A Study of Effective Information for AI-Aided Medical Diagnostics

Alexander Han

Independent Self-Paced Research

Acton-Boxborough Regional High School

Acton, Massachusetts

08/22/2024

Revised on 09/29/2024

Revised on 10/06/2024

Revised on 10/10/2024

Abstract

Rapid advancements in generative AI have shown a great potential in helping people to diagnose illnesses that eluded their doctors. A literature review identified key parameter sets used in generative AI for medical diagnostics—specifically symptoms, medical history, medical tests, and medications. The effectiveness of these parameter sets was evaluated by providing detailed descriptions to AI chatbots GPT-3.5 and GPT-4o, followed by an analysis of their responses. Each response was assigned a qualitative accuracy score to assess diagnostic effectiveness and a quantitative suggestiveness score for statistical analysis. Two-way ANOVA analyses are conducted on the suggestiveness scores for sample diseases, considering both the parameter sets and the chatbots used. Findings reveal that symptoms and medical history are the most critical factors in medical diagnostics. While medical tests play a vital role in diagnosing certain conditions, they may be irrelevant for others. Medications, on the other hand, have a minimal impact on the diagnostic process.

Introduction

A chatbot is a software application designed to simulate conversation with users, often using natural language processing (NLP) to understand and respond to text or voice inputs [1], [2], [3], [4], and [5]. Chatbots can be programmed to handle various tasks, from answering frequently asked questions to providing customer support or assisting with complex queries.

Generative AI refers to a class of artificial intelligence models that can create new content, such as text, images, music, or even video, based on the patterns they have learned from existing data [6], [7], [8], and [9]. These models use complex algorithms to understand and generate human-like responses or creative works. Beyond simple conversation, generative AI can empower chatbots to assist in content creation, such as drafting emails, generating reports, or even composing creative writing based on user prompts.

Chatbots have seen a rapid rise in popularity, with applications spanning multiple sectors worldwide. Among notable examples, OpenAI’s ChatGPT stands out as the most recognized, alongside Google's Bard, Meta's LLaMA, and Anthropic's Claude. Launched on November 30th, 2022, ChatGPT quickly captivated public interest. While not the first of its kind, ChatGPT has garnered significant attention due to its advanced capabilities compared to other chatbots. Numerous remarkable stories have emerged of individuals using ChatGPT to diagnose rare diseases and even save lives.

Literature Review

OpenAI leverages artificial intelligence (AI) and machine learning, enabling ChatGPT to provide accurate responses to inquiries [1], [2], [3], [4], and [5]. When released in March 2023, GPT-3.5 had 20 billion parameters, while GPT-3 had 175 billion parameters, enabling it to perform a wide range of complex tasks effectively [10], [11], and [12]. Having fewer parameters allows for quicker responses but limits the ability to handle more intricate tasks. Recently, OpenAI introduced GPT-4 and GPT-4o, with approximately 175 billion and 200 billion parameters, respectively. These models can perform much more complex functions than any previous chatbot, although at a slower pace than GPT-3.5 [13]. GPT-4o, the latest version, has seen significant improvements in accuracy, processing, and response speed. OpenAI has made GPT-4o accessible for free for the first few questions, and users can choose between GPT-3.5 and GPT-4o. Since the release of ChatGPT, many specialized chatbots have emerged in fields like finance, research, and medicine [14]. It is foreseeable that AI technology will make significant strides in the medical field in the near future.

The development of AI-Aided Medical Diagnostics (AAMD) could greatly benefit individuals traditionally underserved by the healthcare system. In 2021, approximately 30 million Americans (9.2% of the U.S. population) lacked health insurance, often citing high costs and limited coverage as primary reasons. Hispanics were the minority group most likely to be uninsured, with 30.1% of Hispanic adults without health insurance. Consequently, these individuals often face higher medical costs and may avoid seeking medical care. A self-diagnosis tool would allow people to identify potential health issues, facilitating treatment while avoiding the high costs of professional diagnoses. Non-native English speakers could also benefit, as chatbots can communicate in various languages. Additionally, enabling patients to self-diagnose would enhance privacy regarding their symptoms and encourage more active participation in the diagnostic process, fostering a more open and collaborative relationship between patients and healthcare providers [15]. However, AAMD is neither a “magic cure” for healthcare issues nor a replacement for professional medical advice. Instead, it can serve as a valuable supplement to the current healthcare system.

Numerous efforts are underway to integrate AI into the medical field. In 2017, Woebot, a chatbot designed to assist with mental health issues such as depression, anxiety, and addictions, was introduced to the public [16]. Woebot uniquely uses emojis to enhance nonverbal communication and better connect with users. Additionally, hospitals are increasingly utilizing AI for medical image processing, including CAT scans, MRIs, and X-rays, as AI can detect patterns or abnormalities that might be missed by the human eye [17]. Top U.S. hospitals like the Mayo Clinic, Cleveland Clinic, Massachusetts General Hospital, Johns Hopkins Hospital, and UCLA Medical Center have incorporated AI into their programs. Mayo Clinic is working on using AI to provide more personalized treatment options for cancer patients [18], [19], and [20]. Cleveland Clinic employs AI to identify patients at high risk of cardiac arrest who need a vasopressor [21] and [22]. Massachusetts General Hospital uses its extensive collection of 10 billion medical images to train AI for radiology and pathology [23]. Johns Hopkins integrates AI into its command center to improve communication between medical teams and enhance ambulance dispatch, patient triage, and patient discharge processes [24] and [25]. UCLA Medical Center has deployed a chatbot called Virtual Interventional Radiologist (VIR) to help clinicians respond to common questions with evidence-based answers [26]. These AI integrations could significantly impact the future of hospitals, greatly increasing their efficiency and effectiveness [27].

