

Performance of Multimodal GPT-4V on USMLE with Image: Potential for Imaging Diagnostic Support with Explanations

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1-2 sentence description:

In this study the authors show that GPT-4V, a large multimodal chatbot, achieved accuracy on medical licensing exams with images equivalent to the 70th - 80th percentile with AMBOSS medical students. The authors also show issues with GPT-4V, including uneven performance in different clinical subdomains and explanation quality, which may hamper its clinical use.

Abstract

Background: Using artificial intelligence (AI) to help clinical diagnoses has been an active research topic for more than six decades. Past research, however, has not had the scale and accuracy for use in clinical decision making. The power of AI in large language model (LLM)-related technologies may be changing this. In this study, we evaluated the performance and interpretability of Generative Pre-trained Transformer 4 Vision (GPT-4V), a multimodal LLM, on medical licensing examination questions with images.

Methods: We used three sets of multiple-choice questions with images from the United States Medical Licensing Examination (USMLE), the USMLE question bank for medical students with different difficulty level (AMBOSS), and the Diagnostic Radiology Qualifying Core Exam (DRQCE) to test GPT-4V's accuracy and explanation quality. We compared GPT-4V with two state-of-the-art LLMs, GPT-4 and ChatGPT. We also assessed the preference and feedback of healthcare professionals on GPT-4V's explanations. We presented a case scenario on how GPT-4V can be used for clinical decision support.

Results: GPT-4V outperformed ChatGPT (58.4%) and GPT4 (83.6%) to pass the full USMLE exam with an overall accuracy of 90.7%. In comparison, the passing threshold was 60% for medical students. For questions with images, GPT-4V achieved a performance that was equivalent to the 70th - 80th percentile with AMBOSS medical students, with accuracies of 86.2%, 73.1%, and 62.0% on USMLE, DRQCE, and AMBOSS, respectively. While the accuracies decreased quickly among medical students when the difficulties of questions increased, the performance of GPT-4V remained relatively stable. On the other hand, GPT-4V's performance varied across different medical subdomains, with the highest accuracy in immunology (100%) and otolaryngology (100%) and the lowest accuracy in anatomy (25%) and emergency medicine (25%). When GPT-4V answered correctly, its explanations were almost as good as those made by domain experts. However, when GPT-4V answered incorrectly, the quality of generated explanation was poor: 18.2% wrong answers had made-up text; 45.5% had inferencing errors; and 76.3% had image misunderstandings. Our results show that after experts gave GPT-4V a short hint about the image, it reduced 40.5% errors on average, and more difficult test questions had higher performance gains. Therefore, a hypothetical clinical decision support system as shown in our case scenario is a human-AI-in-the-loop system where a clinician can interact with GPT-4V with hints to maximize its clinical use.

Conclusion: GPT-4V outperformed other LLMs and typical medical student performance on results for medical licensing examination questions with images. However, uneven subdomain performance and inconsistent explanation quality may restrict its practical application in clinical settings. The observation that physicians' hints significantly improved GPT-4V's performance suggests that future research could focus on developing more effective human-AI collaborative systems. Such systems could potentially overcome current limitations and make GPT-4V more suitable for clinical use.

Introduction

Using computers to help make clinical diagnoses and guide treatments has been a goal of artificial intelligence (AI) since its inception.¹ The adoption of electronic health record (EHR) systems by hospitals in the US has resulted in an unprecedented amount of digital data associated with patient encounters. Computer-assisted clinical diagnostic support system (CDSS) endeavors to enhance clinicians' decisions with patient information and clinical knowledge.² There is burgeoning interest in CDSS for enhanced imaging³, often termed radiomics, in various disciplines such as breast cancer detection⁴, Covid detection⁵, diagnosing congenital cataracts⁶, and hidden fracture location⁷. For a decision to be trustworthy for clinicians, CDSS should not only make the prediction but also provide accurate explanations.^{8–10} However, most previous imaging CDSS offers only highlight areas deemed significant by AI,^{11–14} providing limited insight into the explanation of the diagnosis.¹⁵

Recent advances in large language models (LLMs) have set much discussion in healthcare. State-of-the-art LLMs include Chat Generative Pre-trained Transformer (ChatGPT), a chatbot released by OpenAI in October 2022, and its successor Generative Pre-trained Transformer 4 (GPT-4) in March 2023. The success of ChatGPT and GPT4 is attributed to their conversational prowess and their performance, which have approached or matched human-level competence in cognitive tasks, spanning various domains including medicine.¹⁶ Both ChatGPT and GPT4 have achieved commendable results in the United States Medical Licensing Examinations, leading to discussions about the readiness of LLM applications for integration into clinical^{17–19} and educational^{20–22} environments.

One limitation of ChatGPT and GPT4 is that they can only read and generate text but are unable to process other data modalities, such as images. This limitation, known as the "single-modality," is a common issue among many LLMs.^{23,24} Advancements in multimodal LLM promise enhanced capabilities and integration with diverse data sources.^{25–27} OpenAI's GPT-4V is a state-of-the-art multimodal LLM equipped with visual processing/understanding ability.²⁸ By incorporating GPT-4V into current imaging CDSS, physicians can ask open-ended questions pertaining to a patient's medical evaluation - taking into account all available information including images, symptoms, and lab results, allowing for an interactive experience where AI suggests both decision and explanation to support physicians.

However, the ability of GPT-4V to analyze medical images remains unknown. For GPT-4V to be useful to medical professionals, it should not only provide correct responses but also reasons for the responses. In this work, we assess GPT-4V performance on medical licensing examination questions with images. We also analyze the explanation of its answers to the examination questions.

Method

This cross-sectional study compared the performance between GPT-4V, GPT-4, and ChatGPT on medical licensing examination questions answering. This study also investigates the quality of GPT-4V explanation in answering these questions. The study protocol was deemed exempt by Institutional Review Board at the VA Bedford Healthcare System and informed consent was waived due to minimal risk to patients. This study was conducted in October 2023.

