Original Paper

Text Dialogue Analysis for Primary Screening of Mild Cognitive Impairment: Development and Validation Study

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Abstract

Background: Artificial intelligence models tailored to diagnose cognitive impairment have shown excellent results. However, it is unclear whether large linguistic models can rival specialized models by text alone.

Objective: In this study, we explored the performance of ChatGPT for primary screening of mild cognitive impairment (MCI) and standardized the design steps and components of the prompts.

Methods: We gathered a total of 174 participants from the DementiaBank screening and classified 70% of them into the training set and 30% of them into the test set. Only text dialogues were kept. Sentences were cleaned using a macro code, followed by a manual check. The prompt consisted of 5 main parts, including character setting, scoring system setting, indicator setting, output setting, and explanatory information setting. Three dimensions of variables from published studies were included: vocabulary (ie, word frequency and word ratio, phrase frequency and phrase ratio, and lexical complexity), syntax and grammar (ie, syntactic complexity and grammatical components), and semantics (ie, semantic density and semantic coherence). We used R 4.3.0. for the analysis of variables and diagnostic indicators.

Results: Three additional indicators related to the severity of MCI were incorporated into the final prompt for the model. These indicators were effective in discriminating between MCI and cognitively normal participants: tip-of-the-tongue phenomenon ($P<.001$), difficulty with complex ideas ($P<.001$), and memory issues ($P<.001$). The final GPT-4 model achieved a sensitivity of 0.8636, a specificity of 0.9487, and an area under the curve of 0.9062 on the training set; on the test set, the sensitivity, specificity, and area under the curve reached 0.7727, 0.8333, and 0.8030, respectively.

Conclusions: ChatGPT was effective in the primary screening of participants with possible MCI. Improved standardization of prompts by clinicians would also improve the performance of the model. It is important to note that ChatGPT is not a substitute for a clinician making a diagnosis.

(J Med Internet Res 2023;25:e51501) doi: 10.2196/51501

KEYWORDS

artificial intelligence; AI; AI models; ChatGPT; primary screening; mild cognitive impairment; standardization; prompt design; design; artificial intelligence; cognitive impairment; screening; model; clinician; diagnosis

Introduction

Alzheimer disease (AD) is the most common form of dementia, causing abnormal mental decline, involving thinking, memory, and language, and severely affecting the patient's quality of life [1]. AD has always been a major health hazard to society and a huge burden to the health care system, and this burden will even increase in the future [2,3]. There is an urgent need for human society to carry out prevention and intervention for AD. Although AD is progressive and incurable, early detection, diagnosis, and treatment can effectively delay its progression and thus significantly improve the quality of life of patients [4]. Mild cognitive impairment (MCI) has been recognized as a strong predictor of AD and represents an early stage of AD; early diagnosis and intervention of MCI will be of great help to human society in the fight against AD [4-6]. However, neuropsychological testing for MCI is time-consuming and rigorous. To accommodate the potentially large population with MCI in society, a variety of validated brief cognitive tests, including language tests, memory tests, the Mini-Mental State Examination (MMSE), and the Montreal Cognitive Assessment (MoCA), are widely used for early screening of the disease [7-9]. Developments in artificial intelligence (AI) are likely to make this process more accessible, enabling a broader group of people to receive its benefit [10].

AI has emerged as a promising tool in health care, particularly in cognitive impairment diagnosis [11,12]. AI can provide a more accurate and standardized process for diagnosing and predicting diseases [13]. Thabtah et al [14] conducted a comprehensive analysis of mobile-based AD and MCI screening apps, highlighting the potential of AI applications for the early detection and diagnosis of dementia. The study also explored the use of AI to improve access to health care services. Kalafatis et al [15] demonstrated the convergent validity of the Integrated Cognitive Assessment (ICA) using cognitive tests, such as the MoCA [15]. The AI model of the ICA was able to detect cognitive impairment with an area under the curve (AUC) of 0.81 for patients with MCI and an AUC of 0.88 for patients with mild AD [15]. In contrast to custom-built AI models, we would like to see if large language models can be applied to this domain with good outcomes [16,17].

ChatGPT is a high-level large language model developed by OpenAI, designed to generate human-like text based on the input it receives [18]. GPT-4, the latest version available as of the September 2021 knowledge deadline, has a larger model size in terms of parameters and improved text generation capabilities than its predecessors [19,20]. The generative pretrained transformer (GPT) model is a neural network architecture for understanding data sequences such as text. ChatGPT is pretrained on a large corpus of text data, enabling it to understand and generate text that is not only grammatically correct but also contextually relevant and coherent over a long period of time [21]. With its powerful text analysis capabilities, we were ready to explore whether ChatGPT could be used for primary screening of MCI based on text conversation analysis under the supervision of neurologists [22]. We will discuss the process and components of a standardized prompt design [23].