Most physicians worldwide are enthusiastic about the potential of AI as a diagnostic tool when used appropriately [28]. A survey of radiologists revealed that 89% were not worried about job loss, and 77% supported the integration of AI into radiology [29] and [30]. Many doctors are particularly excited about AI's potential to enhance the diagnostic process, boost efficiency, and improve clinical outcomes [31]. AI has already made significant progress in diagnosing various types of cancer through machine learning and natural learning capabilities, enabling doctors to provide more accurate treatments and potentially reducing cancer-related deaths significantly [32]. Meanwhile, Harvard Medical School is advancing AI education and implementation in healthcare by allowing students to use chatbots for diagnostic purposes [33].

Public opinion on AAMD is nearly split, with 49% in favor and 51% against AI usage. Those opposed mainly cite concerns about privacy violations and a lack of understanding of how AI operates. Enhancing patient knowledge about AI could significantly improve its perception in the medical field, as 65% of patients indicated they would feel more comfortable if doctors explained how AI is used in medicine and healthcare [28].

To encourage the adoption of AAMD technology, continuous efforts are needed to test and document its strengths and limitations for each specific disease. AAMD chatbots are more likely to misdiagnose rare diseases due to limited training data. Even GPT-4o struggles with rare disease diagnoses but is highly reliable for common illnesses like the flu or COVID-19 [34]. Additionally, chatbots often provide multiple responses rather than a single definitive answer, which can discourage self-diagnosis. Another challenge is determining the necessary information for accurate diagnosis. Some diseases, such as Hepatitis, which is blood-borne, can only be detected through blood tests, making self-diagnosis difficult for patients without the required materials and equipment. A major concern is the risk of private data exposure. As AI becomes more integrated into healthcare, a significant amount of patient information and health records are stored online. Due to the sensitive nature of these records, hackers often target them for fraud, which can remain undetected for extended periods [35].

This study was inspired by anecdotes from my mother and her friends who successfully used ChatGPT to diagnose illnesses that eluded their doctors. However, few people know how to interact with ChatGPT effectively for diagnosis. I hope this study can shed some light on this issue.

Materials and Methods

The medical diagnosis of non-trivial illnesses is a lengthy process. Physicians typically ask a series of questions and may order laboratory tests as required. Accurate symptom descriptions are crucial in this process, as they can significantly narrow the range of potential diseases. A patient’s medical history further refines the diagnostic process, making it more precise and aiding in identifying possible treatments. Lab tests are essential, providing valuable information that helps healthcare providers make informed decisions and manage patient care effectively. Additionally, reviewing a patient’s medication history can enhance the accuracy and safety of the diagnostic process.

Sample Diseases

In this study, to balance the need for a diverse range of cases with time and expertise constraints, three diseases were selected for evaluating the AAMD tools: Influenza, Clostridioides difficile (C. difficile), and Meningitis. These diseases vary significantly in prevalence: Influenza affects about 1 in 16 people in the

US [36], C. difficile occurs in approximately 1 in 1,000 people [37], and Meningitis affects around 1 in 100,000 people [38].

Effectiveness Scores

The effectiveness of the four sets of parameters—symptoms, medical history, test results, and past medications—is measured by evaluating chatbots' diagnostic answers. More specifically, the effectiveness consists of an accuracy score and a suggestiveness score, where

Accuracy Score = 100% if the target disease is included in the response, 0% otherwise;

Suggestiveness Score = 1 / total number of suggested possible diseases, 0 if not suggested.

The accuracy score indicates whether the disease was among the possible conditions identified by the chatbot, while the suggestiveness score reflects the proportion of accurate diagnoses among the suggestions provided.

Chatbots

Given the influence and popularity of various chatbots, we chose to use GPT-3.5 and GPT-4o for this research.

Sample Cases and Parameters

Table 1 presents the details of the cases examined in this study. For each of the three target diseases, three cases are analyzed. The cases and their parameters were gathered from literature and online sources [39], [40], [41]. Unfortunately, since real patient lab tests are not accessible, the "Lab Tests" column includes only the definitive tests necessary to confirm the accuracy of the AAMD tools in diagnosing the disease.

Parameter Transformation

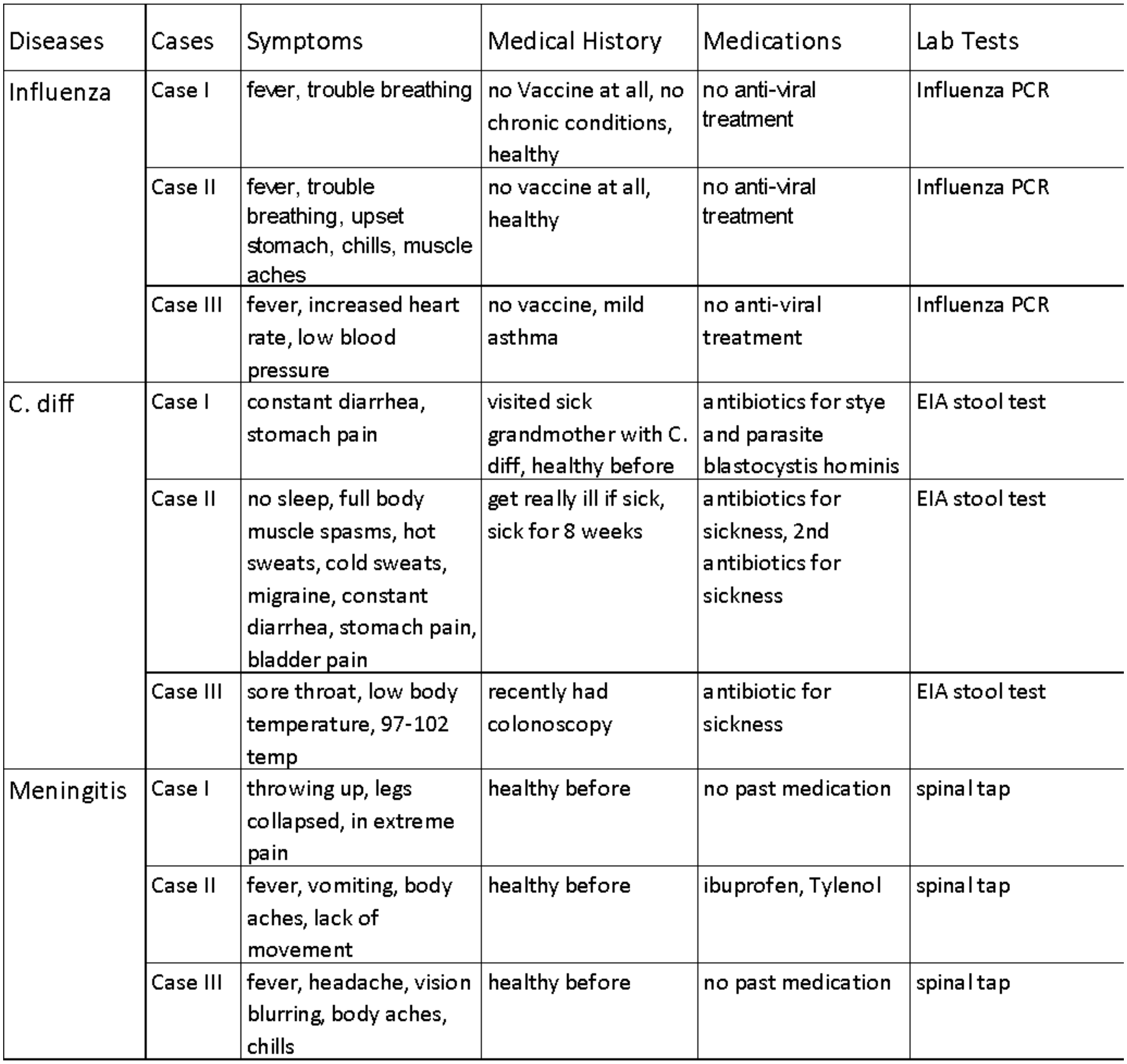
The diagnostic parameters in Table 1 will be transformed into natural language questions and presented to GPT-3.5 and GPT-4o. For example, the symptoms for Meningitis Case III will be framed as, “What do I have if I have a fever, headache, blurry vision, body aches, and chills?” Each model will then generate a list of potential diseases. We will assess their responses and record the accuracy and suggestiveness scores accordingly.

