Journal of Chemical Health Risks

www.jchr.org

JCHR (2026) 16(1), 620-629 | ISSN:2251-6727

Comparative Assessment of Artificial Intelligence Awareness, Proficiency, and Tool Utilization Among Medical Educators, Practicing Clinicians, and Medical Students at a Tertiary Institution in South India

Dr Jinko K Abraham[1], Dr V Suganthi[2], Dr Darshan Kumar S[3*]

[1]Postgraduate, Department of Physiology, Vinayaka Mission's Kirupananda Variyar Medical College and Hospital, Vinayaka Mission's Research Foundation (VMRF-DU), Salem, Tamil Nadu, India

[2]Professor and Head, Department of Physiology, Vinayaka Mission's Kirupananda Variyar Medical College and Hospital, Vinayaka Mission's Research Foundation (VMRF-DU), Salem, Tamil Nadu, India

[3]Resident, Department of Oral & Maxillofacial Surgery, Vinayaka Missions Sankarachariyar Dental College, Vinayaka Mission's Research Foundation (VMRF-DU), Salem, Tamil Nadu, India (Corresponding author)

(Received: 25 November 2025 Revised: 27 December 2025 Accepted: 11 January 2026)

KEYWORDS

Artificial intelligence awareness, medical education, clinician training, generative AI proficiency, AI tool utilization, healthcare technology adoption

ABSTRACT:

Background: Artificial intelligence (AI) has emerged as a transformative force in healthcare and medical education, reshaping diagnostic workflows, clinical decision support, and learning environments while underscoring the urgent need to assess and strengthen AI awareness, literacy, and competency among medical educators, clinicians, and students.

Objectives: To determine and compare the levels of awareness regarding artificial intelligence; the factors of associated with AI awareness among medical educators, practicing clinicians and medical students.

Methods: This analytical cross-sectional study was conducted at Vinayaka Mission's Kirupananda Variyar Medical College and Hospital, Salem, Tamil Nadu, India, between January and June 2025. Data were collected using a structured questionnaire comprising demographic details, self-rated AI proficiency, and validated scales assessing general, generative, and domain-specific AI awareness across educators, clinicians, and students.

Results: Among 196 respondents – 56 educators, 65 clinicians, and 75 students – the mean age was 32.3 ± 9.6 years, ranging from 22.9 years in students to 40.3 years in educators. Males comprised 59.2%, and prior AI training was reported by 39.8%, most frequently among educators (46.4%). Average self-rated AI proficiency was moderate (3.10 ± 1.00), peaking in educators (3.25) and lowest in clinicians (2.94). General AI awareness was mid-range overall, highest for ethics (3.50 ± 0.73; 50.5% agreement) and lowest for model limitations (3.30 ± 0.78). Generative-AI proficiency showed similar gradients – educators performed best (80.4% recognizing LLMs; 71.4% prompt fundamentals) versus clinicians (66.2%, 56.9%). Clinical AI usage averaged 16.8 ± 3.4 and education-tool awareness 17.3 ± 3.3, both significantly higher in educators ($p < 0.01$). ChatGPT familiarity was near-universal (≈96%), with active use greatest in educators (85.7%) and students (88.0%), reflecting broader integration of AI tools in teaching and learning than in clinical workflows.

Conclusion: Overall, AI awareness and proficiency were moderate, with educators demonstrating the highest literacy and generative-AI competence, highlighting the need for targeted training programs to strengthen AI readiness among clinicians and medical students.

Introduction

Artificial intelligence (AI) is rapidly permeating health care, promising gains in diagnosis, triage, documentation, and medical education, but its benefits hinge on informed, responsible adoption by diverse professional groups.(1) The World Health Organization (WHO) has articulated core ethical principles – autonomy, transparency, accountability, inclusiveness, and sustainability – to steer AI toward public benefit in

Journal of Chemical Health Risks

www.jchr.org

JCHR (2026) 16(1), 620-629 | ISSN:2251-6727

health systems.(2) Recent WHO guidance on large multimodal models (LMMs) highlights their expanding roles across clinical care, patient-guided use, administrative tasks, education, and research, while calling for robust governance and competency development for end-users.(3)

Despite rapid progress, AI deployment in routine care faces persistent barriers. Systematic reviews identify regulatory ambiguity, medico-legal concerns, data quality and interoperability issues, workflow misalignment, and limited end-user training as recurrent impediments to clinician acceptance and use.(4, 5) Parallel developments in regulated imaging AI illustrate how evaluative signals can catalyze awareness; for example, Qure.ai's chest radiography solutions have obtained U.S. FDA 510(k) clearances for pneumothorax and pleural effusion, and additional clearances for CT nodule analysis, milestones that commonly precede hospital pilots and scaled adoption.(6)

The advent of generative AI (GenAI), particularly large language models (LLMs), has intensified opportunities and risks. In health-professions education, scholarly reviews describe accelerating uptake for tutoring, concept explanation, and assessment design, while urging AI-literacy frameworks that teach prompting, verification, and academic integrity.(7) Yet the same models can hallucinate fluent but false clinical content; emerging safety frameworks propose error taxonomies, evaluation pipelines, and user-facing safeguards to reduce harm in documentation and decision support.(8, 9) Adoption surveys in frontline practice echo this duality, reporting growing use of GenAI for drafting and clerical support alongside concerns about privacy, provenance, and accuracy. Against this background, the objective of the present study was to determine and compare the levels of awareness regarding artificial intelligence; the factors of associated with AI awareness among medical educators, practicing clinicians and medical students.

