko M, Pusnik M. A meta-analysis of e-learning technology acceptance: The role of user types and e-learning technology types. Computers in Human Behavior 2011;27(6):2067-2077.
14. Venkatesh V, Davis FD. A theoretical extension of the Technology Acceptance Model: Four longitudinal field studies. Management Science 2000;46(2):186-204.
15. Abraham C, Michie S. A taxonomy of behavior change techniques used in interventions. Health Psychol 2008 May;27(3):379-387. [doi: 10.1037/0278-6133.27.3.379] [Medline: 18624603]
16. Michie S, Richardson M, Johnston M, Abraham C, Francis J, Hardeman W, et al. The behavior change technique taxonomy (v1) of 93 hierarchically clustered techniques: building an international consensus for the reporting of behavior change interventions. Ann Behav Med 2013 Aug;46(1):81-95. [doi: 10.1007/s12160-013-9486-6] [Medline: 23512568]
17. Daft RL, Lengel RH. Information Richness - a New Approach to Managerial Behavior and Organization Design. Research in Organizational Behavior 1984;6:191-233.
18. Walther JB, Parks MR. Cues filtered out, cues filtered in: Computer-mediated communicationrelationships, in Handbook of Interpersonal Communication, 3rd Ed., M.L. KnappJ.A. In: Knapp ML, Parks MR, editors. Handbook of Interpersonal Communication, 3rd Ed. Thousand Oaks, CA: Sage Publications; 2002:529-563.
19. Daft RL, Lengel RH. Organizational Information Requirements, Media Richness and Structural Design. Management Science 1986;32(5):554-571.
20. Yardley L, Morrison LG, Andreou P, Joseph J, Little P. Understanding reactions to an internet-delivered health-care intervention: accommodating user preferences for information provision. BMC Med Inform Decis Mak 2010;10:52 [FREE Full text] [doi: 10.1186/1472-6947-10-52] [Medline: 20849599]
21. van Schaik A, Hassenzahl M, Ling J. User-Experience from an Inference Perspective. ACM Trans. Comput.-Hum. Interact 2012 Jul 01;19(2):1-25. [doi: 10.1145/2240156.2240159]
22. Tractinsky N, Katz AS, Ikar D. What is beautiful is usable. Interacting with Computers 2000;13(2):127-145.
23. Liu Y. Engineering aesthetics and aesthetic ergonomics: theoretical foundations and a dual-process research methodology. Ergonomics 2003;46(13-14):1273-1292. [doi: 10.1080/00140130310001610829] [Medline: 14612319]