One unique feature of GPT-3.5 and GPT-4 is their ability to ask follow-up questions within a single chat session. In this study, rather than evaluating individual parameter sets, we will assess the effectiveness of various combinations of parameter sets. Specifically, different parameter sets for the same case will be presented consecutively within a single GPT chat session. This research explores the following parameter sets: 1. Symptoms; 2. Symptoms with Medical History; 3. Symptoms with Medications; and 4. Symptoms with both Medical History and Medications.

Statistical Analysis Methods

Statistical analysis of the suggestiveness scores will be conducted to assess the effectiveness of the parameter sets. Specifically, for each sample disease, the means and standard deviations of the suggestiveness scores will be calculated and displayed using a clustered column chart, with columns representing GPT-3.5 and GPT-4.0.

A two-way ANOVA (Analysis of Variance) is a valuable method for simultaneously analyzing the effects of two independent variables on a dependent variable. To identify the optimal parameter set for AAMD tools, we will conduct a two-way ANOVA to assess how the mean suggestiveness scores vary across different diagnostic parameter sets and sample diseases and to evaluate any interaction effects between these two independent variables.



Diseases	Cases	Symptoms	Medical History	Medications	Lab Tests
Influenza	Case I	fever, trouble breathing	no Vaccine at all, no chronic conditions, healthy	no anti-viral treatment	Influenza PCR
	Case II	fever, trouble breathing, upset stomach, chills, muscle aches	no vaccine at all, healthy	no anti-viral treatment	Influenza PCR
	Case III	fever, increased heart rate, low blood pressure	no vaccine, mild asthma	no anti-viral treatment	Influenza PCR
C. diff	Case I	constant diarrhea, stomach pain	visited sick grandmother with C. diff, healthy before	antibiotics for stye and parasite blastocystis hominis	EIA stool test
	Case II	no sleep, full body muscle spasms, hot sweats, cold sweats, migraine, constant diarrhea, stomach pain, bladder pain	get really ill if sick, sick for 8 weeks	antibiotics for sickness, 2nd antibiotics for sickness	EIA stool test
	Case III	sore throat, low body temperature, 97-102 temp	recently had colonoscopy	antibiotic for sickness	EIA stool test
Meningitis	Case I	throwing up, legs collapsed, in extreme pain	healthy before	no past medication	spinal tap
	Case II	fever, vomiting, body aches, lack of movement	healthy before	ibuprofen, Tylenol	spinal tap
	Case III	fever, headache, vision blurring, body aches, chills	healthy before	no past medication	spinal tap

Table 1. Test Cases and Diagnostic Parameters for the Three Sample Diseases. Diseases: Influenza, C. diff, and Meningitis; Cases: Three Cases for Each Disease; Case Data Collected: Symptom, Medical History, Medications, and Lab Tests.

Results

As described in the Materials and Methods section, the diagnostic parameters shown in Table 1 are transformed into questions and fed to both GPT-3.5 and GPT-4o. The resulting diagnostic answers are used to compile accuracy and suggestiveness scores, which are detailed in Table 2 for GPT-3.5 and Table

3 for GPT-4o. Additionally, the accuracy rates for the definitive lab tests of the sample diseases are 100%, confirming that both GPT-3.5 and GPT-4o meet the basic sanity checks.

