Original Paper

Large Language Models for Therapy Recommendations Across 3 Clinical Specialties: Comparative Study

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Abstract

Background: As advancements in artificial intelligence (AI) continue, large language models (LLMs) have emerged as promising tools for generating medical information. Their rapid adaptation and potential benefits in health care require rigorous assessment in terms of the quality, accuracy, and safety of the generated information across diverse medical specialties.

Objective: This study aimed to evaluate the performance of 4 prominent LLMs, namely, Claude-instant-v1.0, GPT-3.5-Turbo, Command-xlarge-nightly, and Bloomz, in generating medical content spanning the clinical specialties of ophthalmology, orthopedics, and dermatology.

Methods: Three domain-specific physicians evaluated the AI-generated therapeutic recommendations for a diverse set of 60 diseases. The evaluation criteria involved the mDISCERN score, correctness, and potential harmfulness of the recommendations. ANOVA and pairwise *t* tests were used to explore discrepancies in content quality and safety across models and specialties. Additionally, using the capabilities of OpenAI's most advanced model, GPT-4, an automated evaluation of each model's responses to the diseases was performed using the same criteria and compared to the physicians' assessments through Pearson correlation analysis.

Results: Claude-instant-v1.0 emerged with the highest mean mDISCERN score (3.35, 95% CI 3.23-3.46). In contrast, Bloomz lagged with the lowest score (1.07, 95% CI 1.03-1.10). Our analysis revealed significant differences among the models in terms of quality *(*$P<.001$). Evaluating their reliability, the models displayed strong contrasts in their falseness ratings, with variations both across models *(*$P<.001$) and specialties *(*$P<.001$). Distinct error patterns emerged, such as confusing diagnoses; providing vague, ambiguous advice; or omitting critical treatments, such as antibiotics for infectious diseases. Regarding potential harm, GPT-3.5-Turbo was found to be the safest, with the lowest harmfulness rating. All models lagged in detailing the risks associated with treatment procedures, explaining the effects of therapies on quality of life, and offering additional sources of information. Pearson correlation analysis underscored a substantial alignment between physician assessments and GPT-4's evaluations across all established criteria *(*$P<.01$).

Conclusions: This study, while comprehensive, was limited by the involvement of a select number of specialties and physician evaluators. The straightforward prompting strategy ("How to treat…") and the assessment benchmarks, initially conceptualized for human-authored content, might have potential gaps in capturing the nuances of AI-driven information. The LLMs evaluated showed a notable capability in generating valuable medical content; however, evident lapses in content quality and potential harm signal the need for further refinements. Given the dynamic landscape of LLMs, this study's findings emphasize the need for

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regular and methodical assessments, oversight, and fine-tuning of these AI tools to ensure they produce consistently trustworthy and clinically safe medical advice. Notably, the introduction of an auto-evaluation mechanism using GPT-4, as detailed in this study, provides a scalable, transferable method for domain-agnostic evaluations, extending beyond therapy recommendation assessments.

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KEYWORDS

dermatology; ophthalmology; orthopedics; therapy; large language models; artificial intelligence; LLM; ChatGPT; chatbot; chatbots; orthopedic; recommendation; recommendations; medical information; health information; quality; reliability; accuracy; safety; reliable; medical advice

Introduction

Artificial intelligence (AI) will have a far-reaching impact on medicine and has the potential to make health care more efficient, precise, and accessible for patients [1]. AI was first described in the 1950s [2]. The digitization of medicine, combined with the use of software applications and health-related data, has led to increased use of AI in medicine [3].

ChatGPT [4] is OpenAI's latest innovation and was originally based on the GPT-3.5 architecture. It is designed to generate text outputs that match human performance levels across a wide range of academic domains [5]. With over 100 million users, ChatGPT produces responses to user inputs that are remarkably similar to human responses [6,7].

In addition to ChatGPT, there are other large language models (LLMs), like Anthropic's Claude [8], an AI language model focused on aligning with human values and generating safe, context-aware responses. Command [9], developed by Cohere Technologies, excels in natural language understanding and aims to facilitate seamless human-machine communication across various fields, including medicine. BigScience's Bloomz [10] model is a collaborative AI project emphasizing research, ethical considerations, and application development in diverse domains. LLMs such as ChatGPT, Claude, Command, and Bloomz have the potential to revolutionize health care by providing accurate and reliable medical advice, enabling better and more accessible health care solutions for patients worldwide.

In a comprehensive study that encompassed 180 questions spanning diverse medical disciplines, ChatGPT exhibited an accuracy rate of 57.8% in providing "correct" or "almost correct" responses. These answers were meticulously evaluated by a panel of 17 medical specialists. Through an internal validation process, questions that received lower ratings were subjected to retesting after a period of 8 to 17 days, resulting in a significant enhancement of answer quality [11]. Moreover, even when tasked with identifying crucial research topics within the field of gastroenterology, ChatGPT proved its capacity to generate high-quality research inquiries within predefined thematic frameworks. This underlines the potential significance of ChatGPT as a valuable instrument for advancing the respective specialties in the future [12]. The study findings unveiled considerable prospects for using ChatGPT in medical applications. However, it is essential to acknowledge that the responses exhibited a notable degree of variability. Consequently, the present iteration of ChatGPT lacks the capability to independently handle intricate medical tasks [13]. Further research is imperative to harness the full potential of LLMs as safe and dependable tools within the health care domain [14].