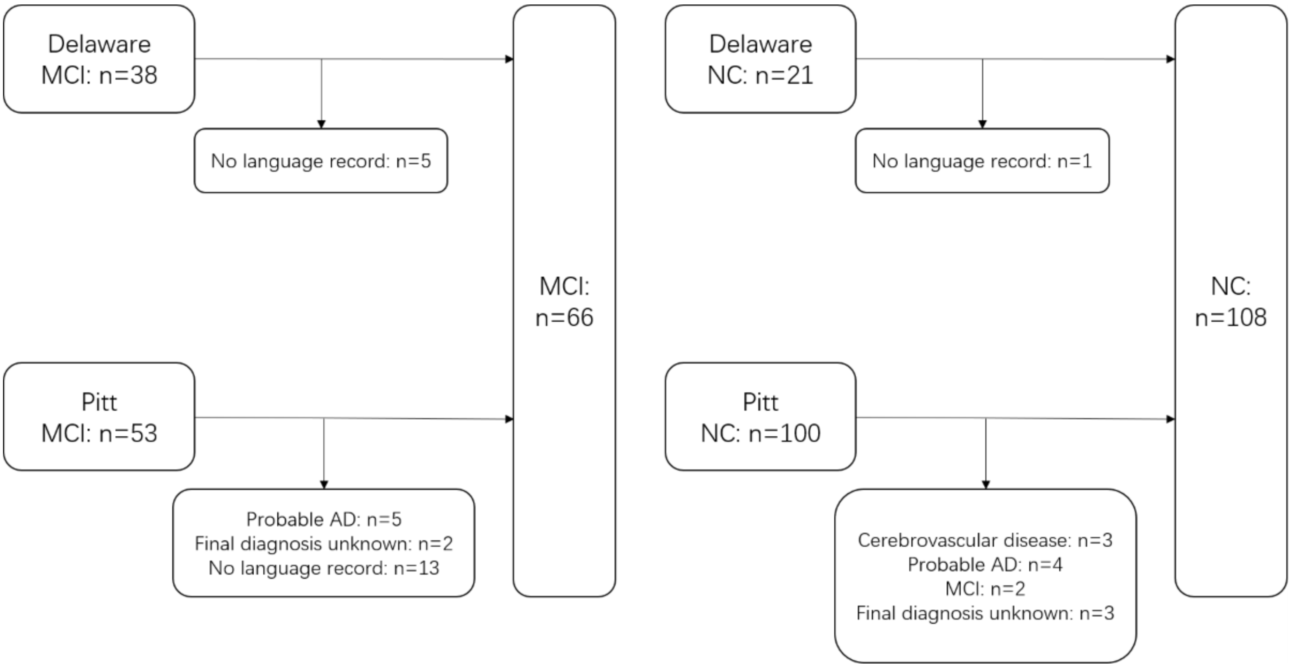
It is crucial to emphasize that ChatGPT is only intended as a primary screening tool and does not have a diagnostic role [24]. This study aims to explore the feasibility of using ChatGPT for the primary screening of MCI through the analysis of text-based conversations. Furthermore, it seeks to establish a standardized protocol for prompt design in this specific application, following the guidance of expert neurologists.

Methods

Inclusion and Exclusion of Participants

We included a total of 174 participants from the DementiaBank English Protocol Delaware Corpus [25] and the DementiaBank English Pitt Corpus [6,26] (Figure 1). The initial data set included participants from the Delaware Corpus and the Pitt Corpus who were assessed using the Everyday Cognition Questionnaire, the Clinical Dementia Rating Scale, and the MMSE score to ensure that participants were accurately classified into the MCI category. Selection criteria for both corpora excluded other systemic diseases or brain disorders that could lead to cognitive decline (Multimedia Appendix 1 includes descriptions and selection criteria for both corpora).

Figure 1. Participants inclusion and exclusion. AD: Alzheimer disease; MCI: mild cognitive impairment; NC: normal cognition.



A total of 66 participants with MCI were included. In the Delaware database, we excluded 5 patients with no language record data and finally included 33 participants. In the Pitt database, we finally included 33 participants; 30 of them were from the dementia group and 3 from the control group. The specific screening method was as follows: we screened 36 participants from the dementia group by initial diagnosis of MCI; we then excluded 5 participants with probable AD, 2 participants with unknown final diagnosis, and 13 participants with no language record data. We also included 3 participants with a final diagnosis of MCI from the control group.

A total of 108 cognitively normal participants were included. In the Delaware database, we excluded 1 patient with no language record data and finally included 20 participants with 20 language records obtained. In the Pitt database, there were a total of 100 participants in the control group with language record data, and we finally included 88 participants. The specific screening method was as follows: we excluded controls with cerebrovascular disease since participants were ultimately diagnosed with probable AD or MCI. Controls without a definitive diagnosis, controls with a final diagnosis of probable AD, controls with a final diagnosis of MCI, and controls with a final diagnosis of cerebrovascular disease were also excluded.

In the end, 66 participants with MCI and 108 participants with normal cognitive function were included.

Ethical Considerations

All data used in this study were obtained from publicly available databases (DementiaBank data set), archived by TalkBank. TalkBank abides by its Code of Ethics, which complements but does not replace the commonly accepted professional codes, such as the American Psychological Association Code of Ethics and the American Anthropological Association Code of Ethics [27]. It should be emphasized that the data do not contain individual patient information, which obviates the need for ethical approval and individual patient consent. In addition, all protected health information was appropriately anonymized to ensure compliance with data protection regulations. Therefore, this study was exempt from ethics approval by the Bioethics Committee of the West China Hospital of Sichuan University.

Data Cleaning and Distribution

First, only the text dialogues “PARTICIPANT” and “INVESTIGATOR” were kept. Then each sentence was cleaned using the macro codes (Multimedia Appendix 1). Finally, a manual check was performed by CW.