Diseases	Cases	Symptoms		Symptoms + Medical History		Symptoms + Medications		Symptoms + Medical History + Medications		Lab Tests
		Acc.	Sug.	Acc.	Sug.	Acc.	Sug.	Acc.	Sug.	Acc.
Influenza	Case I	100%	1 / 7	100%	1 / 6	100%	1 / 8	100%	1 / 7	100%
	Case II	100%	1 / 8	100%	1 / 6	100%	1 / 5	100%	1 / 6	100%
	Case III	0%	0 / 6	100%	1 / 7	0%	0 / 7	100%	1 / 6	100%
C. diff	Case I	0%	0 / 8	0%	0 / 7	100%	1 / 7	100%	1 / 6	100%
	Case II	0%	0 / 7	0%	0 / 8	0%	0 / 7	0%	0 / 8	100%
	Case III	0%	0 / 6	0%	0 / 4	0%	0 / 6	0%	0 / 6	100%
Meningitis	Case I	0%	0 / 5	0%	0 / 7	0%	0 / 5	0%	0 / 6	100%
	Case II	100%	1 / 8	100%	1 / 7	100%	1 / 8	100%	1 / 6	100%
	Case III	100%	1 / 8	100%	1 / 10	100%	1 / 9	100%	1 / 7	100%

Table 2. Diagnostic Accuracy and Suggestiveness Scores for Sample Diseases and Parameter Sets Using GPT-3.5. Accuracy Scores: 100% if the Target Disease in included, 0% otherwise; Suggestiveness Scores (X / Y): X is 1 if the Target Disease is Included and X is 0 Otherwise; Y is the Total Number of Diseases Suggested

Diseases	Cases	Symptoms		Symptoms + Medical History		Symptoms + Medications		Symptoms + Medical History + Medications		Lab Tests
		Acc.	Sug.	Acc.	Sug.	Acc.	Sug.	Acc.	Sug.	Acc.
Influenza	Case I	100%	1 / 12	100%	1 / 10	100%	1 / 12	100%	1 / 14	100%
	Case II	100%	1 / 12	100%	1 / 10	100%	1 / 10	100%	1 / 8	100%
	Case III	0%	0 / 12	100%	1 / 10	100%	1 / 10	100%	1 / 10	100%
C. diff	Case I	0%	0 / 16	0%	0 / 9	100%	1 / 11	100%	1 / 10	100%
	Case II	0%	0 / 10	0%	0 / 8	100%	1 / 12	0%	0 / 18	100%
	Case III	0%	0 / 12	0%	0 / 12	0%	0 / 13	0%	0 / 10	100%
Meningitis	Case I	100%	1 / 10	100%	1 / 10	100%	1 / 10	100%	1 / 12	100%
	Case II	100%	1 / 15	100%	1 / 10	100%	1 / 10	100%	1 / 10	100%
	Case III	100%	1 / 16	100%	1 / 11	100%	1 / 12	100%	1 / 10	100%

Table 3. Diagnostic Accuracy and Suggestiveness Scores for Sample Diseases and Parameter Sets Using GPT-4o. Accuracy Scores: 100% if the Target Disease in included, 0% otherwise; Suggestiveness Scores (X / Y): X is 1 if the Target Disease is Included and X is 0 Otherwise; Y is the Total Number of Diseases Suggested

Referring to Table 2, the initial analysis shows that providing symptoms, medical history, and a list of current medications yields the highest average diagnostic accuracy and suggestiveness scores for GPT-3.5, at 66.7% and 10.3%, respectively. In contrast, applying the same average calculations to the data in Table 3 for GPT-4.0 indicates a different outcome, with the combination of symptoms and medical history resulting in the most accurate prediction (88.9% and 8%, respectively). We will pursue a more in-depth understanding of the data through statistical analysis.

The suggestiveness scores are analyzed using standard statistical methods. The means and standard deviations of these scores are presented in Figures 1, 2, and 3 for Influenza, C. diff, and Meningitis, respectively.

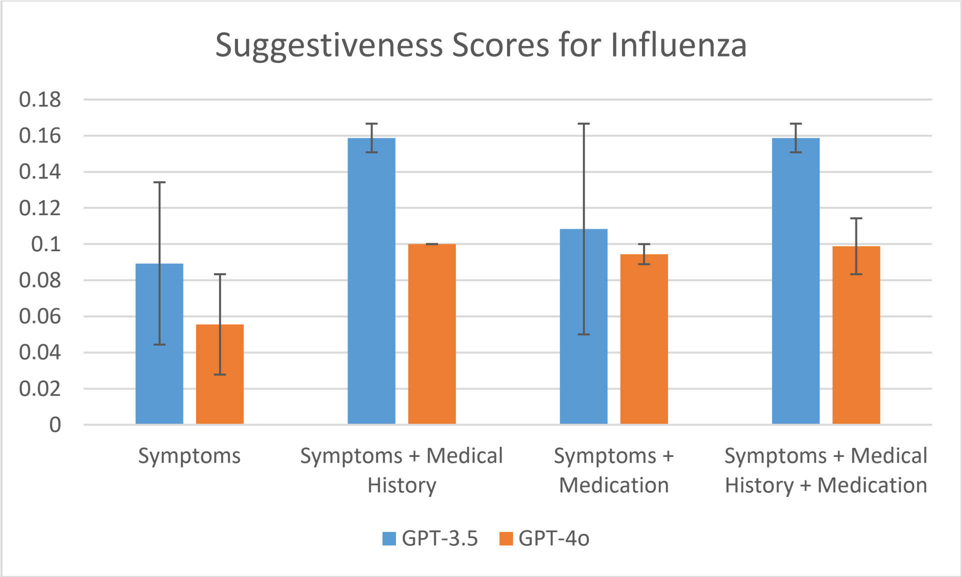


Figure 1. Means and Standard Deviations of Suggestiveness Scores for Influenza by Parameter Sets and GPT Tools. Colored Bars: Means, Black Lines: Standard Deviations.