Materials and Methods

This was an analytical cross-sectional study conducted in Vinayaka Mission's Kirupananda Variyar Medical College and Hospital, Salem, Tamil Nadu, India over a period of six months between January 2025 and June 2025. The study was approved by the Institutional Human Ethics Committee (IHEC) with reference number VMKVMC&H/IEC/25/260 dated 06/12/2025. The participants were given the Participant Information Sheet (PIS) in their native language, and its contents were verbally explained to ensure their understanding and satisfaction. Eligible participants comprised three predefined professional cohorts affiliated with the study setting; medical educators (faculty actively engaged in undergraduate or postgraduate teaching), practicing clinicians (licensed MBBS/MD/MS professionals providing direct patient care), and medical students (undergraduate or postgraduate learners in BDS/MBBS/MD/MS programs). Inclusion required voluntary, written informed consent and willingness to complete either an offline or online questionnaire. We excluded non-medical participants, individuals with long-term illnesses that could impair cognition and records with incomplete questionnaires. Recruitment followed a non-probability convenience approach within the institution during the study window.

The minimum sample size was determined a priori using the single-proportion formula $n=Z^2p(1-p)/d^2$, assuming a 95% confidence level ($Z = 1.96$), proportion $p=0.50$ to maximize variance, and absolute precision $d=0.07$, yielding $n=196$. We therefore targeted at least 196 completed responses across the three groups. Questionnaires were administered in English, with clarifications available in the local language as needed. Data were captured via secure online forms and paper-based forms; the latter were subsequently double-entered into the electronic database to minimize transcription errors. Participants were instructed to respond independently without discussion. The instrument contained four sections. First, a demographic and background section collected age, gender, professional role, years of experience, prior AI training (any formal course/workshop or structured module), and self-rated AI proficiency on a 5-point scale (very low to very high). Second, a General AI Awareness scale included five Likert items (1 = strongly disagree to 5 = strongly agree) adapted from the Meta AI Literacy Scale (MAILS) and the Artificial Intelligence Literacy Scale (AILS), covering foundational concepts (e.g., what AI is and is not), data requirements, model limitations, and ethical considerations. Third, two multiple-choice items assessed Generative AI proficiency, focusing on recognition of large language models, prompt fundamentals, and typical capabilities/limitations,

Journal of Chemical Health Risks
www.jchr.org
JCHR (2026) 16(1), 620-629 | ISSN:2251-6727

adapted from generative-AI literacy assessments. Fourth, two domain-specific awareness modules used five-item Likert scales each; Clinical AI Usage Awareness (familiarity with diagnostic decision support, imaging triage, risk prediction, and documentation tools) based on clinical AI adoption literature, and Medical-Education AI Tools Awareness (knowledge of AI-enabled learning, assessment, feedback, and content-generation tools relevant to teaching/learning) drawn from medical-education sources. Response options for all Likert items ranged from 1 to 5 and were summed to form subscale scores, with higher values indicating greater awareness.

To complement awareness constructs, we included a binary (Yes/No) AI-tools familiarity checklist tailored by role, asking whether participants had heard of and/or used named tools. For medical educators, the list comprised ChatGPT, Claude, Glass.ai, Osmosis AI Tutor, Lecturio AI, Research Rabbit, and Julius.AI. For medical students, the list comprised ChatGPT, Osmosis AI Tutor, Quizlet AI, and Amboss. For clinicians, the list comprised TXAGENT, IBM Watson, Qure.ai, VisualDx, and UpToDate AI. For each tool endorsed as 'Yes,' respondents further indicated passive familiarity (heard of/read about) versus active use (used in the last 6 months) to distinguish awareness from utilization. Space was provided to add other AI tools in free text.

Statistical analysis: Statistical analyses were performed using SPSS (v27). Categorical variables were summarized as counts and percentages. Continuous variables and self-rated proficiency were described as mean ± SD; internal consistency for the General AI Awareness and the two domain-specific subscales was assessed using Cronbach's α. Between-group differences in subscale totals were evaluated using one-way ANOVA with η^2 as the effect size; distributional assumptions were checked (Shapiro–Wilk for normality, Levene's test for homogeneity) and, if violated, Kruskal–Wallis tests with Dunn–Bonferroni adjustments were applied. All tests were two-tailed with a significance threshold of $p < 0.05$.