Random numbers were generated using the RAND and RANK functions to renumber all participants. We used these random numbers to split the data set randomly into 70% training data and 30% test data. The training set contained 44 participants with MCI and 78 participants with normal cognitive function, and the test set contained 22 participants with MCI and 30 participants with normal cognitive function (Multimedia Appendix 2).

Model Prompt Design

Model 1 Prompt

We identified the basic indicators for analyzing language features based on published studies, including vocabulary features, syntax and grammar features, as well as semantics features in 3 main areas, with a total of 7 indicators (Table 1) [28-31].

Table 1. Analysis of indicators and evaluation of indicators.

Classification	Analysis of indicators	Evaluation of indicators
Vocabulary features	Word frequency and word ratio, phrase frequency and phrase ratio, and lexical complexity	Limited vocabulary, increased verbosity, overlearned phrases, improper use of pronouns, hesitation (word-finding difficulties), circumlocution (word-finding difficulties), tip-of-the-tongue phenomenon, and repetition
Syntax and grammar features	Syntactic complexity and grammatical components	simplified sentence structure and grammar, grammatical errors, and difficulty with complex ideas
Semantics features	Semantic density and semantic coherence	Semantic paraphasias, lack of coherence, consistency in errors, lack of semantic fluency, disorganized narrative structure, orientation issues, decline in conversational engagement and responsiveness, memory issues, lack of abstract thinking and synthesis, and abnormal emotions

Model 2 Prompt

At the end of the Model 1 training, participants received Feedback 1, which included more detailed MCI features. This information was used to design the new prompt.

Model 3 Prompt

We set a new prompt based on Feedback 2 generated by Model 2. Differently, we extracted 21 severity assessment indicators related to MCI and designed a scoring system (Table 1).

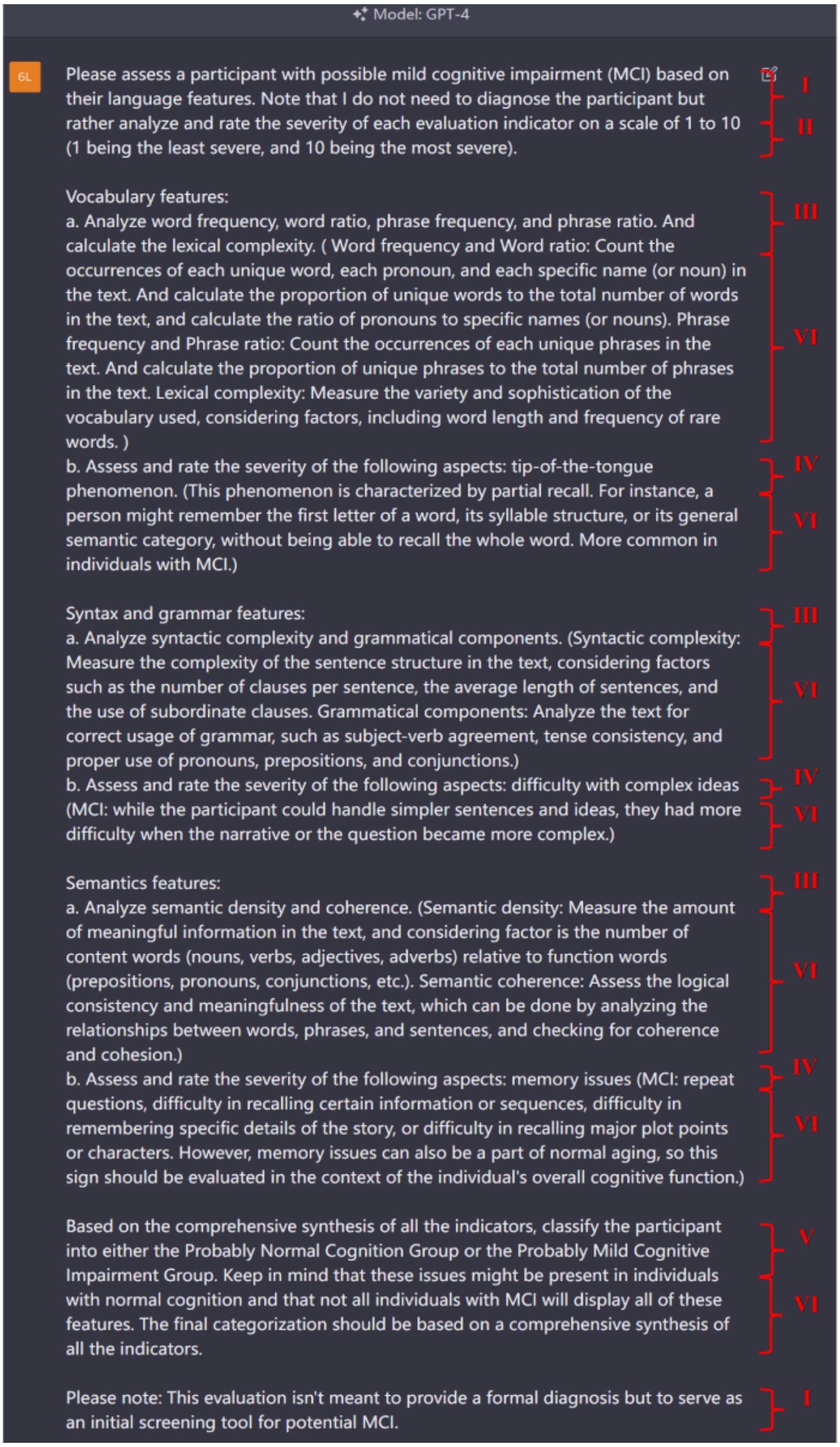
Model 4 Prompt

We allowed GPT-4 to design 3 prompts for itself based on the Model 3 prompt and integrated them. This helped to compare the differences between the manual and robotic designs and standardize the format of the subsequent prompts.