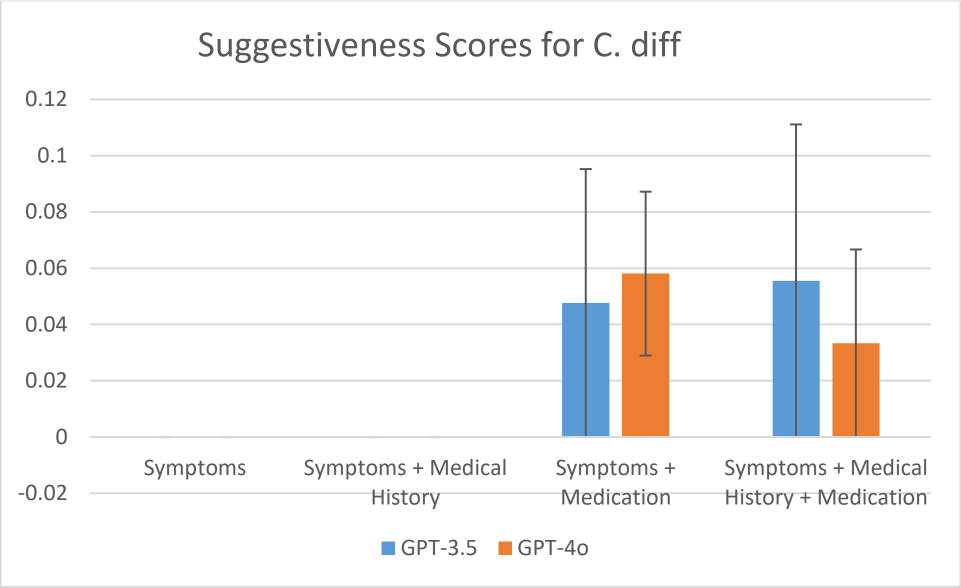


Figure 2. Means and Standard Deviations of Suggestiveness Scores for C. diff by Parameter Sets and GPT Tools. Colored Bars: Means, Black Lines: Standard Deviations.

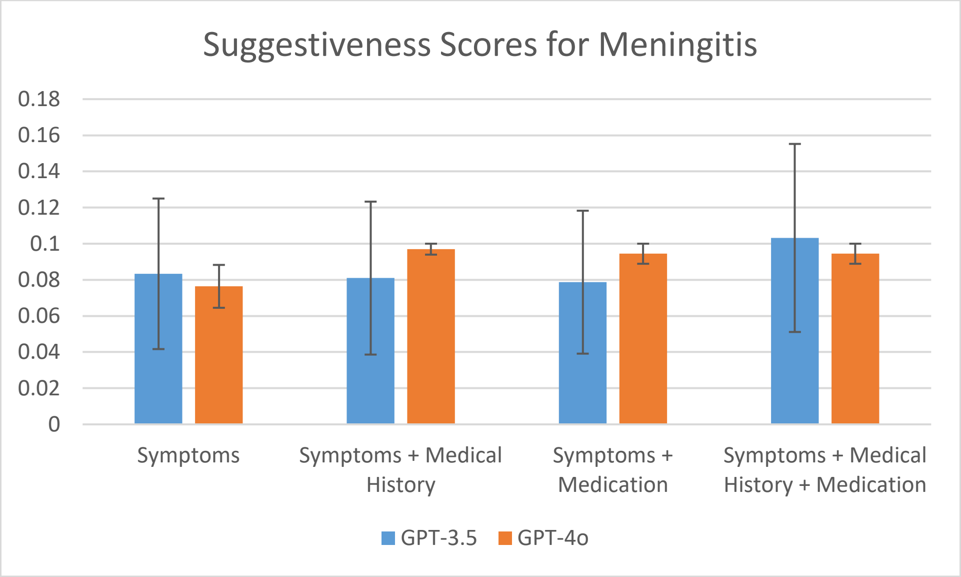


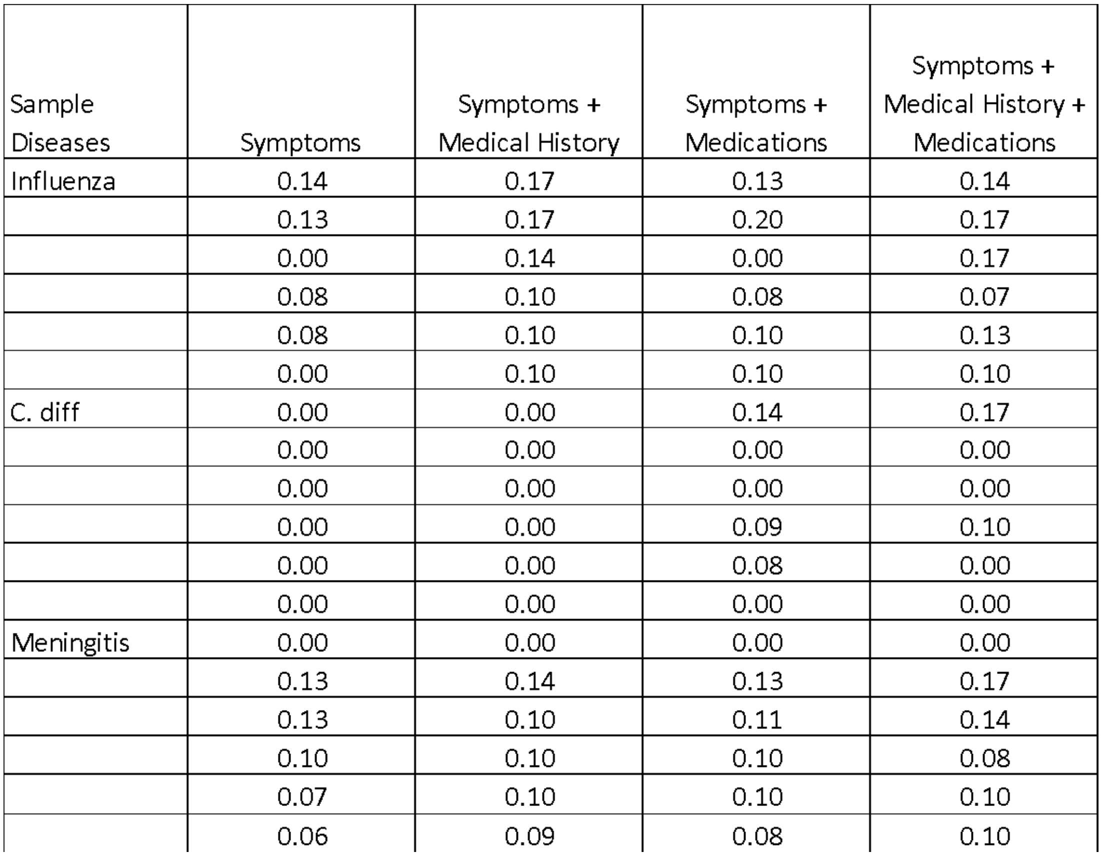
Figure 3. Means and Standard Deviations of Suggestiveness Scores for Meningitis by Parameter Sets and GPT Tools. Colored Bars: Means, Black Lines: Standard Deviations.