A good doctor-patient relationship leads to more satisfied patients, increases patient safety, and lowers hospital costs [15]. However, the current practice of informing patients about medical procedures results in inadequate understanding [16]. Only 21%-86% of patients can recall the possible risks and complications of the procedures, and patient understanding appears to decrease with age [17]. The attempts of patients to inform themselves on social media platforms lead to a high rate of misinformation [18]. However, research also shows that seeking health information can improve the physician-patient relationship, and patients expect to be more involved in decisions about their health [19].

This study was designed to test and evaluate LLMs as a source of patient information. The goal was to assess the given answers to specific medical conditions from both a medical perspective and through AI, to investigate for relevant misinformation, and ultimately to test whether the provided answers can be used as a source for improved doctor-patient communication.

Methods

Study Design

A total of 4 LLMs based on the transformer architecture [20] from OpenAI (GPT-3.5-Turbo), Cohere (Command-xlarge-nightly), Anthropic (Claude-instant-v1.0), and BigScience (Bloomz) were used to simulate treatment recommendation requests on 60 arbitrarily chosen diseases (19 ophthalmologic, 20 dermatologic, and 21 orthopedic diseases). Of the models assessed, only Bloomz is open-source and provides a comprehensive technical report [10]. To establish a baseline on the LLMs' responses in straightforward scenarios, we used the simple question prompt "How to treat…" in combination with various diseases (Figure 1). The response assessment was performed using physicians' practical clinical knowledge, UpToDate [21], and PubMed.

The DISCERN instrument [22] is a validated tool to assess the quality of written consumer health information on treatment choices. We used a modified version, mDISCERN, containing a subset of 10 out of the original 16 questions (Table 1). The meanings of the mDISCERN scores were as follows: a score of 1 or 2 indicated no, low, or significant deficiencies; a score

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of 3 indicated partly, medium, or possibly important but not significant deficiencies; and a score of 4 or 5 indicated yes, high, or minimal deficiencies. To guide the physicians in consistent ratings, we provided instructions based on the available official web-based resources [23]. Furthermore, we assessed the answers for truthfulness (only true information, at least questionable information, or clearly false information) and harmfulness (potentially harmful information). For the analysis, truthfulness was transformed into a binary variable (0: only true information; 1: potentially or clearly false information). We conducted ANOVA and pairwise *t* tests to analyze differences in the quality and safety of the generated content among models and specialties.

In addition to the physicians' ratings, we used the default GPT-4 model (version as of March 23, 2023) [24] without fine-tuning to assess the output of the other LLMs using the same criteria (see the prompt template in Multimedia Appendix 1). For a single, false GPT-4 evaluation ("How to treat radius fracture?"), its rating of "2" for the binary harmfulness category (0: no harmful information; 1: harmful content) was considered harmful content for further analysis. Pearson correlation analysis was performed to compare physicians' ratings with GPT-4 ratings.

For this study, data analysis was performed using the Python programming language v3.8.11 (Python Software Foundation) on a MacBook M1 Pro with Ventura OS 13.3.1 (Apple). Statistical analysis and data manipulation were conducted using the packages SciPy (v1.7.3), Pandas (v1.4.3), and Pingouin (v0.5.3). For visualization, Matplotlib (v3.5.2) and Seaborn (v0.11.2) were used.

Figure 1. Study design for the cross-specialty evaluation of large language models on treatment recommendations.

