

# Hierarchical differences in generative AI impacts and tiered educational support needs among health professions students: A descriptive qualitative study

**Guoxin Zhou**

Guizhou Medical University

**Bo Li**

Guizhou Medical University

**Tingmei Wen**

Guizhou Medical University

**Hongyan Wen**

Guizhou Medical University

**Ting Sun**

Guizhou Medical University

**Haitao Zhang**

Guizhou Medical University

**Xiaoxiao Li**

Guizhou Medical University

**Li Wang**

**L i l y w a n g 4 3 6 4 3 6 @ 1 6 3 . c o m**

Guizhou Medical University

**Yang Wang**

Affiliated Hospital of Guizhou Medical University

---

## Research Article

**Keywords:** generative artificial intelligence, nursing education, medical education, qualitative research, AI literacy, hierarchical differences

**Posted Date:** July 24th, 2026

**DOI:** <https://doi.org/10.21203/rs.3.rs-10347054/v1>

**License:** © ⓘ This work is licensed under a Creative Commons Attribution 4.0 International License.  
[Read Full License](#)

**Additional Declarations:** No competing interests reported.

---

**Version of Record:** A version of this preprint was published at BMC Medical Education on October 17th, 2026. See the published version at <https://doi.org/10.1186/s12909-026-10637-5>.

# Abstract

## Background

Generative artificial intelligence (GAI) has been extensively integrated into nursing and medical education, significantly transforming the academic practices of students. Nonetheless, the varying impacts of GAI on core competency development across educational stages remain ambiguous, with limited empirical evidence on hierarchical educational support needs. This study aimed to investigate the effects of GAI utilization on critical thinking, research competence, and academic integrity among Chinese nursing and medical students at undergraduate, master's, and doctoral levels, and to identify their specific needs for targeted GAI educational support.

## Methods

This descriptive qualitative study analyzed semi-structured interviews with 44 students (16 undergraduate, 16 master's, 12 doctoral) from a western Chinese medical university using inductive content analysis, with TAM and AI Literacy frameworks informing discussion.

## Results

GAI usage patterns varied by academic level: undergraduates for coursework, versus postgraduates for literature reviews, experimental design, and data analysis. The dual academic impact featured enhanced critical thinking and knowledge acquisition, counterbalanced by risks of over-reliance, marginal clinical skill efficacy, and cognitive offloading—with research competency gains largely confined to postgraduates. A pronounced demand for systemic support, including teacher guidance and institutional training, pervaded all levels.

## Conclusion

GAI differentially affects nursing/medical students' progression, warranting stage-specific support. We propose a three-stage TAM-extension model (PEOU-driven, PU-driven, critical-reflective) to capture developmental trajectories, offering empirical grounds for tiered AI literacy curricula.

## Introduction

Generative Artificial Intelligence (GAI), distinguished by its integration of big data, high-performance computing, and sophisticated algorithms, is increasingly being adopted within higher education, exerting particularly transformative effects on nursing and medical education<sup>[1]</sup>. Students in these fields, who represent the future healthcare workforce, engage in complex learning activities that include knowledge

acquisition, clinical skill development, and scientific research, all of which are essential for their academic proficiency and the formation of their professional identities<sup>[2]</sup>.

Nursing and medical education employ a hierarchical training model characterized by stage-specific priorities: undergraduate programs focus on foundational knowledge and clinical skills, master's programs enhance research capabilities, and doctoral training emphasizes innovation and frontier exploration<sup>[3]</sup>. These developmental distinctions lead to variations in cognitive maturity, task complexity, and autonomous learning capacity across academic levels, potentially influencing diverse patterns of GAI adoption and varying requirements for educational support.

This study is informed by two complementary theoretical frameworks that provide interpretive lenses for analyzing our findings. The Technology Acceptance Model (TAM) suggests that the adoption of technology is influenced by perceived usefulness (PU) and perceived ease of use (PEOU), which collectively shape users' attitudes and behavioral intentions<sup>[4]</sup>. TAM is particularly pertinent for investigating how students at various academic stages perceive and engage with GAI tools. In addition to TAM, the AI Literacy framework conceptualizes AI competence across three domains: technical understanding, critical evaluation, and practical application<sup>[5]</sup>. This framework has been increasingly utilized in nursing and medical education to guide curriculum development and inform tiered educational interventions<sup>[6]</sup>.

In this study, we utilize the TAM and the AI Literacy framework as analytical and interpretive lenses, rather than prescriptive coding schemas. Specifically, TAM elucidates the motivational drivers behind the adoption of GAI across various academic levels, while the AI Literacy framework provides a structure for comprehending the progression of students' engagement with GAI, from basic usage to critical evaluation. These frameworks informed the development of our interview guide and, more importantly, serve as the principal interpretive tools in the discussion section, where we contextualize our inductive findings within broader theoretical discourses on technology adoption and competency development.

This investigation centers on three fundamental constructs. Firstly, critical thinking, defined as the capacity to objectively analyze, evaluate, and synthesize information, exhibits variation across academic levels. Undergraduate students primarily focus on verifying factual accuracy, master's students assess methodological rigor, and doctoral candidates engage in epistemological critique. This critique involves the ability to critically examine the credibility, biases, and limitations of AI-generated knowledge from an epistemological perspective, questioning not only the knowledge produced but also the processes of its production and validation<sup>[7, 8]</sup>. Secondly, research competence includes skills such as literature review, study design, data analysis, and scholarly writing, with expectations that become more demanding at advanced stages of academic training<sup>[9]</sup>. Lastly, academic integrity within the context of GAI pertains to the ethical and transparent use of AI tools, which involves proper attribution, the avoidance of plagiarism, and compliance with institutional policies<sup>[10, 11]</sup>.

Although existing literature has explored the overarching impacts of GAI on nursing and medical education, there is a paucity of empirical evidence concerning its nuanced, stage-specific effects on the development of academic competencies and the corresponding educational support needs of undergraduate, master's, and doctoral students. To address this gap, the present descriptive qualitative study examines the multi-level experiences of GAI utilization among nursing and medical students, assesses its dual impact on the development of academic competencies, and identifies differentiated educational support requirements. The findings aim to furnish empirical evidence to inform the design of stratified AI literacy education and targeted interventions within nursing and medical curricula.

## 1 Methods

This study is reported in accordance with the Consolidated Criteria for Reporting Qualitative Research (COREQ) checklist<sup>[12]</sup>.

### 1.1 Participants

This study utilized purposive sampling to recruit full-time undergraduate, master's (encompassing both academic and professional tracks), and doctoral students in clinical medicine and related health disciplines from a comprehensive medical university located in western China, during the period from February to June 2026. Stratified sampling based on academic level was implemented to align the academic task characteristics and AI usage scenarios of each cohort for the purpose of conducting semi-structured interviews.

The inclusion criteria were established as follows: (1) participants must be students currently enrolled in a full-time degree program (bachelor's, master's, or doctoral) in either clinical medicine or nursing science; (2) participants must have self-reported experience with GAI tools for academic learning or research purposes, having utilized these tools at least once per week over the preceding six months (this operational definition was employed to ensure "clear experience"); (3) participants must demonstrate a willingness to engage in semi-structured interviews and provide comprehensive reflections on their GAI usage behaviors, perceived changes in academic competency, and educational support needs; and (4) participants must provide written informed consent prior to the commencement of the interview.