Medical Exams and a Patient Case Report Collection

We obtained study questions from three sources. The United States Medical Licensing Examination (USMLE) consists of three steps required to obtain a medical license in the United States. The USMLE assesses a physician's ability to apply knowledge, concepts, and principles, which is critical to both health and disease management and is the foundation for safe, efficient patient care. The Step1, Step2 clinical knowledge(CK), Step3 of USMLE sample exam released from the National Board of Medical Examiners (NBME) consist of 119, 120, and 137 questions respectively. Each question contained multiple options to choose from. We then selected all questions with images, resulting in 19, 13, and 18 questions from Step1, Step2 CK, and Step3. Medical subdomains include but are not limited to radiology, dermatology, orthopedics, ophthalmology, cardiology, and general surgery.

The sample exam only included limited questions with images. Thus, we further collected similar questions from AMBOSS, a widely used question bank for medical students, which provides exam performance data given students' performance. The performance of past AMBOSS students enabled us to assess the comparative effectiveness of the model. For each question, AMBOSS associated an expert-written hint to tip the student to answer the question and a difficulty level that ranges from 1-5. Levels 1, 2, 3, 4, and 5 represent the easiest 20%, 20-50%, 50%-80%, 80%-95%, and 95%-100% of questions respectively.²⁹ Since AMBOSS is proprietary, we randomly selected and manually downloaded 10 questions from each of the 5 difficulty levels. And we repeated this process for Step1, Step2 CK, and Step3. This resulted in a total number of 150 questions.

In addition, we collected questions from the Diagnostic Radiology Qualifying Core Exam (DRQCE), which is an image-rich exam to evaluate a candidate's core fund of knowledge and clinical judgment across practice domains of diagnostic radiology, being offered after 36 months of residency training. Since DRQCE is proprietary, we randomly selected and manually downloaded 26 questions with images from the preparation exam offered by the American Board of Radiology (ABR). In total, we had 226 questions with images from the three aforementioned sources.

To illustrate GPT-4V's potential as an imaging diagnostic support tool, we modified a patient case report³⁰ to resemble a typical "curbside consult" question between medical professionals.³¹

How to Answer Image Questions using GPT-4V Prompt

GPT-4V took image and text data as inputs to generate textual outputs. Given that input format (prompt) played a key role in optimizing model performance, we followed the standard prompting guidelines of the visual question-answering task. Specifically, we prompted GPT-4V by first adding the image, then appending context (i.e., patient information) and questions, and finally providing multiple-choice options, each separated by a new line. An example user prompt and GPT-4V response are shown in Figure 1. When multiple sub-images existed in the image, we uploaded multiple sub-images to GPT-4V. When a hint is provided, we append it to the end of the question. The response consists of the selected option as an answer, supported by a textual explanation to substantiate the selected decision. When using ChatGPT and GPT-4 models that cannot handle image data, images were omitted from the prompt. Responses were collected from the September 25, 2023 version of models. Each question was manually entered into the ChatGPT website independently (new chat window).

Evaluation Metrics

For answer accuracy, we evaluated the model's performance by comparing the model's choice with the correct choice provided by the exam board or question bank website. We defined accuracy as the ratio of the number of correct choices to the total number of questions.

We also evaluated the quality of the explanation by preference from 3 healthcare professionals (one medical doctor, one registered nurse, and one medical student). For each question from AMBOSS dataset (n=150), we asked the healthcare professionals to choose their preference between an explanation by GPT-4V, an explanation by an expert, or a tie.

Additionally, we also asked healthcare professionals to evaluate GPT-4V explanation from a sufficient and comprehensive perspective.^{32,33} They determined if the following information exists in the explanation:

1. Image interpretation: GPT-4V tried to interpret the image in the explanation, and such interpretation is sufficient to support its choice.
2. Question information: Explanations contained information related to the textual context (i.e., patient information) of the question, and such information was essential for GPT-4V's choice.
3. Comprehensive explanation: The explanation included comprehensive reasoning for all possible evidence (e.g., symptoms, lab results) that leads to the final answer.

Finally, for each question answered incorrectly, we asked healthcare professionals to check if the explanation contained any of the following errors:

1. Image misunderstanding: if the sentence in the explanation showed an incorrect interpretation of the image. Example: GPT-4V said that a bone in the image was for the hand, but it was in fact the foot.
2. Text hallucination: if the sentence in the explanation contained made-up information. Example: Claiming Saxenda was insulin.
3. Reasoning error: if the sentence did not properly infer knowledge in either image or text to an answer. Example: GPT-4V reasoned that a patient took a trip within the last 3 months and therefore diagnosed the patient as having chagas disease, despite the clinical knowledge that chagas disease usually develops 10–20 years after infection.
4. Non-medical error: GPT is known to struggle with tasks requiring precise spatial localization, such as identifying chess positions on the board.²⁸

Statistical Analysis

GPT-4V's accuracies on the AMBOSS dataset were compared between different difficulties using unpaired chi-square tests with a significance level of 0.05. All analysis was conducted in Python software (version 3.10.11).

Results

Overall Answer Accuracy

For all questions in the USMLE sample exam (including ones without image), GPT-4V achieved an accuracy of 88.2%, 90.8%, 92.7% among Step1, Step2CK, and Step3 of USMLE questions respectively, outperforming ChatGPT and GPT-4 by 33.1% and 6.7% in Step1, 31.7% and 10.0% in Step2CK, 31.8% and 4.4% in Step3 (Table 1). The score of GPT-4V passes the standard for the USMLE (about 60%). Performance of GPT-4V across different subdomains is shown in Supplementary Table 1.