The experimental data reveals that diagnosing C. diff is challenging for both GPT-3.5 and GPT-4o, with GPT-3.5 achieving a combined accuracy score of 16.7% and GPT-4o achieving 25%. GPT-3.5 performs well in diagnosing Influenza, with an accuracy score of 83.3% and a suggestiveness score of 12.7%. In contrast, GPT-4o excels in diagnosing Meningitis, achieving a perfect accuracy score of 100% and a suggestiveness score of 8.82%.

The experimental data shows that GPT-4o is more likely to provide the correct diagnosis, with an accuracy score of 72.2%, compared to GPT-3.5's 55.6%. GPT-4o outperforms GPT-3.5 in accuracy across all three diseases tested. However, GPT-4o has a lower suggestiveness score than GPT-3.5, scoring 6.39% compared to 8.16%. On average, GPT-4o suggests 11.3 possible diagnoses, nearly twice the 6.8 options proposed by GPT-3.5.

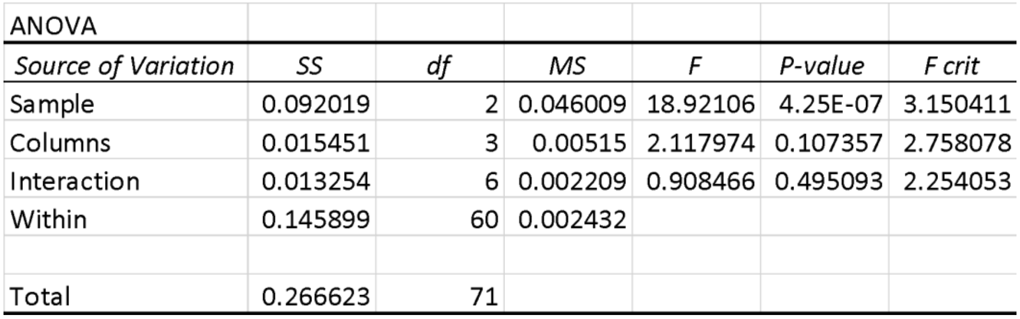
To identify the optimal parameter set for AAMD tools, we conducted a two-way ANOVA (Analysis of Variance) test. This test examines how the mean suggestiveness score changes with different diagnostic parameter sets and sample diseases and whether there is an interaction effect between these two independent variables.

Using data from Tables 2 and 3, Table 4 was created for the two-way ANOVA test, with parameter sets and sample diseases as the independent variables. The results, shown in Table 5, indicate a statistically significant difference in average suggestiveness scores based on the diagnostic parameter sets (F(2)=18.92, $p < 0.001$). However, the sample diseases and the interaction between these variables were insignificant. The combination of symptoms and medical history proved the most effective among the diagnostic parameter sets.



Sample Diseases	Symptoms	Symptoms + Medical History	Symptoms + Medications	Symptoms + Medical History + Medications
Influenza	0.14	0.17	0.13	0.14
	0.13	0.17	0.20	0.17
	0.00	0.14	0.00	0.17
	0.08	0.10	0.08	0.07
	0.08	0.10	0.10	0.13
	0.00	0.10	0.10	0.10
C. diff	0.00	0.00	0.14	0.17
	0.00	0.00	0.00	0.00
	0.00	0.00	0.00	0.00
	0.00	0.00	0.09	0.10
	0.00	0.00	0.08	0.00
	0.00	0.00	0.00	0.00
Meningitis	0.00	0.00	0.00	0.00
	0.13	0.14	0.13	0.17
	0.13	0.10	0.11	0.14
	0.10	0.10	0.10	0.08
	0.07	0.10	0.10	0.10
	0.06	0.09	0.08	0.10

Table 4. Suggestiveness Scores with Diagnostic Parameter Sets and Sample Diseases.



ANOVA						
Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	0.092019	2	0.046009	18.92106	4.25E-07	3.150411
Columns	0.015451	3	0.00515	2.117974	0.107357	2.758078
Interaction	0.013254	6	0.002209	0.908466	0.495093	2.254053
Within	0.145899	60	0.002432			
Total	0.266623	71				

Table 5. Two-Way ANOVA of Suggestiveness Scores with Diagnostic Parameter Sets and Sample Diseases as Independent Variables

Discussion

The study demonstrates that AAMD can aid patients in self-diagnosing within the context of the representative sample diseases we selected. Both GPT-3.5 and GPT-4o perform well in diagnosing influenza and meningitis but have difficulty diagnosing C. diff. A notable concern is that GPT-4o's overall suggestiveness score is lower than that of GPT-3.5. The experiments show no correlation between the rarity of the disease and the effectiveness of AAMD diagnosis by either GPT-3.5 or GPT-4o. Both tools struggled with diagnosing C. diff, a disease of medium rarity, while GPT-4o achieved perfect accuracy in diagnosing meningitis, the rarest disease.

It is noteworthy that excessive information may negatively impact the accuracy of the diagnosis. GPT-4o yields better scores with only symptoms and medicine history than with a full set of parameters, including symptoms, medical history, and medicine history.

As previously noted, GPT-4o is more likely to include the correct diagnosis in its list but provides significantly more options than GPT-3.5. To optimize GPT-4o for accuracy while reducing the number of possible diagnoses, the question structure should be adjusted. The current question was designed for GPT-3.5, which is more open-ended, whereas GPT-4o is limited in response capacity. By removing the "List possible diseases" section from the query, the number of diagnoses generated by GPT-4o decreases. However, omitting this section from GPT-3.5 would significantly reduce its diagnostic effectiveness, as it tends to avoid vague responses and does not directly suggest possible diagnoses.