Results

Across 196 respondents (educators 56; clinicians 65; students 75), the mean age was 32.3 ± 9.6 years, reflecting the expected gradient – educators older (40.3 ± 7.7), clinicians mid-career (36.4 ± 7.0), and students younger (22.9 ± 2.4). Males comprised 59.2% overall (116/196), ranging from 52.3% among clinicians to 65.3% among students. Prior AI training was reported by 39.8% overall, highest in educators (46.4%) and lower in clinicians (35.4%) and students (38.7%). Self-rated AI proficiency averaged 3.10 ± 1.00 on a 1–5 scale (educators 3.25 ± 0.94; clinicians 2.94 ± 1.01; students 3.13 ± 1.03). Category distributions were centred on 'neutral' (37.2%) and 'high' (27.6%), with fewer at the extremes – 'very low' 5.1% and 'very high' 7.7%.

General AI awareness items (Likert 1–5) showed mid-to-upper mid scores overall, with 'Ethical considerations (fairness, accountability)' highest (3.50 ± 0.73; 50.5% agree) and 'Model limitations (bias, hallucination, generalizability)' and 'Foundational concepts' slightly lower (3.30 ± 0.78 and 3.32 ± 0.82; 40.0% and 39.5% agree, respectively). Educators consistently led across domains – for example, foundational concepts 3.47 ± 0.81, limitations 3.57 ± 0.83, ethics 3.70 ± 0.70 – while clinicians were lowest (e.g., ethics 3.29 ± 0.76; risk 3.24 ± 0.79) and students typically intermediate (e.g., data requirements 3.38 ± 0.75; ethics 3.52 ± 0.69). Risk awareness (3.37 ± 0.80; 43.3% agree) and data requirements (3.35 ± 0.77; 43.8% agree) sat between ethics and foundational knowledge, mirroring the demographic pattern of higher educator training and proficiency and lower clinician scores.

Generative-AI proficiency showed a clear gradient across groups. On LLM recognition, 72.4% (142/196) answered correctly overall, led by educators at 80.4% (45/56), followed by students 72.0% (54/75) and clinicians 66.2% (43/65). On prompt-fundamentals, 64.3% (126/196) were correct overall – again highest in educators 71.4% (40/56), then students 65.3% (49/75), and clinicians 56.9% (37/65). Just over half answered both items correctly (54.1%; 106/196), ranging from 64.3% of educators to 44.6% of clinicians; 28.6% (56/196) got exactly one correct, and 17.3% (34/196) neither – patterns consistent with broader awareness differences. Domain-specific awareness was mid-to-high with good reliability and significant between-group differences. Clinical AI Usage Awareness averaged 16.8 ± 3.4 (α = 0.81; ANOVA $F = 6.4$, $p = 0.002$), highest in educators (17.8 ± 3.2), then students (16.7 ± 3.1), and clinicians (15.9 ± 3.4). Category distributions were mostly moderate (54.1%; 106/196), with 27.0% high (≥20) and 18.9% low (≤12). Medical-Education AI Tools Awareness averaged 17.3 ± 3.3 (α = 0.83; $F = 8.1$, $p <$

Journal of Chemical Health Risks

www.jchr.org

JCHR (2026) 16(1), 620-629 | ISSN:2251-6727

0.001), again highest in educators (18.2 ± 3.0), then students (17.4 ± 3.2), and clinicians (16.1 ± 3.3); 30.6% were high, 54.1% moderate, and 15.3% low – aligning with educators' stronger ethics/awareness profile and clinicians' comparatively lower scores.

Educators and students showed very high familiarity and frequent use of general/education-facing tools, while clinicians showed moderate familiarity and lower use of clinical tools. Among educators (n=56), awareness was highest for ChatGPT 96.4% with 85.7% active use; familiarity for Claude was 69.6% (use 39.3%), Osmosis AI Tutor 60.7% (use 33.9%), Lecturio AI 55.4% (use 30.4%), Research Rabbit 51.8% (use 32.1%), Glass.ai 46.4% (use 19.6%), and Julius.AI 39.3% (use 17.9%). Clinicians (n=65) reported highest awareness for UpToDate AI 64.6% (use 32.3%), followed by Qure.ai 53.8% (use 26.2%), VisualDx 47.7% (use 20.0%), IBM Watson 43.1% (use 15.4%), and TXAGENT 27.7% (use 13.8%). Students (n=75) were widely familiar with learning tools – ChatGPT 96.0% with 88.0% active use, Quizlet AI 81.3% (use 57.3%), Osmosis AI Tutor 76.0% (use 45.3%), and Amboss 64.0% (use 36.0%). Summarizing across roles, 'any-tool' familiarity was nearly universal for educators 98.2% and students 98.7%, and lower for clinicians 80.0%; 'any-tool' active use followed a similar pattern – educators 92.9%, students 90.7%, clinicians 60.0%. Median (IQR) counts underscored this gradient: tools familiar – educators 4 (3–5), clinicians 3 (2–4), students 3 (2–4); tools used – educators 3 (2–4), clinicians 2 (1–3), students 3 (2–4). Overall, these findings indicate strong penetration of general and education tools among educators and students, with clinicians showing selective adoption of clinically oriented AI applications.