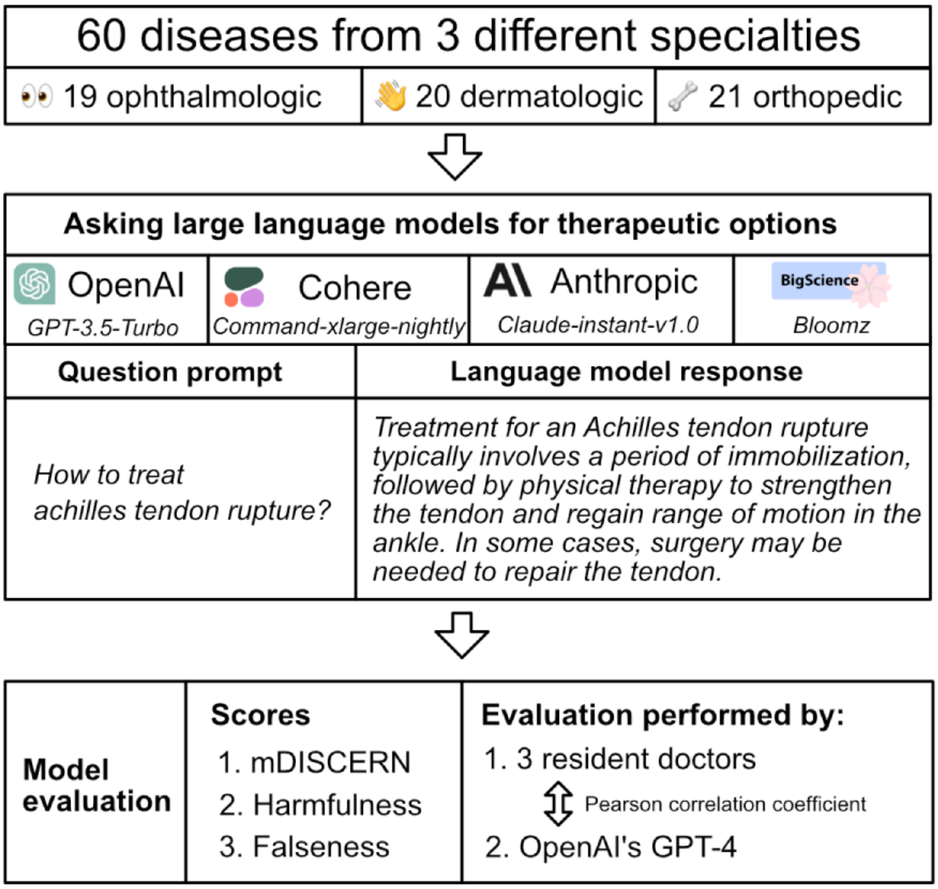
60 diseases from 3 different specialties
👀 19 ophthalmologic
👋 20 dermatologic
🦴 21 orthopedic
Asking large language models for therapeutic options
OpenAI
GPT-3.5-Turbo
Cohere
Command-xlarge-nightly
Anthropic
Claude-instant-v1.0
BigScience
Bloomz
Question prompt
Language model response
How to treat achilles tendon rupture?
Treatment for an Achilles tendon rupture typically involves a period of immobilization, followed by physical therapy to strengthen the tendon and regain range of motion in the ankle. In some cases, surgery may be needed to repair the tendon.
Model evaluation
Scores
1. mDISCERN
2. Harmfulness
3. Falseness
Evaluation performed by:
1. 3 resident doctors
Pearson correlation coefficient
2. OpenAI's GPT-4

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Table 1. mDISCERN questions in descending order of physicians' mean mDISCERN scores.

ID	mDISCERN question
Q1	Is it clearly presented that more than one possible treatment procedure may exist?
Q2	Are the objectives clear and achieved?
Q3	Is the information presented balanced and unbiased?
Q4	Finally, based on the answers to all the preceding questions, rate the answer in terms of its overall quality as a source of information.
Q5	Is the information an aid to "shared decision-making"?
Q6	Is the mode of action of each treatment procedure described?
Q7	Are the benefits of each treatment procedure described?
Q8	Is it described how the treatment procedures affect quality of life?
Q9	Are additional sources of information listed for patient reference?
Q10	Are the risks of each treatment procedure described?

Ethical Considerations

This study centered on assessing AI systems without the direct involvement of human participants. Prioritizing the accuracy of the AI-produced medical content was crucial due to its potential impact on clinical practice. Content generated by the AI models was exclusively used for research purposes.

Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

Grammarly and GPT-4 were used for language improvements and general manuscript revision. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Results

Claude-instant-v1.0 exhibited the highest mean mDISCERN score of 3.35 (95% CI 3.23-3.46), followed by GPT-3.5-Turbo at 2.78 (95% CI 2.67-2.89), Command-xlarge-nightly at 2.17 (95% CI 2.06-2.28), and Bloomz with the lowest score of 1.07 (95% CI 1.03-1.10). A pairwise *t* test using the step-down Bonferroni method revealed significant differences ($P<.001$) among all model pairs, indicating substantial disparities in response quality. Claude-instant-v1.0 outperformed the other models, while Bloomz ranked last based on mean mDISCERN scores across all specialties. Upon detailed examination of the mDISCERN scores, all models demonstrated comparable strengths (Q1-Q3) and weaknesses (Q7-Q10) across all specialties under study (Figure 2A).

The highest mDISCERN scores across all models were seen in the clarity of multiple treatment options (mean 3.42, 95% CI 3.19-3.65), clear and achieved objectives (mean 3.24, 95% CI 3.05-3.42), and balanced and unbiased presentation (mean 2.93, 95% CI 2.73-3.13), and the lowest scores in benefits of treatment procedures (mean 1.99, 95% CI 1.83-2.14), treatment impact on quality of life (mean 1.59, 95% CI 1.45-1.73), provision of additional sources for patient reference (mean 1.55, 95% CI 1.45-1.66), and risks of treatment procedures (mean 1.29, 95% CI 1.20-1.37, Figure 2B).