24. Resnicow K, Davis RE, Zhang G, Konkel J, Strecher VJ, Shaikh AR, et al. Tailoring a fruit and vegetable intervention on novel motivational constructs: results of a randomized study. Ann Behav Med 2008 Apr;35(2):159-169. [doi: 10.1007/s12160-008-9028-9] [Medline: 18401673]
25. Debnath S, Ganguly N, Pabitra M. Feature weighting in content based recommendation system using social network analysis. 2008 Presented at: 17th International Conference on World Wide Web; 2008; Beijing, China.
26. Sarwar B, Karypis G, Konstan J. Item-based collaborative filtering recommendation algorithms. 2001 Presented at: 10th International Conference on World Wide Web; 2001; Hong Kong, China.
27. Linden G, Smith B, York J. Amazon.com recommendations: item-to-item collaborative filtering. IEEE Internet Comput 2003 Jan;7(1):76-80. [doi: 10.1109/MIC.2003.1167344]
28. Tate DF, Jackvony EH, Wing RR. A randomized trial comparing human e-mail counseling, computer-automated tailored counseling, and no counseling in an Internet weight loss program. Arch Intern Med 2006;166(15):1620-1625. [doi: 10.1001/archinte.166.15.1620] [Medline: 16908795]
29. Carlbring P, Maurin L, Törngren C, Linna E, Eriksson T, Sparthan E, et al. Individually-tailored, Internet-based treatment for anxiety disorders: A randomized controlled trial. Behav Res Ther 2011 Jan;49(1):18-24. [doi: 10.1016/j.brat.2010.10.002] [Medline: 21047620]
30. Mohr DC, Duffecy J, Jin L, Ludman EJ, Lewis A, Begale M, et al. Multimodal e-mental health treatment for depression: a feasibility trial. J Med Internet Res 2010;12(5):e48 [FREE Full text] [doi: 10.2196/jmir.1370] [Medline: 21169164]
31. Mohr DC, Duffecy J, Ho J, Kwasny M, Cai X, Burns MN, et al. A randomized controlled trial evaluating a manualized TeleCoaching protocol for improving adherence to a web-based intervention for the treatment of depression. PLoS One 2013;8(8):e70086 [FREE Full text] [doi: 10.1371/journal.pone.0070086] [Medline: 23990896]
32. Arkin RC. Behavior-based robotics. Cambridge MA: MIT Press; 1998.
33. Gonzalez F, Zezzatti AOO, Marin-Urias LF. A hybrid approach in the development of behavior based robotics. Computación y Sistemas 2010;13(4):385-397.
34. Brooks RA. Intelligence without representation. Artificial Intelligence 1991;47(1-3):139-159.
35. Koshy T. Discrete mathematics with applications. Burlington, MA: Elsevier Academic Press; 2004.
36. Bevan N. Classifying and selecting UX and usability measures. 2008 Presented at: Meaningful Measures: Valid Useful User Experience Measurement; 2008; Reykjavik, Iceland.
37. Nielsen J. Usability inspection methods. New York: John Wiley & Sons; 1994.
38. Coleman D, Ash D, Lowther B. Using Metrics to Evaluate Software System Maintainability. Computer 1994;27(8):44-49.
39. Kan SH. Metrics and models in software quality engineering, 2nd edition. Boston, MA: Addison-Wesley Longman Publishing Co; 2003.
40. Duvall PM, Glover A. Continuous integration: improving software quality and reducing risk. Boston, MA: Addison-Wesley Professional Publishing; 2007.
41. Bishop CM. Pattern recognition and machine learning. New York: Springer; 2007.
42. Russell S, Norvig P. Artificial intelligence: a modern approach, 3rd edition. Upper Saddle River: Prentice Hall; 2010.
43. Bickmore TW, Schulman D, Sidner CL. A reusable framework for health counseling dialogue systems based on a behavioral medicine ontology. J Biomed Inform 2011 Apr;44(2):183-197 [FREE Full text] [doi: 10.1016/j.jbi.2010.12.006] [Medline: 21220044]
44. Yarkoni T. Psychoinformatics: New horizons at the interface of the psychological and computing sciences. Current Directions in Psychological Science 2012;21(6):391-397.
45. Brown CH, Mohr DC, Gallo CG, Mader C, Palinkas L, Wingood G, et al. A computational future for preventing HIV in minority communities: how advanced technology can improve implementation of effective programs. J Acquir Immune Defic Syndr 2013 Jun 1;63 Suppl 1:S72-S84. [doi: 10.1097/QAI.0b013e31829372bd] [Medline: 23673892]
46. Mohr DC, Cheung K, Schueller SM, Hendricks Brown C, Duan N. Continuous evaluation of evolving behavioral intervention technologies. Am J Prev Med 2013 Oct;45(4):517-523. [doi: 10.1016/j.amepre.2013.06.006] [Medline: 24050429]
47. Yen PY, Bakken S. Review of health information technology usability study methodologies. J Am Med Inform Assoc 2012;19(3):413-422 [FREE Full text] [doi: 10.1136/amiajnl-2010-000020] [Medline: 21828224]

## Abbreviations

**API:** application programming interface
**BIT:** behavioral intervention technology
**BIT-Tech:** Behavioral Intervention Technology—Technological Instantiation
**FSM:** finite state machine
**HCI:** human computer interaction

*Edited by G Eysenbach; submitted 03.11.13; peer-reviewed by G DDr. Lingg PhD, P Klasnja; comments to author 23.12.13; revised version received 15.03.14; accepted 28.04.14; published 05.06.14.*

*Please cite as:*
*Mohr DC, Schueller SM, Montague E, Burns MN, Rashidi P*
*The Behavioral Intervention Technology Model: An Integrated Conceptual and Technological Framework for eHealth and mHealth Interventions*
*J Med Internet Res 2014;16(6):e146*
*URL: http://www.jmir.org/2014/6/e146/*
*doi:10.2196/jmir.3077*
*PMID:24905070*

Viewpoint

# Home Care Technology Through an Ability Expectation Lens

Gregor Wolbring[1*], PhD; Bonnie Lashewicz[1*], PhD

Community Rehabilitation and Disability Studies, Community Health Sciences, University of Calgary, Calgary, AB, Canada

[*]all authors contributed equally

**Corresponding Author:**
Gregor Wolbring, PhD
Community Rehabilitation and Disability Studies
Community Health Sciences
University of Calgary
3330 Hospital Drive NW
Faculty of Medicine
Calgary, AB, T2N 4N1
Canada
Phone: 1 403 210 7083
Fax: 1 403 220 6494
Email: gwolbrin@ucalgary.ca