We observed an intriguing phenomenon while using GPT-3.5 and GPT-4.0: GPT seems language-dependent, with responses varying significantly when the same question is asked in different languages. This issue of language dependency has been highlighted in a recent Nature Podcast [38]. In short, the performance of large language models varies significantly due to the differences in data and computing power used for training them in different languages. Since patients seeking AAMD may prefer to communicate in their native language, future research could investigate how chat language impacts AAMD's effectiveness. Developing middleware to translate questions and answers between English and other languages automatically could significantly broaden access for many individuals worldwide.

In conclusion, this study evaluates the effectiveness of common parameters provided to generative AI for medical diagnostics, including symptoms, medical history, medical tests, and medications. Statistical analysis of suggestiveness scores indicates that patient symptoms and medical history are the most crucial parameters for AI-assisted medical diagnostics. This study can be expanded to include all diagnosable diseases and other AI tools. Furthermore, evaluating language as a new parameter in effectiveness studies may broaden the reach to a global audience. Overall, AAMD can enhance the efficiency of the diagnostic process for both patients and doctors, potentially saving many lives and reducing costs.

Acknowledgment

I want to extend my heartfelt thanks to Ms. Laura Morales for her invaluable guidance and feedback during this study. Her insightful suggestions on data collection and analysis were instrumental in shaping this project. I also want to express my gratitude to my parents for their constant support and unwavering encouragement throughout this journey.

References

[1] Biswas, S. S. (2023). Potential use of Chat GPT in global warming. Annals of Biomedical Engineering, 51(6), 1126–1127. https://doi.org/10.1007/s10439-023-03171-8

[2] Biswas, S. S. (2023b). Role of Chat GPT in Public Health. Annals of Biomedical Engineering, 51(5), 868–869. https://doi.org/10.1007/s10439-023-03172-7

[3] McGee, R. W. (2023). Annie Chan: Three Short Stories Written with Chat GPT. Available at SSRN 4359403.

[4] McGee, R. W. (2023). Is Chat GPT biased against Conservatives? An Empirical study. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.4359405

[5] Mathew, A. . (2023). Is Artificial Intelligence a World Changer? A Case Study of OpenAI's Chat GPT. Recent Progress in Science and Technology Vol. 5, 35–42. https://doi.org/10.9734/bpi/rpst/v5/1 8240D

[6] Ali, M. J., & Djalilian, A. (2023). Readership Awareness Series – Paper 4: Chatbots and ChatGPT - Ethical Considerations in Scientific Publications. Seminars in Ophthalmology, 38(5), 403–404. https://doi.org/10.1080/08820538.2023.2193444

[7] Rudolph, J., Tan, S., & Tan, S. (2023). ChatGPT: Bullshit spewer or the end of traditional assessments in higher education?. Journal of applied learning and teaching, 6(1), 342-363.

[8] Brown, T. B., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., Agarwal, S., Herbert-Voss, A., Krueger, G., Henighan, T., Child, R., Ramesh, A., Ziegler, D. M., Wu, J., Winter, C., . . . Amodei, D. (2020b, May 28). Language Models are Few-Shot Learners. arXiv.org. https://arxiv.org/abs/2005.14165v4

[9] Naumova, E.N. A mistake-find exercise: a teacher's tool to engage with information innovations, ChatGPT, and their analogs. J Public Health Pol 44, 173–178 (2023). https://doi.org/10.1057/s41 271-023-00400-1

[10] Borji, A. (2023, February 6). A categorical archive of ChatGPT failures. arXiv.org. https://arxiv.org/abs/ 2302.03494

[11] Alkaissi H, McFarlane S I (February 19, 2023) Artificial Hallucinations in ChatGPT: Implications in Scientific Writing. Cureus 15(2): e35179. doi:10.7759/cureus.35179

[12] Frieder, S., Pinchetti, L., Griffiths, R., Salvatori, T., Lukasiewicz, T., Petersen, P., & Berner, J. (2023, December 15). Mathematical capabilities of ChatGPT. https://proceedings.neurips.cc/paper_files /paper/2023/hash/58168e8a92994655d6da3939e7cc0918-Abstract-Datasets_and_Benchmarks.html

[13] Ayub, H. (2024, May 14). GPT-4O: Successor of GPT-4? - Hamid Ayub - Medium. Medium. https://ham idayub.medium.com/gpt-4o-successor-of-gpt-4-8207acf9104e#:~:text=Parameter%20Count,billion%20parameters%20of%20GPT%2D4.

[14] Ray, P. P. (2023). ChatGPT: A comprehensive review on background, applications, key challenges, bias, ethics, limitations and future scope. Internet of Things and Cyber-Physical Systems, 3, 121–154. https://doi.org/10.1016/j.iotcps.2023.04.003

[15] Paulus, N. (2024, May 22). How many Americans are uninsured? MoneyGeek.com. https://www.mo neygeek.com/insurance/health/analysis/americans-without-coverage/

[16] LaPook, J. (2024, July 7). Mental health chatbots powered by artificial intelligence developed as a therapy support tool. CBS News. https://www.cbsnews.com/news/mental-health-chatbots-powe red-by-artificial-intelligence-providing-support-60-minutes-transcript/

[17] Pinto-Coelho, L. (2023). How Artificial intelligence is shaping medical Imaging Technology: A survey of Innovations and applications. Bioengineering, 10(12), 1435. https://doi.org/10.3390/bioengin eering10121435

[18] Emerging capabilities in the science of Artificial Intelligence - Giving to Mayo Clinic. (2024, February 20). https://www.mayoclinic.org/giving-to-mayo-clinic/our-priorities/artificial-intelligence

[19] Noble.Dana. (2024, April 17). AI in healthcare: The future of patient care and health management. Mayo Clinic Press. https://mcpress.mayoclinic.org/healthy-aging/ai-in-healthcare-the-future-of-p atient-care-and-health-management/

[20] Massachusetts Institute of Technology. (2024, March 27). Mayo Clinic's Healthy Model for AI success | Thomas H. Davenport and Randy Bean | MIT Sloan Management Review. MIT Sloan Management Review. https://sloanreview.mit.edu/article/mayo-clinics-healthy-model-for-ai-succ ess/