Model 5 Prompt

The 21 indicators obtained from the GPT-4 Model 3 to assess the severity of MCI were analyzed using statistical methods to select more statistically significant indicators and to reduce bias. The prompt format of Model 4 was then followed for the design. The prompt was designed in 4 steps. In the first step, high-quality literature (preferably high-quality systematic reviews) was found, and proven valid indicators were extracted and added to the prompts with an interpretation of these indicators. In the second step, ChatGPT was required to output the results by analyzing these indicators, while interpreting the association between each patient's symptoms and the indicators. The new explanatory information was collected, organized, reviewed, and finally added to the prompt. In the third step, the indicators were scored, and these scores were statistically analyzed to select those that better discriminated between the experimental and control groups. Finally, by standardizing the format of the prompt, the indicators selected in step 3 were incorporated, and the information collected in step 2 was used to interpret them. The prompt consisted of 5 main parts (Figure 2). The first part was character setting (ie, designing a role for ChatGPT). In this research, ChatGPT was set up as a physician's assistant who, by analyzing indicators, would first classify the participants into the probable MCI group and the probable normal cognitive function group; it would then provide detailed reasons for doing so, to facilitate the diagnosis by physicians. The second part was the establishment of a scoring system. Its purpose was to quantify the narrative indicators to facilitate subsequent statistical analysis. The third part was the definition of indicators. Indicators were divided into those included based on the literature and those included based on the analysis. The quality, rather than the quantity of the included indicators, was ensured. The fourth part was the output setting. This part required matching with the first part. The fifth part was the explanatory information setting. Providing valid explanatory information, derived from the literature or analysis for each indicator, could improve the performance of the models.

Figure 2. Prompt Design. The prompt consists of 5 main parts. The character setting is shown as Ⅰ. The scoring system setting is shown as Ⅱ. The indicator settings are shown as Ⅲ and Ⅳ. Indicators include those included based on literature (ie, shown as Ⅲ) and those included based on analysis (ie, shown as Ⅳ). The output setting is shown as Ⅴ. The explanatory information settings are shown as Ⅵ.



Please assess a participant with possible mild cognitive impairment (MCI) based on their language features. Note that I do not need to diagnose the participant but rather analyze and rate the severity of each evaluation indicator on a scale of 1 to 10 (1 being the least severe, and 10 being the most severe).

Vocabulary features:
a. Analyze word frequency, word ratio, phrase frequency, and phrase ratio. And calculate the lexical complexity. (Word frequency and Word ratio: Count the occurrences of each unique word, each pronoun, and each specific name (or noun) in the text. And calculate the proportion of unique words to the total number of words in the text, and calculate the ratio of pronouns to specific names (or nouns). Phrase frequency and Phrase ratio: Count the occurrences of each unique phrases in the text. And calculate the proportion of unique phrases to the total number of phrases in the text. Lexical complexity: Measure the variety and sophistication of the vocabulary used, considering factors, including word length and frequency of rare words.)
b. Assess and rate the severity of the following aspects: tip-of-the-tongue phenomenon. (This phenomenon is characterized by partial recall. For instance, a person might remember the first letter of a word, its syllable structure, or its general semantic category, without being able to recall the whole word. More common in individuals with MCI.)

Syntax and grammar features:
a. Analyze syntactic complexity and grammatical components. (Syntactic complexity: Measure the complexity of the sentence structure in the text, considering factors such as the number of clauses per sentence, the average length of sentences, and the use of subordinate clauses. Grammatical components: Analyze the text for correct usage of grammar, such as subject-verb agreement, tense consistency, and proper use of pronouns, prepositions, and conjunctions.)
b. Assess and rate the severity of the following aspects: difficulty with complex ideas (MCI: while the participant could handle simpler sentences and ideas, they had more difficulty when the narrative or the question became more complex.)

Semantics features:
a. Analyze semantic density and coherence. (Semantic density: Measure the amount of meaningful information in the text, and considering factor is the number of content words (nouns, verbs, adjectives, adverbs) relative to function words (prepositions, pronouns, conjunctions, etc.). Semantic coherence: Assess the logical consistency and meaningfulness of the text, which can be done by analyzing the relationships between words, phrases, and sentences, and checking for coherence and cohesion.)
b. Assess and rate the severity of the following aspects: memory issues (MCI: repeat questions, difficulty in recalling certain information or sequences, difficulty in remembering specific details of the story, or difficulty in recalling major plot points or characters. However, memory issues can also be a part of normal aging, so this sign should be evaluated in the context of the individual's overall cognitive function.)

Based on the comprehensive synthesis of all the indicators, classify the participant into either the Probably Normal Cognition Group or the Probably Mild Cognitive Impairment Group. Keep in mind that these issues might be present in individuals with normal cognition and that not all individuals with MCI will display all of these features. The final categorization should be based on a comprehensive synthesis of all the indicators.