## Abstract

Home care is on the rise, and its delivery is increasingly reliant on an expanding variety of health technologies ranging from computers to telephone "health apps" to social robots. These technologies are most often predicated on expectations that people in their homes (1) can actively interact with these technologies and (2) are willing to submit to the action of the technology in their home. Our purpose is to use an "ability expectations" lens to bring together, and provide some synthesis of, the types of utility and disadvantages that can arise for people with disabilities in relation to home care technology development and use. We searched the academic databases Scopus, Web of Science, EBSCO ALL, IEEE Xplore, and Compendex to collect articles that had the term "home care technology" in the abstract or as a topic (in the case of Web of Science). We also used our background knowledge and related academic literature pertaining to self-diagnosis, health monitoring, companionship, health information gathering, and care. We examined background articles and articles collected through our home care technology search in terms of ability expectations assumed in the presentation of home care technologies, or discussed in relation to home care technologies. While advances in health care support are made possible through emerging technologies, we urge critical examination of such technologies in terms of implications for the rights and dignity of people with diverse abilities. Specifically, we see potential for technologies to result in new forms of exclusion and powerlessness. Ableism influences choices made by funders, policy makers, and the public in the development and use of home health technologies and impacts how people with disabilities are served and how useful health support technologies will be for them. We urge continued critical examination of technology development and use according to ability expectations, and we recommend increasing incorporation of participatory design processes to counteract potential for health support technology to render people with disabilities technologically excluded and powerless.

***(J Med Internet Res 2014;16(6):e155)*** doi:10.2196/jmir.3135

**KEYWORDS**

ability expectation; ableism; home care; home care technology; health care technology; people with disabilities; sensor devices and platforms; social robotics; health information gathering; participatory design

## Introduction

Home care, consisting of provision of health support and resources within a person's private residence, is an increasingly preferred model of care for older people and people with disabilities who are in constant need of some form of health intervention [1-5]. Health technologies continually reshape what is possible in home care and the creation of home environments that support health clients. Further, a health care discourse is emerging from expectations for health clients to be in control of their health interventions (see concepts of patient-driven health care and people-driven health research) [6]. We see movements towards a "quantified self" (where people diagnose themselves), health social networks, and participatory medicine with an active health science and technology market that makes consumer personalized medicine possible [6]. Furthermore, people increasingly seek health information by themselves.

These developments transform the very meaning of health, health care and rehabilitation [7,8], and the delivery of health care and rehabilitation [9-16] including home care. This in turn changes expectations for the functional abilities of those considered suited for home care support. This shift in understanding of the nature of the health client from a passive recipient to an active shaper, and a corresponding framing of patients and clients as health consumers, has broad implications for people with disabilities.

In this paper, we focus on ways that health technologies may change ability expectations for people receiving home care. We critically examine how technology-driven products and processes, including those related to self-diagnosis, health monitoring, companionship, health information gathering, and care, pose new challenges in terms of physical and cognitive accessibility for people with disabilities. Non-normative body abilities present challenges for physically accessing health technologies while non-normative intellectual abilities raise obstacles for understanding information provided via health technologies and for understanding how to operate a given health technology. In this paper, we use the lens of ability expectations (that one wishes to possess certain abilities and regards these abilities in others as desirable) and ableism (where such ability expectations are viewed as not only desirable but also essential) to examine the impact of ability expectations inherent to using self-diagnosis, health-monitoring, and care devices. In short, this lens is used to focus on what abilities are expected and why, and the impact of such ability expectations [17,18]. We anchor this work in the belief that ableism is an important consideration in how ableist thinking influences the development and use of health technologies and ultimately the direction of advances in health care, health research, health policy, and the utility of these for people with disabilities.

## An Ability Expectation/Ableist Lens Described

The term ableism evolved from the disabled people rights movements in the United States and Great Britain during the 1960s and 1970s [19]. It has been traditionally understood in the disabled people rights movement and in the academic field of disability studies as a grand narrative, that is, a universalized and systematized conception of “ability” oppression based on a set of beliefs, processes, and practices that perceive species-typical normative body structure-based abilities as essential. Ableism was coined to flag that certain physical and mental abilities were not only desired but also viewed as essential. Ableism can lead to the experience of disablism [20], which means a lack of equity for people who do not exhibit expected abilities and are thus labelled as sub-species-typical, namely people labeled as having disabilities. Yet ability expectations and ableism are much broader cultural phenomena not confined to physical and mental abilities. Every individual, household, community, group, sector, region, country, and culture cherishes and promotes numerous abilities while viewing other abilities as non-essential or even undesirable. Many people desire the ability to consume certain products, be competitive, or productive while others desire living in an equitable community. Some desire the ability to drive a car, others the ability to use public transportation. The pervasiveness and infinite possibilities of ability expectations produce a particular understanding of oneself, one’s body, and one’s relationship with others of one’s species, other species [21], and one’s environment [21] based on one’s abilities [17,18]. A self-perpetuating pattern plays itself out through which ability expectations shape health technology development and use. In turn, ability expectations inherent to available health technologies influence the ability expectations of people with disabilities and whether those people can fulfil the ability expectations becomes a defining factor of the utility of such health technology products for people with disabilities.