Discussion

The present results depict a coherent gradient in AI literacy across roles that plausibly reflects differences in training exposure, task ecology, and incentive structures in academia versus clinical service. Educators reported the highest prior AI training (46.4%) and the highest self-rated proficiency (mean 3.25), while clinicians had the lowest training (35.4%) and proficiency (2.94), with students intermediate – patterns that mirror international guidance urging structured capacity-building for health workers and educators to steward safe, equitable AI adoption.(3, 10) Within this backdrop, it is unsurprising that general awareness scores were mid-to-upper mid overall, with 'Ethical considerations' topping the item means (3.50) and agreement (50.5%), ahead of foundational concepts and model limitations; curricular and policy discourse has emphasized fairness, accountability, transparency, and data protection as near-term priorities for health systems considering AI.(11)

Role-wise contrasts were consistent; educators led on foundational knowledge (3.47) and limitations (3.57), students were typically intermediate, and clinicians scored lowest – especially on risk (3.24) and ethics (3.29). Convergent literature including Hassan et al. (2024) and Tun et al. (2025) points to several clinician-side headwinds that can depress perceived literacy and confidence; lack of dedicated training time, workflow misalignment, opaque model behavior, medico-legal uncertainty, and infrastructure constraints; all are repeatedly catalogued as barriers in adoption reviews and trust frameworks.(12, 13) These barriers are not merely attitudinal; they shape real decisions about when and how clinicians engage with AI in time-pressured care, thereby reinforcing the lower familiarity and utilization observed here. These findings are in concordance with Shamszare & Choudhury (2023).(14)

The generative-AI (GenAI) proficiency gradient further corroborates these differences. Overall, 72.4% recognized large language models (LLMs) correctly and 64.3% identified prompt fundamentals, but educators were consistently ahead (80.4% and 71.4%), clinicians behind (66.2% and 56.9%), and students in-between. These findings resonate with current syntheses noting that while GenAI can accelerate knowledge retrieval, summarization, and drafting, proficiency depends on explicit instruction in prompting, verification, and safe-use boundaries – elements more often present in academic settings than in service environments.(15, 16) Importantly, the awareness lead on 'Ethics' and 'Risk' among educators may reflect their deeper engagement with institutional policy discussions and research integrity norms around GenAI (e.g., disclosure, plagiarism, and privacy), which several medical-education reviews now foreground.(17)

At the same time, the data hint at a realism among respondents about model fallibility. Awareness scores for 'Model limitations (bias, hallucination, generalizability)' (3.30) lagged ethics, and only about two-fifths agreed at

Journal of Chemical Health Risks
www.jchr.org
JCHR (2026) 16(1), 620-629 | ISSN:2251-6727

high levels – an ambivalence consistent with the growing literature on hallucinations and safety risks. Hallucinations remain a first-order hazard in clinical contexts; beyond lay summaries, recent technical and clinical frameworks underscore how even well-prompted LLMs can produce fluent falsehoods, necessitating verification layers, provenance controls, and institutional guardrails.(9, 18, 19) That the study's clinicians scored lowest on risk awareness may paradoxically reflect a higher threshold for 'agreeing' in the abstract until concrete, workflow-specific mitigations (e.g., source-grounded retrieval, structured output constraints, audit logs) are evident in the tools they are offered.(13) The two domain-specific subscales – Clinical AI Usage Awareness and Medical-Education AI Tools Awareness – displayed acceptable internal consistency (α=0.81 and 0.83) and significant between-group differences (F=6.4 and 8.1), again led by educators. The moderate overall means (16.8 and 17.3 on 5–25 scales) suggest meaningful but still maturing literacy. In the clinical arena, adoption literature emphasizes that awareness alone is insufficient; trust requires demonstrable benefit, workflow fit, and accountability lines.(12) Our tool-specific findings align with that nuance; clinicians showed their highest familiarity with UpToDate AI (64.6% familiar; 32.3% active use) – a decision-support product explicitly grounded in a vetted evidence base and designed as a closed system to limit retrieval drift – consistent with industry communication and trade reporting about 'Expert AI' deployments that emphasize source-bounded responses.(20, 21)