For questions with image, GPT-4V achieved an accuracy of 84.2%, 85.7%, 88.9% in Step1, Step2CK, and Step3 of USMLE questions accordingly, outperforming ChatGPT and GPT-4 by 42.1% and 21.1% in Step1, 35.7% and 21.4% in Step2CK, 38.9% and 22.2% in Step3 (Table 1). Similarly, GPT-4V achieved an accuracy of 73.1%, outperforming ChatGPT (19.2%) and GPT-4 (26.9%) in DRQCE.

Impact of Difficulty Level and Use of Hints

When asking GPT-4V questions without the hint, it achieved an accuracy of 60%, 64%, and 66% for AMBOSS Step1, Step2CK, and Step3 (Table 2). GPT-4V was in the 72nd, 76th, and 80th percentile with AMBOSS users who were preparing for Step1, Step2CK, and Step3 respectively. When asking GPT-4V questions with the hint, it achieved accuracy of 84%, 86%, and 88% for

AMBOSS Step1, Step2CK, and Step3. Supplementary Figure 1 is an example where GPT-4V switched the answer from incorrect to correct when hint was provided.

Figure 2 shows a decreasing trend in GPT-4V's performance in the AMBOSS dataset when the difficulty of questions increased ($P < 0.05$) without hint. However, with the hint, the performance of GPT-4V plateaued across five difficulty levels. Importantly, the accuracies of both GPT-4V, with or without hint, in general outperformed the accuracies of medical students and the gap between the performance of GPT-4V and medical students increased when the difficulty increased.

As shown in Figure 2, for easy questions (difficulty level =1), the medical students performed between 75% to 99% accuracies. GPT-4V with and without hint performed at 90% and 77%, respectively. When the difficulty level increased to 2, the performance of medical students decreased to between 56% to 68%. In contrast, GPT-4V with and without hint were more stable, performed at 87% and 77% respectively. The performance of medical students continued to decrease lineally to 39% and 55% when the difficulty level was 3. When difficulty levels were 4 and 5, the performance of medical students was very poor, ranging from 27% to 37% and from 14% to 24%, respectively. In contrast, the performance of GPT-4V with hint remained stable and stayed at 83% and 80%, respectively. The performance of GPT-4V without hint decreased when the difficulty level increased from 2 to 3, but then remained stable at 57% and 53% for difficulty levels 4 and 5, respectively.

Quality of Explanation

We evaluated the user's preference among GPT-4V generated explanations and expert generated explanations. When GPT-4V answered incorrectly, our results show that healthcare

professionals overwhelmingly preferred expert explanations as shown in Table 3. When GPT-4V answered correctly, the quality of GPT-4V generated explanations was close to expert generated explanations: out of 95 votes, 19 preferred experts, 15 preferred GPT-4V, and 61 preferred either.

We further evaluated the quality of the GPT-4V generated explanation by verifying if explanation includes image and question text interpretation in Supplementary Table 2. When examining the 95 correct answers, 84.2% (n=80) of the responses contained an interpretation of the image, while 96.8% (n=92) aptly captured the information presented in the question. On the other hand, for the 55 incorrect answers, 92.8% (n=51) interpreted the image, and 89.1% (n=49) depicted the question's details. In terms of comprehensiveness, GPT-4V offered a comprehensive explanation in 79.0% (n=75) of correct responses. In contrast, only 7.2% (n=4) of the wrong responses had a comprehensive explanation that led to the GPT-4V's choice.

We also evaluated the explanations of incorrect responses by GPT-4V image and grouped them into the following categories: image misunderstanding, text hallucination, reasoning error, and non-medical error. Among GPT-4V responses with wrong answers (n=55), we found that 76.3% (n=42) of responses included misunderstanding of the image, 45.5% (n=25) of responses included logic error, 18.2% (n=10) of responses included text hallucination, and no responses included non-medical errors.

A Case Study of Consult Conversation

We present a clinical case study regarding a 45-Year-Old woman with hypertension and altered mental status, where GPT-4V can be used as a clinical decision support system. As shown in Supplementary Figure 2, an interactive design of GPT-4V allows communications between

GPT-4V and physicians. In this hypothetical scenario, GPT-4V initially provided an irrelevant response when asked to interpret the CT scan. However, it was able to adjust its response and accurately identify the potential medical condition depicted in the image after receiving a physician's visual hint - an arrow pointed to a part of the CT scan where physicians desired GPT-4V to analyze.

Through comparing GPT-4V response with the case report, we also found that GPT-4V generally offered responses that were clear and coherent through interaction with experts. When asked about differential diagnosis, GPT-4V listed 3 diseases (Primary Aldosteronism, Hypertension, and Cushing's Syndrome) along with its explanations that were deemed relevant by a medical doctor. Following a query about the subsequent steps to ascertain the origin of the anomaly, GPT-4V recommended a PET-CT scan. Utilizing the patient's PET-CT scan, it was able to locate a tumor in the mediastinum, lending credence to the suspicion of Cushing's Syndrome. Finally, GPT-4V asked for further tests, such as a biopsy of the mass, to confirm the diagnosis.

Discussion

We found that GPT-4V outperformed ChatGPT and GPT-4 (Table 1). When evaluating all questions in the USMLE sample exam, GPT-4V achieved an accuracy of 90.7% outperforming ChatGPT (58.5%) and GPT-4 (83.8%). In comparison, medical students can pass the USMLE exam with $\geq 60\%$ accuracy, indicating that the GPT-4V performed at a level similar to or above a medical graduate in the final year of study. The accuracy of GPT-4V highlights its grasp over biomedical and clinical sciences, essential for medical practice, but also showcases its ability in

patient management and problem-solving skills,³⁴ both of which indicate the potential for clinical routines, such as summarizing radiology reports³⁵ and differential diagnosis^{36,37}.