[21] Clinic, C. (2024, April 30). AI Center to advance care for congenital heart Disease. Cleveland Clinic. ht tps://consultqd.clevelandclinic.org/ai-center-to-advance-care-for-congenital-heart-disease

[22] Cleveland Clinic Children's Center for Artificial Intelligence (C4AI) | Cleveland Clinic Children's. (n.d.). Cleveland Clinic. https://my.clevelandclinic.org/pediatrics/medical-professionals/artificial-intellig ence

[23] AI enables faster, more precise image registration for medical image. (2024, July 29). Mass General Advances in Motion. https://advances.massgeneral.org/radiology/q-a.aspx?id=1028

[24] Medical artificial intelligence with a purpose. (2023, June 21). https://carey.jhu.edu/articles/researc h/medical-artificial-intelligence-purpose#:~:text=Johns%20Hopkins%20is%20a%20pioneer,in%20a%20pediatric%20care%20setting.

[25] Jacobs, D. (2020, February 24). Practical uses for artificial intelligence in health care. Johns Hopkins Medicine. https://www.hopkinsmedicine.org/news/articles/2020/02/practical-uses-for-artificial- intelligence-in-health-care

[26] Artificial intelligence and the future of health care. (2023b, May 25). UCLA Health. https://www.ucla health.org/news/article/artificial-intelligence-and-future-health-care

[27] Sennaar, K. (2020b, March 24). How America's 5 Top Hospitals are Using Machine Learning Today. Emerj Artificial Intelligence Research. https://emerj.com/ai-sector-overviews/top-5-hospitals-usi ng-machine-learning/

[28] Gervais, G. (2023, October 12). Carta Healthcare survey results indicate that education around AI may improve consumer trust. Business Wire. https://www.businesswire.com/news/home/20231 012647360/en/Carta-Healthcare-survey-results-indicate-that-education-around-AI-may-improve-consumer-trust

[29] Al-Medfa, M. K., Al-Ansari, A. M., Darwish, A. H., Qreeballa, T. A., & Jahrami, H. (2023). Physicians' attitudes and knowledge toward artificial intelligence in medicine: Benefits and drawbacks. Heliyon, 9(4), e14744. https://doi.org/10.1016/j.heliyon.2023.e14744

[30] Coppola, F., Faggioni, L., Regge, D. et al. Artificial intelligence: radiologists' expectations and opinions gleaned from a nationwide online survey. Radiol med 126, 63–71 (2021). https://doi.org/10.100 7/s11547-020-01205-y

[31] American Medical Association & American Medical Association. (2024, January 12). Big majority of doctors see upsides to using health care AI. American Medical Association. https://www.ama-ass n.org/practice-management/digital/big-majority-doctors-see-upsides-using-health-care-ai#:~:text=Physicians%20have%20guarded%20enthusiasm%20for,physician%20relationship%20and%20patient%20privacy.

[32] Davenport, T., & Kalakota, R. (2019). The potential for artificial intelligence in healthcare. Future Healthcare Journal, 6(2), 94–98. https://doi.org/10.7861/futurehosp.6-2-94

[33] Kolata, G. (2023, July 23). A Mystery in the E.R.? Ask Dr. Chatbot for a Diagnosis. The New York Times. https://www.nytimes.com/2023/07/22/health/chatbot-medical-mystery-diagnosis.html

[34] Shieh, A., Tran, B., He, G., Kumar, M., Freed, J. A., & Majety, P. (2024). Assessing ChatGPT 4.0's test performance and clinical diagnostic accuracy on USMLE STEP 2 CK and clinical case reports. Scientific Reports, 14(1). https://doi.org/10.1038/s41598-024-58760-x

[35] Khan, B., Fatima, H., Qureshi, A., Kumar, S., Hanan, A., Hussain, J., & Abdullah, S. (2023). Drawbacks of artificial intelligence and their potential solutions in the healthcare sector. Deleted Journal, 1(2), 731–738. https://doi.org/10.1007/s44174-023-00063-2

[36] Weekly U.S. influenza surveillance report. (2024, August 16). Centers for Disease Control and Prevention.
https://www.cdc.gov/flu/weekly/index.htm#:~:text=CDC%20estimates%20that%20there%20have,important%20for%20higher%20risk%20patients.

[37] About C. diff. (2024, March 6). C. Diff (Clostridioides Difficile). https://www.cdc.gov/c-diff/about/ind ex.html#:~:text=%2D%20C.,the%20subsequent%202%2D8%20weeks.

[38] Watkins Health Services | The University of Kansas. (n.d.). Watkins Health Services.
https://studenth
ealth.ku.edu/meningitis#:~:text=Meningococcal%20meningitis%20is%20a%20rare,approximately%20150%20to%20300%20deaths.

[39] Meyer, A. N., Giardina, T. D., Khawaja, L., & Singh, H. (2021). Patient and clinician experiences of uncertainty in the diagnostic process: Current understanding and future

directions. Patient Education and Counseling, 104(11), 2606–2615. https://doi.org/10.1016/j.pec.2021.07.028

[40] Nichol, J. R., Sundjaja, J. H., & Nelson, G. (2024, April 30). Medical history. StatPearls - NCBI Bookshelf. https://www.ncbi.nlm.nih.gov/books/NBK534249/#:~:text=Both%20aspects%20of%20the%20history,and%20determining%20appropriate%20imaging%20modalities.

[41] Francis, M., Deep, L., Schneider, C. R., Moles, R. J., Patanwala, A. E., L, L., DO, Levy, R., Soo, G., Burke, R., & Penm, J. (2022). Accuracy of best possible medication histories by pharmacy students: an observational study. International Journal of Clinical Pharmacy, 45(2), 414–420. https://doi.org/1 0.1007/s11096-022-01516-2

[42] Nick Petrić Howe, (2024, August 9), NATURE PODCAST: ChatGPT has a language problem — but science can fix it. https://www.nature.com/articles/d41586-024-02579-z