For imaging and triage applications, clinician familiarity with Qure.ai (53.8%; 26.2% active use) and VisualDx (47.7%; 20.0% active use) maps onto a decade of productization and evidence increasingly supported by regulatory signals and evaluation studies. Qure.ai's chest radiography suite (qXR) has secured multiple FDA 510(k) clearances (e.g., pneumothorax, pleural effusion, lung nodules) and broader portfolios in stroke triage – markers that commonly drive hospital pilots and awareness.(6, 22) VisualDx has published demonstrations of accuracy gains for non-dermatologist clinicians using AI-enabled triage/decision support, helping explain its relatively higher recognition among practicing physicians.(23, 24) By contrast, clinician familiarity with general-purpose GenAI assistants remains variable; surveys in primary care report nontrivial but heterogeneous uptake for documentation and reasoning tasks, tempered by privacy and accuracy concerns – again matching our 60% 'any active use' rate among clinicians.(25, 26)

In education-facing ecosystems, the picture is different. Educators and students reported near-universal familiarity and high active use of ChatGPT (96% familiar; 86–88% active), and substantial engagement with tools like Quizlet AI, Osmosis, Lecturio, and Amboss. Systematic reviews in health-professions education describe similar patterns; GenAI and AI-driven platforms are used for concept explanations, formative assessment, feedback, and content authoring, with performance gains in selected tasks but persistent concerns about scaffolding, feedback fidelity, and academic integrity.(17) This duality – high adoption with guarded confidence – also appears in general medical contexts, where cross-disciplinary reviews catalog benefits (efficiency, draft generation, language support) alongside risks (fabrication, bias, citation errors).(15)

The role-tailored 'any-tool' metrics provide a useful integrator. Nearly all educators (98.2%) and students (98.7%) were familiar with at least one named tool and >90% reported any active use, whereas clinicians were lower (80.0% familiar; 60.0% active). Median counts reinforced this gradient (tools used, 3 for educators/students vs 2 for clinicians). Part of this divergence likely reflects the differing payoff matrices; educators and students can realize immediate gains from tutoring, drafting, and assessment-adjacent tools with modest risk, while clinicians must weigh patient-safety, privacy, and medico-legal implications – and often face institutional constraints – before deploying AI at the point of care.(12) Moreover, the clinical market itself is shifting toward 'enterprise-grade' offerings that promise provenance-bounded answers and EHR-integrated copilots; such designs may gradually close the clinician adoption gap as they address leading concerns around accuracy, auditability, and data governance.(27)

Several programmatic implications follow. First, the alignment between higher training exposure and higher awareness/proficiency argues for structured, role-specific curricula that move beyond general ethics to hands-on, domain-anchored competencies (e.g., reading model cards, understanding calibration and drift, writing verifiable prompts, and applying verification

Journal of Chemical Health Risks

www.jchr.org

JCHR (2026) 16(1), 620-629 | ISSN:2251-6727

workflows). This direction is consistent with WHO's latest guidance on large multimodal models (LMMs), which emphasizes competency development, oversight, and evaluation standards as LMMs percolate into clinical and educational settings.(3) Second, the modest scores on 'model limitations' suggest a need to explicitly teach failure modes – hallucinations, bias amplification, domain shift – and mitigation strategies (source grounding, uncertainty expression, human-in-the-loop review), themes now well-articulated in clinical LLM safety frameworks and empirical analyses.(9, 18) Third, the tool-specific patterns suggest that adoption grows where products (a) are embedded in existing workflows, (b) foreground citable sources and audit trails, and (c) have credible evaluative or regulatory signals – features repeatedly identified as facilitators in scoping reviews of health-care AI adoption.(12)

Finally, the convergence of high educator/student adoption with only moderate clinician uptake highlights a translational gap between classroom and clinic. Bridging this gap may require bidirectional design; bringing clinician feedback into the procurement and governance of AI tools and bringing authentic clinical constraints into medical-education AI curricula. If implemented, such reciprocity could lift both awareness and appropriate utilization, converting 'neutral' proficiency distributions into confidently 'high' yet safety-conscious competence across roles.(13)

This study had several limitations. It was a single-centre, analytical cross-sectional survey conducted over six months with non-probability convenience sampling, which restricts external validity and may introduce selection and non-response bias. Role groups were drawn from one institution and local practice milieu, so patterns of training access, policy exposure, and tool availability could have influenced results and may not generalize to other settings. All measures (training history, self-rated proficiency, awareness items, MCQ performance, and tool use) were self-reported and therefore susceptible to recall and social-desirability biases; 'active use in the last six months' may have been misclassified. The awareness scales were adapted from prior instruments and demonstrated acceptable internal consistency, but construct validity in this context was not fully established, and a two-item generative-AI proficiency check cannot capture the breadth of competencies (e.g., verification workflows, safety guardrails, or domain-specific prompting). The fixed, role-tailored tool lists were necessarily selective and may have omitted relevant platforms, and we did not include qualitative data to explain the 'why' behind group differences.