For medical exam questions with images, we found that GPT-4V achieved an accuracy of 62%, which was equivalent to the 70th - 80th percentile with AMBOSS medical students. This finding indicates that GPT-4V has the capabilities to integrate information from both text and images to answer questions, making it a promising tool for answering clinical questions based on images. This is the first study that evaluates GPT-4V performance on questions with images. Previous evaluations exclude questions with images as the single-modality limitation of ChatGPT and GPT-4.^{20,38–40}

Our findings revealed that while medical students' performance lineally decreased when the difficulty of questions increased, GPT-4V's performance stayed relatively stable. When hints were provided, GPT-4V's performance stayed almost the same among questions in all difficult levels, as shown in Figure 2. Therefore, compared with medical students, GPT-4V was effective in answering more difficult questions. There may be multiple factors that contribute to this result. Instrument methods (e.g., item response theory (IRT)⁴¹) have been typically used for the construction and evaluation of measurement scales and tests. For example, IRT employs a statistical model that links an individual person's responses to individual test items (questions on a test) to the person's ability to correctly respond to the items and the items' features. Therefore, medical examination test sets have been specifically selected and tailored to medical students' performance with the intended distribution where the performance decreases when the difficulty level increases. Although more evaluation is needed to draw the conclusion that GPT-4V substantially outperformed medical students in difficult questions, our results at least show that GPT-4V performed differently. This may help GPT-4V as a useful clinical decision support system as it may be complementary to physicians' knowledge and thinking.

On the other hand, we found that GPT-4V 's performance was inconsistent among different medical subdomains. As shown in Supplementary Table 1, GPT-4V achieved high accuracy on subdomains such as Immunology (100%), Otolaryngology (100%), and Pulmonology (75%), and low accuracy on others such as anatomy (25%), emergency medicine (25%), and pathology (50%). This suggests that while CDSS shows potential in some specialties or subdomains, they may require further development to be reliable across the board. The uneven performance highlights the need for tailored approaches in enhancing the model's capabilities where it falls short.

In terms of explanation quality, we found that the quality of its generated explanations was close to ones created by domain experts when GPT-4V answered correctly. We also found that more than 80% of responses from GPT-4V provided an interpretation of the image and question of its answer selection, regardless of correctness. This suggests that GPT-4V consistently takes into account both the image and question elements while generating responses. Figure 1 illustrates an example of high-quality explanation that utilizes both text and image in answering a hard question. In this example, more than 70% of students answered incorrectly on the first try, because both bacterial pneumonia and pulmonary embolism may involve symptoms such as cough. To differentiate them, GPT-4V correctly interpreted the X-ray with a radiologic sign of Hampton hump, which further increased the suspicion of pulmonary infarction rather than pneumonia.⁴² To show the need for X-ray as mentioned in the explanation, we removed the image from the input, and GPT-4V switched the answer to bacterial pneumonia while also acknowledging the possibility of pulmonary infarction. This change in response demonstrated the high quality of the GPT-4V explanation, as its explanation about X-ray was not fictional and it truly needed the X-ray to answer this question.

Previous studies have shown limited utilization of current CDSS as most of them offered limited decision explanation and thus gained limited trust among physicians (unlike their colleagues).^{43–}

⁴⁶ In comparison, GPT-4V could enhance the effectiveness and trustworthiness of CDSS by providing high-quality, expert-preferred explanations, encouraging broader adoption and more confident utilization among physicians.

On the other hand, we found that the quality of generated explanations was poor when GPT-4V answered incorrectly. Manual analyses by healthcare professionals concluded that image misunderstanding was the primary reason why GPT-4V answered incorrectly. Out of 55 wrong responses, 42 (76.3%) were due to misunderstanding of the image. In comparison, only 10 (18.2%) of the mistakes were attributed to text misinterpretation. Clearly, GPT-4V's proficiency in processing images was considerably lagging behind its text-handling capability. To circumvent its image interpretation issue, we additionally prompted GPT-4V with a short hint that described the image. We found that 40.5% (17 out of 42) responses switched to the correct answer. Corrections from the hint indicated that GPT-4V could be easily persuaded. Within a conversational interface, medical professionals can readily guide and refine GPT-4V's initial outputs. This adaptability could be advantageous for physicians, as it allows for real-time adjustments and ensures that the generated information aligns more closely with the clinical context or the specific details of a patient's case.⁴⁷ With customized hints from physicians, GPT-4V enhances the usefulness and reliability as an auxiliary tool.

Another significant drawback of GPT-4V involved its tendency to produce factually inaccurate responses, a problem often referred to as the hallucination effect, which is prevalent among many large language models such as GPT-4V.⁴⁸ We found that more than 18% of GPT-4V explanations contain hallucinations. Thus when designing clinical support tools for high-risk situations such as patient diagnosing, it is crucial to integrate GPT-4V and a probabilistic model

with confidence interval and citation from credible sources to show the reliability of the response.^{49,50} This integration would enhance the reliability of the CDSS response when additional physician review is warranted.¹⁵

Limitations

This study has several limitations. First, our findings are constrained in their applicability due to the modest sample size. We gathered 226 questions from a total of 28 subdomains or specialties that included images, which might not comprehensively represent all medical disciplines. Second, the exams used to test GPT-4V are written in English. Future work could explore other languages. Finally, while GPT-4V has demonstrated proficiency in medical license examination, its CDSS ability remains untested. Medical exams provide options, but such options would rarely be provided by physicians during CDSS. While we show that GPT4V could act as a CDSS tool without options in our case study, more cases with clinician questions should be explored to confirm our findings before clinical integration. Therefore, while the results are promising, extrapolating the efficacy of GPT-4V to broader clinical applications requires appropriate benchmarks and further research.