Please note: This evaluation isn't meant to provide a formal diagnosis but to serve as an initial screening tool for potential MCI.

For clarity, our experiments were conducted from May 11, 2023, to June 1, 2023. During this period, we specifically used GPT-4 and GPT-3.5. This ensures that all responses analyzed were consistent in terms of the version's capabilities and potential biases. All model prompts, feedback, and detailed explanations of each indicator are available in the Multimedia Appendix 1.

Statistics Analysis

The outcome of our study is the diagnosis of MCI, and the independent variables are the responses generated by GPT-3.5 and GPT-4 to the prompts designed across different models.

Descriptive statistics, including the calculation of mean, SD, median, IQR, as well as minimum and maximum values were performed for each variable in each group. We then analyzed the normal distribution and the homogeneity of variance test of the data for all variables. On the one hand, if the variables were normally distributed and had a uniform variance, a one-way ANOVA was used for the 4 groups—true positive (TP), false positive (FP), false negative (FN), and true negative (TN)—and an independent samples *t* test (2-tailed) was used for the 2 groups—positive and negative. If there were differences in the results of the one-way ANOVA, a two-way comparison was performed using the Tukey Honestly Significant Difference test as a post hoc test. On the other hand, if the variables were not normally distributed, the Kruskal-Wallis *H* test was used for the 4 groups, and the Mann-Whitney *U* test was used for the 2 groups. If there were differences in the results of the Kruskal-Wallis *H* test, the Dunn test was applied as a post hoc test (Multimedia Appendix 2). Finally, the visualization of violin plots was used to compare the degree of concentration and dispersion of each variable.

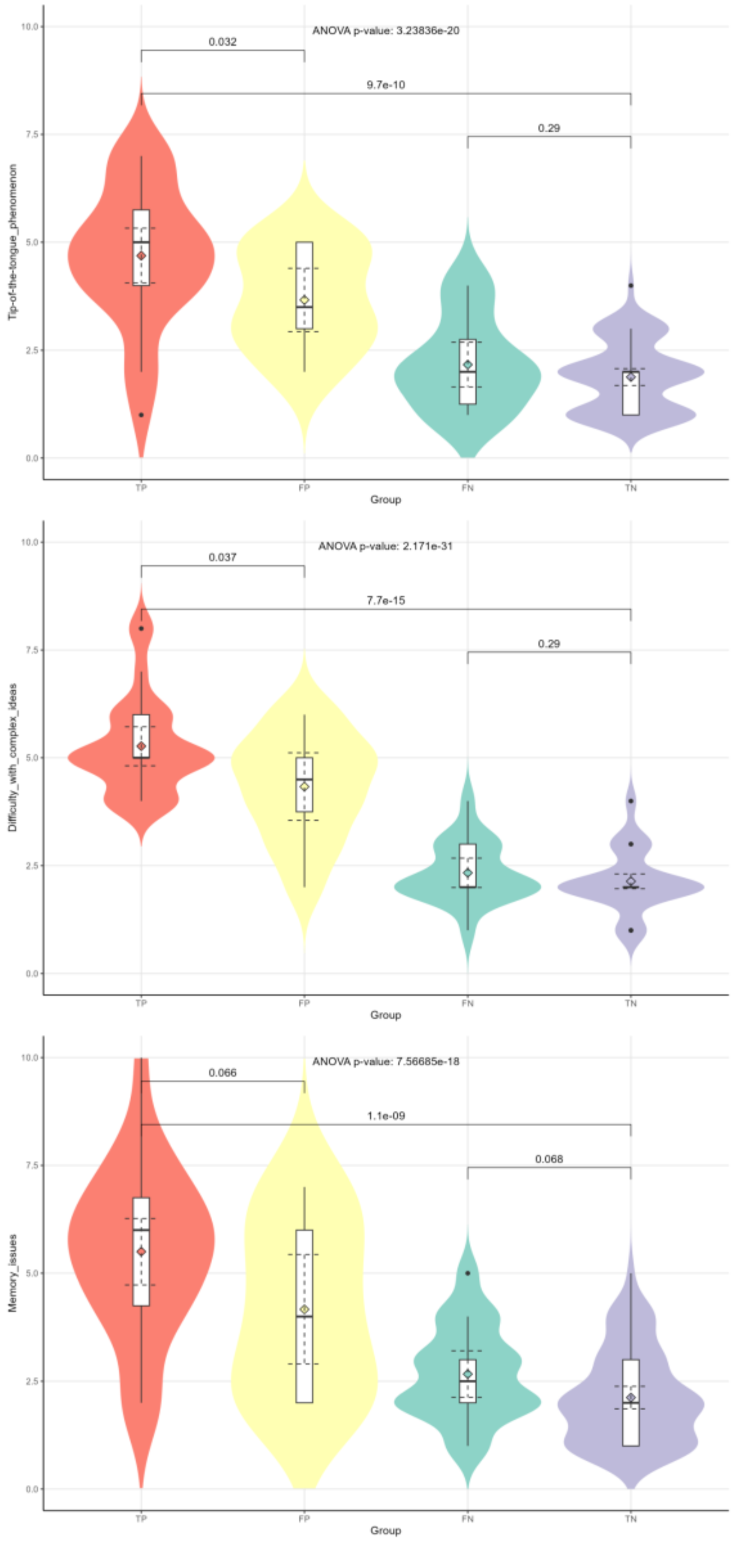
Sensitivity, specificity, positive predictive value, negative predictive value, positive likelihood ratios, negative likelihood ratios, accuracy, receiver operating characteristics curve, and the AUC of the different models were compared (Multimedia Appendix 2). Analysis was performed using R 4.3.0 (R Foundation for Statistical Computing). All R codes can be found in Multimedia Appendix 1.