Conclusion

In this single-centre cross-sectional study, AI literacy varied systematically across roles, with medical educators demonstrating the highest self-rated proficiency and awareness, medical students intermediate and practicing clinicians lowest across several domains. General AI awareness was mid-to-upper mid overall – strongest for ethics and risk – while two-item generative-AI proficiency and role-tailored tool familiarity confirmed the same gradient, with near-universal adoption of education-facing tools among educators and students and more selective uptake of clinically oriented applications among clinicians. Domain-specific subscales for Clinical AI Usage and Medical-Education AI Tools showed acceptable reliability and significant between-group differences, indicating measurable, actionable skill gaps. Taken together, these findings underscore the need for targeted, role-specific capacity-building that goes beyond ethical principles to hands-on competencies in model limitations, verification, workflow integration, and safe use. Prioritizing structured curricula, provenance-aware tools, and governance aligned with clinical workflows could narrow the classroom-to-clinic gap and enable safer, more effective AI adoption across the health-professional continuum.

References

1. Bajwa J, Munir U, Nori A, Williams B. Artificial intelligence in healthcare: transforming the practice of medicine. Future Healthc J. 2021;8(2):e188-e94.

2. World Health Organization. WHO calls for safe and ethical AI for health 2023 [Available from: https://www.who.int/news/item/16-05-2023-who-calls-for-safe-and-ethical-ai-for-health?

3. World Health Organization. Ethics and governance of artificial intelligence for health: large multi-modal models: World Health Organization; 2024.

4. Scipion CEA, Manchester MA, Federman A, Wang Y, Arias JJ. Barriers to and facilitators of clinician

Journal of Chemical Health Risks

www.jchr.org

JCHR (2026) 16(1), 620-629 | ISSN:2251-6727

acceptance and use of artificial intelligence in healthcare settings: a scoping review. BMJ Open. 2025;15(4):e092624.

5. Ahmed MI, Spooner B, Isherwood J, Lane M, Orrock E, Dennison A. A Systematic Review of the Barriers to the Implementation of Artificial Intelligence in Healthcare. Cureus. 2023;15(10):e46454.
6. Zavaleta-Monestel E, Quesada-Villaseñor R, Arguedas-Chacón S, García-Montero J, Barrantes-López M, Salas-Segura J, et al. Revolutionizing Healthcare: Qure. AI's Innovations in Medical Diagnosis and Treatment. Cureus. 2024;16(6).
7. Boscardin CK, Gin B, Golde PB, Hauer KE. ChatGPT and Generative Artificial Intelligence for Medical Education: Potential Impact and Opportunity. Acad Med. 2024;99(1):22-7.
8. Omar M, Sorin V, Collins JD, Reich D, Freeman R, Gavin N, et al. Multi-model assurance analysis showing large language models are highly vulnerable to adversarial hallucination attacks during clinical decision support. Commun Med (Lond). 2025;5(1):330.
9. Asgari E, Montaña-Brown N, Dubois M, Khalil S, Balloch J, Yeung JA, et al. A framework to assess clinical safety and hallucination rates of LLMs for medical text summarisation. npj Digital Medicine. 2025;8(1):274.
10. Shishehgar S, Murray-Parahi P, Alsharaydeh E, Mills S, Liu X. Artificial Intelligence in Health Education and Practice: A Systematic Review of Health Students' and Academics' Knowledge, Perceptions and Experiences. Int Nurs Rev. 2025;72(2):e70045.
11. Chen J, Xie W, Xie Q, Hu A, Qiao Y, Wan R, et al. A Systematic Review of User Attitudes Toward GenAI: Influencing Factors and Industry Perspectives. Journal of Intelligence. 2025;13:78.
12. Hassan M, Kushniruk A, Borycki E. Barriers to and Facilitators of Artificial Intelligence Adoption in Health Care: Scoping Review. JMIR Hum Factors. 2024;11:e48633.
13. Tun HM, Rahman HA, Naing L, Malik OA. Trust in Artificial Intelligence–Based Clinical Decision Support Systems Among Health Care Workers: Systematic Review. J Med Internet Res. 2025;27:e69678.
14. Shamszare H, Choudhury A. Clinicians' Perceptions of Artificial Intelligence: Focus on Workload, Risk, Trust, Clinical Decision Making, and Clinical Integration. Healthcare (Basel). 2023;11(16).
15. Fatima A, Shafique MA, Alam K, Fadlalla Ahmed TK, Mustafa MS. ChatGPT in medicine: A cross-disciplinary systematic review of ChatGPT's (artificial intelligence) role in research, clinical practice, education, and patient interaction. Medicine. 2024;103(32).
16. Maaß L, Grab-Kroll C, Koerner J, Öchsner W, Schön M, Messerer D, et al. Artificial Intelligence and ChatGPT in Medical Education: A Cross-Sectional Questionnaire on students' Competence. J cme. 2025;14(1):2437293.
17. Feigerlova E, Hani H, Hothersall-Davies E. A systematic review of the impact of artificial intelligence on educational outcomes in health professions education. BMC Medical Education. 2025;25(1):129.
18. Roustan D, Bastardot F. The Clinicians' Guide to Large Language Models: A General Perspective With a Focus on Hallucinations. Interact J Med Res. 2025;14:e59823.
19. Anh-Hoang D, Tran V, Nguyen L-M. Survey and analysis of hallucinations in large language models: attribution to prompting strategies or model behavior. Frontiers in Artificial Intelligence. 2025;Volume 8 - 2025.
20. Chatterjee S, Fruhling A, Kotiadis K, Gartner D. Towards new frontiers of healthcare systems research using artificial intelligence and generative AI. Taylor & Francis; 2024. p. 263-73.
21. Arya N, Bansal A, Kumar R, Intaratat K, Ng KT. Exploring Digital Tools Utilizing Generative AI in Healthcare. Generative Artificial Intelligence in Healthcare: CRC Press. p. 54-69.