This paper is our attempt to momentarily apprehend this ever-evolving pattern to draw out the utility and potential disadvantages so-called supportive technologies may pose for people with disabilities. We approach this through a critical examination of a selection of academic literature. We collected articles from the academic databases Scopus (n=72), Web of Science (n=19), EBSCO ALL (n=27), IEEE Xplore (n=6), and Compendex (n=6) that had the term “home care technology” in the abstract or as a topic (in the case of Web of Science) (May 10, 2014). We also used our background knowledge and related academic literature pertaining to self-diagnosis, health monitoring, companionship, health information gathering, and care that we have used in earlier work. We examined these articles in terms of ability expectations assumed in the presentation of home care technologies, or discussed in relation to home care technologies. Our purpose is to bring together, and provide some synthesis of, the types of utility and disadvantages that can arise for people with disabilities in home care technology development and use.

## Living in an Age of Health Support From the Convenience of Home

### Health Information Gathering

As part of a widespread “do-it-yourself” move towards obtaining health information from online sources without involving a health practitioner, health clients increasingly expect to be in the driver’s seat with their health interventions [22]. Ideas of *patient-driven health care* have become central in policy discussions as quantified self-movements continue to gather momentum predicated on people’s ability to diagnose themselves [6,10-13]. A 2006 survey of more than 8000 Americans responding to an offer of free Internet access in exchange for completing occasional surveys, yielded findings that “populations with serious health needs and those facing significant barriers in accessing health care in traditional settings turn to the Internet for health information” [23]. Indeed, people increasingly self-diagnose aspects of their “health” [12]. According to the Wisconsin Longitudinal Study Graduate Sample, 40% of respondents with Internet access reported using the Internet to look for advice or information about health or health care in 2001 [24]. Findings from a US study show that 80% of American Internet users have searched for information on at least one of 17 health topics [25]. According to USA Today, search engines such as AOL and Google (whose top 10 list of most frequently visited sites for 2009 overlaps somewhat with AOL's) are typically the first place Internet health information seekers visit, rather than academic medical center or hospital websites [26]. The Pew Research Center's Internet & American Life Project, which consists of ongoing surveys about the social impact of the Internet, concurs that in 2008, "8 in 10 Internet users, or 61% of US adults, have looked online for health information" [27]. In fact, 60% of respondents to that survey indicated the information found online affected a decision about how to treat an illness or condition while 56% say it changed their overall approach to maintaining their health or the health of someone for whom they provide care [27].

### Health Monitoring and Care at Home: Sensors, Assistive Devices, and Social Robotics

The Ontario Homecare Association [28] highlights the responsive and fiscally beneficial nature of home care:

> *Home care has evolved by responding to changes that have occurred in the hospital sector (bed closures, increase in ambulatory care clinics, and day surgery) and in the long term care facilities sector (waiting lists for beds, limited availability). As a result, home care has emerged as an integral component of Canada's health care system and essential to its sustainability. Home and community care comprises 4.25% of the overall spending on health care within provincial budgets*

Health technology developments expand the ways in which the home is part of health care delivery. Sensor networks and ubiquitous computing are two leading technology developments that enable what is being termed "smart home care". Smart home care entails, among other things, the use of miniature sensors and is designed to assist the elderly and chronic patient in ways that "integrate with existing medical practices and technology" and "enable real-time, long-term, remote monitoring" [29]. Sensors can be implanted into the body, externally attached to bodies (wearable sensors), and/or positioned in the walls and floors of a home [6]. Sensors are used for disabled people in areas such as health monitoring (eg, physiological monitoring such as through using sensor pillow systems to monitor for cardiorespiratory and posture movements during sleep, monitoring of movement, and detection of falls during waking hours) and provision of information (eg, assistance with indoor navigation or evacuation and rescue instructions in case of emergencies) [6].

Interactive devices also occupy an expanding place in home health monitoring and care. For example, wireless personal digital assistants (PDA) for telemedical diabetes care enable communication between a glucometer, an insulin pump, and a continuous glucose sensor controlled through the patient's PDA device and responded to by the patient through a user-friendly interface [30]. Expanding on home health support possibilities is the newly emerging field of social robotics [31]. Social robots are designed to perform functions previously performed by health care staff ranging from monitoring nutrition and hydration and providing reminders to take medications to performing household tasks such as cleaning to highly interactive functions such as providing assistance with movement, providing companionship, and even offering motivational advice for physical activities [31].

## An Ability Expectations Critique

### *Overview*

While we applaud advances in health care support made possible through emerging technologies, we urge critical examination of such technologies and their implications for the rights and dignity of people with diverse abilities. Using an ability expectation lens to examine technologies, we note concerns with potential for technologies to result in new forms of exclusion and powerlessness.