Results

Inclusion of Variables

In addition to the 8 analytic indicators that had been explicitly included in the Model 5 prompts, we included 3 evaluative indicators in the final prompt. These 3 indicators were generated from 21 indicators (Table 1) that assessed the severity of MCI, and they were effective in discriminating between MCI and cognitively normal participants, namely tip-of-the-tongue phenomenon (*P*<.001), difficulty with complex ideas (*P*<.001), and memory problems (*P*<.001; Figure 3). Although most of the indicators were effective in distinguishing FP-FN, TP-FN, TN-FP, and TP-TN, only the tip-of-the-tongue phenomenon (without adjustment for multiple comparisons: *P*=.03; with adjustment for multiple comparisons: *P*=.04), difficulty with complex ideas (without adjustment for multiple comparisons: *P*=.04; with adjustment for multiple comparisons: *P*=.01), and memory problem (without adjustment for multiple comparisons: *P*=.07; with adjustment for multiple comparisons: *P*=.03) could effectively discriminate TP-FP (Figure 3). The statistical analysis of all indicators can be found in Multimedia Appendix 1.

Figure 3. The violin plots of the selected evaluation metrics. Tip-of-the-tongue phenomenon, difficulty with complex ideas, and memory problems, 3 metrics for evaluating participants' cognitive functioning, were included in the prompt of Model 5. The violin plots include *P* values from one-way ANOVA and *P* values from the Tukey Honestly Significant Difference test without adjustment for multiple comparisons.



Model Comparison

We found that ChatGPT had acceptable performance in screening for MCI by text analysis alone (Table 2 and Figure 4). On the training set, the sensitivity, specificity, and AUC of the GPT-4 Model 5 reached 0.8636, 0.9487, and 0.9062, respectively; on the test set, the sensitivity, specificity, and AUC reached 0.7727, 0.8333, and 0.8030, respectively. The prompt of Model 5 consisted of 5 main parts, including character setting, scoring system setting, indicator setting, output setting, and explanatory information setting.

Table 2. Diagnostic evaluation indicators.

Dataset	model	TP[a]	FN[b]	FP[c]	TN[d]	Sensitivity	Specificity	PPV[e]	NPV[f]	PLR[g]	NLR[h]	Accuracy
Training set	Gpt-4 Model 1	10	34	5	73	0.2273	0.9359	0.6667	0.6822	3.5455	0.8257	0.6803
Training set	GPT-4 Model 2	20	24	6	72	0.4545	0.9231	0.7692	0.7500	5.9091	0.5909	0.7541
Training set	GPT-4 Model 3	26	18	12	66	0.5909	0.8462	0.6842	0.7857	3.8409	0.4835	0.7541
Training set	GPT-4 Model 4	16	28	13	65	0.3636	0.8333	0.5517	0.6989	2.1818	0.7636	0.6639
Training set	GPT-4 Model 5	38	6	4	74	0.8636	0.9487	0.9048	0.9250	16.8409	0.1437	0.9180
Training set	GPT-3.5 Model 1	13	31	14	64	0.2955	0.8205	0.4815	0.6737	1.6461	0.8587	0.6311
Training set	GPT-3.5 Model 2	22	22	24	54	0.5000	0.6923	0.4783	0.7105	1.6250	0.7222	0.6230
Training set	GPT-3.5 Model 3	26	18	28	50	0.5909	0.6410	0.4815	0.7353	1.6461	0.6382	0.6230
Training set	GPT-3.5 Model 4	22	22	31	47	0.5000	0.6026	0.4151	0.6812	1.2581	0.8298	0.5656
Training set	GPT-3.5 Model 5	25	19	21	57	0.5682	0.7308	0.5435	0.7500	2.1104	0.5909	0.6721
Test set	GPT-4 Model 5	17	5	5	25	0.7727	0.8333	0.7727	0.8333	4.6364	0.2727	0.8077
Test set	GPT-3.5 Model 5	12	10	9	21	0.5455	0.7000	0.5714	0.6774	1.8182	0.6494	0.6346

[a] TP: true positive.

[b] FN: false negative.

[c] FP: false positive.

[d] TN: true negative.

