International Journal of Evaluation and Research in Education (IJERE)
Vol. 15, No. 6, December 2026, pp. 5210~5220
ISSN: 2252-8822, DOI: 10.11591/ijere.v15i6.38766

Responsible adoption of AI in clinical reasoning education: balancing benefits and ethical risks

Hamza Abu Owida[1], Yazeed Alsarhan[2], Ayoub Alsarhan[3], Areen Arabiat[4]
[1]Department of Medical Engineering, Faculty of Engineering, Al-Ahliyya Amman University, Amman, Jordan
[2]Department of Computer Science, Faculty of Information Technology, Al-Ahliyya Amman University, Amman, Jordan
[3]Department of Data Science and Artificial Intelligence, Faculty of Information Technology, Al-Ahliyya Amman University, Amman, Jordan
[4]Department of Communications and Computer Engineering, Faculty of Engineering, Al-Ahliyya Amman University, Amman, Jordan

Article Info

Article history:

Received Jan 19, 2026
Revised May 2, 2026
Accepted Aug 6, 2026

Keywords:

Artificial intelligence
Clinical reasoning
Educational technology
Ethics
Medical education

ABSTRACT

Clinical reasoning is central to safe medical practice, yet traditional approaches to teaching and evaluating this competency remain resource-intensive, variably standardized, and often limited in the immediacy of feedback they provide. This scoping review synthesizes literature on the use of artificial intelligence (AI), with particular attention to large language models (LLMs) and generative systems, in clinical reasoning education. The review draws on targeted searches of the medical education and health informatics literature and includes studies that examined AI-supported teaching, simulation, assessment, or feedback related to clinical reasoning development. Across the reviewed literature, AI was consistently described as supporting adaptive learning, dynamic virtual patient simulation, formative feedback, and longitudinal monitoring of learner performance. At the same time, the literature emphasizes important limitations related to reliability, hallucinations, bias, implementation burden, assessment validity, and the risk of learner overreliance on automated outputs. From an educational perspective, the most meaningful contribution of AI lies in its capacity to strengthen practice opportunities and feedback cycles while preserving human judgment, reflective learning, and professional autonomy. The review therefore argues that responsible AI integration in medical education should be aligned with competency-based curricula and evaluation frameworks that prioritize ethical use, critical thinking, and authentic clinical reasoning performance.

This is an open access article under the CC BY-SA license.

Corresponding Author:

Areen Arabiat
Department of Communications and Computer Engineering, Faculty of Engineering
Al-Ahliyya Amman University
Amman, Jordan
Email: a.arabiat@ammanu.edu.jo

1. INTRODUCTION

Clinical reasoning is the quintessential cognitive skill in medicine, representing an intricate balance between analytical and non-analytical thinking that enables clinicians to transition from a patient's presenting complaint to a defensible diagnosis and management plan. Within medical education, however, clinical reasoning is not only a clinical outcome but also a learning process that must be deliberately taught, practiced, observed, and evaluated. This educational framing is essential because difficulty in reasoning often reflects not merely a knowledge gap, but also weaknesses in hypothesis generation, problem representation, feedback uptake, and reflective judgment [1].

From an educational research perspective, these limitations create a clear need for learning environments that provide repeated practice, tailored feedback, and valid evidence of learner progress. Accordingly, this manuscript focuses specifically on clinical reasoning education rather than discussing artificial intelligence (AI) in education at a broad level. The central question is how AI can support the teaching, feedback, and evaluation of diagnostic thinking without weakening the metacognitive and humanistic capacities that define expert clinical practice. Using a scoping review approach, the paper maps the current literature, identifies major pedagogical opportunities and constraints, and synthesizes implications for educational design and learning evaluation.

Clinical reasoning education can also be interpreted through established educational and cognitive frameworks. Dual process theory is particularly relevant because it conceptualizes diagnostic thinking as an interaction between rapid pattern recognition and slower analytical reasoning [2], [3]; AI-supported cases and feedback may help learners move explicitly between these modes while reflecting on errors and uncertainty. Experiential learning theory likewise offers a useful lens, as AI-enabled simulations create repeated cycles of case encounter, feedback, reflection, and revised action. In addition, cognitive apprenticeship helps explain the educational value of AI when systems are used to scaffold reasoning, model expert questioning, and gradually reduce support as learners become more capable. Taken together, these frameworks provide a stronger theoretical basis for evaluating whether AI supports not only performance, but also the development of reflective, transferable clinical reasoning.

The rapid advancement of AI, particularly in natural language processing and machine learning (ML), is reshaping this educational landscape [4]. Yet, the relevance of AI for clinical reasoning education cannot be judged only by technical capability. A more analytical reading of the literature shows that the value of AI depends on whether a tool supports authentic case engagement, encourages justification of diagnostic choices, and produces feedback that is educationally meaningful rather than merely fast or impressive. In this sense, AI should be evaluated not only as a technological innovation but also as a pedagogical intervention. The application of AI in medical education is not an entirely new phenomenon, though its focus has shifted dramatically with recent technological breakthroughs. Early work primarily involved rule-based expert systems and intelligent tutoring systems (ITS) [5]. For instance, the DxR Clinician platform was a pioneering effort to use computer-based virtual patients to assess and teach clinical reasoning through scripted cases and pre-defined scoring rubrics [6]. These systems, while useful, were limited by their rigidity and inability to handle the open-ended, probabilistic nature of real-world clinical reasoning. However, Figure 1 depicts the intelligent tutoring system.