### *Exclusion*

At first blush, the pervasiveness of accessing health information from online sources appears to be an important step towards a democratization of health information. Yet ease of access is far from democratic. For example, 3000 randomly sampled adults (2006) expressed frustration with a lack of information or an inability to find what they were looking for online, while 18% indicated feeling confused by information they found online [25]. These results may be unsurprising given that health information is not often presented in plain language and contradictory claims about health conditions are not uncommon. At the same time, the online or telephone survey designs of these large scale studies imply that respondents were of cognitively normative functional ability as a prerequisite for participation. If a significant proportion of these study respondents express frustration or confusion in relation to Internet health information, how might people labelled cognitively impaired be able to generate and evaluate Internet health information? Of related concern are ability issues for people with sensory differences (eg, blindness). Most webpages are not accessible to people who are blind or partially sighted [32]. Thus difficult questions arise over how people with sensory differences might be excluded from accessing information about their health.

Additional layers of exclusion arise given potential for use of sensors or robots by people with disabilities to result in decreased human interaction owing to sensors or robots replacing hands on/relationship-based health care providers [6]. Tiwari et al (2010) take concerns over reduced human interaction a step further as they speak about diminished interactions not with paid health providers, but rather with family caregivers. Specifically, Tiwari et al raise the potential for use of robots to give "permission" for family caregivers to abdicate responsibility in the lives of people with impairments (in this case, frail elders) on the pretext that their elders have artificial company [33].

### *Powerlessness*

Health technologies raise a host of potential for people with disabilities to experience powerlessness through restrictions of access to, and control over, devices, along with restrictions in the very processes of consenting/approving use of devices.

Many, if not all, health technologies that expect "patient" interaction, such as the telemedical diabetes care devices, raise questions about "user friendliness" given that procedures requiring patients to generate, interpret, and relay information may not be accessible for people with physical or cognitive differences. Similarly, some functions of social robots require cognitive, physical, and in some cases, emotional abilities from the disabled person in order for the social robot to be of use.

Other monitoring and support features of devices and social robots may be viewed as "ability neutral" in terms of interaction expectations placed on the person being monitored, that is, the person is not required to program, interpret, or actively respond. However, these devices and robots raise ethical concerns pertaining to the ability of people with impairments to fully understand use of the devices, which in turn raises potential for invasions of privacy [6,24]. And what about instances where people may understand but not agree to terms of use? Tiwari et al (2010) discuss potential dilemmas over when and how individuals control their use of technology: "The ethical dilemma arises as to when to give a choice, where a user may allow or block certain features, eg, a user should have choice when not to allow observational recording but it also may be a compromise on safety when a potentially lifesaving device was turned off and it was needed" [33]. Indeed, several authors covering home care technologies mention the lack of ethical considerations [33,34], and one study highlighted that there are various ethical issues that have to be overcome and that ethics issues are very complex and subject to change as technology advances [35].

# Discussion

## The Need for Participatory Design Processes

Although the relative abundance and accessibility of prescribed health monitoring and support devices and Internet-based health information have expanded the reach of health support in general, accessibility and utilization for people with physical, cognitive, or sensory differences have not been accounted for in the design of many such health technologies. We argue that physical and social realities of people with disabilities command greater attention toward understanding and increasing accessibility of health technologies. People with disabilities are likely to experience more intense and complex health needs as they have relatively less access to social determinants of health such as economic security, social inclusion, and access to health promotion [36]. Further, adults with disabilities are not likely to have spouses and children to turn to for support [37,38]. While this population has high needs for access to health support, the technology advancements in health support discussed above may constitute a further layer of health support disadvantage owing to ableist attitudes and policies and practices flowing from such ableist attitudes. Through bringing together and synthesizing the types of disadvantages that can arise for people with disabilities in home care technology development and use, we delineate these disadvantages as falling into two main categories of exclusion and powerlessness. We conclude with resources and recommendations for taking steps to address these disadvantages.

Consistent with the principles indicated in research guidelines, which require collaboration with patients/participants [39], we suggest that problems of technology-driven exclusion can be addressed by product development that uses participatory design principles [40,41], where co-designing with generative design tools is one possible avenue to perform participatory design [42,43].

At the same time, a number of researchers point out difficulties associated with participation by people with disabilities [39,44,45] including needs for adapting processes through which informed consent, as well as study-topic related needs and preferences, are provided by participants. We refer readers to resources created to facilitate such adapted processes including Alberta Human Services, Adult Guardianship and Trusteeship Act (AGTA), which details guidelines for supporting adults who need assistance with decision making, and the Law Commission of Ontario, which provides a recent (2014) collection of commissioned papers pertaining to capacity, decision-making, and guardianship.