The exclusion criteria were defined as follows: (1) students enrolled in disciplines other than medicine and nursing, such as pharmacy, public health, or biomedical engineering; (2) students currently on official academic leave or engaged in long-term external placements exceeding three months in duration; and (3) individuals with a documented history of severe psychiatric disorders or cognitive impairments that could hinder effective communication during the interview process.

This descriptive qualitative study established the sample size based on the principle of data saturation, which was defined as the point at which three consecutive interview transcripts produced no new themes or additional insights. The final sample consisted of 44 participants, including 16 undergraduate students, 16 master's students, and 12 doctoral candidates. The study received approval from the

Institutional Review Board of Guizhou Medical University (Approval No. 2026 – 201). All procedures adhered to the ethical principles of respect, beneficence, justice, and non-maleficence. Anonymity was preserved throughout the study, and all interview data were de-identified.

## **1.2 Data Collection**

### **1.2.1 Interview Guide Development**

Based on the study objectives, literature review, and team discussions, a preliminary interview guide was developed by two researchers in medical education (holding a doctoral and a master's degree, respectively), both experienced in qualitative interviewing and formally trained in the relevant methodologies. Following expert review, the guide was pilot-tested through interviews conducted by the same researchers with one undergraduate, one master's, and one doctoral student. Revisions were subsequently made based on pilot feedback, yielding the final interview guide. The semi-structured protocol comprised the following core questions: "Describe your typical AI usage in academic/research settings (frequency, scenarios, task types). "How do you usually process or interact with AI-generated responses? "What changes, if any, have you observed in your academic workflow or learning since using AI? "Describe a specific instance where AI output did not meet expectations or required verification. "Looking back, what stands out most about your AI experience (tool performance, personal reactions, outcomes)? "Characterize your teachers'/supervisors' current role in your AI use and any interactions you have had. "Describe the current institutional environment (curriculum, workshops, policies) regarding student AI use, with relevant observations. "What possibilities, hopes, or uncertainties do you foresee for AI integration into medical/nursing education?

### **1.2.2 Interview Procedures**

A descriptive qualitative research design with semi-structured in-depth interviews was employed for data collection<sup>[13]</sup>. The research team identified eligible participants by applying specific inclusion and exclusion criteria, subsequently contacting them to obtain informed consent. Interview schedules, venues, and formats (in-person) were organized in accordance with the preferences of the participants. All interviews were conducted in a quiet and private setting, devoid of third-party presence, to ensure participant comfort, minimize external distractions, and protect confidentiality. Interviewers commenced each session by introducing themselves, elucidating the study's purpose and methodology, and assuring participants of confidentiality. With the consent of the participants, all interviews were audio-recorded. Non-verbal behaviors, such as tone, facial expressions, and gestures, were systematically documented. Throughout the interviews, the research team employed active listening techniques, provided timely feedback, and sought clarification without imparting suggestive guidance.

### **1.2.3 Data Analysis**

The methodological approach and its theoretical significance in this study are articulated as follows. Inductive content analysis was selected as the primary analytical strategy because it allows themes to emerge directly from the empirical data, unencumbered by pre-established theoretical frameworks. This

characteristic makes it particularly well-suited for exploratory investigations into phenomena that have been minimally studied<sup>[14]</sup>. Regarding theoretical application, the frameworks of the TAM and AI Literacy were not utilized as a priori coding templates that would impose existing categories onto the data. Rather, they served as sensitizing concepts, providing theoretical orientations that informed our research questions and the design of the interview protocol. Subsequently, they offered interpretative lenses through which the inductively derived themes were analyzed in the discussion section. This design maintains the integrity of inductive exploration while concurrently facilitating theoretically informed interpretation. A team of three researchers (two female, one male), all with expertise in medical education scholarship, conducted the interviews. Each interviewer had completed postgraduate training in qualitative research methodologies and had prior experience in conducting semi-structured interviews. Furthermore, none of the interviewers had any pre-existing relationships with the participants, thereby minimizing potential biases in the data collection process.

All audio recordings were transcribed verbatim within 48 hours of each interview. One researcher performed transcription, and a second researcher verified accuracy. Transcripts were coded and analyzed using inductive content analysis with NVivo 15 software.

A rigorous analysis of the interview data was undertaken, strictly following Colaizzi's seven-step analytical framework<sup>[15]</sup>. This procedural sequence comprised: (1) iteratively perusing the transcripts to cultivate an overarching comprehension of the dataset; (2) isolating salient statements directly relevant to the research focus; (3) deriving formulated meanings from these statements through systematic coding practices; (4) consolidating the codes into preliminary thematic groupings; (5) synthesizing these thematic groupings into a cohesive and exhaustive narrative; (6) distilling the essential architecture of the phenomenon to pinpoint pivotal core themes; and (7) returning the synthesized outcomes to the participants for validation via member-checking.

## **1.2.4 Trustworthiness**

To enhance the trustworthiness of the study, a multifaceted approach was adopted. Member checking was implemented by providing participants with their transcribed interviews to verify accuracy. Peer debriefing was facilitated through regular team discussions regarding coding decisions and emerging themes with researchers who were not involved in the data collection process. An audit trail was meticulously maintained, documenting all research decisions, coding processes, and analytical memos. Inter-coder reliability was assessed by having two researchers independently code 30% of the transcripts, resulting in an initial agreement rate of 87.6%. Discrepancies, primarily related to the coding of meaning units associated with critical thinking, were resolved through team discussions to achieve consensus. To ensure transparency and enable readers to evaluate the alignment between data and interpretations, findings are presented with direct quotations from participants.

## **1.3 Ethical Considerations**

This study received ethical approval from the Institutional Review Board of Guizhou Medical University (Approval No. 2026 – 201). All participants provided written informed consent after receiving comprehensive information about the study purpose, procedures, potential risks and benefits, and their rights to withdraw at any time. Data were anonymized and stored securely. The study adhered to the ethical principles of respect for persons, beneficence, justice, and non-maleficence.

## 2 Results

A total of 44 health professions students participated in the interviews: 16 undergraduates (coded B1–B16), 16 master's students (coded M1–M16), and 12 doctoral students (coded P1–P12). All interviews were conducted in quiet, private settings (meeting rooms or classrooms) either face-to-face, lasting 30–60 minutes. Three overarching themes were identified. Participant demographics are presented in Table 1.