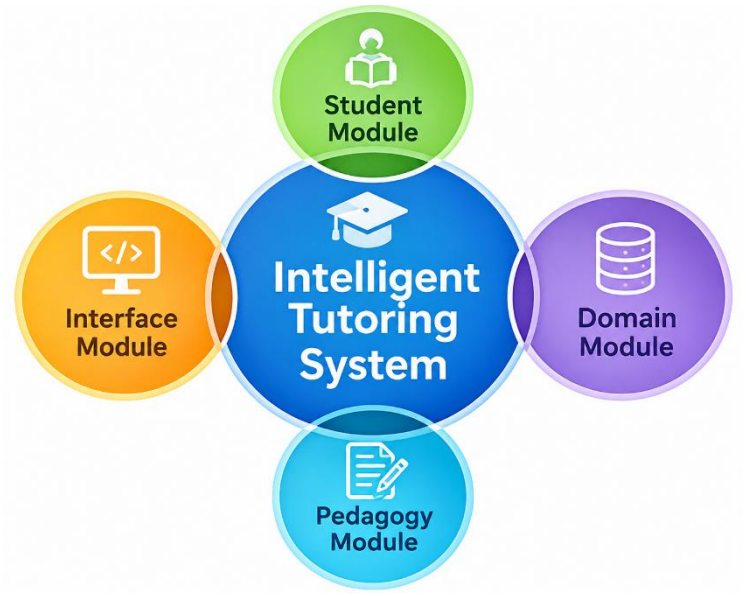


Figure 1. Intelligent tutoring system

Over the past decade, research has increasingly explored adaptive ML and AI approaches to support clinical reasoning education. Early studies investigated the use of AI to analyze student transcripts during patient encounters to identify diagnostic errors and cognitive biases, highlighting the influence of contextual

factors in clinical decision-making [7]. Other work examined automated assessment of clinical reasoning in written case summaries, demonstrating correlations between ML-derived metrics and expert human evaluations of clinical competence [8]. In parallel, researchers explored integrating AI with immersive technologies such as virtual reality (VR) to create simulated clinical environments where learners interact with AI-driven avatars, although these systems were often constrained by high costs and limited conversational realism [9]. A major turning point occurred with the emergence of advanced large language models (LLMs) such as GPT-4, which demonstrated broad reasoning capabilities and sparked significant interest in AI-assisted medical education [10]. Subsequent benchmarking studies showed that these models can achieve passing or high scores on medical licensing examinations, suggesting a substantial repository of medical knowledge [11]. Building on these developments, preliminary studies found that LLMs can generate clinically plausible patient cases and differential diagnoses comparable to those produced by clinical experts [12], [13]. Recent literature further indicates that AI-enabled virtual patients and conversational systems may expand opportunities for deliberate practice in clinical reasoning, although their educational effectiveness depends on structured feedback mechanisms, case authenticity, and appropriate faculty oversight [14], [15]. Consequently, the scholarly focus is shifting from whether AI systems can produce plausible clinical responses to how they should be effectively integrated, evaluated, and governed within clinical reasoning curricula.

Despite rapid growth in this field, the existing evidence remains largely based on small-scale pilots and proof-of-concept studies, with limited large-scale longitudinal research demonstrating sustained improvements in clinical reasoning performance attributable to AI interventions. In response to this gap, this scoping review critically examines the role of AI in clinical reasoning education, emphasizing educational opportunities, implementation barriers, ethical implications, and consequences for learning evaluation, while clarifying where current evidence meaningfully supports clinical reasoning development and where responsible safeguards for integration into competency-based medical education remain necessary. To improve the review structure, the manuscript now separates descriptive review findings from later interpretive discussion. The results section first reports the search and the characteristics of the included literature, after which the discussion synthesizes the pedagogical opportunities, implementation barriers, and ethical implications of AI in clinical reasoning education.

2. METHOD

This scoping review, aligned with the Arksey and O'Malley framework and the preferred reporting items for systematic reviews and meta-analyses extension for scoping reviews (PRISMA-ScR) checklist, aims to map the use of AI in teaching, simulation, assessment, and feedback in clinical reasoning education. The revised manuscript includes a structured method statement detailing database searches in PubMed/MEDLINE, Scopus, Web of Science, and ERIC, along with eligibility criteria for studies involving AI in medical education that connect to clinical reasoning. Exclusions were made for studies focusing solely on diagnostic performance without educational relevance. The selection process involved screening titles and abstracts, followed by full-text reviews, with transparency in reporting the number of records screened, excluded, and included. Data charting captured essential information such as study design and key findings. The findings were synthesized descriptively, emphasizing major themes, with detailed discussion on opportunities, challenges, and future implications reserved for the discussion section.

3. RESULTS

To make the evidence base visible, the manuscript now includes an evidence-mapping table summarizing the principal studies informing this review, as shown in Table 1. Four key themes emerged from the reviewed studies: i) AI in clinical reasoning; ii) personalized learning; iii) feedback-rich simulation; and iv) AI competency development. LLMs showed promise in evaluating medical knowledge and generating clinically realistic differential diagnoses [11], [13]. Virtual patients and conversational AI allowed for interactive clinical reasoning practice, communication skills training, and instant feedback [14]. Another area of evidence was the potential for personalizing learning through the use of adaptive cases, explanations, and feedback provided to the learner by the AI [13]. The competencies that were linked to AI integration were found to be increasing in need for critical evaluation, AI literacy, bias recognition and verification of AI-generated information [4]. Challenges that arose, however, involved hallucinations, bias, lack of transparency, privacy issues, and the danger of relying too heavily on AI [9]. In summary, the literature suggests that the use of AI in clinical reasoning training is promising, but further research is needed to assess learning outcomes and transfer to real-world clinical scenarios, particularly using mixed methods and longitudinal studies.

Table 1. Summary of key studies mapped in the revised scoping review

Study	Design/type	AI focus	Educational context	Main contribution to review
[4]	Perspective	AI in medical education	Medical education broadly	Established the need to prepare curricula for the AI era.
[11]	Benchmark study	ChatGPT/LLM	Medical licensing examination context	Showed that LLMs can perform strongly on medical knowledge assessments.
[16]	Review	LLMs	Medical education	Summarized early educational uses and limitations of LLMs.
[14]	Systematic review	Virtual patients with feedback	Clinical reasoning education	Demonstrated the importance of feedback-rich virtual patient design.
[17]	Hybrid systematic review	Virtual patients and ChatGPT	Clinical reasoning support	Synthesized evidence on virtual patients for reasoning practice.
[9]	Narrative systematic review	AI applications in medical education	Medical education broadly	Mapped current applications, challenges, and future directions.
[13]	Diagnostic accuracy study	GPT-3 differential diagnosis generation	Clinical decision support relevance to education	Showed that LLMs can generate clinically plausible differential lists.
[18]	Usability study	LLM-based patient simulation	Health professions communication training	Provided evidence for conversational simulation and usability.
[19]	Review	AI in medical education	Medical education broadly	Outlined pedagogical, ethical, and implementation challenges.
[20]	Commentary/curricular analysis	AI competencies	Medical students	Clarified learner competencies required for AI-informed practice.