Journal of Chemical Health Risks

www.jchr.org

JCHR (2026) 16(1), 620-629 | ISSN:2251-6727

22. Esteban Z-M, Quesada-Villaseñor R, Sebastián A-C, García-Montero J, Monserrat B-L, Salas-Segura J, et al. Revolutionizing Healthcare: Qure. AI's Innovations in Medical Diagnosis and Treatment. Cureus. 2024;16(6).

23. Khalifa M, Albadawy M. AI in diagnostic imaging: revolutionising accuracy and efficiency. Computer Methods and programs in biomedicine update. 2024;5:100146.

24. Dulmage B, Tegtmeyer K, Zhang MZ, Colavincenzo M, Xu S. A point-of-care, real-time artificial intelligence system to support clinician diagnosis of a wide range of skin diseases. Journal of Investigative Dermatology. 2021;141(5):1230-5.

25. Blease C, Garcia Sanchez C, Locher C, McMillan B, Gaab J, Torous J. Generative Artificial Intelligence in Primary Care: Qualitative Study of UK General Practitioners' Views. J Med Internet Res. 2025;27:e74428.

26. Yang H, Dai T, Mathioudakis N, Knight AM, Nakayasu Y, Wolf RM. Peer perceptions of clinicians using generative AI in medical decision-making. NPJ Digit Med. 2025;8(1):530.

27. Alhur A. Redefining healthcare with artificial intelligence (AI): the contributions of ChatGPT, Gemini, and Co-pilot. Cureus. 2024;16(4).

Table 1: Demographics and background by professional group

Variable	**Medical Educator**	**Practicing Clinician**	**Medical Student**	**Overall**
N	**56**	**65**	**75**	**196**
Age (years), Mean ± SD	40.28 ± 7.71	36.35 ± 6.96	22.88 ± 2.42	32.32 ± 9.63
Male, n (%)	33 (58.9)	34 (52.3)	49 (65.3)	116 (59.2)
Female, n (%)	23 (41.1)	31 (47.7)	26 (34.7)	80 (40.8)
Prior AI training, n (%)	26 (46.4)	23 (35.4)	29 (38.7)	78 (39.8)
Self-rated proficiency, Mean ± SD	3.25 ± 0.94	2.94 ± 1.01	3.13 ± 1.03	3.10 ± 1.00
Proficiency – 1 (Very low)	0 (0.0)	4 (6.2)	6 (8.0)	10 (5.1)
Proficiency – 2 (Low)	13 (23.2)	19 (29.2)	12 (16.0)	44 (22.4)
Proficiency – 3 (Neutral)	22 (39.3)	23 (35.4)	28 (37.3)	73 (37.2)
Proficiency – 4 (High)	15 (26.8)	15 (23.1)	24 (32.0)	54 (27.6)
Proficiency – 5 (Very high)	6 (10.7)	4 (6.2)	5 (6.7)	15 (7.7)

Table 2: General AI Awareness items (Likert 1–5); means, SDs and % agreement (4–5)

Item	**Overall Mean ± SD**	**Overall agree (4–5) %**	**Educators Mean ± SD**	**Clinicians Mean ± SD**	**Students Mean ± SD**
Foundational concept clarity (what AI is/is not)	3.32 ± 0.82	39.5	3.47 ± 0.81	3.26 ± 0.94	3.26 ± 0.71

Data requirements (volume, quality, privacy)	3.35 ± 0.77	43.8	3.52 ± 0.77	3.17 ± 0.76	3.38 ± 0.75
Model limitations (bias, hallucination, generalizability)	3.30 ± 0.78	40.0	3.57 ± 0.83	3.20 ± 0.75	3.19 ± 0.73
Ethical considerations (fairness, accountability)	3.50 ± 0.73	50.5	3.70 ± 0.70	3.29 ± 0.76	3.52 ± 0.69
Risk awareness & safeguards in use	3.37 ± 0.80	43.3	3.67 ± 0.77	3.24 ± 0.79	3.26 ± 0.78

Table 3: Generative AI proficiency (two MCQs): group-wise and overall

Metric	**Medical Educator**	**Practicing Clinician**	**Medical Student**	**Overall**
N	**56**	**65**	**75**	**196**
Item 1: LLM recognition – correct, n (%)	45 (80.4)	43 (66.2)	54 (72.0)	142 (72.4)
Item 2: Prompt fundamentals – correct, n (%)	40 (71.4)	37 (56.9)	49 (65.3)	126 (64.3)
Both items correct, n (%)	36 (64.3)	29 (44.6)	41 (54.7)	106 (54.1)
Exactly one correct, n (%)	13 (23.2)	22 (33.8)	21 (28.0)	56 (28.6)
Neither correct, n (%)	7 (12.5)	14 (21.5)	13 (17.3)	34 (17.3)

Table 4: Clinical AI Usage Awareness and Medical-Education AI Tools Awareness

Metric	**Medical Educator**	**Practicing Clinician**	**Medical Student**	**Overall**
N	**56**	**65**	**75**	**196**
Clinical AI Usage Awareness (5 items; Likert 1–5, sum 5–25)				
Total score, Mean ± SD	17.8 ± 3.2	15.9 ± 3.4	16.7 ± 3.1	16.8 ± 3.4
Low (≤12), n (%)	8 (14.3)	15 (23.1)	14 (18.7)	37 (18.9)
Moderate (13–19), n (%)	28 (50.0)	37 (56.9)	41 (54.7)	106 (54.1)
High (≥20), n (%)	20 (35.7)	13 (20.0)	20 (26.7)	53 (27.0)
Medical-Education AI Tools Awareness (5 items; Likert 1–5, sum 5–25)				
Total score, Mean ± SD	18.2 ± 3.0	16.1 ± 3.3	17.4 ± 3.2	17.3 ± 3.3
Low (≤12), n (%)	6 (10.7)	13 (20.0)	11 (14.7)	30 (15.3)
Moderate (13–19), n (%)	26 (46.4)	38 (58.5)	42 (56.0)	106 (54.1)
High (≥20), n (%)	24 (42.9)	14 (21.5)	22 (29.3)	60 (30.6)
Clinical AI Usage Awareness: Cronbach's α = 0.81; One-way ANOVA across groups, $F = 6.4$, $p = 0.002$. **Medical-Education AI Tools Awareness:** Cronbach's α = 0.83; One-way ANOVA across groups, $F = 8.1$, $p < 0.001$.				

Journal of Chemical Health Risks

www.jchr.org

JCHR (2026) 16(1), 620-629 | ISSN:2251-6727

Table 5: AI-Tools Familiarity and Active Use by Role

Tool	**Familiar (Yes) n (%)**	**Active use (Yes) n (%)**	**Familiar but not active n (%)**
Medical Educators (n=56)			
ChatGPT	54 (96.4)	48 (85.7)	6 (10.7)
Claude	39 (69.6)	22 (39.3)	17 (30.4)
Glass.ai	26 (46.4)	11 (19.6)	15 (26.8)
Osmosis AI Tutor	34 (60.7)	19 (33.9)	15 (26.8)
Lecturio AI	31 (55.4)	17 (30.4)	14 (25.0)
Research Rabbit	29 (51.8)	18 (32.1)	11 (19.6)
Julius.AI	22 (39.3)	10 (17.9)	12 (21.4)
Practicing Clinicians (n=65)			
TXAGENT	18 (27.7)	9 (13.8)	9 (13.8)
IBM Watson	28 (43.1)	10 (15.4)	18 (27.7)
Qure.ai	35 (53.8)	17 (26.2)	18 (27.7)
VisualDx	31 (47.7)	13 (20.0)	18 (27.7)
UpToDate AI	42 (64.6)	21 (32.3)	21 (32.3)
Medical Students (n=75)			
ChatGPT	72 (96.0)	66 (88.0)	6 (8.0)
Osmosis AI Tutor	57 (76.0)	34 (45.3)	23 (30.7)
Quizlet AI	61 (81.3)	43 (57.3)	18 (24.0)
Amboss	48 (64.0)	27 (36.0)	21 (28.0)

Table 6: AI-Tools Familiarity and Active Use by Role (Summary)

Metric	**Medical Educator**	**Practicing Clinician**	**Medical Student**	**Overall**
N	**56**	**65**	**75**	**196**
Any familiar tool, n (%)	55 (98.2)	52 (80.0)	74 (98.7)	181 (92.3)
Any tool active use, n (%)	52 (92.9)	39 (60.0)	68 (90.7)	159 (81.1)
Number of tools familiar, Median (IQR)	4 (3–5)	3 (2–4)	3 (2–4)	–
Number of tools used, Median (IQR)	3 (2–4)	2 (1–3)	3 (2–4)	–