Rice et al (2007) discuss elder-friendly technology development and offer strategies for addressing an array of issues related to anxiety with technology, needs for concrete examples, and reluctance to complain [46]. Goodman et al also discuss difficulties engaging elders in product design and propose a model of "development by proxy" instructive to participatory work with people with disabilities [47]. Goodmann et al discuss the Prosumer (producer+consumer) Model of participatory design of technology for home health, which is based on a user-centered design process consisting of user needs assessment, technology prototype deployment to the home, in-home usability testing, feedback, and iterative design [47]. Prosumers with severe physical disabilities are trained in techniques of introspection and self-reporting to assist them to participate in usability studies. Their residences are being equipped with Internet-connected PCs that are smart-home interfaces with control and data logging software [47].

## Conclusions

We have provided a glimpse of what is possible, and for whom, in home self-diagnosis, health monitoring, companionship, health information gathering, and care. Ableism influences choices made by funders, policy makers, and the public in the development and use of home health technologies and impacts how people with disabilities are served and how useful health support technologies will be for them. We urge continued critical examination of technology development and use according to ability expectations, and we recommend increasing incorporation of participatory design processes to counteract potential for health support technology to render people with disabilities technologically excluded and powerless.

## Conflicts of Interest

None declared.

## References


1. Gottlieb LM. Learning from Alma Ata: the medical home and comprehensive primary health care. J Am Board Fam Med 2009 May;22(3):242-246 [FREE Full text] [doi: 10.3122/jabfm.2009.03.080195] [Medline: 19429729]
2. Simonsen-Rehn N, Laamanen R, Sundell J, Brommels M, Suominen S. Determinants of health promotion action in primary health care: comparative study of health and home care personnel in four municipalities in Finland. Scand J Public Health 2009 Jan;37(1):4-12. [doi: 10.1177/1403494808096171] [Medline: 19039090]
3. Berenson RA, Hammons T, Gans DN, Zuckerman S, Merrell K, Underwood WS, et al. A house is not a home: keeping patients at the center of practice redesign. Health Aff (Millwood) 2008;27(5):1219-1230 [FREE Full text] [doi: 10.1377/hlthaff.27.5.1219] [Medline: 18780904]
4. Caplan A. Minn. hospital bets home care will cut outpatient surgery LOS. Healthc Syst Strategy Rep 1995 Jul 7;12(14):11. [Medline: 10152369]
5. Benjamin AE. An Historical Perspective on Home Care Policy. The Milbank Quarterly 1993;71(1):129. [doi: 10.2307/3350277]
6. Wolbring G, Leopatra V. Sensors: Views of Staff of a Disability Service Organization. JPM 2013 Feb 22;3(1):23-39. [doi: 10.3390/jpm3010023]
7. Wolbring G. HTA Initiative #23 The triangle of enhancement medicine, disabled people,the concept of health: a new challenge for HTA. health research, and health policy. Alberta Heritage Foundation for Medical Research (AHFMR) webpage: Alberta Heritage Foundation for Medical Research (AHFMR); 2005. URL: http://www.ihe.ca/documents/HTA-FR23.pdf [accessed 2011-01-29] [WebCite Cache ID 5w6s4TiL8]