4. DISCUSSION

4.1. Opportunities for AI in clinical reasoning education

In the revised structure, this discussion section interprets the patterns identified across the mapped literature rather than functioning as the primary results report. Across the included studies, five interpretive themes were especially prominent: personalization, simulation, feedback, assessment, and longitudinal learning analytics. First, AI enables an unprecedented level of personalized and adaptive learning. Traditional curricula often take a one-size-fits-all approach, but AI-powered systems can tailor educational content to the individual learner's knowledge gaps, pace, and preferred learning style [21]. By analyzing a student's interactions with virtual patients—their questions, physical exam choices, and diagnostic hypotheses—an AI tutor can dynamically adjust the complexity of the case, introduce specific clinical findings to challenge misconceptions, or provide targeted feedback on areas of weakness, such as premature closure or faulty illness script development [22]. This creates a mastery-based learning environment where progression is determined by competency rather than time [23].

Second, AI excels at creating high-fidelity, dynamic virtual patients. Unlike static paper cases or pre-scripted computer programs, LLM-driven patients can exhibit natural, open-ended conversations, respond unpredictably to a learner's line of questioning, and present with evolving symptoms over simulated time [24]. This moves beyond simple diagnosis to encompass the entire patient journey, including management decisions and treatment responses [25]. Furthermore, AI can generate a near-infinite variety of cases, ensuring exposure to both common conditions and rare diseases that a student might not encounter during their clinical rotations [26]. This ability to practice in a consequence-free environment is invaluable for building confidence and competence. The virtual medical coach model leverages multi-modal data inputs—such as physiological signals, medical imaging, wearable sensor data, and patient-reported outcomes—combined with advanced algorithms to deliver individualized health guidance. By integrating AI and predictive analytics, it can monitor patient progress, detect anomalies, and recommend personalized interventions in real time. This model enhances preventive care, optimizes treatment adherence, and empowers patients through adaptive feedback tailored to their specific health profiles. Ultimately, it bridges the gap between continuous digital monitoring and precision, patient-centered medical support. Figure 2 demonstrates the virtual medical coach model with multi-modal data inputs and algorithms to provide individualized guidance.

Third, AI offers powerful tools for formative assessment and feedback. It can transcribe and analyze a learner's verbal or written reasoning process in real-time, identifying logical fallacies, missed data points, or inappropriate prioritization of differential diagnoses [27]. The AI can then provide immediate, specific feedback, perhaps by asking Socratic questions like, “What is your rationale for prioritizing pneumonia over pulmonary embolism, given the patient’s recent long-haul flight?” This mirrors the ideal preceptor-learner interaction but is available on demand, 24/7 [28]. Such just-in-time feedback is crucial for reinforcing correct reasoning patterns and correcting errors before they become ingrained.

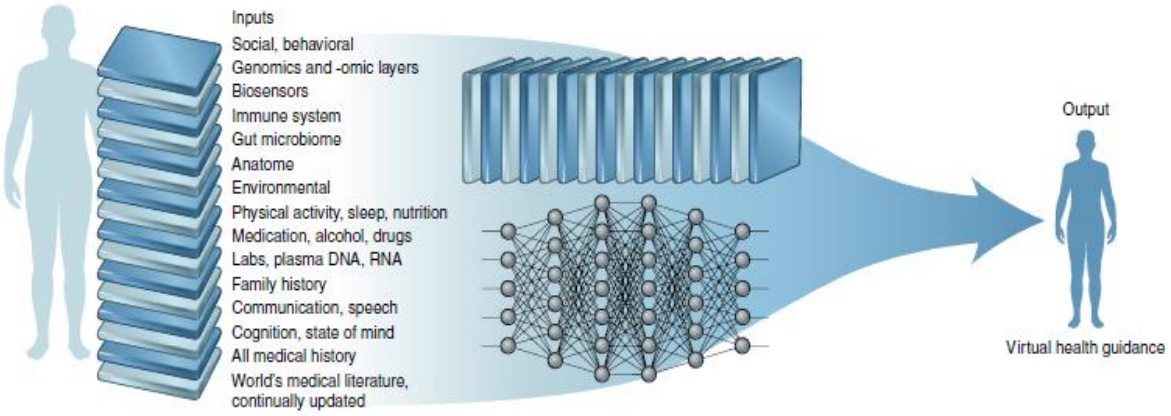


Figure 2. The virtual medical coach model with multi-modal data inputs and algorithms to provide individualized guidance

Fourth, AI can function as a simulation of diagnostic reasoning support tools. In modern clinical practice, physicians increasingly interact with AI for tasks like image interpretation or sepsis prediction. Using educational AI tools allows students to develop the critical skill of appropriately interacting with and interpreting the output of clinical AI, learning to use it as a "second opinion" rather than a definitive authority [29]. This prepares them for the technologically integrated clinical environments they will inevitably enter.

Finally, AI can facilitate the longitudinal tracking of reasoning development. By aggregating data from thousands of learner interactions, AI systems can provide educators with dashboards that visualize class-wide trends, common pitfalls, and individual student progress over time [17]. This data-driven insight can inform curriculum design and allow for early intervention for struggling learners, moving assessment from a snapshot to a continuous movie of skill acquisition. Table 2 demonstrates a summary of opportunities for AI in clinical reasoning education.

However, AI technologies have the potential to revolutionize clinical reasoning education by enabling personalized and adaptive learning experiences in line with constructivist learning theories. AI-driven systems can customize content for individual learners, offering targeted feedback to enhance understanding of complex concepts. Additionally, AI enhances formative assessments with immediate feedback, reinforcing correct reasoning and allowing real-time error correction. By tracking learner interactions over time, educators gain insights into progress and common challenges, ensuring assessments accurately reflect true skill acquisition. This framework not only emphasizes AI's transformative potential but also its effectiveness in educational contexts.