Conclusion

In this study, GPT-4V showcased remarkable overall accuracy on medical licensing examination and provided high-quality explanations when answered correctly. Our findings demonstrate that GPT-4V knows essential biomedical and clinical sciences for medical practice, and thus is potentially ready for clinical decision support with images. These findings must be interpreted with caution, however, since GPT-4V accuracy is inconsistent among different medical

subdomains, and GPT-4V showed several severe issues in its explanation. While some issues could be mitigated by interactions with physicians through hints, future studies evaluating GPT-4V on real-world clinician questions are needed before clinical integration as CDSS tool. As research and development persist, we anticipate a more extensive and profound integration of AI in the medical domain.

Reference

1. Shortliffe EH, Cimino JJ. *Biomedical Informatics: Computer Applications in Health Care and Biomedicine*. Springer; 2014.
2. Sutton RT, Pincock D, Baumgart DC, Sadowski DC, Fedorak RN, Kroeker KI. An overview of clinical decision support systems: benefits, risks, and strategies for success. *NPJ Digital Medicine*. 2020;3.
3. Rajpurkar P, Lungren MP. The Current and Future State of AI Interpretation of Medical Images. *The New England journal of medicine*. 2023;388 21:1981-1990.
4. Aggarwal R, Sounderajah V, Martin G, et al. Diagnostic accuracy of deep learning in medical imaging: a systematic review and meta-analysis. *NPJ Digital Medicine*. 2021;4. <https://api.semanticscholar.org/CorpusID:233139020>
5. Wang L, Lin ZQ, Wong A. COVID-Net: a tailored deep convolutional neural network design for detection of COVID-19 cases from chest X-ray images. *Scientific Reports*. 2020;10. <https://api.semanticscholar.org/CorpusID:215768886>
6. Long E, Lin H, Liu Z, et al. An artificial intelligence platform for the multihospital collaborative management of congenital cataracts. *Nature Biomedical Engineering*. 2017;1. <https://api.semanticscholar.org/CorpusID:113460889>
7. Rayan JC, Reddy N, Kan JH, Zhang W, Annapragada AV. Binomial Classification of Pediatric Elbow Fractures Using a Deep Learning Multiview Approach Emulating Radiologist Decision Making. *Radiology Artificial intelligence*. 2019;1 1:e180015.
8. Bussone A, Stumpf S, O'Sullivan D. The Role of Explanations on Trust and Reliance in Clinical Decision Support Systems. *2015 International Conference on Healthcare Informatics*. Published online 2015:160-169.
9. Panigutti C, Beretta A, Giannotti F, Pedreschi D. Understanding the impact of explanations on advice-taking: a user study for AI-based clinical Decision Support Systems. *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*. Published online 2022. <https://api.semanticscholar.org/CorpusID:248419322>
10. Gaube S, Suresh H, Raue M, et al. Non-task expert physicians benefit from correct explainable AI advice when reviewing X-rays. *Scientific reports*. 2023;13(1):1383.
11. Singh A, Mohammed AR, Zelek JS, Lakshminarayanan V. Interpretation of deep learning using attributions: application to ophthalmic diagnosis. In: *Optical Engineering + Applications*. ; 2020. <https://api.semanticscholar.org/CorpusID:221616930>
12. Eitel F, Ritter K. Testing the Robustness of Attribution Methods for Convolutional Neural Networks in MRI-Based Alzheimer's Disease Classification. In: Suzuki K, Reyes M, Syeda-Mahmood T, et al., eds. *Interpretability of Machine Intelligence in Medical Image Computing and Multimodal Learning for Clinical Decision Support*. Springer International Publishing; 2019:3-11.

13. Papanastasopoulos Z, Samala RK, Chan HP, et al. Explainable AI for medical imaging: deep-learning CNN ensemble for classification of estrogen receptor status from breast MRI. In: *Medical Imaging*. ; 2020. <https://api.semanticscholar.org/CorpusID:216291456>
14. Shamout FE, Shen Y, Wu N, et al. An artificial intelligence system for predicting the deterioration of COVID-19 patients in the emergency department. *NPJ Digital Medicine*. 2021;4. <https://api.semanticscholar.org/CorpusID:220968946>
15. Shen Y, Heacock L, Elias J, et al. ChatGPT and Other Large Language Models Are Double-edged Swords. *Radiology*. Published online 2023:230163.
16. OpenAI. GPT-4 Technical Report. *ArXiv*. 2023;abs/2303.08774. <https://api.semanticscholar.org/CorpusID:257532815>
17. Goodman RS, Patrinely JR, Stone J Cosby A, et al. Accuracy and Reliability of Chatbot Responses to Physician Questions. *JAMA Network Open*. 2023;6(10):e2336483-e2336483. doi:10.1001/jamanetworkopen.2023.36483
18. Decker H, Trang K, Ramirez J, et al. Large Language Model–Based Chatbot vs Surgeon-Generated Informed Consent Documentation for Common Procedures. *JAMA Network Open*. 2023;6. <https://api.semanticscholar.org/CorpusID:263774434>
19. Ayers JW, Poliak A, Dredze M, et al. Comparing Physician and Artificial Intelligence Chatbot Responses to Patient Questions Posted to a Public Social Media Forum. *JAMA internal medicine*. Published online 2023. <https://api.semanticscholar.org/CorpusID:258375371>
20. Kung TH, Cheatham M, Medenilla A, et al. Performance of ChatGPT on USMLE: Potential for AI-assisted medical education using large language models. *PLOS Digital Health*. 2022;2.
21. Thirunavukarasu AJ, Hassan R, Mahmood S, et al. Trialling a Large Language Model (ChatGPT) in General Practice With the Applied Knowledge Test: Observational Study Demonstrating Opportunities and Limitations in Primary Care. *JMIR Medical Education*. 2023;9. <https://api.semanticscholar.org/CorpusID:258259005>
22. Cooper AZ, Rodman A. AI and Medical Education - A 21st-Century Pandora's Box. *The New England journal of medicine*. Published online 2023. <https://api.semanticscholar.org/CorpusID:260322445>
23. Khader F, Müller-Franzes G, Wang T, et al. Multimodal Deep Learning for Integrating Chest Radiographs and Clinical Parameters: A Case for Transformers. *Radiology*. 2023;309 1:e230806.
24. Topol EJ. As artificial intelligence goes multimodal, medical applications multiply. *Science*. 2023;381 6663:adk6139.
25. Zhang S, Xu Y, Usuyama N, et al. Large-Scale Domain-Specific Pretraining for Biomedical Vision-Language Processing. *ArXiv*. 2023;abs/2303.00915. <https://api.semanticscholar.org/CorpusID:257280046>