Table 1  
Participant demographics (n = 44)

| <b>Code</b> | <b>Gender</b> | <b>Age</b> | <b>Level</b>  | <b>Major/Specialty</b> |
|-------------|---------------|------------|---------------|------------------------|
| B1          | Female        | 22         | Undergraduate | Nursing                |
| B2          | Female        | 21         | Undergraduate | Nursing                |
| B3          | Female        | 23         | Undergraduate | Nursing                |
| B4          | Male          | 23         | Undergraduate | Nursing                |
| B5          | Male          | 23         | Undergraduate | Nursing                |
| B6          | Female        | 20         | Undergraduate | Nursing                |
| B7          | Female        | 22         | Undergraduate | Nursing                |
| B8          | Female        | 21         | Undergraduate | Clinical Medicine      |
| B9          | Female        | 22         | Undergraduate | Clinical Medicine      |
| B10         | Female        | 22         | Undergraduate | Clinical Medicine      |
| B11         | Male          | 23         | Undergraduate | Clinical Medicine      |
| B12         | Female        | 21         | Undergraduate | Clinical Medicine      |
| B13         | Female        | 22         | Undergraduate | Clinical Medicine      |
| B14         | Female        | 23         | Undergraduate | Nursing                |
| B15         | Female        | 21         | Undergraduate | Nursing                |
| B16         | Female        | 23         | Undergraduate | Clinical Medicine      |
| M1          | Female        | 34         | Master's      | Nursing                |
| M2          | Female        | 25         | Master's      | Nursing                |
| M3          | Female        | 27         | Master's      | Nursing                |
| M4          | Male          | 22         | Master's      | Clinical Medicine      |
| M5          | Female        | 23         | Master's      | Clinical Medicine      |
| M6          | Female        | 28         | Master's      | Nursing                |
| M7          | Female        | 24         | Master's      | Nursing                |
| M8          | Female        | 23         | Master's      | Nursing                |
| M9          | Female        | 23         | Master's      | Clinical Medicine      |
| M10         | Female        | 25         | Master's      | Clinical Medicine      |
| M11         | Female        | 23         | Master's      | Nursing                |

| Code | Gender | Age | Level    | Major/Specialty               |
|------|--------|-----|----------|-------------------------------|
| M12  | Female | 24  | Master's | Nursing                       |
| M13  | Female | 28  | Master's | Nursing                       |
| M14  | Male   | 23  | Master's | Clinical Medicine             |
| M15  | Male   | 24  | Master's | Nursing                       |
| M16  | Female | 23  | Master's | Nursing                       |
| P1   | Male   | 28  | Doctoral | Pathology and Pathophysiology |
| P2   | Female | 34  | Doctoral | Pathology and Pathophysiology |
| P3   | Male   | 37  | Doctoral | Clinical Nursing              |
| P4   | Male   | 31  | Doctoral | Orthopedics                   |
| P5   | Male   | 35  | Doctoral | Pathology and Pathophysiology |
| P6   | Female | 26  | Doctoral | Pathology and Pathophysiology |
| P7   | Female | 27  | Doctoral | Clinical Nursing              |
| P8   | Female | 34  | Doctoral | Otorhinolaryngology           |
| P9   | Female | 30  | Doctoral | Neurology                     |
| P10  | Male   | 27  | Doctoral | Stomatology                   |
| P11  | Female | 34  | Doctoral | Clinical Nursing              |
| P12  | Female | 36  | Doctoral | Clinical Nursing              |

## 2.1 Theme 1: GAI Widely Applied in Daily Learning and Research

Health professions students reported high-frequency, broad-scope GAI usage with concentrated tool preferences. Approximately half of the participants used GAI tools daily, with the remainder using them 1–5 times per week. Commonly used tools included ChatGPT, DeepSeek, Doubao, Kimi, Wenxin Yiyan, with Baidu Wenku and Tongyi Qianwen mentioned occasionally.

Undergraduate students primarily utilized GAI for completing coursework, retrieving information, and preparing PowerPoint presentations. For instance, participant B10 remarked, "I employ it for completing assignments and for looking up keywords mentioned by the instructor that I do not fully comprehend." Likewise, participant B1 observed, "When writing papers for class assignments, I utilize AI to locate pertinent references and to gain a general understanding of the topic." This trend was consistently observed among undergraduate participants, who highlighted the convenience and efficiency that GAI offered for routine academic tasks.

Master's and doctoral students increasingly utilize GAI in advanced academic settings, encompassing tasks such as paper writing, experimental design, research projects, literature reviews, and data analysis. As M11 noted, "I use it for literature searches, research design, and also for some group tasks." P11 further elaborated, "I employ AI in academic contexts approximately 95% of the time, with the remaining 5% dedicated to everyday inquiries." Doctoral students, in particular, reported leveraging GAI for intricate research activities, including the identification of research gaps and the assessment of methodological approaches.

## **2.2 Theme 2: Impact on Academic Behaviors and Competency Development**

### **2.2.1 Critical Thinking**

The majority of participants indicated that the necessity to verify and critique content generated by GAI contributed to an enhancement in their critical thinking skills. This enhancement was evident through various mechanisms across different academic levels, thereby revealing a developmental trajectory in critical engagement.

Undergraduate students predominantly engage in the fact-checking and verification of basic information. Participant B16 elucidated: "Our medical programs necessitate precision in professional terminology, and occasionally, AI provides responses that lack standardization or rigor—thus, I must assess their accuracy." Similarly, participant B6 remarked: "When AI supplies information on diseases, I consistently cross-reference it with my textbooks to ensure its correctness." This trend indicates that undergraduates utilize Generative Artificial Intelligence (GAI) as a catalyst for verifying factual knowledge rather than as a source of definitive answers, thereby cultivating essential critical appraisal skills. However, a subset of undergraduates demonstrated patterns of passive acceptance. Participant B15 admitted: "I personally prioritize the outcome—once I have answered the question, I proceed. People tend to be lazy—when there is a ready-made answer, who wants to explore further?" This contrasting pattern underscores the diverse strategies students employ when interacting with GAI outputs, bearing significant implications for educational outcomes.

Master's students exhibited a more advanced level of critical engagement by rigorously assessing AI outputs in terms of relevance, methodology, and contextual applicability. As M13 articulated, "It is essential to consider whether the AI output can be effectively applied to the intended context, assess its authenticity, and continuously refine the input instructions to achieve more precise results." Similarly, M12 emphasized, "I do not simply accept the AI's output at face value. I critically evaluate whether it aligns with my research question and whether the methodology is sound." This proactive evaluative approach signifies a higher degree of critical thinking compared to undergraduate students, reflecting the increased research demands and methodological awareness inherent in master's-level education.

Doctoral students demonstrated the highest degree of critical reflection, perceiving AI-generated content as a preliminary platform for deeper intellectual exploration rather than as conclusive solutions.

Participant 6 (P6) observed: "Prior to utilizing AI tools, I would consult literature and engage in independent thought, seldom subjecting my self-generated materials to further critique and verification. However, with AI-generated responses, I actively pursue additional verification, which has substantially enhanced my critical thinking skills." Similarly, Participant 11 (P11) remarked: "AI offers a framework, yet I consistently question its underlying assumptions and seek alternative perspectives within the literature." Importantly, doctoral students engaged in what we define as epistemological critique—the ability to critically assess the credibility, biases, and limitations of AI-generated knowledge from an epistemological perspective. Participant 5 (P5) exemplified this approach: "The inquiry extends beyond the correctness of the AI's response to include the origins of this knowledge, the assumptions it contains, and its suitability for my specific research context."