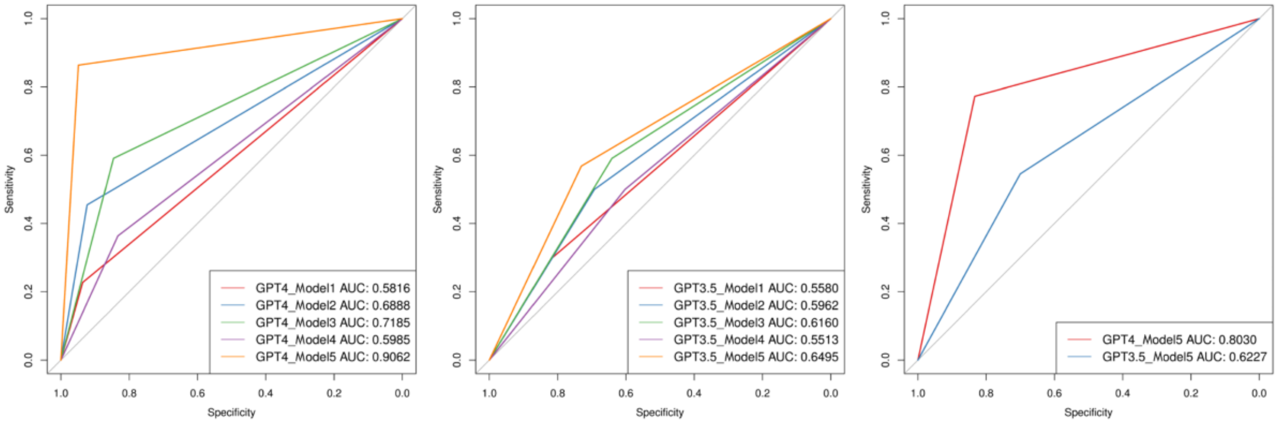
[e] PPV: positive predictive value.

[f] NPV: negative predictive value.

[g] PLR: positive likelihood ratio.

[h] NLR: negative likelihood ratio.

Figure 4. Receiver operating characteristic curve. In the training set, the final Model 5 achieves an area under the curve (AUC) of 0.9062 in GPT-4 and 0.6459 in GPT-3.5. Model 5 outperforms Models 1-4 in both GPT-4 and GPT-3.5. In the test set, Model 5 achieves an AUC of 0.8030 in GPT-4 and 0.6227 in GPT-3.5.



By comparing Model 1, Model 2, and Model 3 (GPT-4 AUC for the models: 0.5816, 0.6888, and 0.7185, respectively; GPT-3.5 AUC for the models: 0.5580, 0.5962, and 0.6160, respectively), we found that providing ChatGPT with more detailed prompts would effectively improve its ability to screen for MCI.

In addition, comparing model 3 and model 4 (GPT-4 AUC: 0.7185 and 0.5985, respectively; GPT-3.5 AUC: 0.6160 and 0.5513, respectively) showed that the physician-designed prompt was superior to the ChatGPT designed prompt.

The analysis and screening of the included indicators would effectively improve the performance of the model, as shown by the comparison of model 3 and model 5 (GPT-4 AUC: 0.7185 and 0.9062, respectively; GPT-3.5 AUC: 0.6160 and 0.6495, respectively).

We also verified that GPT-4 outperformed GPT-3.5 in terms of logical ability, which was reflected in the following two points: first, the AUC of GPT-4 was consistently higher than that of GPT-3.5 under the same model in the same data set; second, the improvement in the prompt was more significant for the performance improvement of GPT-4 compared to GPT-3.5.

Discussion

Main Findings

In our study, we used a text-dialogue analysis approach to evaluate the suitability of ChatGPT for primary screening for MCI and developed a standardized methodology for the design of prompts in this application. Comparative analyses across various ChatGPT models revealed that the more detailed prompts crafted by medical professionals (Model 5) significantly outperformed the less detailed prompts generated by ChatGPT (Models 1-4). This underscored the valuable role of human expertise in enhancing model performance. Furthermore, GPT-4 consistently outperformed GPT-3.5 across all models, demonstrating its superior logical capabilities and responsiveness to cue enhancements.

In exploring the art of prompt creation, we proposed a comprehensive and multifaceted approach. First, we conducted a thorough literature search, focusing on systematic reviews, to systematically identify and understand reliable indicators. Next, ChatGPT played a crucial role in uncovering the relationships between these indicators and patient symptoms, helping us to incorporate this knowledge into the prompt. We then used statistical analyses to score and discriminate the key indicators that differentiate between the experimental and control groups. The outcome of this process was the development of a coherent prompt blueprint that prioritized consistency and clarity. To ensure the effectiveness of the prompt, we recommend incorporating 5 essential pillars, as follows:

1. Character definition: this pillar involves framing ChatGPT as a physician’s assistant, establishing a professional persona that aligns with the intended purpose.
2. Robust scoring mechanism for narrative indicators: developing a reliable system for quantitatively assessing narrative indicators.
3. Integration of literature-informed and analysis-driven indicators: combining indicators gleaned from the literature with those derived from statistical analysis, while emphasizing their quality and relevance.
4. Alignment with established character: ensuring that the output generated by ChatGPT resonates with the established character, maintaining consistency in the model’s responses.
5. Explanatory information: providing coherent explanatory information alongside each indicator to potentially enhance the model's diagnosis performance and comprehensibility.

Comparison to Prior Work

The diagnostic process for MCI encompasses a multifaceted evaluation, integrating clinical observations, cognitive assessments, and feedback from both individuals and their family members regarding their daily functioning [32]. Language analysis can be a valuable tool, but it is just one aspect of the overall assessment [33]. Generally, individuals with MCI may exhibit subtle differences in their language use compared to those with normal cognitive abilities. Some potential indications of MCI in language use include 8 lexical features: limited vocabulary, increased verbosity, overlearned phrases, incorrect use of pronouns, hesitation (reflecting word-finding difficulties), circumlocution (indicative of word-finding difficulties), the tip-of-the-tongue phenomenon, and repetition [28,30,31,34]. Additionally, 3 syntactic and grammatical features include simplified sentence structures and grammar, grammatical errors, and challenges in handling complex ideas. Furthermore, 10 semantic features encompass semantic paraphasias, lack of coherence, consistent errors, diminished semantic fluency, disjointed narrative structure, orientation issues, declining engagement and responsiveness during conversation, memory-related issues, reduced capacity for abstract thinking and synthesis, and emotional aberrations [35-37]. Our research highlights the significance of paying attention to the tip-of-the-tongue phenomenon, difficulties with complex ideas, and memory-related issues when assessing individuals with MCI.