26. Tu T, Azizi S, Driess D, et al. Towards Generalist Biomedical AI. *ArXiv*. 2023;abs/2307.14334. <https://api.semanticscholar.org/CorpusID:260164663>
27. Cao Y, Xu X, Sun C, Huang X, Shen W. Towards Generic Anomaly Detection and Understanding: Large-scale Visual-linguistic Model (GPT-4V) Takes the Lead. *ArXiv*. 2023;abs/2311.02782. <https://api.semanticscholar.org/CorpusID:265033115>
28. Yang Z, Li L, Lin K, et al. The Dawn of LMMs: Preliminary Explorations with GPT-4V(ision). *ArXiv*. 2023;abs/2309.17421. <https://api.semanticscholar.org/CorpusID:263310951>
29. AMBOSS. AMBOSS Question difficulty. Published 10/15/12023. <https://support.amboss.com/hc/en-us/articles/360035679652-Question-difficulty>
30. Pallais JC, Fenves AZ, Lu MT, Glomski K. Case 18-2018: A 45-Year-Old Woman with Hypertension, Fatigue, and Altered Mental Status. *The New England journal of medicine*. 2018;378 24:2322-2333.
31. Lee P, Bubeck S, Petro J. Benefits, Limits, and Risks of GPT-4 as an AI Chatbot for Medicine. *The New England journal of medicine*. 2023;388 25:2399.
32. Yu M, Chang S, Zhang Y, Jaakkola T. Rethinking Cooperative Rationalization: Introspective Extraction and Complement Control. In: *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*. Association for Computational Linguistics; 2019:4094-4103. doi:10.18653/v1/D19-1420
33. Zaidan O, Eisner J, Piatko C. Using "Annotator Rationales" to Improve Machine Learning for Text Categorization. In: *Human Language Technologies 2007: The Conference of the North American Chapter of the Association for Computational Linguistics; Proceedings of the Main Conference*. Association for Computational Linguistics; 2007:260-267. <https://aclanthology.org/N07-1033>
34. The Federation of State Medical Boards (FSMB) and the National Board of Medical Examiners® (NBME®). Step 3 - United States Medical Licensing Examination. Published online 2023. <https://www.usmle.org/step-exams/step-3>
35. Elkassem AMA, Smith AD. Potential Use Cases for ChatGPT in Radiology Reporting. *AJR American journal of roentgenology*. Published online 2023. <https://api.semanticscholar.org/CorpusID:258003533>
36. Hirosawa T, Harada Y, Yokose M, Sakamoto T, Kawamura R, Shimizu T. Diagnostic Accuracy of Differential-Diagnosis Lists Generated by Generative Pretrained Transformer 3 Chatbot for Clinical Vignettes with Common Chief Complaints: A Pilot Study. *International Journal of Environmental Research and Public Health*. 2023;20. <https://api.semanticscholar.org/CorpusID:256936867>
37. Shea YF, Lee CMY, Ip WCT, Luk DWA, Wong SSW. Use of GPT-4 to Analyze Medical Records of Patients With Extensive Investigations and Delayed Diagnosis. *JAMA Network Open*. 2023;6. <https://api.semanticscholar.org/CorpusID:260885460>

38. Bhayana R, Krishna S, Bleakney RR. Performance of ChatGPT on a Radiology Board-style Examination: Insights into Current Strengths and Limitations. *Radiology*. Published online 2023:230582.
39. Gilson A, Safranek CW, Huang T, et al. How Does ChatGPT Perform on the United States Medical Licensing Examination? The Implications of Large Language Models for Medical Education and Knowledge Assessment. *JMIR Medical Education*. 2023;9. <https://api.semanticscholar.org/CorpusID:256663603>
40. Brin D, Sorin V, Vaid A, et al. Comparing ChatGPT and GPT-4 performance in USMLE soft skill assessments. *Scientific Reports*. 2023;13(1):16492. doi:10.1038/s41598-023-43436-9
41. Lalor JP, Wu H, Yu H. Learning Latent Parameters without Human Response Patterns: Item Response Theory with Artificial Crowds. In: *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*. Association for Computational Linguistics; 2019:4240-4250. doi:10.18653/v1/D19-1434
42. Patel UB, Ward TJ, Kadoch MA, Cham MD. Radiographic features of pulmonary embolism: Hampton's hump. *Postgraduate Medical Journal*. 2014;90:420-421.
43. Liberati EG, Ruggiero F, Galuppo L, et al. What hinders the uptake of computerized decision support systems in hospitals? A qualitative study and framework for implementation. *Implementation Science* □: IS. 2017;12. <https://api.semanticscholar.org/CorpusID:9726465>
44. Strohm L, Hehakaya C, Ranschaert ER, Boon WPC, Moors EHM. Implementation of artificial intelligence (AI) applications in radiology: hindering and facilitating factors. *European Radiology*. 2020;30:5525-5532.
45. Cauwenberge DV, Biesen W van, Decruyenaere JM, Leune T, Sterckx S. "Many roads lead to Rome and the Artificial Intelligence only shows me one road": an interview study on physician attitudes regarding the implementation of computerised clinical decision support systems. *BMC Medical Ethics*. 2022;23. <https://api.semanticscholar.org/CorpusID:248547001>
46. Jones C, Thornton J, Wyatt JC. Artificial intelligence and clinical decision support: clinicians' perspectives on trust, trustworthiness, and liability. *Medical law review*. Published online 2023. <https://api.semanticscholar.org/CorpusID:258844404>
47. Lourenco AP, Slanetz PJ, Baird GL. Rise of ChatGPT: It May Be Time to Reassess How We Teach and Test Radiology Residents. *Radiology*. Published online 2023:231053.
48. Ji Z, Lee N, Frieske R, et al. Survey of Hallucination in Natural Language Generation. *ACM Computing Surveys*. 2022;55:1-38.
49. Jiang S, Xu YY, Lu X. ChatGPT in Radiology: Evaluating Proficiencies, Addressing Shortcomings, and Proposing Integrative Approaches for the Future. *Radiology*. 2023;308 1:e231335.