The ANOVA demonstrated significant differences in harmfulness ratings among models ($F_{3,228}=4.412$, $P=.005$, $\eta^2=0.055$) but not across specialties ($F_{2,228}=1.670$, $P=.19$, $\eta^2=0.014$); the interaction between specialty and model was also nonsignificant ($F_{6,228}=1.798$, $P=.10$, $\eta^2=0.045$). Consequently, model differences in potential harmfulness were unrelated to the specialty under consideration. GPT-3.5-Turbo exhibited the lowest harmfulness rating without a single potentially harmful piece of information (0%, 95% CI 0%-0%). Claude-instant-v1.0 exhibited the highest number of potentially harmful recommendations (13.3%, 95% CI 4.7%-22%), followed by Bloomz (8.3%, 95% CI 1.3%-15.4%) and Command-xlarge-nightly (1.7%, 95% CI –1.6% to 4.9%).

An ANOVA demonstrated significant main effects of specialty ($F_{2,228}=8.523$, $P<.001$, $\eta^2=0.070$) and model ($F_{3,228}=14.455$, $P<.001$, $\eta^2=0.160$) on falseness ratings. However, the interaction between specialty and model was not statistically significant ($F_{6,228}=1.694$, $P=.12$, $\eta^2=0.043$). These findings indicate that the performance of each model differs across medical domains, with the overall effect of specialty and model on the likelihood of providing potentially or clearly false information being statistically significant.

The mean falseness ratings with 95% CIs revealed differences in the extent of potentially or clearly false information provided by each model. Claude-instant-v1.0 demonstrated the highest falseness ratings in ophthalmology (68.4%, 95% CI 47%-89.9%) and dermatology (65%, 95% CI 43.6%-86.4%), while GPT-3.5-Turbo exhibited the lowest rating in dermatology (0%, 95% CI 0%-0%). The overall accuracy, defined as the absence of harmfulness and falseness, was highest for GPT-3.5-Turbo (88.3%, 95% CI 80.1%-96.5%) and was lowest for Claude-instant-v1.0 (48.3%, 95% CI 35.6%-61.1%). The complete list of responses is included in Multimedia Appendix 2. A comparative overview of mDISCERN, falseness, and harmfulness ratings, together with the accuracy among all LLMs, is provided in Table 2, and a few selected examples for each specialty are shown in Table 3.

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Figure 2. Evaluation of the therapy recommendations by large language models (LLMs). (A) Mean mDISCERN scores separated by LLMs and mDISCERN questions. (B) Mean mDISCERN scores across all specialties (dermatology, ophthalmology, and orthopedics) and LLMs. Most responses clearly show more than one therapeutic option, whereas risks and additional sources of information were lacking. All error bars show 95% CIs of the mean.

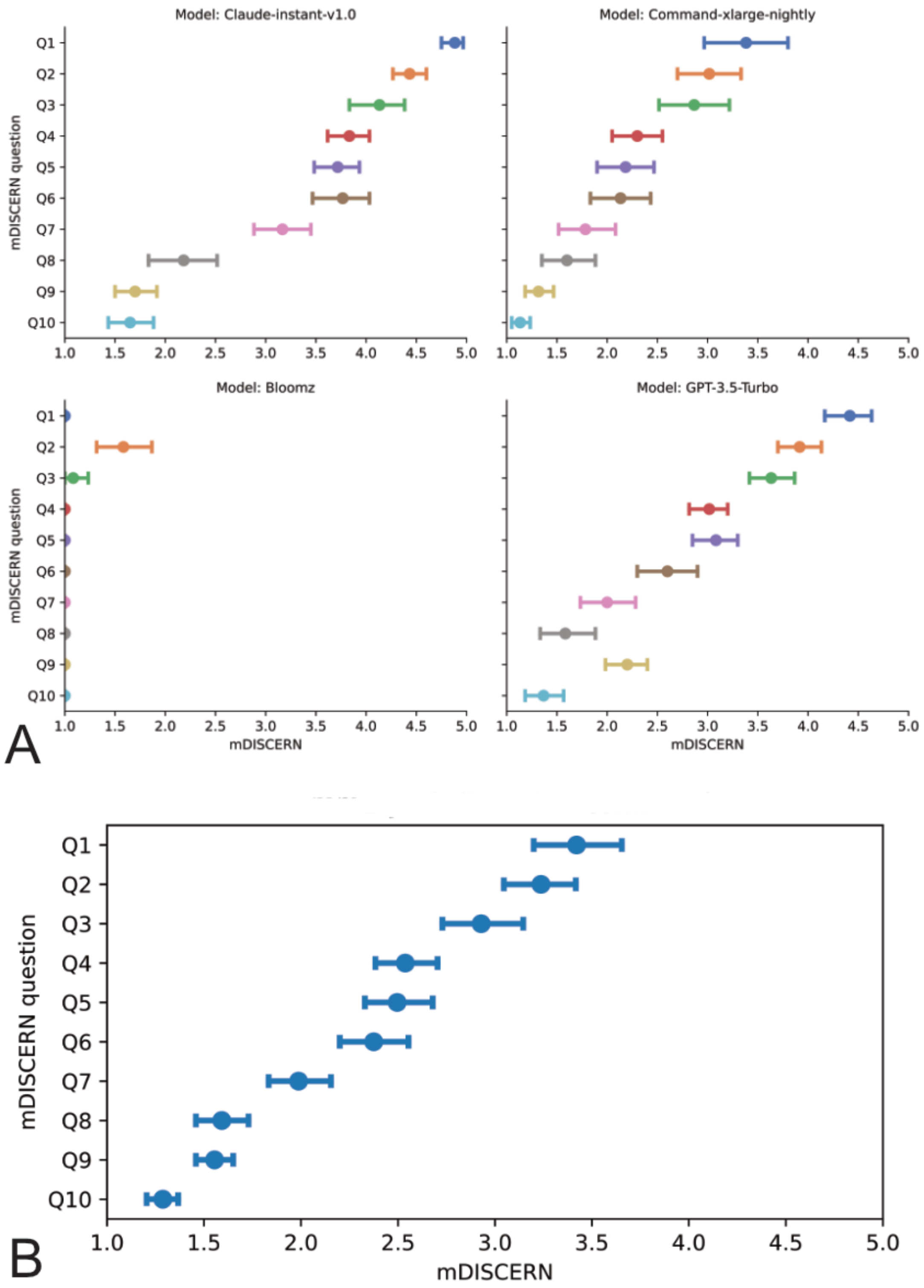

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Table 2. Comparison of the mDISCERN quality score (1: low quality; 5: high quality), the percentage of potentially incorrect and harmful responses, and the accuracy (defined by the absence of both falseness and harmfulness) for all 4 large language models on treatment recommendations for all 60 diseases (19 ophthalmologic, 20 dermatologic, and 21 orthopedic diseases).

Large language model (n=60 each)	mDISCERN quality score (n=240), mean (95% CI)	Falseness (n=240), % (95% CI)	Harmfulness (n=240), % (95% CI)	Accuracy (n=240), % (95% CI)
Claude-instant-v1.0	3.4 (3.2-3.5)	51.7 (38.9-64.4)	13.3 (4.7-22.0)	48.3 (35.6-61.1)
GPT-3.5-Turbo	2.8 (2.7-2.9)	11.7 (3.5-19.9)	0 (0-0)	88.3 (80.1-96.5)
Command-xlarge-nightly	2.2 (2.1-2.3)	16.7 (7.2-26.2)	1.7 (–1.6 to 4.9)	83.3 (73.8-92.8)
Bloomz	1.1 (1.0-1.1)	15 (5.9-24.1)	8.3 (1.3-15.4)	83.3 (73.8-92.8)

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Table 3. Examples of comments by physicians and GPT-4 on the given responses.

Specialty	Question	Answer (model)	Physician comment	GPT-4 comment
Dermatology	How to treat a clavus?	A clavus is a nail deformity that can be caused by several different things, including injury, infection, or fungus. Treatment for a clavus will depend on the cause. If the clavus is caused by an injury, it may be treated with a splint or cast to help the nail grow back correctly. If the clavus is caused by an infection, it may be treated with antibiotics. If the clavus is caused by a fungus, it may be treated with antifungal medication. In some cases, a clavus may need to be surgically removed. (Command-xlarge-nightly)	A clavus is not a nail deformity.	The provided answer contains incorrect information about a clavus. A clavus is actually a type of callus, not a nail deformity. The answer's content is not relevant to the treatment of a clavus.
	How to treat tinea corporis?	Tinea corporis is a fungal infection of the skin that causes a red, scaly, itchy rash. It is also known as athlete's foot or jock itch. Treatment for tinea corporis usually involves the use of topical antifungal creams or lotions. These can be purchased over the counter or prescribed by a doctor. It is important to follow the instructions on the package carefully and to continue using the cream or lotion for the full course of treatment, even if the rash appears to be gone. If the rash is severe or does not respond to topical treatment, oral antifungal medications may be prescribed. These are taken by mouth and can be used to treat more severe or stubborn cases of tinea corporis. (Command-xlarge-nightly)	"Tinea corporis" is not known as an athlete's foot or jock itch.	Note: The provided answer contains a minor error. Tinea corporis is not the same as athlete's foot or jock itch. Athlete's foot is known as tinea pedis, and jock itch is known as tinea cruris. Tinea corporis is a term for a fungal infection affecting other areas of the body.
Ophthalmology	How to treat viral conjunctivitis?	Use an eye drop to treat the infection. (Bloomz)	The common adenovirus conjunctivitis cannot be cured by eye drops. However, moisturizing eye drops can relieve symptoms. It is not said what types of eye drops to use. Transmission prophylaxis is not mentioned.	Explanation: The answer provided is oversimplified and does not accurately represent the management of viral conjunctivitis. Antiviral eye drops are not typically used for this condition, as it is usually self-limiting and resolves on its own. Instead, supportive care measures such as cool compresses and artificial tears are more appropriate.
	How to treat herpes ceratitis?	Use a cotton swab to apply a small amount of tea tree oil to the sore. (Bloomz)	*<Marked as a false answer, no further comment>*	Tea tree oil should not be used to treat herpes keratitis. The answer contains potentially harmful information because applying tea tree oil to the eye can cause irritation and further complications. The correct approach is to use prescribed antiviral medications under the supervision of a healthcare professional.

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Specialty	Question	Answer (model)	Physician comment	GPT-4 comment
Orthopedics	How to treat palmar fibromatosis?	Here are some of the main treatment options for palmar fibromatosis: • Surgery: Partial or complete excision of the tumor mass is often the most effective treatment for palmar fibromatosis. The goal is to remove as much of the tumor as possible while preserving function and anatomy. Surgery may need to be repeated for recurrences. Flexor tendon reconstruction or release may also be needed in some cases. • Steroid injections: Corticosteroid injections can help reduce inflammation and slow the growth of the tumor. They are often used pre-operatively to shrink the tumor and make it easier to excise. Multiple injections are usually required. • Radiation therapy: In some cases, radiation therapy can be used to destroy tumor cells. It is usually reserved for unresectable or recurrent disease. • Chemotherapy: Anti-cancer drugs have shown little benefit for palmar fibromatosis and are rarely used. Some case reports suggest newer targeted drug therapies may have some effect. • Physical therapy: After surgery or other procedures, physical therapy can help improve hand mobility and function. Splinting or bracing may also be used to maintain joint positioning and prevent contractures. • Close monitoring: For some small or slow-growing tumors, close follow-up monitoring with periodic imaging and clinical exams may be the most appropriate approach, at least initially. Surgery can then be considered if the tumor grows significantly or causes problems. • Combination approach: Often, a combination of these treatments is used to maximize effectiveness. For example, surgery may be combined with steroid injections or radiation therapy for difficult or recurrent cases. The ultimate goal of all treatment is to minimize recurrence, preserve hand function, and provide palliative relief of symptoms like pain, swelling, or limitations in movement. Close monitoring is needed lifelong due to the high recurrence rates of this condition. (Claude-instant-v1.0)	There are many therapy options presented overall. However, neither with advantages and disadvantages nor with reasons for the respective therapy	The answer contains at least questionable information as it does not mention non-surgical treatments such as radiation therapy or corticosteroid injections, which can also be used to manage palmar fibromatosis. < Authors' note: The model failed to recognize certain non-surgical treatment strategies shown in the model's answer>
	How to treat achilles tendon rupture?	Rest, ice, compression, elevation (Bloomz)	*<The response was not considered questionable by the author due to missing information. However, the author agrees with ChatGPT that the therapy options were not fully mentioned.>*	The answer contains at least questionable information, as it only suggests rest, ice, compression, and elevation (RICE) as the treatment for an Achilles tendon rupture. While these methods may help alleviate pain and swelling, they do not address the full extent of the injury. Treatment often involves immobilization, physical therapy, and in some cases, surgery.

In our analysis of mDISCERN questions for the evaluation of model responses using independent *t* tests and Bonferroni correction, we found differences in scores between specialties across all models combined. Specifically, the scores for mDISCERN question Q2 (“Are the objectives clear and achieved?”) were higher in ophthalmology compared to orthopedics and dermatology (*P*<.05). In addition, the scores for Q6 to Q8 (pertaining to the mode of action, benefits, and effect on quality of life of therapies, respectively) were higher for orthopedics compared to dermatology (*P*<.05). Particularly for Q8, the scores were also significantly higher for orthopedics compared to ophthalmology (*P*<.001). Aside from these findings, no other significant differences were observed in the comparisons between specialties (Table 4).

A Pearson correlation analysis assessing the relationship between physician- and GPT-4-generated ratings across the 12 evaluated criteria showed positive, statistically significant correlations *(P*<.05) of varying strengths (Table 5). The strongest correlations emerged for “overall quality as a source of information” (Q4; *r*=0.686, 95% CI 0.61-0.75, *P*<.001), “aid to shared decision-making” (Q5; *r*=0.665, 95% CI 0.59-0.73,*P*<.001), and “mode of action description” (Q6; *r*=0.638, 95% CI 0.56-0.71, *P*<.001). The weakest correlations were observed for “additional sources listed for patient reference” (Q9; *r*=0.186, 95% CI 0.06-0.31, *P*=.004), “contains false information” (*r*=0.187, 95% CI 0.06-0.31, *P*=.004), and “contains potentially harmful information” (*r*=0.188, 95% CI 0.06-0.31, *P*=.003).

These findings suggest that GPT-4-generated ratings exhibit a considerable degree of alignment with physician ratings across various criteria, indicating the model’s potential to generate useful, unbiased, and accurate information for patients. However, the weaker correlations observed for specific criteria, particularly those related to potential harm and false information, emphasize the need for caution and continued refinement of AI-generated content intended for patient use. Future research should focus on improving these AI models to minimize the likelihood of providing harmful or false information, ensure patient safety, and enhance the overall utility of AI-generated content in health care.