8. Andersen R, Newman JF. Societal and Individual Determinants of Medical Care Utilization in the United States. Milbank Quarterly 2005 Dec;83(4):Online-only. [doi: 10.1111/j.1468-0009.2005.00428.x]
9. Chaudhry B. Systematic Review: Impact of Health Information Technology on Quality, Efficiency, and Costs of Medical Care. Ann Intern Med 2006 May 16;144(10):742. [doi: 10.7326/0003-4819-144-10-200605160-00125]
10. Swan M. Emerging patient-driven health care models: an examination of health social networks, consumer personalized medicine and quantified self-tracking. Int J Environ Res Public Health 2009 Feb;6(2):492-525 [FREE Full text] [doi: 10.3390/ijerph6020492] [Medline: 19440396]
11. Dvorsky G. The quantified self: 6 tools to help you get started. URL: http://ieet.org/index.php/IEET/more/dvorsky20101106 [accessed 2014-06-01] [WebCite Cache ID 6Pzg2w3oI]
12. Wolf G. The quantified self.: TED URL: http://www.ted.com/talks/gary_wolf_the_quantified_self [accessed 2014-06-01] [WebCite Cache ID 6PzgF9iBZ]
13. Blaze Carlson K. The National Post. 2010 Oct 02. The quantified self URL: http://news.nationalpost.com/2010/10/02/the-quantified-self-by-the-numbers/ [accessed 2014-06-09] [WebCite Cache ID 6QCriSDoH]
14. Bloss CS, Ornowski L, Silver E, Cargill M, Vanier V, Schork NJ, et al. Consumer perceptions of direct-to-consumer personalized genomic risk assessments. Genet Med 2010 Sep;12(9):556-566. [doi: 10.1097/GIM.0b013e3181eb51c6] [Medline: 20717041]
15. Guttmacher AE, McGuire AL, Ponder B, Stefánsson K. Personalized genomic information: preparing for the future of genetic medicine. Nat Rev Genet 2010 Feb;11(2):161-165. [doi: 10.1038/nrg2735] [Medline: 20065954]
16. Keller MA, Gordon ES, Stack CB, Gharani N, Sill CJ, Schmidlen TJ, et al. Coriell Personalized Medicine Collaborative: a prospective study of the utility of personalized medicine. Personalized Medicine 2010 May;7(3):301-317. [doi: 10.2217/pme.10.13]
17. Wolbring G. Why NBIC? Why human performance enhancement? Innovation: The European Journal of Social Science Research 2008 Mar;21(1):25-40. [doi: 10.1080/13511610802002189]
18. Wolbring G. Expanding Ableism: Taking down the Ghettoization of Impact of Disability Studies Scholars. Societies 2012 Jul 06;2(4):75-83. [doi: 10.3390/soc2030075]
19. Albrecht GL. Encyclopedia of disability. Thousand Oaks, CA: Sage Pub; 2006.
20. Miller P, Parker S, Gillinson S. Disablism. How to tackle the last prejudice. London, UK: Demos; 2004.
21. Wolbring G. Ecohealth through an ability studies and disability studies lens. In: Gislason MK, editor. Ecological Health: Society, Ecology and Health. London, UK: Emerald; 2013:91-107.
22. Coughlin JF. Old Age, New Technology, and Future Innovations in Disease Management and Home Health Care. Home Health Care Management & Practice 2006 Apr 01;18(3):196-207. [doi: 10.1177/1084822305281955]
23. Bundorf MK, Wagner TH, Singer SJ, Baker LC. Who searches the internet for health information? Health Serv Res 2006 Jun;41(3 Pt 1):819-836 [FREE Full text] [doi: 10.1111/j.1475-6773.2006.00510.x] [Medline: 16704514]
24. Baker L, Wagner TH, Singer S, Bundorf MK. Use of the Internet and e-mail for health care information: results from a national survey. JAMA 2003 May 14;289(18):2400-2406. [doi: 10.1001/jama.289.18.2400] [Medline: 12746364]
25. Fox S. Online Health Search. Pew Internet and American Life project: Pew Research Centre; 2006. URL: http://www.pewinternet.org/files/old-media//Files/Reports/2006/PIP_Online_Health_2006.pdf.pdf [accessed 2014-06-09] [WebCite Cache ID 6QCsWPQtb]