Table 2. Opportunities of AI in clinical reasoning education

Category	Opportunity	Description/impact	Reference
Personalization and adaptive learning	Individualized learning pathways	AI tailor's instruction based on learner's knowledge gaps, pace, and reasoning style, fostering mastery-based progression rather than time-based advancement.	[21], [22]
Dynamic virtual patients	High-fidelity simulation	AI enables lifelike virtual patients with open-ended, evolving cases; enhances exposure to diverse clinical conditions in a safe environment.	[23], [24]
Formative assessment and feedback	Real-time feedback loops	AI analyzes learner's reasoning process to provide immediate, targeted feedback through Socratic questioning and adaptive case complexity.	[25], [26]
Diagnostic reasoning simulation	AI as learning partner	Learner's practice interacting with AI diagnostic tools, developing critical evaluation skills for future clinical practice.	[27]
Learning analytics	Longitudinal performance tracking	Aggregates learner data to identify trends, inform curriculum design, and allow early interventions for struggling students.	[28]

4.2. Challenges of AI integration

Despite its promise, the integration of AI into clinical reasoning education is constrained by interrelated technical, pedagogical, and institutional limitations that require critical scrutiny rather than

simple enthusiasm. In educational settings, the question is not only whether an AI system can produce clinically plausible outputs, but whether those outputs are reliable enough for learners, equitable across patient representations, and feasible to implement in real curricula. The most immediate limitation concerns factual accuracy and reliability, including the well-described problem of hallucination [30]–[32]. For novice learners, even occasional confident inaccuracies can distort illness scripts, reinforce unsafe shortcuts, and weaken trust in assessment processes. Educational use is therefore especially sensitive: a system that is acceptable for brainstorming may still be unacceptable as a feedback source unless its outputs are curated, checked against evidence-based references, and embedded within supervised learning activities.

A second limitation is bias and representational unfairness. Because AI models learn from historically produced data, they may reproduce skewed associations involving race, gender, language, socioeconomic context, or disease prevalence [33]–[35]. In clinical reasoning education, this is particularly concerning because biased simulations do not merely misclassify cases; they may actively teach distorted diagnostic habits, normalize stereotypes, and reduce the educational validity of simulated encounters.

A third challenge is the possibility that AI support may reduce, rather than strengthen, learner reasoning if it is used as a substitute for justification and reflection. Overreliance on autogenerated differentials, summaries, or management suggestions can weaken metacognitive monitoring and discourage tolerance of ambiguity, both of which are core features of expert clinical reasoning [19], [36]. For this reason, instructional design should require learners to articulate their own reasoning before interacting with AI feedback.

Implementation in clinical education also presents substantial barriers. Crowded curricula, limited faculty preparedness, uneven institutional infrastructure, data governance requirements, and uncertainty about cost-effectiveness can all reduce the practical value of AI tools even when their technical performance appears promising [18]–[20]. Without faculty development and clear governance structures, AI risks becoming an add-on technology rather than a well-integrated educational strategy.

From an implementation perspective, curriculum integration and faculty development present substantial hurdles. Medical curricula are already overcrowded, and finding space for new AI-driven activities requires difficult trade-offs [19]. Furthermore, many current faculty members are not digitally fluent and may lack the confidence or skills to effectively facilitate AI-based learning sessions. A significant investment in faculty development is essential to create a generation of educators who can critically evaluate AI tools, guide students in their use, and help them interpret and challenge AI-generated outputs [37]. Table 3 demonstrated summary of challenges of AI in clinical reasoning education.

Table 3. Challenges of AI in clinical reasoning education

Challenge area	Description/issue	Implication/risk	Reference
Factual reliability (hallucinations)	AI may generate inaccurate or fabricated medical information.	Misconceptions can be learned as truth by novices; threatens patient safety and educational credibility.	[17], [29], [30]
Bias and representational fairness	Training data may encode social or demographic biases.	Perpetuates stereotypes, healthcare disparities, and biased diagnostic reasoning.	[31], [32]
Algorithmic dependency	Over-reliance on AI reasoning outputs.	Erodes independent clinical judgment and metacognitive skill development.	[33]
Curriculum integration	Difficulty incorporating AI within crowded medical curricula.	Competes with existing content; may lead to superficial implementation.	[34]
Faculty development	Educators may lack digital literacy and confidence with AI.	Ineffective facilitation and misinterpretation of AI-generated insights.	[35]
Technical and infrastructural limitations	High cost, maintenance needs, and cybersecurity concerns.	Creates inequity between resource-rich and resource-poor institutions.	[36]
Assessment validity	Difficulty evaluating real-world reasoning improvements.	Traditional metrics fail to capture depth of AI-driven learning outcomes.	[19]

Technical and infrastructural barriers also shape who can benefit from AI-enhanced education. Institutions with stronger digital infrastructure, protected datasets, and dedicated informatics expertise are better positioned to deploy and evaluate such systems, while under-resourced programs may face widening inequity. These implementation realities should be considered part of the educational critique, not a peripheral operational issue.

However, assessment validity remains unresolved. Evidence that learners enjoy AI-supported activities or perceive them as useful does not automatically demonstrate improved clinical reasoning performance with real patients. Future evaluation should therefore combine usability findings with stronger outcome measures, including performance tasks, longitudinal follow-up, and explicit alignment between AI-supported learning activities and competency-based assessment frameworks [20], [38].

Finally, there is the challenge of assessment. How do we validly measure whether an AI-based educational intervention has genuinely improved a student's clinical reasoning ability in the real world, with real patients? [38] Traditional metrics may not capture the nuanced skills developed through interaction with AI. Developing new, validated assessment tools that can discern between rote mimicry of an AI and deep, conceptual understanding is a critical area for future research.