Table 4. Mean mDISCERN scores for all questions for each specialty.

mDISCERN question	mDISCERN score, mean (95% CI)		
	Orthopedics	Dermatology	Ophthalmology
Q1	3.39 (3.02-3.77)	3.58 (3.19-3.96)	3.29 (2.88-3.70)
Q2	2.83 (2.54-3.12)	3.08 (2.77-3.38)	3.86 (3.52-4.19)
Q3	2.92 (2.61-3.22)	2.88 (2.55-3.20)	3.00 (2.60-3.40)
Q4	2.67 (2.38-2.96)	2.62 (2.34-2.91)	2.30 (2.03-2.57)
Q5	2.64 (2.35-2.94)	2.58 (2.29-2.86)	2.25 (1.96-2.54)
Q6	2.77 (2.47-3.08)	1.99 (1.73-2.24)	2.34 (2.00-2.68)
Q7	2.26 (1.99-2.53)	1.65 (1.43-1.87)	2.04 (1.74-2.34)
Q8	2.36 (2.07-2.64)	1.27 (1.13-1.42)	1.08 (0.96-1.19)
Q9	1.81 (1.58-2.04)	1.43 (1.30-1.55)	1.41 (1.30-1.52)
Q10	1.35 (1.20-1.49)	1.19 (1.07-1.31)	1.33 (1.15-1.51)

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Table 5. Correlation between physicians' and GPT-4-generated ratings for given questions.

Question	Pearson, *r*	95% CI	*P* value	Bayes factor	Power[a]
Finally, based on the answers to all the preceding questions, rate the answer in terms of its overall quality as a source of information.	0.686	0.61-0.75	<.001	3.346×10^{31}	>.999
Is the information an aid to "shared decision-making"?	0.665	0.59-0.73	<.001	6.52×10^{28}	>.999
Is the mode of action of each treatment procedure described?	0.638	0.56-0.71	<.001	5.017×10^{25}	>.999
Are the objectives clear and achieved?	0.635	0.55-0.71	<.001	2.419×10^{25}	>.999
Is it clearly presented that more than one possible treatment procedure may exist?	0.612	0.53-0.69	<.001	8.752×10^{22}	>.999
Is the information presented balanced and unbiased?	0.609	0.52-0.68	<.001	4.15×10^{22}	>.999
Are the benefits of each treatment procedure described?	0.518	0.42-0.61	<.001	8.705×10^{14}	>.999
Is it described how the treatment procedures affect quality of life?	0.441	0.33-0.54	<.001	9.425×10^{09}	>.999
Are the risks of each treatment procedure described?	0.388	0.27-0.49	<.001	1.842×10^{7}	>.999
Does the answer contain potentially harmful information?	0.188	0.06-0.31	.003	5.618	0.835
Does the answer contain false information?	0.187	0.06-0.31	.004	5.498	0.833
Are additional sources of information listed for patient reference?	0.186	0.06-0.31	.004	5.185	0.828

[a] The statistical power indicates the likelihood of correctly rejecting the null hypothesis, which assumes no linear relationship between the physicians' and GPT-4-generated ratings.

Discussion

The current study investigated the performance of 4 LLMs in generating medical information across 3 clinical specialties (ophthalmology, dermatology, and orthopedics). Our results revealed considerable variability in the quality, potential harmfulness, and falseness of the information provided by the LLMs. These findings hold important implications for potential applications and limitations of AI-generated content in health care.

Claude-instant-v1.0 consistently exhibited the highest mean mDISCERN scores, followed by GPT-3.5-Turbo, Command-xlarge-nightly, and Bloomz. These differences were statistically significant, suggesting notable disparities in the overall quality of information generated by the models. However, despite its superior performance in the mDISCERN evaluation, Claude-instant-v1.0 demonstrated the highest falseness and harmfulness ratings, contradicting its "helpful, honest, and harmless AI systems" slogan [8] in the medical domain. The disparity between high mDISCERN scores and instances of falseness or harmfulness highlights a crucial challenge: while richness in content might suggest comprehensive information, it doesn't guarantee accuracy or safety. This emphasizes the imperative of ongoing refinement in AI-driven medical content to reconcile the depth of information with its clinical accuracy and safety. The overall low mDISCERN scores observed for the Bloomz model should not be interpreted as a definitive disqualification for patient recommendation. Instead, these findings should motivate the scientific community to explore and enhance the potential of this model through advanced fine-tuning techniques [25] and more effective prompting strategies, especially given that it is the sole open-source model within the examined cohort. Other general factors that might have an impact on model performance are the complexity and diversity of the training data, the presence of inherent biases in the data, the computational resources available during training, general model architecture, and the ongoing adjustments and updates made to the model postdeployment to respond to real-world feedback.

The mDISCERN score revealed limitations in all assessed AI models regarding the discussion of treatment risks and benefits, the impact on quality of life, and the provision of supplementary resources for patients. Microsoft's recently released AI-powered Bing search [26] and the new version of ChatGPT [27], both of which use GPT-4 and have the ability to include links in responses, could potentially address these concerns. Furthermore, knowledge about areas where mDISCERN scores are low can be used for targeted improvements of existing models using reinforcement learning through human feedback [28].

The analysis revealed a significant effect of specialty and model on falseness ratings. This suggests that the performance of the models may not be consistent across different medical domains. Consequently, LLM developers should pay special attention to the unique demands and requirements of different specialties to optimize the quality and accuracy of the generated content.