26. Mary Brophy Marcus. USA Today. 2009 Dec 07. Here's to your health searches, via AOL and Google engines URL: http://usatoday30.usatoday.com/news/health/2009-12-07-websearch07_ST_N.htm [accessed 2014-06-09] [WebCite Cache ID 6QCsfmFtU]
27. Fox S, Jones S. Pew Internet and Life Project. Washington, DC: Pew Research Centre; 2011. The social life of health information URL: http://www.pewinternet.org/files/old-media//Files/Reports/2011/PIP_Social_Life_of_Health_Info.pdf [accessed 2014-06-09] [WebCite Cache ID 6QCsvTfa2]
28. Ontario Home Care Association. An Introduction to Home Care. URL: http://www.homecareontario.ca/public/about/home-care/General/index.cfm [accessed 2014-06-01] [WebCite Cache ID 6PzgqMuFQ]
29. Stankovic JA, Cao Q, Doan T, Fang L, He Z, Kiran R, et al. Conference Proceedings: High Confidence Medical Device Software and Systems (HCMDSS) Workshop. Wireless sensor networks for in-home healthcare: Potential and challenges URL: http://www.cs.virginia.edu/~adw5p/pubs/hcmdss05-wsn.pdf [accessed 2014-06-01] [WebCite Cache ID 6PzgwyKGj]
30. García-Sáez G, Hernando ME, Martínez-Sarriegui I, Rigla M, Torralba V, Brugués E, et al. Architecture of a wireless Personal Assistant for telemedical diabetes care. Int J Med Inform 2009 Jun;78(6):391-403. [doi: 10.1016/j.ijmedinf.2008.12.003] [Medline: 19162538]
31. Yumakulov S, Yergens D, Wolbring G. Imagery of people with disabilities within social robotics research. In: ICSR, LNAI. 2012 Presented at: International Conference on Social Robotics; 29-31 October, 2012; Chengdu, China p. 168-177. [doi: 10.1007/978-3-642-34103-8_17]
32. Schitai A. Ableism and inequality online: Analysis of Web accessibility policymaking and implementation in higher education. Long Beach, CA: University of California, Irvine and California State University; 2008.
33. Tiwari P, Warren J, Day KJ, McDonald B. Health Care and Informatics Review Online. 2010. Some non-technology implications for wider application of robots assisting older people URL: http://www.hinz.org.nz/uploads/file/2009conference/P36_Tiwari.pdf [accessed 2014-06-01] [WebCite Cache ID 6PzgyrtJU]
34. Demiris G, Rantz M, Aud M, Marek K, Tyrer H, Skubic M, et al. Older adults' attitudes towards and perceptions of "smart home" technologies: a pilot study. Med Inform Internet Med 2004 Jun;29(2):87-94. [doi: 10.1080/14639230410001684387] [Medline: 15370989]
35. Clark J, McGee-Lennon M. A stakeholder-centred exploration of the current barriers to the uptake of home care technology in the UK. Journal of Assistive Technologies 2011;5(1):12-25. [doi: 10.5042/jat.2011.0097]
36. Connolly BH. General Effects of Aging on Persons with Developmental Disabilities. Topics in Geriatric Rehabilitation 1998;13(3):1-18. [doi: 10.1097/00013614-199803000-00003]
37. Pruchno RA, Patrick JH, Burant CJ. Aging Women and Their Children with Chronic Disabilities: Perceptions of Sibling Involvement and Effects on Well-Being. Family Relations 1996 Jul;45(3):318. [doi: 10.2307/585504]
38. Weeks LE, Nilsson T, Bryanton O, Kozma A. Current and future concerns of older parents of sons and daughters with intellectual disabilities. Journal of Policy and Practice in Intellectual Disabilities 2009;6(3):180-188. [doi: 10.1111/j.1741-1130.2009.00222.x]
39. Brett J, Staniszewska S, Mockford C, Herron-Marx S, Hughes J, Tysall C, et al. Mapping the impact of patient and public involvement on health and social care research: a systematic review. Health Expect 2012 Jul 19:-. [doi: 10.1111/j.1369-7625.2012.00795.x] [Medline: 22809132]
40. Millen L, Cobb S, Patel H. Participatory design approach with children with autism. International Journal on Disability and Human Development 2011;10(4):289-294. [doi: 10.1515/IJDHD.2011.048]
41. Alper M, Hourcade JP, Gilutz S. Interactive technologies for children with special needs. 2012 Presented at: 11th International Conference on Interaction Design and Children; June 12-15, 2012; Bremen, Germany.
42. Hussain S, Sanders EB. Fusion of horizons: Co-designing with Cambodian children who have prosthetic legs, using generative design tools. CoDesign 2012 Mar;8(1):43-79. [doi: 10.1080/15710882.2011.637113]
43. Wolbring G, Diep L, Yumakulov S, Ball N, Yergens D. Social Robots, Brain Machine Interfaces and Neuro/Cognitive Enhancers: Three Emerging Science and Technology Products through the Lens of Technology Acceptance Theories, Models and Frameworks. Technologies 2013 Jun 10;1(1):3-25. [doi: 10.3390/technologies1010003]
44. Mooney LR, Lashewicz B. Voices of care for adults with disabilities and/or mental health issues in Western Canada: what do families and agencies need from each other? Health Soc Care Community 2014 Mar;22(2):178-186. [doi: 10.1111/hsc.12074] [Medline: 24118309]
45. BOOTH T, BOOTH W. Sounds of Silence: Narrative research with inarticulate subjects. Disability & Society 1996 Mar;11(1):55-70. [doi: 10.1080/09687599650023326]
46. Rice M, Newell A, Morgan M. Forum Theatre as a requirements gathering methodology in the design of a home telecommunication system for older adults. Behaviour & Information Technology 2007 Jul;26(4):323-331. [doi: 10.1080/01449290601177045]
47. Goodman CA, Jimison HB, Pavel M. Participatory design for home care technology. 2002 Presented at: 24th Annual Conference and the Annual Fall Meeting of the Biomedical Engineering Society EMBS/BMES Conference; October 23-26, 2002; Houston, TX p. 23-26.

*Edited by G Eysenbach; submitted 26.11.13; peer-reviewed by D Juzwishin, R Kobb; comments to author 31.01.14; revised version received 19.05.14; accepted 31.05.14; published 20.06.14.*

*Please cite as:*
*Wolbring G, Lashewicz B*
*Home Care Technology Through an Ability Expectation Lens*
*J Med Internet Res 2014;16(6):e155*
*URL: http://www.jmir.org/2014/6/e155/*
*doi:10.2196/jmir.3135*
*PMID:24956581*

Publisher:
JMIR Publications
130 Queens Quay East.
Toronto, ON, M5A 3Y5
Phone: (+1) 416-583-2040
Email: support@jmir.org