50. Sallam M. ChatGPT Utility in Healthcare Education, Research, and Practice: Systematic Review on the Promising Perspectives and Valid Concerns. *Healthcare*. 2023;11.
<https://api.semanticscholar.org/CorpusID:257650377>

Tables

Table 1. Performance of ChatGPT, GPT-4, and GPT-4V on USMLE sample exam from NBME.

Step of exam	Agents	Performance	
		questions with Image	all questions
USMLE Sample Exam - Step1 ^a			
	ChatGPT	42.1%	55.1%
	GPT-4	63.2%	81.5%
	GPT-4V	84.2%	88.2%
	Passing	-	~60%
USMLE Sample Exam - Step2CK ^b			
	ChatGPT	50.0%	59.1%
	GPT-4	64.3%	80.8%
	GPT-4V	85.7%	90.8%
	Passing	-	~60%
USMLE Sample Exam- Step3 ^c			
	ChatGPT	50.0%	60.9%
	GPT-4	66.7%	88.3%
	GPT-4V	88.9%	92.7%
	Passing	-	~60%

Note: ^a19 questions with Image and 119 questions in total in step1; ^b14 questions with Image and 120 questions in total in Step2CK; ^cthere were 18 questions with Image and 137 questions in total in Step3.

Table 2. Performance of GPT-4V on AMBOSS. For each step, overall: n=50; difficulty 1: n=10; difficulty 2: n=10; difficulty 3: n=10; difficulty 4: n=10; difficulty 5: n=10.

		GPT-4V accuracy on AMBOSS					
AMBOSS Steps	Hint Availability	Overall	1	2	3	4	5
Step1							
	Without Hint	60%	70%	70%	30%	70%	60%
	Expert Hint	84%	80%	80%	80%	90%	90%
Step2CK							
	Without Hint	64%	80%	70%	70%	50%	50%
	Expert Hint	86%	100%	90%	100%	70%	70%
Step3							
	Without Hint	66%	80%	90%	60%	50%	50%
	Expert Hint	88%	90%	90%	90%	90%	80%

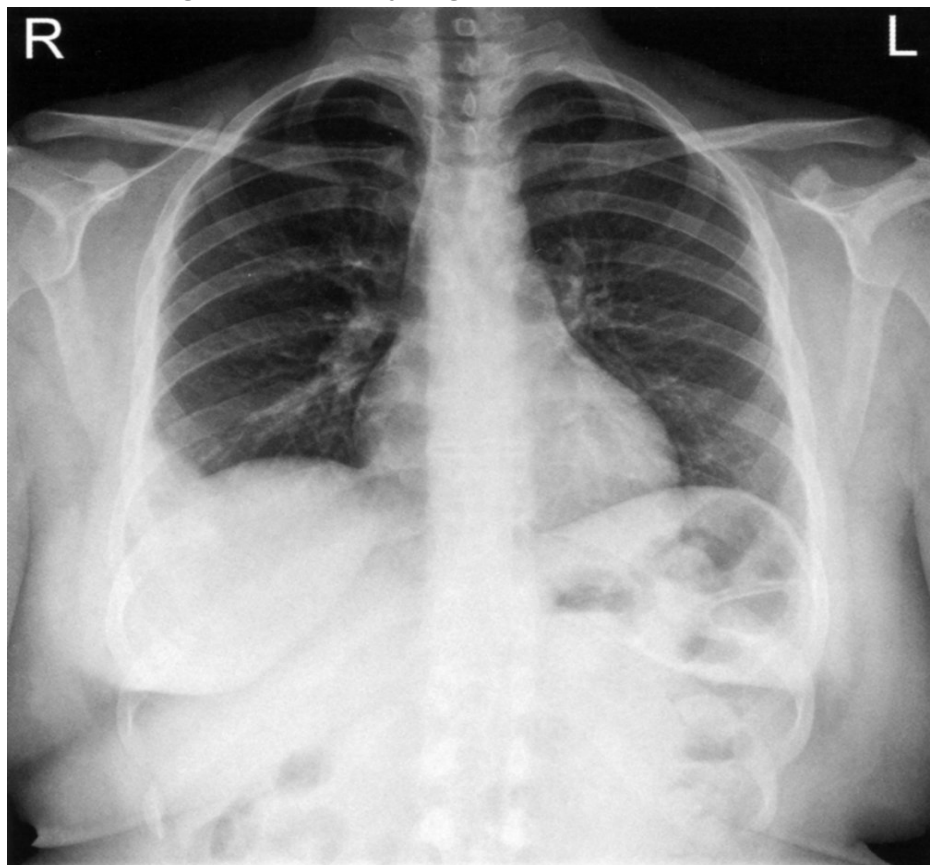
Table 3. Healthcare professionals preferred explanation for 150 AMBOSS questions.