4.3. Ethical reflections

Adoption of AI in such a formative field as clinical reasoning teaching necessitates careful and ongoing ethical consideration. Beyond simple technical application, ethical issues are fundamental to professional identity and the doctor-patient interaction. It is crucial to make a clear connection between the ethical issues raised and the methods used in education for learning and evaluation. For example, data privacy and confidentiality are not merely technical issues; they have a direct influence on how teachers create tests and gather information about students. Strong data governance procedures that put student privacy first must be put in place by institutions to guarantee that information gathered during AI interactions is used in evaluation procedures in an ethical and open manner [39]. The ownership, use, and potential commercialization of this data raise serious questions. Could this data be used to unfairly label or assess students? Could it be sold to third parties? Robust data governance policies, transparent informed consent processes, and strong cybersecurity measures are non-negotiable prerequisites [40].

The “black box” problem of many complex AI models poses a significant ethical challenge to education. If neither the student nor the educator can understand why an AI tutor provided a specific piece of feedback or suggested a particular diagnosis, it undermines the principles of transparency and trust that are foundational to education [41]. A learner has a right to understand the rationale behind the guidance they receive. This argues for the development of “explainable AI” (XAI) in educational contexts, where the system can not only provide an answer but also articulate the evidence and logical steps that led to it [42].

As previously mentioned, algorithmic bias and justice are profound ethical issues. An AI system that perpetuates biases does active harm by miseducating future physicians, who may then go on to provide inequitable care [43]. The ethical imperative is not merely to detect and mitigate bias reactively but to proactively design for fairness and representativeness from the outset. This requires diverse development teams and ongoing audits of AI system outputs for biased patterns [44].

Perhaps the most profound ethical reflection centers on the preservation of professional autonomy and humanistic values. Clinical reasoning is not a purely mechanistic, diagnostic process; it is imbued with empathy, intuition, and a deep understanding of the patient's narrative and context [45]. Over-reliance on AI could lead to a de-skilling of clinicians, reducing their role to mere validators of algorithmic outputs. The ethical goal must be to use AI to augment human intelligence, not replace it—to free up the clinician's cognitive space for more complex, human-centric tasks like empathy, communication, and shared decision-making [46]. Education must therefore emphasize that the AI is a tool in the service of the patient's holistic well-being, not the arbiter of truth.

Finally, there is an ethical dimension to access and equity. If high-quality AI medical education tools become proprietary and expensive, they risk creating a two-tiered system where only students at affluent institutions have access to the best educational technologies [16], [47]–[51]. This would worsen existing disparities in the physician workforce. A commitment to open-source platforms, public-private partnerships, and subsidized access for resource-poor institutions is an ethical necessity to ensure that the benefits of AI in medical education are distributed justly [18], [52]–[55]. Table 1 concluding the opportunities, challenges, and ethical reflections related to the integration of AI in clinical reasoning education. Table 4 demonstrated summary of ethical reflections AI in clinical reasoning education.

Table 4. Ethical reflections on AI in clinical reasoning education

Ethical domain	Key concern/question	Ethical implication	Reference
Data privacy and ownership	Collection of learner reasoning data and behavioral analytics.	Risk of misuse, profiling, or commercialization of educational data; necessitates informed consent and governance.	[20], [37]
Transparency and explainability	Opaque decision-making (“black box”) in AI tutors.	Undermines educational trust and understanding; calls for XAI.	[38], [39]
Algorithmic justice and fairness	Bias embedded in AI systems.	Ethical duty to design for inclusivity, prevent harm, and ensure equitable learning outcomes.	[40], [41]
Professional autonomy and humanism	Potential erosion of clinician’s cognitive and empathetic roles.	AI must augment, not replace, human reasoning—preserving empathy, communication, and holistic care.	[42], [43]
Access and equity	Proprietary nature of advanced AI tools.	Risk of educational inequity; ethical imperative for open-source or subsidized models.	[44]

5. FUTURE DIRECTIONS

The trajectory of AI development suggests several emerging directions that may shape clinical reasoning education; however, the current evidence base remains incomplete, and these developments should be interpreted as plausible directions rather than definitive predictions. One emerging direction is the use of AI within longitudinal, competency-based education. Recent literature suggests that AI systems may eventually support progress monitoring across multiple stages of training by tracking recurrent reasoning patterns, identifying persistent weaknesses, and linking feedback to competency milestones. At present, however, this remains an area of active development rather than an established educational standard. A second developing area involves multimodal and embodied AI. Existing research already indicates interest in combining text-based reasoning support with image interpretation, speech interaction, and simulation technologies. Even so, the educational effectiveness of fully integrated multimodal platforms still requires stronger empirical evaluation before broad claims can be made.

The literature also points toward human-AI collaborative reasoning as an important educational target. Rather than treating AI as an answer engine, future curricula may need to teach learners how to question, verify, and appropriately challenge AI-generated suggestions. This direction is more strongly supported when framed as a curricular need emerging from current practice trends rather than as a guaranteed future endpoint.

Another possible development is the use of aggregated learner interaction data to refine curriculum design. While learning analytics may help educators identify common reasoning errors and optimize case design, further research is needed to determine how reliably such data can be translated into valid curricular decisions across institutions. Finally, there is growing interest in specialized medically tuned AI models. Such systems may offer advantages in relevance and factual consistency when compared with general-purpose models, but claims regarding superior educational safety or effectiveness should remain cautious until comparative evidence in real teaching settings becomes more robust.

6. CONCLUSION

The integration of AI into clinical reasoning education represents a pivotal moment in the history of medical training. Its potential to democratize access to high-quality, personalized, and deliberate practice is unparalleled, offering a solution to the scalability and standardization constraints of traditional methods. Through dynamic virtual patients, real-time analytical feedback, and adaptive learning pathways, AI can serve as a powerful force multiplier for educators, helping to cultivate a generation of clinicians with more robust, bias-resistant, and sophisticated diagnostic skills.

However, this promise is contingent upon our ability to navigate a formidable array of challenges and ethical quandaries. The issues of factual inaccuracy, embedded bias, the risk of algorithmic dependency, and the “black box” nature of AI are not minor technical hurdles but fundamental threats to the integrity of medical education and the future of the profession. The ethical imperative to use this technology justly, transparently, and in a way that preserves the humanistic core of medicine cannot be overstated. This scoping review highlights that the educational value of AI in clinical reasoning lies not only in automation, but in the quality of feedback, simulation authenticity, curricular integration, and assessment alignment that the technology enables. Future work should prioritize longitudinal and mixed-methods studies that examine learner outcomes, faculty readiness, bias mitigation, and transfer of reasoning performance to authentic clinical settings. Medical educators should therefore adopt AI as a carefully governed educational partner that supports critical thinking, reflective judgment, and humanistic clinical practice rather than replacing them.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Hamza Abu Owida	✓	✓		✓	✓	✓	✓		✓			✓	✓	
Yazeed Alsarhan		✓			✓	✓			✓		✓			✓
Ayoub Alsarhan		✓				✓				✓	✓	✓		
Areen Arabiat		✓								✓	✓	✓	✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this paper.

REFERENCES

[1] L. Rehmat, S. Fatima, R. A. Mazhar, S. S. Fatima, and R. Rehman, "Innovations in Case-Based Learning to Enhance Clinical Reasoning among Graduate Students: A Mixed-Methods Study," *Journal of Postgraduate Medical Institute*, vol. 39, no. 4, pp. 284–291, Dec. 2025, doi: 10.54079/jpmi.39.4.3791.

[2] C. Smith *et al.*, "Diagnostic Reasoning across the Medical Education Continuum," *Healthcare*, vol. 2, no. 3, pp. 253–271, Jul. 2014, doi: 10.3390/healthcare2030253.

[3] T. Fan, J. Song, and Z. Guan, "Integrating diagnostic assessment into curriculum: a theoretical framework and teaching practices," *Language Testing in Asia*, vol. 11, no. 1, p. 2, Jan. 2021, doi: 10.1186/s40468-020-00117-y.

[4] S. A. Wartman and C. D. Combs, "Medical Education Must Move From the Information Age to the Age of Artificial Intelligence," *Academic Medicine*, vol. 93, no. 8, pp. 1107–1109, Aug. 2018, doi: 10.1097/ACM.0000000000002044.

[5] M. Sand, J. M. Durán, and K. R. Jongsma, "Responsibility beyond design: Physicians' requirements for ethical medical AI," *Bioethics*, vol. 36, no. 2, pp. 162–169, 2022, doi: 10.1111/bioe.12887.

[6] S. Monteiro, A. Keuhl, M. Lee, and T. M. Chan, "ReThinking clinical reasoning: A paradigm shift," *Journal of Evaluation in Clinical Practice*, vol. 30, no. 5, pp. 766–773, Aug. 2024, doi: 10.1111/jep.13986.

[7] K. Schuler, I.-C. Jung, M. Zerlik, W. Hahn, M. Sedlmayr, and B. Sedlmayr, "Context factors in clinical decision-making: a scoping review," *BMC Medical Informatics and Decision Making*, vol. 25, no. 1, p. 133, Mar. 2025, doi: 10.1186/s12911-025-02965-1.

[8] M. Hasnain, K. J. Connell, S. M. Downing, A. Olthoff, and R. Yudkowsky, "Toward Meaningful Evaluation of Clinical Competence: The Role of Direct Observation in Clerkship Ratings," *Academic Medicine*, vol. 79, pp. S21–S24, Oct. 2004, doi: 10.1097/00001888-200410001-00007.

[9] Z. Ahsan, "Integrating artificial intelligence into medical education: a narrative systematic review of current applications, challenges, and future directions," *BMC Medical Education*, vol. 25, no. 1, p. 1187, Aug. 2025, doi: 10.1186/s12909-025-07744-0.

[10] S. Bubeck *et al.*, "Sparks of Artificial General Intelligence: Early experiments with GPT-4," arXiv:2303.12712, 2023, doi: 10.48550/arXiv.2303.12712.

[11] T. H. Kung *et al.*, "Performance of ChatGPT on USMLE: Potential for AI-assisted medical education using large language models," *PLOS Digital Health*, vol. 2, no. 2, p. e0000198, Feb. 2023, doi: 10.1371/journal.pdig.0000198.

[12] D. M. Levine *et al.*, "The diagnostic and triage accuracy of the GPT-3 artificial intelligence model: an observational study," *The Lancet Digital Health*, vol. 6, no. 8, pp. e555–e561, 2024, doi: 10.1016/S2589-7500(24)00097-9.

[13] T. Hirosawa, Y. Harada, M. Yokose, T. Sakamoto, R. Kawamura, and T. Shimizu, "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*, vol. 20, no. 4, p. 3378, Feb. 2023, doi: 10.3390/ijerph20043378.

[14] R. Jay *et al.*, "The Use of Virtual Patients to Provide Feedback on Clinical Reasoning: A Systematic Review," *Academic Medicine*, vol. 100, no. 2, pp. 229–238, Feb. 2025, doi: 10.1097/ACM.0000000000005908.

[15] D. Mukunya *et al.*, "Utilisation of ChatGPT and other Artificial Intelligence tools among medical faculty in Uganda: a cross-sectional study," *MedEdPublish*, vol. 14, p. 245, Apr. 2025, doi: 10.12688/mep.20554.3.

[16] A. Abd-alrazaq *et al.*, "Large Language Models in Medical Education: Opportunities, Challenges, and Future Directions," *JMIR Medical Education*, vol. 9, p. e48291, Jun. 2023, doi: 10.2196/48291.

[17] D. García-Torres, M. A. V. Ripoll, C. F. Peris, and J. J. M. Solves, "Enhancing Clinical Reasoning with Virtual Patients: A Hybrid Systematic Review Combining Human Reviewers and ChatGPT," *Healthcare*, vol. 12, no. 22, p. 2241, Nov. 2024, doi: 10.3390/healthcare12222241.

[18] A. Elhilali, A. S.-H. Ngo, D. Reichenpfader, and K. Denecke, "Large Language Model–Based Patient Simulation to Foster Communication Skills in Health Care Professionals: User-Centered Development and Usability Study," *JMIR Medical Education*, vol. 11, p. e81271, Dec. 2025, doi: 10.2196/81271.

[19] M. M. Civaner, Y. Uncu, F. Bulut, İ. Ercan, and S. Mülazımoğlu, "Artificial intelligence in medical education: a cross-sectional needs assessment," *BMC Medical Education*, vol. 22, no. 1, p. 772, 2022.

[20] L. G. McCoy, S. Nagaraj, F. Morgado, V. Harish, S. Das, and L. A. Celi, "What do medical students actually need to know about artificial intelligence?" *npj Digital Medicine*, vol. 3, no. 1, p. 86, Jun. 2020, doi: 10.1038/s41746-020-0294-7.
[21] M. L. Graber *et al.*, "Improving diagnosis by improving education: a policy brief on education in healthcare professions," *Diagnosis*, vol. 5, no. 3, pp. 107–118, Sep. 2018, doi: 10.1515/dx-2018-0033.
[22] T. Wang, S. Li, X. Huang, Z. Pan, and S. P. Lajoie, "Examining students' cognitive load in the context of self-regulated learning with an intelligent tutoring system," *Education and Information Technologies*, vol. 28, no. 5, pp. 5697–5715, 2023, doi: 10.1007/s10639-022-11357-1.
[23] Q. Cui *et al.*, "Overview of AI and communication for 6G network: fundamentals, challenges, and future research opportunities," *Science China Information Sciences*, vol. 68, p. 171301, 2025, doi: 10.1007/s11432-024-4337-1.
[24] J. M. Gesulga, A. Berjame, K. S. Moquiala, and A. Galido, "Barriers to Electronic Health Record System Implementation and Information Systems Resources: A Structured Review," *Procedia Computer Science*, vol. 124, pp. 544–551, 2017, doi: 10.1016/j.procs.2017.12.188.
[25] A. Al-Ghraibah, M. Altayeb, and F. A. Alnaimat, "An automated system to distinguish between Corona and Viral Pneumonia chest diseases based on image processing techniques," *Computer Methods in Biomechanics and Biomedical Engineering: Imaging & Visualization*, vol. 11, no. 7, Jan. 2024, doi: 10.1080/21681163.2023.2261575.
[26] S. H. Park, K.-H. Do, S. Kim, J. H. Park, and Y.-S. Lim, "What should medical students know about artificial intelligence in medicine?" *Journal of Educational Evaluation for Health Professions*, vol. 16, p. 18, Jul. 2019, doi: 10.3352/jeehp.2019.16.18.
[27] W. Jerjes and D. Harding, "Redefining medical education: harnessing the power of patient feedback," *Frontiers in Medicine*, vol. 11, Oct. 2024, doi: 10.3389/fmed.2024.1453262.
[28] K. Ishizuka *et al.*, "Enhancing clinical reasoning skills in medical students through team-based learning: a mixed-methods study," *BMC Medical Education*, vol. 25, no. 1, p. 221, Feb. 2025, doi: 10.1186/s12909-025-06784-w.
[29] E. J. Topol, "High-performance medicine: the convergence of human and artificial intelligence," *Nature Medicine*, vol. 25, no. 1, pp. 44–56, Jan. 2019, doi: 10.1038/s41591-018-0300-7.
[30] Z. Ji *et al.*, "Survey of Hallucination in Natural Language Generation," *ACM Computing Surveys*, vol. 55, no. 12, pp. 1–38, Dec. 2023, doi: 10.1145/3571730.
[31] H. Alkaissi and S. I. McFarlane, "Artificial Hallucinations in ChatGPT: Implications in Scientific Writing," *Cureus*, vol. 15, no. 2, Feb. 2023, doi: 10.7759/cureus.35179.
[32] A. J. Thirunavukarasu, D. S. J. Ting, K. Elangovan, L. Gutierrez, T. F. Tan, and D. S. W. Ting, "Large language models in medicine," *Nature Medicine*, vol. 29, no. 8, pp. 1930–1940, Aug. 2023, doi: 10.1038/s41591-023-02448-8.
[33] Z. Obermeyer, B. Powers, C. Vogeli, and S. Mullainathan, "Dissecting racial bias in an algorithm used to manage the health of populations," *Science*, vol. 366, no. 6464, pp. 447–453, Oct. 2019, doi: 10.1126/science.aax2342.
[34] D. A. Vyas, L. G. Eisenstein, and D. S. Jones, "Hidden in Plain Sight — Reconsidering the Use of Race Correction in Clinical Algorithms," *New England Journal of Medicine*, vol. 383, no. 9, pp. 874–882, Aug. 2020, doi: 10.1056/NEJMms2004740.
[35] Q. Shambour, M. Abualhaj, and A. Shareha, "An Effective Doctor Recommendation Algorithm for Online Healthcare Platforms," *Romanian Journal of Information Science and Technology*, vol. 2024, no. 1, p. 81, 2024, doi: 10.59277/ROMJIST.2024.1.06.
[36] S. Iftikhar and G. Farid, "Digital Medical Education: Opportunities and Challenges in a Transforming Landscape," *Pakistan Journal of Medical and Health Sciences*, vol. 19, no. 08, pp. 1–2, Sep. 2025, doi: 10.53350/pjmhs02025198.1.
[37] A. Musamih, K. Salah, R. Jayaraman, S. Ellaham, M. Omar, and I. Yaqoob, "Blockchain and NFT-Based Solution for Genomic Data Management, Sharing, and Monetization," *IEEE Access*, vol. 13, pp. 35780–35804, 2025, doi: 10.1109/ACCESS.2025.3544643.
[38] N. Christensen, L. Black, J. Furze, K. Huhn, A. Vendrely, and S. Wainwright, "Clinical Reasoning: Survey of Teaching Methods, Integration, and Assessment in Entry-Level Physical Therapist Academic Education," *Physical Therapy*, vol. 97, no. 2, pp. 175–186, Feb. 2017, doi: 10.2522/ptj.20150320.
[39] W. N. Price and I. G. Cohen, "Privacy in the age of medical big data," *Nature Medicine*, vol. 25, no. 1, pp. 37–43, Jan. 2019, doi: 10.1038/s41591-018-0272-7.
[40] S. Gerke, T. Minssen, and G. Cohen, "Ethical and legal challenges of artificial intelligence-driven healthcare," in *Artificial Intelligence in Healthcare*, Elsevier, 2020, pp. 295–336, doi: 10.1016/B978-0-12-818438-7.00012-5.
[41] J. Amann, A. Blasimme, E. Vayena, D. Frey, and V. I. Madai, "Explainability for artificial intelligence in healthcare: a multidisciplinary perspective," *BMC Medical Informatics and Decision Making*, vol. 20, no. 1, p. 310, Dec. 2020, doi: 10.1186/s12911-020-01332-6.
[42] A. Adadi and M. Berrada, "Peeking Inside the Black-Box: A Survey on Explainable Artificial Intelligence (XAI)," *IEEE Access*, vol. 6, pp. 52138–52160, 2018, doi: 10.1109/ACCESS.2018.2870052.
[43] R. B. Parikh, S. Teeple, and A. S. Navathe, "Addressing Bias in Artificial Intelligence in Health Care," *JAMA*, vol. 322, no. 24, p. 2377, Dec. 2019, doi: 10.1001/jama.2019.18058.
[44] A. Rajkomar, M. Hardt, M. D. Howell, G. Corrado, and M. H. Chin, "Ensuring Fairness in Machine Learning to Advance Health Equity," *Annals of Internal Medicine*, vol. 169, no. 12, pp. 866–872, Dec. 2018, doi: 10.7326/M18-1990.
[45] K. Montgomery, *How Doctors Think*. New York, NY, USA: Oxford University Press, 2005, doi: 10.1093/oso/9780195187120.001.0001.
[46] A. Fiske, P. Henningsen, and A. Buyx, "Your Robot Therapist Will See You Now: Ethical Implications of Embodied Artificial Intelligence in Psychiatry, Psychology, and Psychotherapy," *Journal of Medical Internet Research*, vol. 21, no. 5, p. e13216, May 2019, doi: 10.2196/13216.
[47] F. Busch, L. C. Adams, and K. K. Bressem, "Biomedical Ethical Aspects Towards the Implementation of Artificial Intelligence in Medical Education," *Medical Science Educator*, vol. 33, no. 4, pp. 1007–1012, Jun. 2023, doi: 10.1007/s40670-023-01815-x.
[48] A. Esteva *et al.*, "A guide to deep learning in healthcare," *Nature Medicine*, vol. 25, no. 1, pp. 24–29, Jan. 2019, doi: 10.1038/s41591-018-0316-z.
[49] A. Stylianides, J. Mantas, Z. Roupa, and E. Yamasaki, "Development of an Evaluation Framework for Health Information Systems (DIPSA)," *Acta Informatica Medica*, vol. 26, no. 4, pp. 230–234, 2018, doi: 10.5455/aim.2018.26.230-234.
[50] R. H. Ellaway, M. V. Pusic, R. M. Galbraith, and T. Cameron, "Developing the role of big data and analytics in health professional education," *Medical Teacher*, vol. 36, no. 3, pp. 216–222, Mar. 2014, doi: 10.3109/0142159X.2014.874553.
[51] D. Gomes, "A Comprehensive Study of Advancements in Intelligent Tutoring Systems Through Artificial Intelligent Education Platforms," in *Advances in educational technologies and instructional design book series*, IGI Global Publishing, 2025, pp. 213–244, doi: 10.4018/979-8-3693-6170-2.ch008.
[52] S. Liu, A. B. McCoy, and A. Wright, "Improving large language model applications in biomedicine with retrieval-augmented generation: a systematic review, meta-analysis, and clinical development guidelines," *Journal of the American Medical Informatics Association*, vol. 32, no. 4, pp. 605–615, Apr. 2025, doi: 10.1093/jamia/ocaf008.

[53] A. Arabiat, H. A. Owida, and M. Altayeb, "A comparative analysis of hypertension risk detection using machine learning and deep learning techniques," *Journal of Advances in Information Technology*, vol. 17, no. 5, pp. 846–856, 2026, doi: 10.12720/jait.17.5.846-856.
[54] K. Singhal *et al.*, "Large language models encode clinical knowledge," *Nature*, vol. 620, no. 7972, pp. 172–180, Aug. 2023, doi: 10.1038/s41586-023-06291-2.
[55] J. Garzón, E. Patiño, and C. Marulanda, "Systematic Review of Artificial Intelligence in Education: Trends, Benefits, and Challenges," *Multimodal Technologies and Interaction*, vol. 9, no. 8, 2025, doi: 10.3390/mti9080084.

BIOGRAPHIES OF AUTHORS



Hamza Abu Owida is a Ph.D. in Biomedical Engineering, assistant professor at the Department of Medical Engineering, Al-Ahliyya Amman University, Jordan. His research interests focused on biomedical sensors, nanotechnology, and tissue engineering. He can be contacted at email: h.abuowida@ammanu.edu.jo.



Yazeed Alsarhan is a Ph.D. in Internet of Things, assistant professor at the Faculty of Information Technology, Al-Ahliyya Amman University, Amman, Jordan. His research interests focused on wireless sensor networks, internet of things, and wireless communication. He can be contacted at email: y.alsarhan@ammanu.edu.jo.



Ayoub Alsarhan received the Ph.D. degree in Computer Engineering in the field of cyber security and wireless networks from Concordia University, Canada. He is currently a full professor with the Department of Data Science and Artificial Intelligence, Faculty of Information Technology, Al-Ahliyya Amman University, Jordan. He contributed to several journal and conference papers. His research interests include cybersecurity, network security, wireless networks, and cloud computing. He can be contacted at email: a.alsarhan@ammanu.edu.jo.



Areen Arabiat earned her B.Sc. in Computer Engineering and her M.Sc. in intelligent transportation systems (ITS). She is currently a computer lab supervisor and researcher in the Department of Communications and Computer Engineering at Al-Ahliyya Amman University. Her research interests are focused on the following areas: machine learning, data mining, image processing, internet of things (IoT), cyber security, wireless sensor network (WSN), artificial intelligence, and intelligent transportation system (ITS). She can be contacted at email: a.arabiat@ammanu.edu.jo.