## **2.2.2 Professional Knowledge and Clinical Skills**

The majority of participants recognized the significant advantages of GAI in enhancing professional knowledge acquisition, although its influence on clinical skills was perceived as limited.

Regarding knowledge acquisition, students at all levels valued GAI's capacity to synthesize and update information. Participant P9 elucidated: "AI effectively integrates numerous knowledge points. When clinical responsibilities are demanding, we sometimes overlook certain aspects, particularly guideline updates that we cannot always track in real-time. However, AI provides timely updates, which is immensely beneficial for accumulating disease-related knowledge." Similarly, participant M2 remarked: "AI assists me in efficiently summarizing extensive information on a topic, which is particularly advantageous when I am initially exploring a new area." Participant B8 further commented: "I utilize it to obtain quick clarifications when I am perplexed by concepts from lectures. It is more time-efficient compared to consulting multiple sources."

Regarding clinical skills, students consistently reported that GAI had minimal impact on their development. M4 explained: "For professional knowledge accumulation, it does help me a lot. But for clinical skills, at most I use it to check what a medication does. But regarding the specific state of a particular patient, I still trust myself and my clinical teachers' experiential judgment more." P9 similarly stated: "No amount of AI-generated information can replace the hands-on experience of examining a patient or the nuanced decision-making required in clinical practice." This consistent finding across all academic levels highlights the irreplaceable role of experiential learning in clinical skill acquisition.

A paradoxical impact on deep learning was identified, especially among undergraduate students, who indicated that the convenience of GAI hindered deep learning and knowledge retention. This sentiment was reflected in B15's earlier observation about prioritizing "more on the result," and was reiterated by B7, who noted that directly copying AI-generated responses often resulted in diminished recall. M3 similarly observed that the rapid use of AI to answer questions circumvented the independent problem-solving process, which is crucial for learning. This paradox—where enhanced efficiency may compromise the depth of learning—poses a significant challenge for educators.

## **2.2.3 Research Competence**

Graduate students at both the master's and doctoral levels reported a significant enhancement in their research-related skills, including literature review, data analysis, writing proficiency, and methodological understanding. Participant M2 articulated: "When drafting a passage and struggling to find the appropriate phrasing or professional terminology, AI assists by providing these elements. Additionally, if I wish to explore a topic but am uncertain about the appropriate methodologies, it suggests suitable options." Participant M5 further stated: "AI has been invaluable in aiding my comprehension of complex statistical methods and in interpreting my data." Participant P11 elaborated: "In terms of experimental methods and literature review, AI assists by outlining the article's framework, thereby rendering my literature reading more coherent." Similarly, Participant P3 observed: "When composing research proposals, AI aids in organizing my ideas and identifying connections that I might have overlooked."

Undergraduates, however, reported minimal research competence enhancement due to limited research experience. B14 stated: "I feel it's only at the level of comprehension. If you're talking about substantial help, the results help me a lot, but the process doesn't help much." B11 similarly noted: "We only do basic research methodology courses; I don't think I have enough research experience to really use AI to enhance my research skills." This finding reflects the hierarchical structure of health professions education, where research competency is primarily developed at the postgraduate level.

## **2.2.4 Academic Integrity**

Perceptions of academic integrity in relation to GAI usage varied by academic level. Undergraduates reported having insufficient academic practice experience to have encountered such issues. Most master's and doctoral students reported not having experienced academic integrity problems because they used GAI as a supplementary tool with appropriate verification. M12 stated: "I don't completely rely on it academically—I verify and adjust things myself, so I haven't encountered academic integrity issues so far." M15 added: "I treat AI as a brainstorming partner, not a writing assistant. I never copy text directly."

However, certain participants, notably doctoral students, recognized distinct risks to academic integrity. Participant 10 cautioned: "Utilizing AI to directly compose or translate content may involve the use of pre-existing material from online databases, thereby constituting academic fraud." Similarly, Participant 8 warned: "There is a risk that some students might present AI-generated content as their own work, without fully comprehending the ethical ramifications."

Several doctoral students notably conceptualized academic integrity as primarily a reflection of personal character, rather than an inherent characteristic of the tool itself. Participant 4 observed, "I believe academic integrity is minimally related to AI; it fundamentally concerns an individual's academic quality. If someone inherently lacks academic quality, they would resort to other means to engage in unethical practices, even in the absence of AI." Participant 3 concurred, stating, "The tool itself is neutral. The critical issue lies in its application. Individuals with strong research integrity will utilize AI responsibly, whereas those lacking integrity will find ways to circumvent ethical standards regardless."

## **2.3 Theme 3: High Expectations for Educational Support**

Students at all levels reported difficulties and challenges when using GAI, including unclear prompt formulation and unreliable generated content. They expressed strong desires for teacher guidance and institutional training, with content preferences varying by academic level.

### **2.3.1 Teacher Guidance Needs**

All students affirmed the necessity of teacher guidance and expressed preferences for diverse formats including teaching demonstrations, training sessions, distribution of user guides, and in-person monitoring. P5 explained: "Guidance and instruction are definitely needed. The user documentation released by AI companies isn't something everyone can understand—it involves professional matters that need someone to teach, using more accessible language." B11 suggested: "Some teachers also use AI to find research topics, write articles, or polish their writing. If we have teachers who are skilled in these areas, could they give us a sharing session when we're writing our own papers?"

The nature of preferred guidance differed according to academic level. Undergraduate students expressed a preference for fundamental operational instruction. Participant B5 articulated: "Simply explain how to use it, but do not require me to understand its underlying logic, as it is unnecessary." Similarly, participant B2 remarked: "I am primarily interested in learning how to use it effectively for my coursework; the technical details are not pertinent to me." Participant B7 further added: "If training is provided, I would prefer it to be practical, with examples demonstrating how to utilize AI for various types of assignments."

Master's and doctoral students expressed a preference for guidance on algorithmic logic, academic applications of AI, and usage standards to enhance their research endeavors. Participant M12 elaborated: "Primarily in the academic context, I require assistance in utilizing AI to refine research concepts, generate analytical results, and inspire writing for discussion sections. This is my most pressing need at this stage. Additionally, I seek support in data analysis, as my statistical skills are not strong, leading to considerable time spent on interpreting results." Participant P2 articulated a desire for instruction from educators on the correct use of AI to prevent issues related to academic integrity, emphasizing the need for clear delineation of boundaries by instructors. Similarly, Participant P6 highlighted the necessity for guidance on distinguishing acceptable use in academic writing from actions that constitute academic misconduct.

### **2.3.2 Institutional Training Needs**

Students across all levels held positive attitudes toward AI development and believed AI literacy should become an essential competency for every health professions student. They viewed systematic institutional training as indispensable. P9 stated: "AI will likely become more common in our lives. If we incorporate it into the educational system, it will make knowledge acquisition more convenient for students and make us more competitive after graduation."

Training content preferences differed by level. Undergraduates focused on prompt language instruction. B7 explained: "If the school is going to introduce AI tools, I think it should briefly introduce how to use them—no need for deep digging." B16 added: "I'd like a session on how to write good prompts to get accurate answers, especially for medical topics."