AMBOSS Steps	Correctness of GPT-4V responses	Healthcare professionals' preference		
		Prefer expert	Ties	Prefer GPT-4V
Step1	Correct	4	23	3
	Incorrect	16	4	0
Step2CK	Correct	10	15	7
	Incorrect	18	0	0
Step3	Correct	5	23	5
	Incorrect	13	5	0

Figures

Figure 1. A case study of GPT-4V in answering USMLE questions with chest x-ray. Input prompt and output response are separated by “GPT Response Below”. Option D is the correct answer and is selected by GPT-4V without hint.

Question: A 55-year-old woman comes to the physician because of a 4-day history of chest pain and coughing up blood. The chest discomfort is characterized as piercing and aggravated by coughing. She encountered symptoms of a sore throat and nasal congestion 11 days prior. She was diagnosed with multiple sclerosis 15 years ago and utilizes a wheelchair for movement. A 40-year history of smoking a pack of cigarettes daily is noted, but she abstains from alcohol. Her current prescriptions include ocrelizumab and dantrolene. Temperature is 37.9°C (100.2°F), pulse is 105/min, and blood pressure is 110/60 mm Hg. Lung auscultation reveals occasional inspiratory crackles in the right lower lobe, while the cardiac exam shows no abnormalities. Neurologic examination shows stiffness and decreased sensation of the lower extremities; there is diffuse hyperreflexia. An x-ray of the chest is provided. Which of the following is the most likely diagnosis?



Options:

- A: Sarcoidosis
- B: Pericarditis
- C: Bacterial pneumonia

D: Pulmonary embolism

E: Pneumothorax

Let's think step by step. First, analyze each option one by one, and then give your final prediction and reasons to be sure we have the right answer.

GPT Response Below:

Let's go through the information provided and evaluate each option based on the clinical picture and the chest x-ray:

****Clinical Information**:**

- 55-year-old woman
- Smoked for 40 years (20 pack-years)
- Recent upper respiratory tract symptoms
- 3-day history of chest pain and cough with blood-tinged sputum
- Chest pain is sharp, stabbing, and worsened with coughing
- History of multiple sclerosis and uses a wheelchair
- On ocrelizumab and dantrolene
- Vital signs show mild fever and elevated pulse
- Auscultation shows crackles in the right lower lung

****Chest X-ray**:**

Hampton hump is a radiologic sign which consists of a shallow wedge-shaped opacity in the periphery of the lung.

****Options**:**

A: ****Sarcoidosis**** - Sarcoidosis often presents with bilateral hilar lymphadenopathy on chest x-ray. The given image doesn't seem to show this. Additionally, the acute symptoms don't align well with a diagnosis of sarcoidosis.

B: ****Pericarditis**** - This would present with chest pain that's positional and relieved by sitting forward. The x-ray provided doesn't suggest pericardial effusion. Unlikely.

C: ****Bacterial pneumonia**** - Given her symptoms and the crackles in the right lower lung, this is a possibility. However, the chest x-ray would typically show a lobar consolidation or infiltrate which isn't clearly seen here.

D: ****Pulmonary embolism**** - Given her history of immobility (uses a wheelchair) and the acute onset of sharp, stabbing chest pain exacerbated by coughing, this is a strong contender. The presence of a Hampton Hump should further increase suspicion of a PE.

E: ****Pneumothorax**** - This would present with sudden onset chest pain and shortness of breath. On x-ray, you'd expect to see a clear line indicating the collapsed lung and no lung markings beyond that line. This is not evident in the provided image.

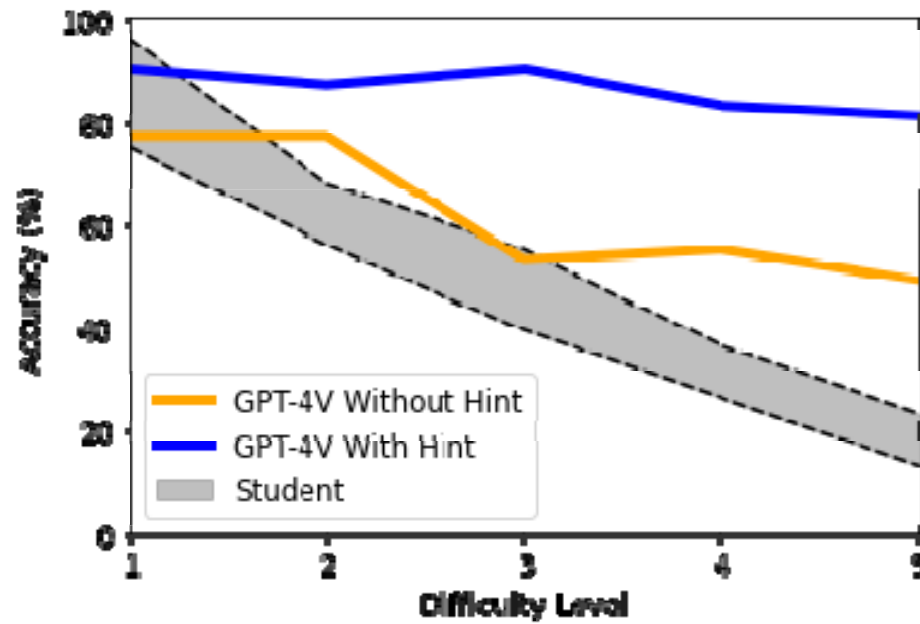
****Conclusion**:**

Based on the provided information and the chest x-ray, the most likely diagnosis is:

****D: Pulmonary embolism**.**

The reason for this choice is the combination of her risk factors (immobility, smoking), her clinical presentation (sharp, stabbing chest pain exacerbated by coughing, blood-tinged sputum), and the fact that the x-ray doesn't clearly support the other diagnoses.

Figure 2. Performance of GPT-4V and students on AMBOSS with different difficulty levels.



Conflicts of Interest

The authors declare no conflict of interests.