We have observed distinct error patterns that warrant attention. Foremost, there were instances where the models recommended therapy options, such as corticosteroids, without the necessary accompaniment of antibiotics for infectious diseases. Additionally, diagnoses or therapies were occasionally confused (eg, interchange of topical and systemic administration routes or conflation of standard arteriovenous cardiological bypass procedures with those of an experimental nature in the ocular context), pointing toward a potential risk of misdirection in

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treatment options. Furthermore, some advice appeared broad or nonspecific, highlighting the necessity for professional oversight.

In the field of ophthalmology, our findings underscore the imperative for LLMs to furnish more nuanced patient information, considering the fragile aspect of ocular health and proactive eyesight preservation—notably in the preservation of eyesight for diseases like endophthalmitis [29]. Similarly, for dermatology, with a broad spectrum of conditions ranging from benign to malignant, the variability in the information generated emphasizes the necessity for accuracy and the potential risks of misinformation, especially for time-sensitive therapies, such as in the case of melanoma [30]. Orthopedics, being a specialty heavily reliant on procedural interventions, necessitates information on risks, benefits, and postoperative care, areas where the LLMs displayed noticeable limitations. Higher evaluations in orthopedics for treatment efficacy (Q6), benefits (Q7), and effect on the quality of life (Q8) may be attributed to the intuitive and relatively simple nature of conservative therapies, such as rest, ice, compression, and elevation, as well as common treatment protocols involving physical therapy and pharmacological interventions [31-33]. Counterintuitively, in dermatology, actions like scratching can worsen symptoms [34].

Our findings also demonstrated significant correlations between physician ratings and GPT-4-generated ratings for the 12 assessed criteria. This suggests that GPT-4 may hold the potential for evaluating the overall quality of patient information. However, the weaker correlations observed in certain criteria, particularly those related to potential harm and false information, underscore the need for continued improvements in using AI systems for the evaluation of patient content. Ensuring patient safety and providing reliable information should be primary goals for the developers of these models. This will be an essential step in enhancing the trustworthiness and overall utility of AI-generated content in health care.

Our study encountered several limitations. While we sought to validate physicians' ratings using GPT-4 and demonstrated a high correlation among numerous ratings, a more robust validation of the method would require the inclusion of a larger number of physician specialists and an expanded range of clinical specialties. This is particularly important when dealing with subjective scores, such as the mDISCERN used in this study. In our evaluation, we used straightforward prompts to reflect typical real-world queries and gauge primary model outputs. For example, one question (Q9) assessed if models inherently provided additional sources. Yet, prompt nuances can change results, and directly asking, "Can you list the sources of information for this topic?" could have resulted in better model responses. Moreover, our investigation represents a snapshot of the rapidly evolving landscape of LLMs. Since the beginning of our study, new models like Alphabet's Bard [35] and Meta's LlaMA2 [36] have been released, showcasing potential advancements in medical applications. These developments highlight the necessity for continuous evaluation of LLMs in health care, as newer models may offer enhanced capabilities. Consequently, this study should be perceived less as a definitive critique of the drawbacks of such models and more as a framework to guide future research in evaluating the capabilities and performances of these increasingly sophisticated systems. We endeavored to closely emulate real-world scenarios; by using more advanced prompting techniques, the quality of the responses could potentially be further enhanced [37].

In conclusion, this study highlights the potential of LLMs in generating medical information across various specialties while also emphasizing the need for continued advancements in AI-generated content to ensure patient safety and provide reliable, accurate information. By addressing the identified limitations and tailoring the development of LLMs to the unique requirements of different medical specialties, AI-generated content could become a valuable resource for patients and health care providers alike.

Data Availability

The complete data set with the corresponding mDISCERN, falseness, and truthfulness ratings of all 3 physicians and GPT-4 can be found in Multimedia Appendix 2.

Authors' Contributions

JR, TIW, and RK were involved in the conceptualization and methodology of the study. JR and RK curated the data, while TIW and RK performed the formal analysis. RK was responsible for project administration, software development, and supervision. JR and TIW provided resources for the study. Validation was carried out by JR, TIW, and RK. RK and TIW created the visualizations for the manuscript. The writing process involved JR, RK, and TIW, with RK and JR preparing the original draft and JR, TIW, and RK taking part in the review and editing process. All authors have directly accessed and verified the underlying data reported in the manuscript. TIW and JR are shared first authors, having contributed equivalently to the primary research components of this study. RK is the sole last author with contributions equivalent in scale to the first authors.

Conflicts of Interest

None declared.

Multimedia Appendix 1

GPT-4 evaluation prompt for the therapy recommendations of the other models.
[PDF File (Adobe PDF File), 102 KB-Multimedia Appendix 1]

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Multimedia Appendix 2

Data set of all 60 diseases with questions, responses, and ratings from the 3 physicians and GPT-4.
[XLSX File (Microsoft Excel File), 105 KB-Multimedia Appendix 2]

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Abbreviations

AI: artificial intelligence
LLM: large language model

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