Master's students placed a significant emphasis on the integration of AI applications within academic writing and research. Participant M14 articulated the following: "For medical students across all levels—undergraduate, master's, or doctoral—the primary demand is likely centered on acquiring skills related to article composition, including literature searching, proposal writing, and editing. Additionally, the ability to summarize national policies and identify grant opportunities is crucial, and educational institutions should prioritize these areas in their curricula." Furthermore, participant M2 emphasized the necessity for training that focuses specifically on the application of AI in research contexts, rather than on general usage.

Doctoral students stressed the importance of usage standards and research integrity. P6 cautioned that maintaining research integrity is crucial, as some students either avoid AI or overly rely on it, leading to unreliable results. P1 reflected the broader concern, stating that if courses are introduced, they should teach students to view AI as a helpful but double-edged tool, emphasizing the need for independent judgment and thought.

### **3 Discussion**

This qualitative study explored how GAI affects academic competency development in nursing and medical students at undergraduate, master's, and doctoral levels, identifying their educational support needs. Key findings include: (1) GAI's varying roles across academic levels, explained by the Technology Acceptance Model; (2) hierarchical differences in GAI's impact on competencies, showing a shift from dependence to reflective use; and (3) the pressing need for tiered AI literacy education. These findings are discussed in the context of recent studies, with a focus on nursing education due to the consistent inclusion of nursing students at all levels in the sample.

#### **3.1 Extending TAM: A Three-Stage Model of GAI Adoption in Health Professions Education**

Our study indicates that the functional positioning of health professions students regarding GAI exhibits notable hierarchical characteristics, aligning with the theoretical framework of TAM<sup>[16]</sup>. According to the TAM, technology adoption is chiefly governed by two pivotal perceptions, namely PU and PEOU, which jointly influence user attitudes and behavioral intentions. Nevertheless, our empirical data indicate that this bifactorial structure may not adequately delineate the comprehensive developmental dynamics of GAI adoption within educational settings. In response to these findings, we advocate for a theoretical augmentation of TAM, formalized as a Three-Stage Model of Technology Adoption in Education. This

proposed framework is specifically designed to accommodate the progressive evolution of student engagement with GAI tools.

**Stage 1: PEOU-Driven Adoption (Undergraduate Level).** Undergraduate students in our study predominantly employed GAI in non-academic contexts, including daily learning and routine assistance, with a primary emphasis on its capacity to deliver rapid responses and resolve queries. This usage pattern corresponds to what we designate as the PEOU-dominant stage of technology adoption<sup>[16, 17]</sup>, in which initial motivation for use arises chiefly from operational ease rather than from a substantive recognition of instrumental value. Given their limited research exposure and a central focus on foundational knowledge acquisition, undergraduates have not yet developed the cognitive frameworks required to fully appreciate GAI's utility for more advanced academic endeavors. This finding is consistent with Mondal et al.'s qualitative study of Indian medical students, which reported that undergraduates primarily utilized large language models for "clarifying complex topics, solving multiple-choice questions, and streamlining assignments"<sup>[18, 19]</sup>. Likewise, a qualitative investigation into Saudi medical students' earliest experiences with ChatGPT revealed that initial usage was marked by exploratory and convenience-oriented behaviors, as opposed to strategic academic integration<sup>[20]</sup>.

**Stage 2: PU-Driven Adoption (Master's Level).** Master's students, in contrast, exhibited usage patterns predominantly driven by PU, applying GAI to sophisticated academic endeavors such as paper writing, research design, literature synthesis, and data analysis. This usage pattern corresponds to the advanced-stage adoption trajectory predicted by TAM, wherein users have acquired sufficient competence to recognize and capitalize on the technology's instrumental value for performance enhancement<sup>[21]</sup>. The extent to which GAI is integrated into academic contexts appears to be linked to both the complexity of the tasks at hand and the depth of students' prior research experience. This association is consistent with the findings of a grounded theory study examining Chinese medical postgraduates' intentions regarding AIGC usage<sup>[22]</sup>.

**Stage 3: Critical-Reflective Adoption (Doctoral Level).** Notably, doctoral students in our study exhibited a further developmental stage beyond PU-dominance: they engaged in critical reflection on GAI's limitations and ethical implications, advocating for academic self-discipline and appropriate boundaries. This transition from what TAM would characterize as a "tool user" to a "tool critic" represents a stage not captured by TAM's original formulation. This finding suggests that TAM may benefit from extension to account for reflective technology appraisal, wherein experienced users develop metacognitive awareness of technology's limitations and exercise deliberate restraint.

This hierarchical differentiation, which ranges from convenience-driven adoption to strategic integration and finally to critical reflection, provides a framework for understanding why previous studies have yielded mixed findings regarding GAI's educational impact. The effect of GAI is not monolithic but varies systematically with educational level<sup>[16]</sup>. Multiple studies in postgraduate health professions education have consistently confirmed that artificial intelligence is now an irreversible reality, and that pedagogical frameworks which neglect its integration ultimately place learners at a disadvantage<sup>[23, 24]</sup>. Our findings

provide empirical grounding for this assertion by documenting the concrete ways in which master's and doctoral students benefit from GAI in research activities, and they also demonstrate that "embracing" requires nuanced, stage-appropriate guidance rather than uncritical adoption. Our study extends their work by specifying what "embracing" should look like at different educational levels.

This three-stage model carries substantial implications for both theory and practice. From a theoretical perspective, it expands TAM by integrating a developmental dimension that captures users' progressively changing relationship with technology as their domain expertise and critical awareness evolve. On the practical front, the model implies that educational interventions should be tailored to distinct stages of learner progression. Undergraduate curricula ought to concentrate on cultivating foundational awareness and basic operational skills. Master's programs should prioritize the strategic incorporation of GAI into research workflows. Doctoral education, in turn, needs to foster critical appraisal abilities and ethical governance competencies.

## **3.2 Hierarchical Differences in Academic Competency Impacts: Mechanisms and Paradoxes**

Our findings reveal that GAI's impact on academic competencies varies significantly by academic level, following a developmental trajectory from dependence to collaboration to reflective use. However, a nuanced examination reveals important mechanisms and paradoxes that complicate this trajectory.

Our data reveal a counterintuitive finding that constitutes the critical thinking paradox. While GAI use was associated with enhanced critical thinking among students who actively verified and critiqued outputs, it was simultaneously associated with shallow learning and cognitive inertia among those who passively accepted AI answers. This paradox can be illuminated by the concept of cognitive offloading, which refers to the tendency to rely on external tools to reduce cognitive load<sup>[25]</sup>. Students who employed GAI as a cognitive prosthesis, such as B15's remark that "once there's a ready-made answer, who wants to delve deeper?", exhibited diminished engagement with learning material. In contrast, those who utilized it as a cognitive scaffold through active verification and critique developed enhanced analytical skills.

This finding offers a mechanism-level explanation for the negative correlation between critical thinking and generative AI dependency that has been documented in previous studies<sup>[26]</sup>. Our qualitative data suggest that dependency is not an inevitable consequence of GAI use but is mediated by usage strategies: passive acceptance of GAI outputs engenders dependence and shallow learning, while active verification and critique foster critical thinking development. Critically, our findings reveal that the negative correlation between dependency and critical thinking may be explained by the predominance of passive usage strategies among certain students, with doctoral students demonstrating the lowest dependency and highest critical engagement, suggesting that research training may foster more sophisticated GAI usage strategies.

This insight has important implications for educational practice: interventions should focus not on prohibiting GAI use but on cultivating strategies for critical engagement. A recent study on the impact of

AIGC on medical students' critical thinking similarly found that the relationship is complex and mediated by multiple factors, including usage patterns, task characteristics, and individual differences<sup>[8]</sup>. Our findings contribute to this understanding by identifying academic level as a key moderating factor and by specifying the differential mechanisms through which GAI affects critical thinking across stages.

Regarding the clinical skills gap, students across all levels consistently reported that GAI had minimal impact on clinical skills, a finding that underscores the irreplaceable role of experiential learning in clinical education. This aligns with the broader literature on AI in medical education, which suggests that while AI can enhance knowledge acquisition and clinical reasoning in simulated settings, it cannot substitute for the hands-on experience and embodied learning essential for clinical competence<sup>[27]</sup>. This finding has important curricular implications: as GAI becomes increasingly integrated into health professions education, educators must ensure that clinical skills training remains experiential and patient-centered, resisting the temptation to replace clinical encounters with AI-mediated learning.

The research competence hierarchy: Our finding that research competence enhancement was primarily observed among postgraduate students reflects the hierarchical structure of health professions education, where research skills are systematically developed at the graduate level. This finding aligns with the notion of AI serving as a "second supervisor" in research training—one that can inspire research ideas and refine writing logic<sup>[28]</sup>. Evidence demonstrates that performance expectancy, defined as the conviction that AIGC tools improve research output, is the foremost antecedent of usage intention, and that its influence operates through the mediating pathways of task-related and technology-related factors<sup>[29]</sup>. Our findings extend this by showing that master's students not only perceive GAI's utility but actively develop sophisticated strategies for prompt engineering and output verification.

### **3.3 The Dark Side of the Double-Edged Sword: Cognitive Offloading and Educational Risks**

While our findings confirm GAI's benefits for knowledge acquisition and research efficiency, they also illuminate the darker dimensions of the "double-edged sword" metaphor that require deeper theoretical and practical attention.

**Cognitive Offloading and Diminished Learning.** The concept of cognitive offloading, defined as the tendency to use external tools to reduce cognitive effort, provides a relevant framework for understanding the paradoxical effect reported by several participants<sup>[30]</sup>. When students employ GAI to circumvent the cognitive processes involved in information retrieval, synthesis, and critical evaluation, they may achieve short-term efficiency gains at the expense of long-term learning outcomes. This observation aligns with research on the "generation effect" within cognitive psychology, which indicates that actively generating information, as opposed to passively receiving it, enhances memory retention and comprehension<sup>[31]</sup>. Our finding that undergraduates who passively accepted AI answers exhibited shallow learning suggests that GAI may inadvertently undermine the very learning processes it purports to enhance.

Knowledge atrophy and skill erosion. Beyond immediate learning outcomes, there is growing concern regarding longer-term knowledge atrophy. Several participants observed that using GAI diminished their engagement with foundational knowledge acquisition, which may consequently impair the development of core competencies. This concern is consistent with research on "digital amnesia" or the "Google effect", referring to the tendency to forget information that is readily accessible through external sources<sup>[32]</sup>. Furthermore, this observation corroborates the well-recognized dual-edged role of AI in education and simultaneously echoes the widespread apprehensions about "digital dependency" that pervade digitally mediated learning environments, as extensively discussed in the literature<sup>[33]</sup>.

A more subtle yet potentially profound risk concerns the homogenization of thinking and innovation. When students rely on GAI for idea generation, research design, and writing, they may produce more standardized outputs that reflect the "average" of available knowledge rather than generating novel insights. This concern was articulated by doctoral students, who emphasized the importance of independent thinking and preserving one's "individual consciousness." As P1 stated, "Don't let AI control your thinking. Be a new generation of youth with individual consciousness and independent thought." This concern echoes broader critiques that AI-mediated learning may undermine the development of creative and critical thinking skills essential for scientific innovation<sup>[34]</sup>. Additionally, our findings suggest that GAI dependence may diminish students' confidence in their own cognitive abilities, a finding consistent with research on learned helplessness and self-efficacy in technology-mediated learning environments<sup>[25]</sup>. For health professions students, who will ultimately be responsible for independent clinical and research decisions, the erosion of self-efficacy through technology dependence represents a serious concern.

### **3.4 Educational Support Needs and Tiered AI Literacy Education: Implications for Medical Curricula**

Our findings revealed a substantial demand for AI educational support across all academic levels, with distinct content preferences that varied according to students' stage of study. This hierarchical pattern of needs is consistent with a three-tiered AI literacy framework recently proposed for health professions education, which encompasses foundational knowledge, applied judgment, and data governance<sup>[35]</sup>. It also resonates with the Medical AI Competency Framework, developed by integrating UNESCO's AI framework with Miller's pyramid, which distinguishes among knowing, knowing how, and showing how in the context of AI competence development<sup>[36]</sup>.

**Undergraduate needs: Foundational AI literacy.** Undergraduates in our study expressed a preference for basic operational guidance and task-specific support, corresponding to what the AI Literacy framework designates as the foundational level<sup>[37]</sup>. Their primary interest lay in understanding "how to use" GAI, rather than in comprehending algorithmic logic or ethical complexities. For medical undergraduate curricula, this implies that AI literacy should be integrated into foundational courses such as Medical Informatics or Evidence-Based Practice. Specific learning objectives should include: (a) basic prompt engineering for effective GAI use in medical knowledge retrieval; (b) information verification skills to

evaluate GAI outputs against established clinical guidelines; (c) awareness of GAI's limitations and appropriate use cases in medical coursework; and (d) fundamental academic integrity principles related to GAI use in medical assignments.

Master's students sought training in research design, academic writing, and data analysis applications, corresponding to the applied judgment dimension of AI literacy<sup>[38]</sup>. Their needs reflect the research-intensive nature of master's education. Given that the majority of master's participants in our study were medical students, our findings are particularly pertinent to medical master's education. This suggests that AI training at this level should be embedded in medical research methodology courses, with emphasis on: (a) using GAI for medical literature review and systematic review methodologies; (b) incorporating GAI into research design and methodology selection for medical studies; (c) using GAI for data analysis and interpretation in medical research; (d) defining appropriate boundaries for GAI use in academic writing and research proposals; and (e) developing prompt engineering strategies tailored to medical research tasks.

Doctoral needs: Doctoral students emphasized ethics, data security, and research integrity, reflecting the governance and critical evaluation dimensions of AI literacy. For doctoral medical education, this suggests that curricula should prepare students for leadership in AI governance, including: (a) critical appraisal of AI-generated knowledge from an epistemological standpoint, questioning not only accuracy but also the validity and applicability of AI-generated evidence for medical practice; (b) understanding of AI's limitations and biases in the context of medical and healthcare research; (c) application of ethical frameworks for responsible GAI use in medical research and practice; (d) engagement with institutional governance mechanisms for GAI use in medical education; and (e) leadership in developing AI usage standards in medical practice and research.

Governance and educator roles. Beyond student-level adaptations, our findings have implications for educational governance and faculty development. The widespread adoption of GAI is reshaping teaching and research functions in health professions education. Faculty members must transition from knowledge transmitters to learning facilitators and AI literacy mentors, a transformation that requires both pedagogical retraining and institutional support<sup>[24]</sup>. Our study extends prior observations that AI serves as an "external catalyst" for assessment reform, by demonstrating that students actively seek faculty guidance on appropriate AI use. This finding suggests that faculty AI literacy is not merely a matter of professional development, but a prerequisite for aligning with student expectations<sup>[39]</sup>. Institutional governance mechanisms are equally critical. As our doctoral participants emphasized, clear policies on AI usage boundaries in academic writing, research assistance, and coursework are essential to prevent academic misconduct while enabling productive use. This aligns with previous recommendations that medical education should strategically reposition generative AI as a "cognitive scaffold" through the implementation of standardised usage guidelines<sup>[32]</sup>. Institutions should develop comprehensive AI governance frameworks that specify permissible uses, attribution requirements, and consequences of misuse, while concurrently providing the training and support necessary for responsible implementation.

The urgency of tiered AI literacy education is underscored by recent policy developments. The American Medical Association has adopted policy to advance AI literacy in medical education<sup>[40]</sup>, and China's "New Medical Education" initiative explicitly calls for standardized AI literacy frameworks for medical students<sup>[41]</sup>. Our findings provide empirical evidence to inform these efforts by specifying what each academic level requires, with particular relevance for nursing education where the evidence base for tiered GAI training has been especially limited.

### 3.5 Limitations

This study has several limitations. The master's level sample was mostly nursing students, with 11 out of 16 participants, and only five clinical medicine students. This imbalance limits the generalizability of our findings to clinical medicine students, who may have different research training and GAI usage patterns due to their dual focus on clinical training and research. The master's level findings mainly reflect nursing students' experiences, so caution is needed when generalizing to clinical medicine or other health professions. The strong presence of nursing students, especially at the master's level, makes the study highly relevant to nursing education and supports the need for AI literacy interventions in nursing curricula. Future research should include more balanced samples across different health professions at the master's level to see if these patterns hold true in other fields. Data collection was confined to one medical university in western China, limiting the findings' transferability due to regional differences in AI infrastructure, institutional policies, and student digital literacy. The use of self-reported data may introduce biases like social desirability and recall biases. The study's cross-sectional design captures perceptions at one point in time, highlighting the need for longitudinal studies to track changes in GAI usage and its effects over students' academic careers. Lastly, while our sample size achieved qualitative saturation, it might not reflect the full range of experiences across all health profession specialties.

## 4 Conclusion

This qualitative study reveals a hierarchical use of generative AI in medical and nursing education: undergraduates use it for efficiency in learning, master's students for research support, and doctoral students for critique and ethical reflection. We introduce a Three-Stage Model of Technology Adoption in Education, expanding the TAM to reflect this progression. While AI enhances critical thinking and research, it risks cognitive offloading, reduced self-efficacy, and weakened clinical skills. Concerns about academic integrity and the impact on deep learning persist. Educational support needs differ by level, with a strong demand for teacher guidance and institutional training across all stages.

Nursing and medical educators should create tiered AI literacy programs tailored to students' educational levels: undergraduates should learn basic AI awareness and information verification, master's students should focus on research methods and AI ethics, and doctoral candidates should develop skills in critical evaluation and AI governance. Institutions need to set clear AI usage guidelines and help faculty shift from traditional teaching to AI literacy mentorship. Future research should assess AI literacy education standards and intervention models for safe and effective AI integration in nursing

and medical training. Longitudinal studies are essential to monitor GAI usage patterns, their impact on competency development, and to validate the proposed Three-Stage Model of Technology Adoption in Education.

## Declarations

### Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Consent for publication

Not applicable.

### Competing interests

The authors declare no competing interests.

## Clinical trial number

Not applicable.

### Ethics declarations

This study was approved by the Ethics Review Committee of Guizhou Medical University (Approval No. 2026 – 201). All study participation was completely voluntary, and all data were collected anonymously. Written informed consent was obtained from all participants prior to their enrollment in the study. The entire research procedure was performed in strict accordance with the principles of the Declaration of Helsinki.

## User Involvement

Student participants were recruited for participation in the present study. Each participant completed paper-based evaluation questionnaires and attended one-on-one in-person interviews to provide authentic and first-hand research data.

## CRedit Authorship Contribution Statement

Guoxin Zhou, Bo Li and Tingmei Wen: Writing – review & editing, Writing – original draft, Validation, Project administration, Methodology, Formal analysis, Conceptualization. Li Wang and Yang Wang:

Writing – review & editing, Validation, Supervision, Formal analysis. Hongyan Wen: Validation, Methodology, Formal analysis. Ting Sun: Validation, Methodology, Formal analysis. Haitao Zhang and Xiaoxiao Li: Writing – review & editing, Validation, Methodology, Formal analysis, Conceptualization.

## Funding

This work was supported by Guizhou Provincial Health Commission Science and Technology Fund Project (Project No.: gzwkj2023-461), Guizhou Provincial Postgraduate Education Innovation Project (Project No.:2025YJSJGXX072), General Program of Guizhou Provincial Department of Science and Technology(Project No.: Qiankehe Basic MS (2026) 519), Guizhou Medical University Educational Content and Curriculum System Reform Project (Project No.: JG2025036, JG2025061) and Teaching Feedback Program of the Affiliated Hospital of Guizhou Medical University (Project No.: gyfykj-2025-z04, gyfykj-2025-y22). Additionally, the researchers' time was covered by their respective university affiliations.

## Author Contribution

Guoxin Zhou, Bo Li and Tingmei Wen: Writing – review & editing, Writing – original draft, Validation, Project administration, Methodology, Formal analysis, Conceptualization. Li Wang and Yang Wang: Writing – review & editing, Validation, Supervision, Formal analysis. Hongyan Wen: Validation, Methodology, Formal analysis. Ting Sun: Validation, Methodology, Formal analysis. Haitao Zhang and Xiaoxiao Li: Writing – review & editing, Validation, Methodology, Formal analysis, Conceptualization.

## Acknowledgement

The authors extend their sincere gratitude to all students who participated in this study for generously sharing their experiences and insights.

## Data Availability

Data are available from the corresponding author upon reasonable request.

## References

1. Durmuş Sarıkahya S, et al. The impact of ChatGPT on nursing education: A qualitative study based on the experiences of faculty members. Nurse Educ Today. 2025;152:106755.
2. Gordon M, et al. A scoping review of artificial intelligence in medical education: BEME Guide 84. Med Teach. 2024;46(4):446–70.

3. Liu X et al. *Medical Education Systems in China: Development, Status, and Evaluation*. Academic Medicine: Journal of the Association of American Medical Colleges, 2023. 98(1): pp. 43–49.
4. Adnan A, et al. Improving Acceptability of mHealth Apps-The Use of the Technology Acceptance Model to Assess the Acceptability of mHealth Apps: Systematic Review. *J Med Internet Res*. 2025;27:e66432.
5. Alturkustani S, et al. Measuring students' perceptions of virtual reality for learning anatomy using the general extended technology acceptance model for E-learning. *Anat Sci Educ*. 2025;18(6):579–95.
6. Preiksaitis C, Rose C. Opportunities, Challenges, and Future Directions of Generative Artificial Intelligence in Medical Education: Scoping Review. *JMIR Med Educ*. 2023;9:e48785.
7. Fisher J. Critical Thinking and Mental Health Nurse Education. *Int J Ment Health Nurs*. 2025;34(2):e70021.
8. Xin Y et al. AI literacy mediates AI assisted diagnosis participation and critical thinking among medical students under supervision. *NPJ Digit Med*, 2026. 9(1).
9. Maxwell SA, et al. Guiding Preclinical Medical Students in Finding, Synthesizing, and Communicating Translational Basic Research Literature: Roles for Basic Science Research Mentors. *Acad Med*. 2022;97(5):684–8.
10. Luo X, et al. Reporting guideline for the use of Generative Artificial intelligence tools in MEDical Research: the GAMER Statement. *BMJ Evid Based Med*. 2025;30(6):390–400.
11. Schwendicke F, et al. Generative AI: Opportunities, Risks, and Responsibilities for Oral Sciences. *J Dent Res*. 2025;104(13):1429–31.
12. Diallo EM et al. Healthcare providers' knowledge, perceptions and practices of malaria control strategies in the Republic of Guinea: insights from a qualitative study. *BMJ Glob Health*, 2026. 11(3).
13. Mastropolo R, et al. Patient, Caregiver, and Clinician Perspectives on Core Components of Therapeutic Alliance for Adolescents and Young Adults With Advanced Cancer: A Qualitative Study. *JAMA Netw Open*. 2023;6(8):e2328153.
14. Clarke AR, et al. Men's sexual and reproductive health in cystic fibrosis in the era of highly effective modulator therapies-A qualitative study. *J Cyst Fibros*. 2022;21(4):657–61.
15. Vignato J, et al. Computer-Assisted Qualitative Data Analysis Software, Phenomenology, and Colaizzi's Method. *West J Nurs Res*. 2022;44(12):1117–23.
16. Matthes J, et al. Predicting the Intention to Use Generative Artificial Intelligence for Health Information: Comparative Survey Study. *J Med Internet Res*. 2026;28:e75648.
17. Wang EY, et al. A technology acceptance model to predict anesthesiologists' clinical adoption of virtual reality. *J Clin Anesth*. 2024;98:111595.
18. Borowitz MJ, et al. Large Language Models Can Generate High-Quality Pathology Multiple-Choice Questions Comparable With Questions Written by a Human Expert. *Mod Pathol*. 2026;39(1):100940.

19. Jackson FI, et al. Large Language Model Clinical Vignettes and Multiple-Choice Questions for Postgraduate Medical Education. *Acad Med.* 2025;100(10):1163–6.
20. Cheng Y, Zhu L. A review of ChatGPT in medical education: exploring advantages and limitations. *Int J Surg.* 2025;111(7):4586–602.
21. Chen Y, et al. Radiology Residents' Perceptions of Artificial Intelligence: Nationwide Cross-Sectional Survey Study. *J Med Internet Res.* 2023;25:e48249.
22. Duan S, et al. Integrating AI in medical education: a comprehensive study of medical students' attitudes, concerns, and behavioral intentions. *BMC Med Educ.* 2025;25(1):599.
23. Howley LD, Whelan AJ. From the World Wide Web to AI: Why We Must Learn From Our Past to Transform the Future of Medical Education. *Acad Med.* 2025;100(9S Suppl 1):S30–3.
24. Turner L, Zhou C, Burk-Rafel J. It Takes More Than Enthusiasm: The Missing Infrastructure to Unlock AI's Potential in Medical Education. *Acad Med.* 2025;100(9S Suppl 1):S34–8.
25. Lin Z, Sohail A. Recalibrating academic expertise in the age of generative AI. *Patterns (N Y).* 2026;7(1):101473.
26. Izquierdo-Condoy JS, et al. Generative Artificial Intelligence in Medical Education: Enhancing Critical Thinking or Undermining Cognitive Autonomy? *J Med Internet Res.* 2025;27:e76340.
27. Thesen T, Park SH. A generative AI teaching assistant for personalized learning in medical education. *NPJ Digit Med.* 2025;8(1):627.
28. Wang R, Liu C, Yi F. Reconfiguring tutor-peer roles to foster critical thinking in medical PBL assisted by tutor-managed chatGPT. *Med Educ,* 2025.
29. Wang C, et al. The Influencing Factors of Medical Postgraduates' Usage Intention Toward Artificial Intelligence-Generated Content Tools in Academic Research: Qualitative Analysis. *J Med Internet Res.* 2026;28:e77928.
30. Biswas A, Venkatesaramani R. Encouraging productive struggle in the age of generative AI. *Patterns (N Y).* 2026;7(5):101540.
31. Hunt VM, et al. What the AI era doctor should know: a scoping review of proposed artificial intelligence competencies for medical education. *NPJ Digit Med;* 2026.
32. Boscardin CK, et al. ChatGPT and Generative Artificial Intelligence for Medical Education: Potential Impact and Opportunity. *Acad Med.* 2024;99(1):22–7.
33. Yang H, et al. Peer perceptions of clinicians using generative AI in medical decision-making. *NPJ Digit Med.* 2025;8(1):530.
34. Levin C, et al. Nursing judgment in the age of generative artificial intelligence: A cross-national study on clinical decision-making performance among emergency nurses. *Int J Nurs Stud.* 2025;172:105216.
35. Jiang J. Marathon Without a Finish Line: A Learner's Perspective on AI in Medical Education. *Acad Med.* 2025;100(9S Suppl 1):S43–5.
36. Schubert T, et al. AI education for clinicians. *EClinicalMedicine.* 2025;79:102968.

37. Singla R, et al. Developing a Canadian artificial intelligence medical curriculum using a Delphi study. NPJ Digit Med. 2024;7(1):323.
38. Wu Y. Future-proofing medical assessment: evaluating collaborative intelligence in the age of artificial intelligence. Acad Med. 2026;101(2):152–9.
39. Tan T, Fischer K. Innovating instructional design through generative AI prompt engineering for health professions educators. Acad Med. 2026;101(6):652–6.
40. Daram NR et al. *Can artificial intelligence improve the readability of patient education information in gynecology?* Am J Obstet Gynecol, 2025. 233(6): p. 640.e1-640.e9.
41. Wang Q et al. CPFformer: A Hierarchical-Based Graph Modeling Fusion Framework for Making the Emotional Features of Chinese Poetry Pronunciation More Controllable. IEEE Trans Neural Netw Learn Syst, 2026. Pp.