Strengths of the Study

This study developed a standardized methodology for designing prompts for MCI screening using ChatGPT. The comparative analysis provided valuable insights into the capabilities of different ChatGPT models and versions, contributing to the understanding of their potential applications within the medical domain. Our research results highlighted the superior performance of prompts created by physicians compared to those generated by ChatGPT. Specifically, Model 4 outperformed both Model 3 and Model 5. This finding strongly suggests that, despite ChatGPT’s advanced abilities, human expertise in health care is essential for making effective decisions. This is especially evident in ChatGPT’s difficulty in determining which indicators are most important in the decision-making process.

The combination of prompts generated by human experts and the computational capabilities of ChatGPT shows great potential in clinical applications. This collaborative approach can be a valuable tool for physicians, offering initial insights and analyses based on relevant indicators. As a result, it can streamline the diagnostic process and potentially enhance overall clinical decision-making.

Study Limitations

First, our investigation has uncovered a lack of valid indicators that can accurately distinguish between TNs and FNs. This finding raises concerns about the potential for ChatGPT to make mistakes in categorizing participants into the potentially cognitively normal group. Second, our study focused solely on comparing GPT-4 with GPT-3.5. Although the prompts were carefully reviewed by clinical experts and the model exhibited favorable statistical performance, additional validation is necessary to determine whether ChatGPT can be reliably used as a primary screening tool for MCI. In future research endeavors, we intend to expand upon this comparative analysis by evaluating the effectiveness of GPT-4 for clinicians with varying levels of expertise, aiming to elucidate its clinical utility in primary screening. Third, our test data set used never-trained data, all of which had to be requested and some of which were only published in 2022, but there was still no guarantee that ChatGPT had not learned them, which is a concern in the era of large models. To mitigate this concern, we augmented our data set with patient information from our institution to ensure complete novelty for ChatGPT. Finally, our study did not comprehensively address the consistency and variability of ChatGPT responses. Using ChatGPT to generate only 1 response may introduce bias. In the context of our study, the primary aim was to establish a conceptual framework for ChatGPT prompts. Consequently, a single prompt per model was considered sufficient to demonstrate the potential and trajectory of our immediate design evolution. In the subsequent study of GPT-4 comparisons with different levels of clinicians, we reassessed our results by sending each prompt multiple times to the GPT-4 Model 5 and used statistical methods to measure the distribution and concentration trends of ChatGPT responses to repeated prompts.

Conclusions

In both the training and test sets, ChatGPT could effectively discriminate participants with possible MCI. Meanwhile, standardization of prompts by physicians would improve the performance of the model. It should be noted, however, that the use of ChatGPT must follow medical ethics and cannot replace doctors in diagnosis. Through the study, we hope to screen people who may have MCI and help them get to the hospital for diagnosis, so that early detection, early diagnosis, and early treatment can be achieved, delaying or even preventing the progression of MCI to AD.

Acknowledgments

All authors would like to thank DementiaBank for corpus support. The data were provided by DementiaBank and partly supported by grants from the National Institutes of Health (NIH; AG03705 and AG05133). CW would like to thank Sichuan University for providing support in reviewing the literature.

Data Availability

The DementiaBank data set [38] used in this research is safeguarded by a password, and access is restricted to members of the DementiaBank Consortium Group. Permission to access this data set can be obtained by becoming a member of the DementiaBank Consortium Group. Informed consent was provided by all subjects according to the DementiaBank.

Authors' Contributions

JL, SL, and CW conceived the study. JL, CW, SL, and AL performed the data analysis, interpreted the results, and drafted the manuscript. All authors revised the manuscript. All authors read and approved the final manuscript.

The manuscript was written entirely by humans. All authors are responsible and accountable for the originality, accuracy, and integrity of the work.

Conflicts of Interest

None declared.

Multimedia Appendix 1

Supplementary information.

[DOCX File , 1299 KB-Multimedia Appendix 1]

Multimedia Appendix 2

Participant information.

[XLSX File (Microsoft Excel File), 77 KB-Multimedia Appendix 2]

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Abbreviations

AD: Alzheimer disease
AI: artificial intelligence
AUC: area under the curve
FN: false negative
FP: false positive
GPT: generative pretrained transformer
ICA: Integrated Cognitive Assessment
MCI: mild cognitive impairment
MMSE: Mini-Mental State Examination
MoCA: Montreal Cognitive Assessment
TN: true negative
TP: true positive

Edited by T de Azevedo Cardoso; submitted 02.08.23; peer-reviewed by MO Khursheed, L Zhu; comments to author 18.09.23; revised version received 28.09.23; accepted 27.11.23; published 29.12.23

Please cite as:
Wang C, Liu S, Li A, Liu J
Text Dialogue Analysis for Primary Screening of Mild Cognitive Impairment: Development and Validation Study
J Med Internet Res 2023;25:e51501
URL: https://www.jmir.org/2023/1/e51501
doi: 10.2196/51501
PMID: