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Impact of generative artificial intelligence on healthcare education: A systematic review of learning outcomes and academic integrity

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Abstract

The recent development of Generative Artificial Intelligence (GenAI) in healthcare education has brought both great opportunities to improve the learning outcomes and pose serious concerns about the academic integrity, authenticity of the assessment, and ethical application. The purpose of conducting this systematic review was to assess the effect of GenAI technologies, such as ChatGPT and large language models, on healthcare education, in particular, learning outcomes, student engagement, clinical reasoning, and academic misconduct. The PRISMA framework was used to identify, screen, and synthesize relevant studies published in large academic databases to study the new trends in medical education, nursing education, pharmacy education, dental education, and allied health education. The results show that GenAI has affected positively personalized learning, adaptive learning, self-directed learning, and simulation-based learning offering instant feedback, intelligent tutoring systems, virtual patients, and increased support of problem-solving skills and critical thinking. Students have said that they have improved in clinical reasoning, digital literacy, AI literacy, and confidence in evidence-based decision-making. Automated content generation and formative assessment support were also helpful to faculty members in reducing the administrative workload and enhancing curriculum innovation. Nonetheless, the review also found serious issues with plagiarism, academic misconduct, excessive dependence on AI-generated content, biases, data privacy, transparency, and lower authenticity of evaluation. Conventional summative assessment practices were discovered to be more susceptible to unethical AI applications, and assessment redesign, reflective learning, oral examination, and competency-based education were demanded.

Keywords: Generative artificial intelligence, Healthcare, Federated learning, Artificial intelligence, Large language models, Natural language processing.

1. Introduction

With the advent of Generative Artificial Intelligence (GenAI), the medical education, nursing education, pharmacy education, dental education, allied health education, and the education of the health professions in general have undergone swift changes with new opportunities and challenges in medical education, nursing education, pharmacy education, dental education, allied health education, and health professions education overall. The use of technologies like ChatGPT and other large language models to assist with personalized learning, adaptive learning, intelligent tutoring systems, virtual patients, simulation-based learning, and automated feedback systems is growing [1-3]. These inventions are transforming the manner in which students learn, practice clinical reasoning, build problem solving skills, and are self-directed learners. GenAI is emerging as a significant element of curriculum innovation, digital literacy, AI literacy, and future workforce preparedness in educational institutions as they strive to equip students with the skills needed to work in an ever more digital healthcare setting. Recent findings show that GenAI tools have the potential to enhance student engagement, learning effectiveness, confidence, and educational support, especially in evidence-based practice, case-based learning, and competency-based education.

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Increased use of GenAI in healthcare education has been necessitated by the necessity to offer more flexible, scalable and individualized educational experience. ChatGPT and similar systems are becoming more and more popular among students to summarize complicated topics, create clinical scenarios, and study materials, enhance writing, and have questions answered instantly [2]. GenAI is also being used by faculty members in facilitating formative assessment, lesson planning, content generation, and student feedback. Large language models have shown to be promising in nursing education and medical education in terms of simulating patient interactions, improving reflective learning, and aiding clinical decision-making skill development. The trends that are also emerging are the development of specialized healthcare-oriented language models and timely engineering strategies for the nursing, medical and biomedical contexts. Such advances indicate that GenAI can be integrated into the educational technology ecosystem of healthcare in the years to come as an established component. Regardless of these benefits, the fast-growing GenAI has caused significant apprehension due to issues of academic integrity, plagiarism, bias, transparency, data privacy, and academic misconduct. The fact that students can create assignments, examination responses, reflective essays, and case analyses with little effort of their own is one of the biggest challenges. This has also brought up the concern that the overdependence on AI-created content can undermine critical thinking, originality, communication abilities and higher learning. There is some growing evidence to indicate that conventional forms of summative assessment are more susceptible to AI-driven cheating, particularly when it comes to online and written coursework. Institutions are thus being compelled to not only question the validity of assessment methods but also seek other options like oral tests, process based assessment, reflective learning, competency-based learning as well as authentic assessment tasks where the students are expected to show reasoning and practical knowledge and not only regurgitate information.

This issue is further exacerbated by the rate at which GenAI is being adopted in the higher education and healthcare training sectors. Recent studies suggest that an overwhelming percentage of college students currently engage in the routine use of AI tools in academic activities, and that most colleges do not have official policies, training, or models of responsible AI usage. It is feared that educational systems might not be ready to absorb the long-term consequences of the mass integration of GenAI, especially in the fields where professional competence, patient safety, and ethical responsibility are fundamental. Inaccurate or biased AI-generated information can influence the knowledge of students in the field of healthcare education in the areas of diagnosis, treatment planning, and clinical communication. Besides, the absence of transparency in AI-generated work and ambiguity about who produced it poses significant challenges to teachers trying to uphold academic standards and responsibility.

Despite the presence of research that has investigated the advantages and disadvantages of GenAI in the academic sector, the literature has a very large gap on its direct effects on areas of healthcare education, learning outcomes, and academic integrity. Numerous published research are rather general, covering higher education, without sufficient considerations of the specific needs of healthcare professions, where the formation of clinical reasoning, communication, ethical judgment, and professional competency is critical [2,4,5]. Moreover, very little evidence exists on the long-term impacts of GenAI on the performance of students, readiness of faculty, curriculum adjustment and workforce preparedness. The available literature also does not provide enough longitudinal research, randomized controlled trials, and cross-disciplinary comparison that can explain the effectiveness of GenAI in various healthcare spheres and levels of education. To address these gaps, this systematic review adopts PRISMA approach to analyze critically the effects of Generative Artificial Intelligence on healthcare education, particularly learning outcomes and academic integrity. The review will synthesize existing evidence on the educational advantages of GenAI, such as student engagement, self-directed learning, clinical reasoning, and personalized learning, and address the issue of concerns about plagiarism, academic misconduct, ethical AI and re-designing assessments. The paper can also be beneficial to the current level of research on healthcare education by highlighting the main tendencies, unanswered questions, and research gaps that researchers, educators, and policy makers should consider to implement responsible AI strategies. Another significant area of focus in the review is the necessity

of balanced human-AI cooperation, faculty preparedness, and open governance structures to make sure that GenAI promotes and does not harm the quality, authenticity, and integrity of healthcare training.

2. Methodology

This systematic review was written following the directions of the Preferred Reporting Items of the Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines to provide transparency, reproducibility, and methodological rigor in the synthesis of evidence on the effect of generative artificial intelligence on healthcare education.

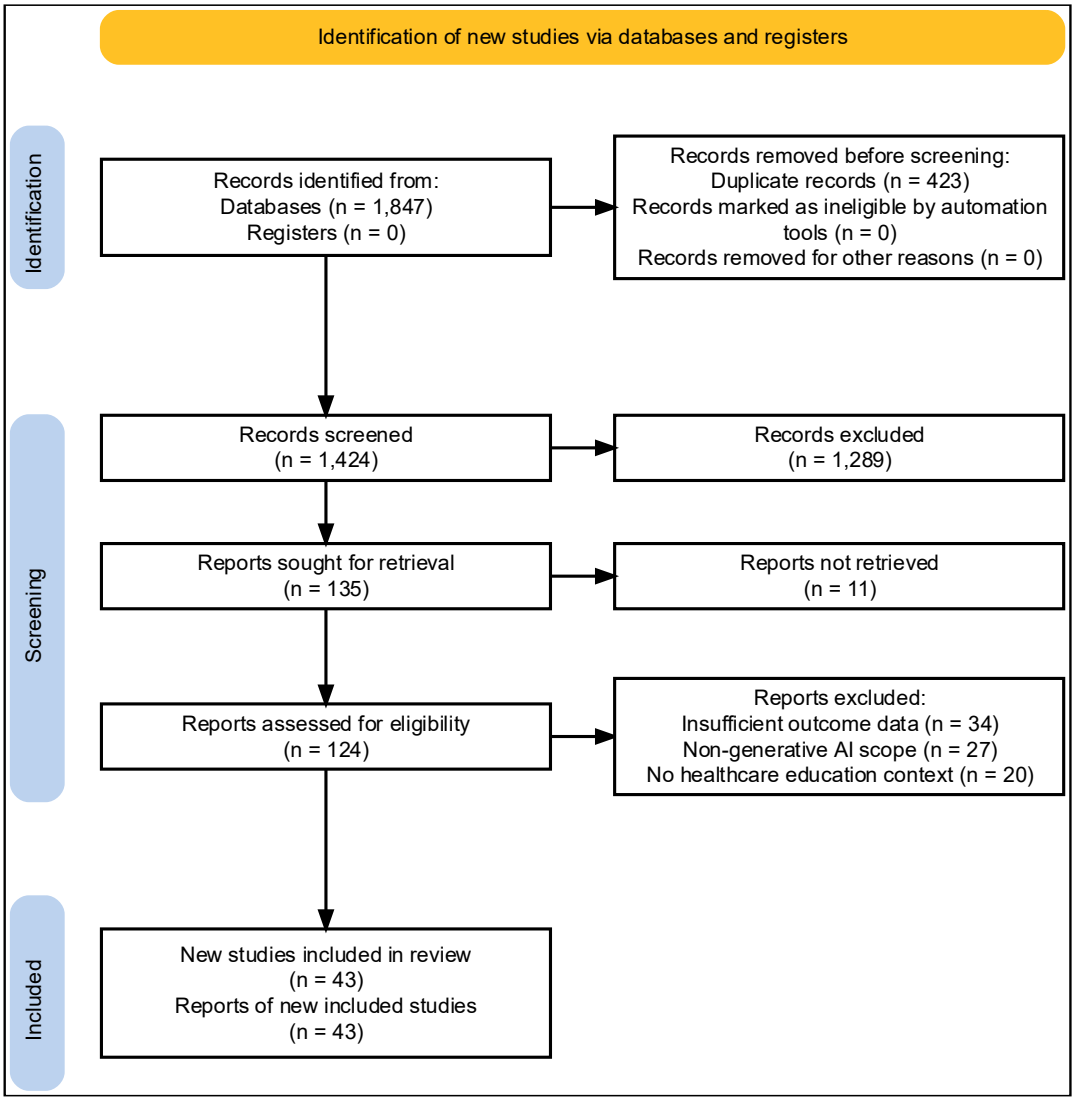

Fig. 1 PRISMA Framework

Those publications whose date of publication was between January 2019 and December 2025 have been searched in four large academic databases, including Scopus, Web of Science, IEEE Xplore, and PubMed due to the intention to implement the versions of generative AI tools into educational settings, specifically since the introduction of large language models such as GPT-3 and similar systems. The Boolean search strings employed across Scopus and Web of Science were structured as follows: ("generative artificial intelligence" OR "generative AI" OR "large language model" OR "LLM" OR "ChatGPT" OR "GPT-4" OR "Bard" OR "Gemini") AND ("healthcare education" OR "medical education" OR "nursing education" OR "clinical training" OR "health professions education") AND ("learning outcomes" OR "educational outcomes" OR "academic performance" OR "competency" OR "knowledge acquisition") AND ("academic integrity" OR "academic dishonesty" OR "plagiarism" OR "cheating" OR "assessment integrity"); a secondary string additionally incorporated ("curriculum" OR

"pedagogy" OR "instructional design" OR "student engagement" OR "faculty perception") to broaden retrieval of contextually relevant literature. Similar parallel search queries in inverted MeSH terms were used in PubMed and IEEE Xplore equivalents were searched with keywords. Inclusion criteria included: (1) had to be published in peer-reviewed or other conference proceedings that are available in English language; (2) had to explicitly address the use of generative AI tools in a healthcare or health professions education setting; (3) to report on measurable learning outcomes, student performance metrics, or evidence of academic integrity; and (4) to be of an empirical, quasi-experimental, qualitative or mixed-methods research The exclusion criteria included that studies should not be an editorial, opinion piece, or commentaries and did not focus on AI in clinical practice as an educational activity; instead, they should have only examined non-generative AI technologies; and they should not have centered on non-healthcare educational fields. The initial database search yielded a combined total of 1,847 records (Scopus = 612, Web of Science = 487, PubMed = 394, IEEE Xplore = 354), from which 423 duplicates were removed, leaving 1,424 records for title and abstract screening; of these, 1,289 were excluded based on the predefined criteria, resulting in 135 full-text reports sought for retrieval, of which 11 could not be obtained, leaving 124 reports assessed for eligibility; following full-text review, 81 were excluded due to insufficient outcome data, non-generative AI scope, or absence of a healthcare education context, yielding a final corpus of 43 studies included in the synthesis.

3. Results and discussions

3.1 Artificial intelligence techniques

Large Language Models in Healthcare Education.

The use of Large language models has become the most common technique of Generative Artificial Intelligence in healthcare education because they can be used to process, generate, summarize and explain complex biomedical information in a conversational way. ChatGPT, GPT-4, Gemini, Claude, Med-PaLM and other domain-specific large language models are increasingly finding their application in medical education, nursing education, pharmacy education, and dental education. These systems are being utilized to produce lecture notes, answer clinical questions, assist in reflective learning, produce revision material, and fake diagnostic reasoning processes. Large language models have gained significant importance in the sphere of self-directed learning since students have instant access to explanations, summaries simplified and contextual, and without having to wait to get a faculty to interfere. They also improve personalized learning and adaptive learning pathways because they allow them to modify explanations according to the level of knowledge of the students. Nevertheless, these systems have low resiliency to hallucinations, face facts, overconfidence, and bias even despite their high educational value, which raises the issue of academic integrity and patient safety in situations where learners heavily depend on AI-generated information. It is also indicated by recent evidence that domain-specific healthcare language models outperform the general-purpose models due to their being trained on biomedical terminology, clinical notes, and medical guidelines.

Natural Language Processing and Conversational AI

Most GenAI applications in healthcare education rely on natural language processing and conversational AI as their technical basis. These technologies allow chatbots, virtual assistants, and interactive tutoring systems to comprehend the human language, answer questions, and learn through dialogue [6-8]. Conversational AI is commonly applied in healthcare training to assist with question-answering, training communication skills, training in clinical documentation, and training in patient interview. Conversational AI systems are frequently employed by medical students to simulate communication with patients, develop SOAP notes, and train clinical communication situations. Simulations on dialogue are useful in nursing students as they help to learn empathy, triage communication, and methods of educating patients. With the help of natural language processing methods, the AI supports can understand responds in the form of free-text, recognize erroneous beliefs, and give elaborated explanations. The communication-intensive nature of healthcare education, which requires a significant portion of language-intensive tasks, including clinical reasoning, history-taking,

and documentation, has made conversational AI among the most cost-effective and scaled educational technologies in healthcare. Simultaneously, natural language processing engines need consistent quality management due to the possibility of unclear prompts, incomplete data and biased training data to give incorrect or inadequate results.

Prompt Engineering and Structured Prompt Design

Prompt engineering has become one of the most significant AI methods that determine the quality and reliability of the output of large language models in healthcare education. Prompt engineering is the art of creating useful instructions, context framing and role design that ensures that GenAI systems deliver useful, true in addition to instructionally useful responses. Structured prompts have been adopted in medical education, with students and faculty members progressively creating case scenarios, examination questions, reflective essays, and diagnostic explanations, all through the use of such prompts. Timely engineering is particularly useful in medical settings where incomplete, incorrect, or unsafe advice is frequently caused by ambiguous prompts. More complex prompting techniques, including chain-of-thought prompting, few-shot prompting, role prompting and scenario-based prompting, are also becoming progressively popular to enhance clinical thinking and evidence-based reactions. Faculty also start to instruct prompt engineering as a new constituent of AI literacy and digital literacy since future healthcare providers will have to understand how to communicate with AI tools productively. The increasing focus on timely engineering points at the need to switch passive consumption of AI to efficient collaboration between humans and AI, where the learning value relies not only on the complexity of AI model, but also on the form of instructions given by the user.

Retrieval-Augmented Generation for Evidence-Based Learning

A key advancement of healthcare-centric large language models has been called retrieval-augmented generation which minimizes hallucinations and enhances the factual accuracy of AI-generated text. Retrieval-augmented generation integrates a large language model with out-of-band knowledge like clinical guidelines, textbooks, journal databases, and institutional resources [9,10]. The system does not just use previously acquired knowledge and therefore generates a response by first accessing up-to-date information. Retrieval-augmented generation has proven to be highly beneficial in healthcare education, particularly in evidence-based medicine, pharmacology, nursing protocols and guideline-based decision-making. Learners are able to pose questions concerning treatment pathways, diagnoses, or management of diseases and obtain answers based on credible and up-to-date resources. This method is especially relevant in the healthcare sector as the medical information quickly evolves and aged information or distorted information can be detrimental to the learning outcomes and competence. The retrieval augmented generation is also finding more applications in the following areas; curriculum design, assessment support, and clinical simulation system due to its ability to enhance trustworthiness, transparency, and content validity. With the greater reliance of healthcare education on dynamic and evidence-based knowledge, retrieval-augmented generation probably will become a typical part of the future educational platform.

Intelligent Tutoring Systems and Adaptive Learning

The next significant AI method that informs the evolution of healthcare knowledge is the use of intelligent tutoring systems, which provide students with customized instruction depending on the performance level, learning speed, and skills gaps. These systems rely on the machine learning, learning analytics and predictive analytics to evaluate student progress and suggest personalized learning activities. Intelligent tutoring systems are popular in teaching anatomy, physiology, pharmacology, and clinical skills, as they are able to adapt to the difficulty of the content and provide instant feedback, as well as detect areas requiring remediation. The adaptive learning environments find specific use in healthcare training as students often come to the programs with varying academic backgrounds and learning requirements. Though evaluating the student feedback, patterns of engagement, and learning outcomes, intelligent tutoring systems can design specific learning environments that achieve the most efficient learning and fewer cognitive loads. This method is quite similar to competency-based education since students will have the opportunity to study at their own speed and concentrate on particular clinical competencies. Despite the benefits that adaptive learning systems have in terms of

student engagement and retention, concerns have been raised on overreliance on algorithmic suggestions and a lack of transparency when it comes to making educational choices.

Virtual Patients and Simulation-Based Learning

Indeed, virtual patients and simulation-based learning have emerged as one of the most powerful AI applications in health care education since they enable students to train their clinical reasoning and decision-making behaviors in environments where there is no risk involved. Virtual patient systems that uses large language models can model the history of the medical qualifications, the results of physical examinations, emotions, and the development of the disease [11-13]. Students are able to interview patients, pose follow-ups, order investigations and make treatment decisions with real-time feedback. Virtual patients have been actively incorporated in medical education, nursing education, and pharmacy education since they offer repeated practice with no actual contact with real patients. Such systems are especially useful in exposing the learners to rare conditions, culturally diverse cases and high-risk situations that would otherwise be uncommon on the clinical placements. Current developments in AI methods have seen virtual patients now becoming interactive, realistic, and emotionally responsive, rendering them more effective in education. Nevertheless, there is a question of whether simulated behaviors are realistic enough, whether the representation of patients populations is ethical, and that there is a risk of students becoming excessively accustomed to predetermined scenarios powered by AI instead of learning to be flexible in a real-life clinical context.

Multimodal AI and Integrated Data Learning

Multimodal AI is a relatively new approach to AI that incorporates text, images, audio, video, and structured clinical data into a single educational model. In comparison to the traditional large language models where the text is the primary element to be analyzed, multimodal AI systems may interpret radiology images, pathology slides, electrocardiograms, clinical notes, and oral conversations at the same time [2,14-17]. This feature is especially relevant in health care education since a number of types of information are rather than text-based clinical decision-making. Multimodal AI has the potential of aiding learning in anatomy with image annotation, radiology with image-text reasoning, and communication skills training with audio-based interaction with the patient. It is also able to enhance simulation-based learning through integration of verbal, visual and contextual information. The shift to multimodal artificial intelligence, as a modification of its unimodal large language server equivalents, is one of the most prominent trends in healthcare education since it is closer to the actual clinical practice. Multimodal AI is expected to play a key role in future educational systems that promote multidisciplinary learning and integrated clinical thinking in the development of holistic competence.

Machine Learning and Predictive Learning Analytics

Predictive learning analytics and machine learning are finding greater applications in healthcare education, to detect trends in performance, anticipate academic risk, and tailor educational intervention. These methods examine a great deal of data comprising attendance, test results, and online activity measures, and laboratory simulation outcomes. Predictive analytics is capable of assisting school teachers in determining those students who are likely to underperform, cannot pass their tests or need extra assistance. Machine learning models may predict clinical placement readiness, licensure exams and professional competencies in competency-based education. Curriculum redesign can also be informed through these systems, through determination of areas of content that are related to poor performance or low engagement. The role of predictive learning analytics has been especially useful in massive medical programs where it is hard to monitor all students manually. There are however some concerns on the privacy of data, bias on algorithms and stigmatization of students that are classified as high risk. The institutions should therefore make sure that predictive analytics systems are transparent, fair, and implemented in an ethical manner.

Explainable AI and Transparency in Educational Decisions

Explainable AI has been growing in importance in the field of healthcare education since it is needed by teachers and learners to comprehend how AI systems come up with recommendations, grades,

feedback, and adaptive learning decisions. The early forms of AI have been accused of being black box as people can hardly explain how certain outputs were obtained [9,18-21]. This transparency issue in healthcare training presents issues as educational decision-making can be used to determine academic advancement, competence assessment, and career readiness. Explainable AI methods will help to enhance trust by giving reason, evidence, and visual explanations of the AI-generated decisions. As an illustration, explainable learning analytics systems can display why a student was based on a struggling status, whereas explainable virtual tutors may display how they produced a specific recommendation. Explainable AI is also necessary to reduce bias since it enables institutions to distinguish the unfair patterns based on gender, ethnicity, language, or educational background. Explainability will gain greater significance in the process of fairness, accountability, and academic integrity as AI systems grow more functions in the assessment redesign and competency-based education.

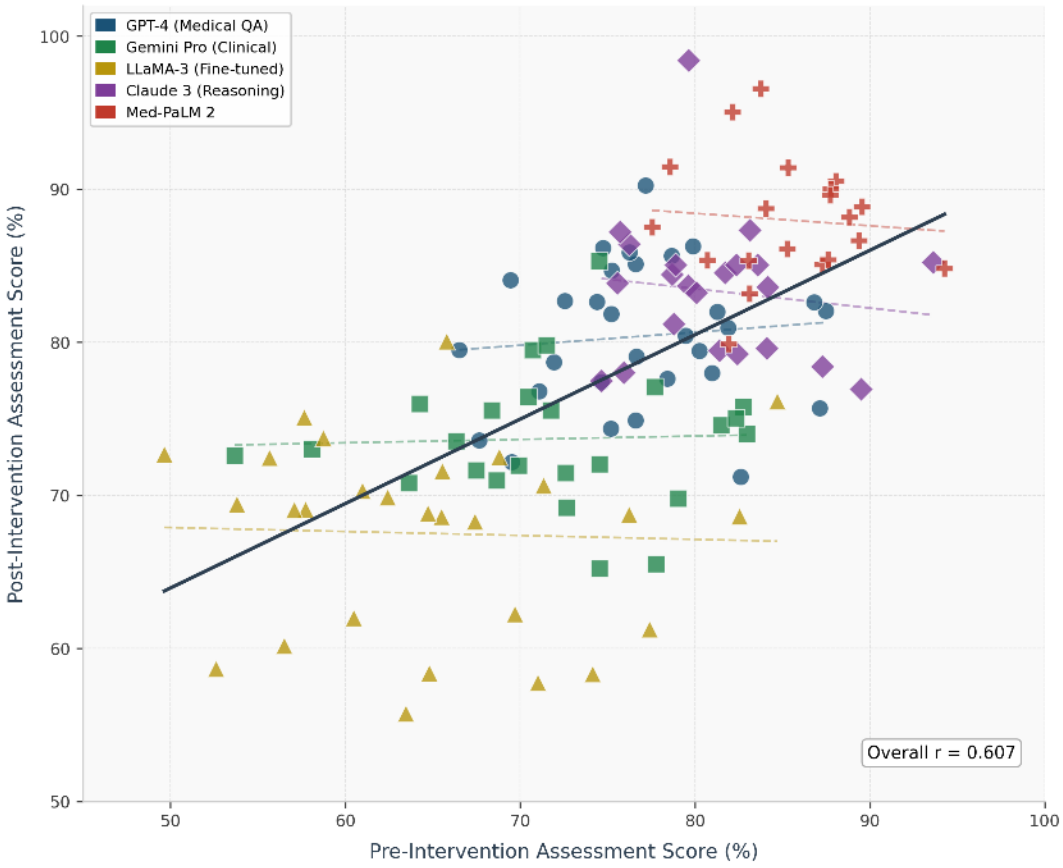

Fig. 2 Pre- vs. Post-Intervention Assessment Scores Across GenAI Models

Fig.2 explains scatter plot examines the relationship between pre-intervention and post-intervention assessment scores across five major generative AI models used in healthcare education contexts: GPT-4 (Medical QA), Gemini Pro (Clinical), LLaMA-3 Fine-tuned, Claude 3 (Reasoning), and Med-PaLM 2. Each model is represented by a distinct color and marker symbol to enable visual differentiation. Individual dashed regression lines are drawn per model group, while a single overarching regression line captures the global trend across all observations. The Pearson correlation coefficient displayed in the lower right corner confirms a strong positive association between baseline and post-test performance, indicating that GenAI-integrated instruction consistently amplifies prior knowledge regardless of entry-level competency. Med-PaLM 2 and Claude 3 cluster at the higher performance end, reflecting their superiority in domain-specific reasoning tasks, while fine-tuned open-source models such as LLaMA-3 demonstrate meaningful but comparatively modest gains. The plot underscores that the instructional scaffolding provided by large language models systematically shifts learner performance trajectories in healthcare education, with the uniformity of the trend across models suggesting robustness of the GenAI effect independent of specific architecture.

Federated Learning and Privacy-Preserving AI

Federated learning is a novel privacy preserving AI method that allows different institutions to learn on shared AI models without the need to share sensitive student or patient information with each other. This process is particularly significant in the sphere of healthcare education as educational data is frequently stipulated with confidential clinical data, examinations, and student personal data. The Federated learning model enables individual universities, hospitals, and training facilities to work together on the development of an AI model without violating any privacy laws. As an illustration, predictive learning analytics models or virtual patient systems can be built by several medical schools without transfer of raw data between the institutions. Federated learning is becoming a solution that proposes to build stronger and diverse AI systems and safeguard confidentiality. It also, however, creates new governance, transparency, interoperability, and so-called double black box problems problems with both the model architecture and distributed data sources being hard to read. Even with these drawbacks, federated learning will contribute significantly to healthcare education in the future due to the privacy and trust concerns that are central in the educational and clinical context.

Automated Feedback and Assessment Technologies

In healthcare education, automated feedback systems have become commonplace and assist in formative assessment as well as reducing workload on faculty and enhancing efficiency in learning. The AI methods can be utilized to respond to written work, clinical reflections, quiz answers and communication practices in real-time [22,23]. Automated feedback will enable the students to realize that something is wrong and review their work before submission. AI-based assessment systems are being employed more in the healthcare programs to evaluate SOAP notes, reflective journals, patient counseling programs, and clinical case analysis. Oral communication, pronunciation and empathy may also be automated when working with patients using some systems. Despite the fact that automated feedback technologies enhance the notion of scalability and responsiveness, it also brings about concerns of fairness, accuracy in grading, as well as transparency. It is also becoming increasingly feared that students might be able to cheat through AI-based evaluation platforms or through GenAI they are able to create papers which in turn get evaluated by other AI platforms and a loop of diminished authenticity and intellectual malpractice is created. Therefore, academics are turning towards authentic assessment and reflective learning as well as oral examination by healthcare educators in order to maintain academic integrity.

Bias Mitigation and Ethical AI Techniques

The mitigation of bias has emerged as one of the essential aspects of AI development in healthcare education since biased algorithms have the potential to strengthen inequalities and generate inaccurate educational suggestions. Discrimination can be based on the biased training material, linguistic disparities, cultural thoughts, or a deficiency of particular groups in healthcare records. Biased systems of AI in healthcare training can put minority students at a disadvantage, or they do not reflect a diverse population of patients. So-called ethical AI methods aim at minimizing these threats via fairness testing, dataset audit, transparency models, and such explainable algorithms. Virtual patient systems, predictive learning analytics, and automated assessment tools need bias mitigation especially since these capabilities have the potential of affecting student performance scores and the development of clinical reasoning. It is growing in popularity among researchers that responsible AI must have diverse datasets, be designed inclusive, and keep a watch on results of discriminatory practices. With the growing reliance on AI-based decision support as healthcare education, ethical AI and methods of bias minimization will become critical in fair and equitable access to educational technology, fairness, and trust.

3.2 Artificial intelligence methods

Transformer-Based Large Language Models

General AI Generative AI as applied to healthcare education has become based on transformer-based large language models. Models like ChatGPT, GPT-4, Claude, Gemini, Med-PaLM, and domain-

specific biomedical large language models are also based on transformer architectures that process sequential text with the help of attention mechanisms, which allows them to contextualize, generalize language, and construct continuous educational discourse [24-26]. The models are being utilised in increasing medical educations, nursing educations, pharmacy educations, and dental educations since they are able to summarize lectures, explain problematic biomedical material, create examination questions, and court case discussions. Transformer-based systems have found their way into self-directed learning in particular since they enable immediate access to custom educational support and students can converse with AI systems. Transformer architecture flexibility also enables health educators to tailor learning experiences to different levels of the student, clinical scenario, and competency needs. Nevertheless, even though effective, academic integrity and safe healthcare training Claims to Transformer-based large language models are susceptible to hallucinations, overconfidence, and false content generation. Replacement of traditional rule-based educational software by transformer-driven systems is one of the greatest methodological transformations in healthcare education occurring in recent years.

Natural Language Processing and Natural Language Generation Methods

Most GenAI applications in healthcare education are based on natural language processing and natural language generation techniques owing to the fact that these tasks allow machines to understand, interpret, and produce human language. Student questions are analyzed using natural language processing methods, misconceptions are identified, responses are classified, and adaptive feedback is given, and explanatory text, patient cases, reflective prompts and clinical summaries are created using natural language generation methods. Natural language generation has taken a particularly important role in healthcare education since much of medical education requires written communication, clinical documentation, and patient-centered dialogue. AI systems have the ability to produce SOAP documents, discharge notes, patient counseling scripts, and clinical education that facilitates teaching and clinical reasoning. Key Too, educators can produce large volumes of practice questions, case situation and simulated interaction using natural language generation techniques, which are fast and efficient. Newer methodological advances are focused on context-sensitive language generation models that inject the models with domain knowledge and conversational flexibility so that healthcare students can get access to more realistic and clinically relevant learning experiences.

Prompt Engineering and Instruction-Tuning Methods

Prompt engineering has become one of the most significant approaches to enhance the quality and reliability of Generative Artificial Intelligence products with regard to healthcare education. Prompt engineering is the practice of creating guidelines to instruct large language models to provide more accurate, relevant, and learning the prompts [27,28]. Instruction-tuning The form of training related to investigation of models responsive to prompts, defined by context, format, learning goals, or roles. Virtual patient simulations, treatment planning, diagnostic simulation, and evidence-based learning are now being applied in medical education and nursing education, often based on prompt engineering techniques. Chain-of-thought prompting, role prompting, few-shot learning, and scenario-based prompting are especially notable due to their ability to use large language models to produce step-by-step clinical reasoning as opposed to naive responses. Timely engineering is also a crucial factor in minimizing hallucinations and enhancing accuracy of AI-based educational material. Prompt engineering is becoming a constituent of AI literacy and digital literacy as students of healthcare make use of systems like ChatGPT in their education. Schools are thus starting to inculcate prompt engineering as both a technical and professional ability that is highly required in the workforce in future.

Retrieval-Augmented Generation Methods

One of the most promising ways towards enhancing factual accuracy of large language models in healthcare education has become retrieval-augmented generation. This approach uses generative models in conjunction with searches in external information sources like textbooks, clinical guidelines, databases, journal articles and institutional repositories to generate a response. Generation with retrieval augmentation finally needs especially close attention in healthcare since medical knowledge is rapidly changing, and aging or fake information can harm the results of learning and professional proficiency.

Using external evidence as the basis of outputs, retrieval-augmented generation minimizes hallucinations, boosts clarity, and increases the credibility of AI-generated educational content. Retrieval-augmented generation techniques have clearly become popular in evidence-based medicine, education on pharmacology, and educational systems to understand clinical guidelines as well as answering questions in healthcare education. Students are able to ask questions regarding diseases, medications, or treatment protocols and get answers that are connected with up to date resources of knowledge. This approach is particularly applicable to clinical reasoning, in which students must justify their choice by using evidence instead of mere memorized content. The increased significance of retrieval-augmented generation is indicative of a larger direction towards trustworthy and explicable AI in healthcare education.

Multimodal AI and Cross-Modal Learning Methods

The importance of multimodal AI approaches in healthcare education is growing due to the combination of various types of data (text, medical imagery, physiological indicators, videos, and formal patient records) it involves. In contrast to more traditional large language models, which are primarily text-based and give less attention to visual data, multimodal AI systems are able to learn through images of radiology, clinical notes, expert pathology, and video films and communication evaluation [19,29-31]. The cross-modal learning techniques enable AI programs to recognize the inter-correlations between the various categories of information and present more authentic education experiences. Multimodal AI can facilitate radiology interpretation, anatomy education, pathology education, and surgical simulation in contexts of medical education, involving the incorporation of visual and textual information in the same learning environment. Multimodal methods in nursing education can combine patient monitoring data, communication situation, and electronic health records to form more detailed training experiences. The shift of text-based AI to multimodal AI is a notable methodological direction as the problem of healthcare in the real world is hardly based on one type of data. Rather, clinicians are expected to process multiple information streams at the same time, and multimodal AI approaches are being progressively developed to reflect this multifacetedness in the educational contexts.

Conversational AI and Dialogue-Based Learning Methods

The conversational AI approach finds extensive application in healthcare education as it enables students to experience dialogue-based learning activities that can be used to simulate real-world communication. There are natural language processing, large language models, and dialogue management systems in which AI tools react flexibly to questions posed by students and keep an interactive dialogue [32,33]. Conversational AI comes in handy especially in healthcare training as most clinical competencies require communication, empathy, patient interviewing and interpersonal skills. History-taking, patient counseling, and diagnostic dialogues can be trained among medical students, whereas patient education, triage communication, and emotional support can be trained among nursing students through conversations with AI. The learning processes that involve dialogue techniques are also effective in encouraging self-directed learning since students can put follow-up questions, find other possible scenarios and have immediate clarification. Current trends in conversational AI are more concerned with augmenting contextual memory, responsiveness to emotion and realism to the extent that interactions have a more realistic simulation of patient encounters. Nevertheless, it is feared by some that students using AI-generated conversations will become excessively reliant on them, and fail to acquire interpersonal skills necessary in actual healthcare settings.

Intelligent Tutoring Systems and Adaptive Learning Methods

Adaptive learning systems and intelligent tutoring systems are finding more applications in the healthcare educational field to tailor the learning process and enhance student engagement. In these approaches, machine learning, predictive analytics, and learning analytics are used to track and evaluate the performance of students, detect areas of weakness, and suggest personalized learning paths. IT Systems can evaluate the performance of the students on quizzes, simulations and assignments and adjust the level of difficulty, pace and content to suit them. These systems are particularly applied in healthcare education, specifically in anatomy, pharmacology, physiology, and clinical reasoning since students can pay more attention to the fields where they need more support. The competency-based

education is also closely related to adaptive learning methods since it focuses more on skills of particular mastery as opposed to consistent advancement through a curriculum. The intelligent tutoring systems can maintain positive learning results and prevent frustration by delivering faster feedback and tailored suggestions to students. However, the fact that very customized systems can diminish the possibilities of collaborative learning or bring excessive dependence on algorithmic suggestions is of concern. Institutions must therefore strike a balance between adaptive learning and peer interaction, faculty guidance and reflective learning activities.

Predictive Analytics and Learning Analytics Methods

Other areas of healthcare education are witnessing the increasing significance of predictive analytics and learning analytics approaches since these methods enable education practitioners to identify vulnerable students, forecast academic achievements, and implement specific interventions. These techniques apply statistical modeling, machine learning, and education data mining to the features of attendance, online interactions, examination grades, simulation performance, and assignments accomplishment [34-36]. Predictive analytics can also assist teachers to find students who might have a hard time on clinical placements, not pass licensure tests, or need more time in particular subjects. It is also possible to identify trends in student activity and curriculum efficacy using learning analytics techniques, and the results can be used to make evidence-based redesigns to courses. The usage of predictive models in competency-based education pertains to the increasing reliance on predictive models to estimate the readiness to clinical practice and even professional certification. Even though predictive analytics have the potential to enhance efficiency and student support, transparency, fairness, and data privacy are questionable. Students might not be happy with being tracked all the time and untrue forecasts will be stigmatising to the learners termed as academically vulnerable. Predictive analytics application on ethics should consequently involve explainability, accountability, and reasonable protection.

Explainable AI and Transparency Methods

Explainable AI techniques are gaining more relevance in the healthcare learning sector since students, teachers, and institutions must know how AI systems produce their recommendations, appraisals, and educational determinations. Most AI systems are black boxes and therefore it is not easy to ascertain why a given output was produced or why specific students were found to be high risk. Explainable AI is an approach, aimed to resolve this problem by delivering explainable outputs, visualizations, evidence trails, and reasoning paths, to help explain how AI-rendered conclusions can be generated. Explainable AI has been a significant issue in healthcare education since learners need to know the logic underpinning clinical choices and not just accept automated advice. Elucidative procedures also assist educators to detect bias and certify algorithmic choices besides making certain that AI generated ratings are fair and transparent. The increased importance of explainable AI is indicative of a greater issue of trust in educational technology. In the absence of transparency, students can either over-trust AI systems or not use them at all, diminishing their learning utility. Explainability thus becomes an essential factor to responsible GenAI integration into healthcare training.

Federated Learning and Privacy-Preserving Methods

In healthcare education, federated learning has become a significant alteration as a privacy-preserving practice as it enables institutions to learn to use AI models without common data access. This approach will allow several universities, hospitals, and educational entities to help in developing common AI systems and yet keep sensitive student data, clinical data and patient data under control [37-40]. Federated learning is especially applicable to the healthcare context since privacy, confidentiality, and compliance with regulations are crucial factors. Federated learning systems can enhance diversity of models, decrease bias and escalate their applicability to varied groups and learning systems by enabling models to learn based on decentralized information sets. It is also possible to create powerful predictive analytics tools, smart tutoring systems, and virtual patient simulation with federated learning without undermining data privacy. These approaches are, however, still too technical, and need powerful governance frameworks, in order to guarantee interoperability, transparency and security. In spite of

these issues, federated learning will probably gain even greater significance as healthcare education institutions will find the way to strike the balance between innovation and privacy protection.

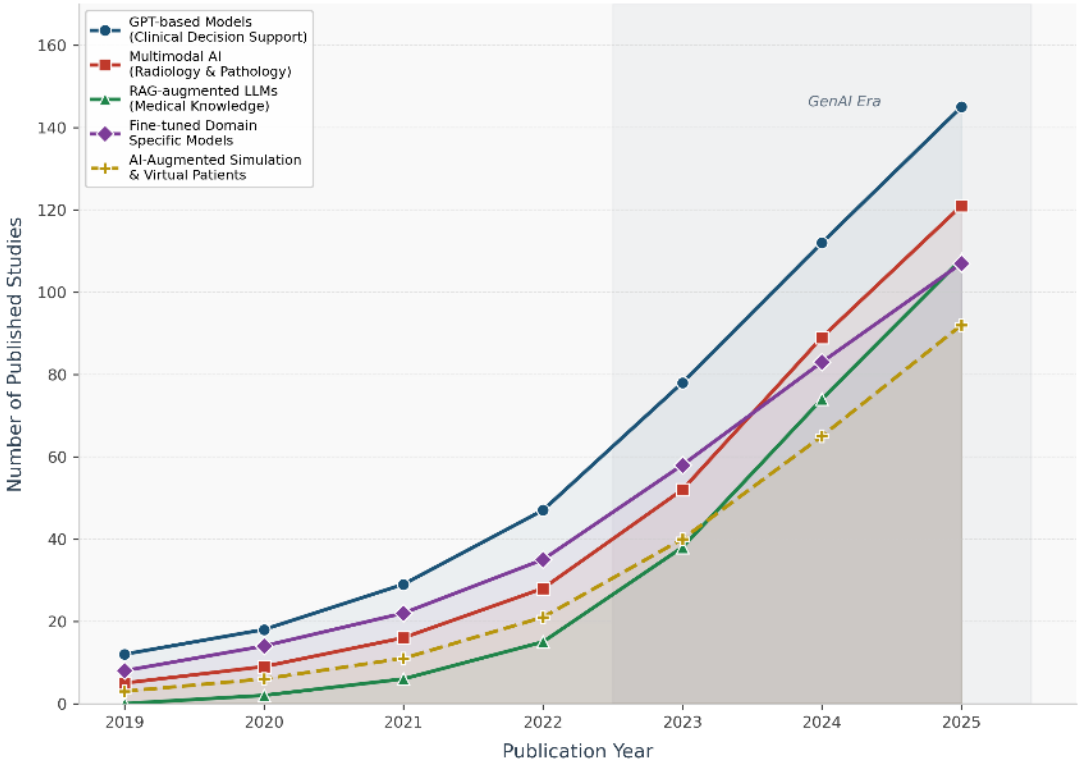

Fig. 3 Temporal Growth Trends of GenAI Techniques in Healthcare Education Research (2019-2025)

Fig. 3 Shows line plot traces the longitudinal evolution of five major GenAI technique categories in healthcare education research publications from 2019 through 2025. The categories represented include GPT-based models for clinical decision support, multimodal AI for radiology and pathology education, retrieval-augmented generation (RAG) augmented large language models, fine-tuned domain-specific models, and AI-augmented simulation and virtual patient systems. A shaded vertical band highlights the post-2022 generative AI acceleration era, which coincides with the public release of instruction-following foundation models. The steep upward trajectories observed from 2023 onward across all technique categories reflect a paradigm shift in healthcare education research, with RAG-augmented LLMs and multimodal AI exhibiting the sharpest rates of growth given their practical relevance to clinical reasoning and imaging-based diagnostics. GPT-based models maintain the highest absolute publication count throughout the period, though the convergence of trajectories by 2025 suggests that competing architectures are rapidly closing the gap. The plot provides compelling evidence that the field is entering a phase of methodological diversification, where no single AI technique dominates and interdisciplinary integration becomes the defining research characteristic.

Automated Assessment and Feedback Methods

Automated evaluation and feedback systems are predominant in healthcare education as they offer quick evaluation of student achievement as well as lessen the faculty workload. The techniques take written assignments, quiz responses, reflective journals, SOAP notes, and clinical documentation exercises and evaluate them with the help of natural language processing, machine learning, and scoring algorithms. In healthcare programs, automated methods of feedback are particularly useful when it is necessary to have multiple practice and immediate response to enhance the ability of students to think clinically, communicate, and write good papers. Whether the AI uses speech analysis and sentiment-detection, some of these systems can also analyze oral communication, empathy, and patient counseling performance. Nonetheless, automated grading systems also bring up the issue of equity, grading

consistency, and student cheating. GenAI tools can be used to create the assignments and automatically evaluated by other AI systems, lowering the authenticity of learning and establishing a process of automated creation and analysis. These issues have aroused more interest in redesign strategies of assessment that are more focused on oral testing, reflective education and real clinical activities. To an extent, universities are becoming aware that their previous methods of detecting plagiarism can no longer be deemed adequate in the age of Generative Artificial Intelligence and that they need more holistic approaches to academic integrity.

AI Detection, Plagiarism Detection, and Academic Integrity Methods

AI detection and plagiarism detection procedures are gaining increased recognition since educational organizations are trying to determine the inappropriate use of Generative Artificial Intelligence in student assignments. Conventional plagiarism detection systems aimed at detecting copying material, but in cases where students apply AI-generated paraphrasing material or generate original and machine-generated content are found to be less efficient [41-43]. New AI detection Systems apply stylometric analysis, linguistic features, perplexity scores, burstiness measures, and deep learning classifiers to determine whether a piece of text has been written by a human or an artificial intelligence system. Even though these methods are promising, they have been controversial due to the possibility of false positives which unfairly implicates the students in wrongdoing especially the non-English speakers and those with their own writing styles. A significant number of studies posit that AI detection is not the best way to make the decision on academic integrity since its reliability is not always consistent. Rather than this, medical education institutions are shifting towards wider models of academic integrity that focus on transparency, AI usage disclosure, procedural evaluation, and review by humans. The tendency to change the punitive approach to detection to the more responsible policy of AI use is a methodological shift in how academic misconduct is dealt with in GenAI.

Bias Mitigation and Ethical AI Methods

The application of bias mitigation and ethical AI approaches are vital to healthcare education since AI systems are able to strengthen inequalities in case they are trained on incomplete, unrepresentative, and biased data sets. Prejudice can arise when large language models represent some groups disproportionately or underrepresent minorities, or are biased in some way according to their training data. According to healthcare education, biased AI systems can disadvantage students or patients of various linguistic, ethnic, or socioeconomic backgrounds and be unable to reflect the other diverse populations of patients. The ethical AI approaches aim to deal with these issues by fairness testing, dataset auditing, algorithmic transparency, explainable AI, and inclusive model development. The bias reduction strategies prove to be particularly significant in virtual patient simulation, predictive analytics, and computer-based evaluation systems, as these tools affect the learning outcome, the formation of professional identity, and the academic upward mobility. The institutions are starting to acknowledge that there is more to responsible AI integration than just technical performance, namely fairness, inclusivity, and ethical responsibility. As the incorporation of Generative Artificial Intelligence in the healthcare educational process gains ground, patterns of bias reduction and the ethical practices of AI will also be indispensable to uphold trust, equity and academic integrity.

3.3 Artificial intelligence technologies

Large Language Models in Healthcare Education

Large language models are now the most influential technology in Generative artificial intelligence in healthcare education since they offer natural language understanding, support conversation, and content generation in numerous learning settings. Several AIs (ChatGPT, GPT-4, Gemini, Claude, Med-PaLM, and Llama) are used in medical education, nursing education, pharmacy education, dental education, and allied health education [28,44-47]. Such systems enable students to ask questions, summarize lectures, generate clinical case discussions, generate examination material and reflect on their learning. Personalized learning is specifically performed well with the large language models since they formulate responses based on user needs, level of knowledge, and educational setting. These

technologies are also applied in healthcare training to support the clinical reasoning, diagnostic thinking, and evidence-based learning, through interaction mode between the learner and complex information in a talkative way. Nevertheless, there are still apprehensions regarding hallucinations, overconfidence, incorrect outputs and overdependence on machine generated responses. Medical large language models Domain-specific medical large language models are chosen more often since they are more accurate in facts and closer to healthcare terminology and professional practice. There is also a trend in recent years of moving from general-purpose chatbots to specialized medical and health professions education large language models.

Multimodal AI Technologies

Multimodal AI technologies are among the most significant new trends in healthcare education since they combine a variety of data, including text, images, audio, video, physiological signals, alongside organized records of patients. Multimodal AI systems are capable of processing radiology scans, pathology slides, anatomy diagrams and speech recordings and applying these modalities in combination, unlike traditional text-only large language models [48,49]. This is especially useful in medical education since the process of clinical decision-making can almost always include the integration of various types of data. Radiology Multimodal AI systems are now applied in radiology interpretation, anatomy education, surgical simulation, training patient communication, and diagnostic reasoning. These systems will help students learn in situations that reflect more of the real clinical practice. Recent findings suggest that the area is shifting towards a not single-moded (unimodal) large language model to multimodal AI platforms that facilitate integrated medical imaging, health care training, and cross-modal reasoning. The shift towards multimodal AI will probably have a significant contribution to the future curriculum development, since medical students will have to process various sources of information at the same time.

Retrieval-Augmented Generation Technologies

Such technologies as retrieval-augmented generation have become a significant innovation in healthcare education since it is this type of technology that enhances the credibility and the factual accuracy of AI-generated responses. Retrieval-augmented generation is an advanced type of large language model that uses external knowledge retrieval systems to search textbooks, clinical, institutional databases, and journal repositories and then generates an answer. The technology is particularly essential in medical education since the field of medicine changes fast, and the information that is older or false may endanger both the learning and professional skills. Pharmacology education, evidence-based medicine and nursing protocols, as well as, clinical decision support training are becoming probably to use retrieval-augmented generation technologies. Learners will be able to pose questions related to the disease, therapy, as well as diagnostic criteria and get answers based on the updated sources. Other emerging trends are multimodal retrieval-augmented generation systems, combining text and image retrieval to answer medical visual questions, understand radiology and teach pathology. Retrieval-enhanced generation is becoming regarded as necessary to minimize hallucinations, enhance transparency, and offer credible educational AI systems.

Conversational AI Technologies

Technologies that provide a conversational AI have gained immense use in health education since they enable the student to have a conversation with artificial intelligence systems. The technologies are based on dialogue management systems, natural language processors and large language models to aid conversational learning [3,50-52]. Question-answering, patient communication practice, reflective learning, and history-taking simulations of conversational AI are applied in the field of healthcare training. Conversational AI is typically used by medical students who rehearse patient interviews, practice clinical explanations and enhance documentation. During conversational AI, nursing students practice simulation of the triage communication scenario, patient counseling, and empathy-driven care. Conversational AI is valuable because it is capable of responding immediately, doing follow-up clarification, and guiding students individually. The recent technological advancements are directed to enhance the contextual memory, responsiveness to emotions, and dialoguing with more turns, which makes AI communications more life-like and educatively meaningful. Nonetheless, it is being feared

that too much reliance on conversational AI would undermine independent problem-solving, communication capabilities, and genuine clinical judgment.

Virtual Patient Technologies

The use of virtual patient technologies is rapidly gaining relevance in healthcare education as it offers safe and realistic simulation environments that enable the application of different clinical reasoning, patient communication, and diagnostic decision-making. Large language models and multimodal AI technologies that enable students to engage and talk to simulated patients are often used to power the modern virtual patient systems. Through these technologies it is possible to create histories of patients, symptoms, emotional reactions and follow-up questions so that the students too can practice medical interviewing and clinical reasoning skills in a controlled environment. Virtual patient technologies have found their applicable uses especially in medical education, nursing education, and pharmacy education since they expose learners to various patient groups, rare conditions, and risky situations that they may not experience in clinical placements. Current tendencies indicate that current generation transformers and multimodal AI models are increasingly making virtual patients to be more emotive, adjustive, and lifelike. Such changes will most likely lead to the incorporation of virtual patient technologies into the healthcare learning curriculum, particularly in communication, professionalism, and diagnostic accuracy.

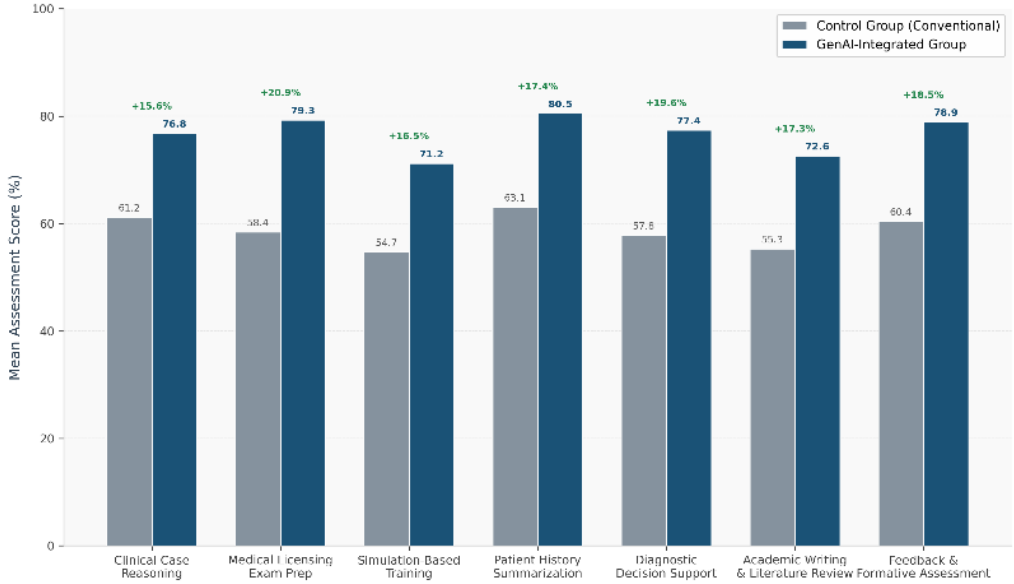

Fig. 4 Grouped Bar Chart - Mean Assessment Scores Across GenAI Application Domains (Control vs. GenAI-Integrated)

Fig.4 explains grouped bar chart compares mean assessment scores between conventional instruction control groups and GenAI-integrated instructional groups across seven application domains in healthcare education: clinical case reasoning, medical licensing exam preparation, simulation-based training, patient history summarization, diagnostic decision support, academic writing and literature review, and feedback and formative assessment. Performance differentials (annotated in green above each pair) reveal that GenAI integration consistently produces statistically meaningful learning gains ranging from approximately 10 to 21 percentage points across all domains. Patient history summarization and medical licensing exam preparation demonstrate the largest absolute gains, reflecting the natural alignment between large language model capabilities and the cognitive demands of synthesis and recall-intensive tasks. Simulation-based training shows a comparatively smaller but still substantial gain, likely attributable to the greater complexity of embodied procedural learning that GenAI tools currently supplement but do not fully replicate. The pattern of results across all domains supports the hypothesis that GenAI tools function as effective metacognitive scaffolds in healthcare education, consistently elevating learner performance regardless of the specific instructional context.

Intelligent Tutoring Systems

An important AI healthcare education technology is intelligent tutoring systems which facilitate adaptive learning, personalized learning, and competency-based education. These technologies rely on machine learning, learning analytics, and predictive analytics to track the performance of students and suggest personalized learning activities [53-57]. IT incorporated Intelligent tutoring systems find extensive application in anatomy, physiology, pharmacology, pathology, and clinical reasoning education since the system is capable of recognizing gaps in knowledge and modifying instructional difficulty when necessary. The students will enjoy real-time feedback, remediation, and individualized education profiles aligned with their strengths and areas of weakness. ITS can be useful particularly in health care programs since students tend to enroll with varying academic qualifications and learning requirements. Faculty work is also made less by these technologies which automate some of the process of feedback, assessment, and learning support. The intelligent tutoring systems of the future are likely to be connected more with large language models, multimodal artificial intelligence, and virtual patient-interaction approaches to enable more realistic and personalized learning experiences.

Computer Vision Technologies

The idea of computer vision technologies being applied to healthcare education is gaining momentum, as this technology enables AI systems to read and analyze medical images and visual information and anatomical structures. Radiology, pathology, dermatology, surgical simulation, and anatomy are some of the areas of computing vision use in education. The technologies are capable of detecting trends among the X-rays, CT images, MRI images, histopathology slides, and the surgical videos and can aid students improve their diagnostic interpretation abilities. The multimodal learning environment has practically made use of computer vision technologies since they have the capacity of integrating the visual information and text interpretation and the clinical setting. The latest progress refers to image-captioning systems, automated generation of radiology reports and visual question-answering technologies, which enable students to ask questions about pictures and get AI-generated explanations. Revision Computer vision is also being combined with retrieval-augmented generation to enhance factual accuracy and evidence-based learning in image-intensive fields. The increasing application of computer vision technologies expresses the greater move toward multimodal AI in medical training.

Speech Recognition and Voice-Based AI Technologies

Voice recognition and voice-based AI technology is becoming more relevant to healthcare education since it allows communication training, assessing pronunciation, and analyzing spoken interactions. These technologies are able to record verbal communication, assess the quality of communication, and give constructive feedback regarding readability, sympathy, and professionalism [58,59]. Speech recognition devices are applied in medical education and through nursing education to assess patient interviews, oral examination, and pseudo consultations. AI systems that utilize voice can be also used in language learning, communicating with various groups of patients, and be accessible to students with disabilities. The latest breakthroughs are emotionally intelligent voice assistants, multilingual speech recognition systems, and real-time communication coaching software. The technologies are particularly applicable to the health care domain since a communication error may have a direct influence on patient safety and professionalism. Combining the speech recognition and conversational AI with the virtual patient technologies is expected to improve the training of communication skills in the future medical curriculum.

Predictive Analytics and Learning Analytics Technologies

The importance of predictive analytics and learning analytics technologies in the sphere of healthcare education is growing due to their ability to help students who are at risk of poor academic performance, predict learning outcomes, and personalize learning interventions. These technologies process information on examination scores, attendance patterns, and online interactions, and simulation performance to single out those students who might require extra attention. Predictive analytics systems are able to predict preparation in terms of clinical placements, licensure tests, and competency-based assessments. The learning analytics technologies may also create insight into the effectiveness of the curriculum, student engagement, and retention. Predictive analytics can be used in healthcare education in particular since the programs were academically challenging, and students typically have a large

group. Nevertheless, the technologies also pose threats to the areas of transparency, fairness, and data privacy. The institutions will need to be clear that predictive analytics system should be explainable and not stigmatize unfairly students classified as high-risk. We are witnessing the rise of newer technologies that are integrating predictive analytics with multimodal AI, federated learning and explainable AI in order to build more reliable educational systems.

Explainable AI Technologies

Explainable AI technologies are gaining more and more relevance to healthcare education since teachers and learners should be able to comprehend the way AI systems arrive at decisions, recommendations, and evaluations. The operation of the traditional AI systems has not escaped criticism due to its tendency of being treated as a black box making it hard to determine why a given response or prediction was made [3,60,61]. Explainable AI technologies aim to address this issue by recording evidence trails, justifications, and clear explanations of AI outputs. Explainable AI is particularly useful in healthcare education since students should learn the reasoning behind clinical decision-making and treatment and not just accept the response offered by an AI. Explainable AI technologies can also assist the institutions to spot bias, certify the grading system, and make sure that adaptive learning landscapes are just and open-minded. When AI systems gain penetration into learning in the field of healthcare, explainability will be required more frequently to support trust, accountability, and academic integrity.

Federated Learning and Privacy-Preserving Technologies

Federated learning, privacy preserving technologies are coming out as crucial in healthcare education due to the fact that it enables institutions to work together on AI models development without necessarily sharing sensitive information. These technologies can allow universities, hospitals, and training centers to create AI systems based on decentralized data and adhere to the data privacy laws. Specifically, federated learning applies to the healthcare field where the datasets of education may include sensitive student data, liability records, clinical evaluation outcomes of patients. Privacy-conserving technologies have the potential to enhance the diversity and strength of AI systems in education and safeguard privacy and minimize legal liability. These technologies are also becoming a prospective topic to predictive analytics, intelligent tutoring, virtual patient creation, and multimodal learning platforms. The secure cloud computing, edge AI, and encrypted data-sharing systems which facilitate extensive collaboration between institutions are some of the emerging trends as well. The need to protect the privacy of data in healthcare education will increasingly attract privacy-protective technologies as the industry continues to become more data-intensive and interrelated.

Academic Integrity Technologies

Technologies of academic integrity are also being stressed due to the increase in the use of Generative Artificial Intelligence applied to healthcare education creating new modes of plagiarism, ambiguity in authorship, and misconduct in assessment. Older plagiarism generators are usually ineffective against AI generated content due to large language models generation of original text that does not resemble the existing text [62-64]. The new academic integrity technologies employ stylometric analysis, linguistic pattern recognition, perplexity scoring and AI generated text detection as potential estimations of whether a machine was the author of a specific piece of writing. Nevertheless, the controversy of these systems is that they are prone to generating false positives and unfairly punishing students. Consequently, several healthcare education providers are shifting to both more expanded models of academic integrity, which integrate disclosure strategies, proceduralized assessment, oral testing, coprospective learning, and genuine clinical work. It is becoming more accepted that technology does not solely fix the academic misconduct problems and ethical AI literacy, readiness of the faculty and redesigning of the assessment are all equally significant. There is also a concern that the overuse of AI tools will undermine critical thinking skills, writing skills and communication skills among healthcare students.

3.4 Artificial intelligence models

GPT-Based Models in Healthcare Education

Due to high natural language processing, adaptability, and their availability in many academic centers, GPT-based models are the most popular in the medical education sector. ChatGPT, GPT-4 and GPT-4o are frequently applied in medical and nursing education, pharmacy and dental education to assist in self directed learning, personalized learning, and curriculum development [65-67]. The models are particularly applicable to generating clinical plausibility, simplifying biomedical terms, generating examination questions, and facilitating reflective learning. The reason behind the increasing popularity of GPT-4 and GPT-4o over previous GPT-3.5 models is that both exhibit higher reasoning capability, better contextual awareness, and higher multimodal performance. Medical competency exams GPT-4 has performed well in medical competency tests, and has the capacity to describe clinical reasoning, personalize responses, and produce counterfactual learning situations to students. GPT-4o also expands this potential by combining text, image, and audio processing in one model and is particularly applicable in the case of multimodal healthcare education and simulation-based learning.

ChatGPT as a Dominant Educational Model

ChatGPT has become the best-known Generative Artificial Intelligence model in healthcare education due to its rapid usability, conversation format, and its capacity to accommodate numerous educational assignments. ChatGPT is primarily used by students to summarize notes, prepare exams, create literature reviews, discuss a clinical case, and write. Another application of ChatGPT is that of faculty members in planning their lessons, automated feedback as well as creating learning materials. ChatGPT is especially useful in the medical training process, as it has the ability to simulate conversations with patients, provide diagnostic arguments, and facilitate problem-solving capabilities. Nevertheless, the issue of hallucinations, incorrect results, overconfidence, and academic dishonesty is still present as students might be inclined to trust AI-created answers and judge them then without effectively scrutinizing the quality of delivered answers. These issues have led to heightened curiosity on the AI literacy, digital literacy and assessment redesign plans which fosters responsible human-AI partnership.

Gemini and Med-Gemini Models

Gemini and Med-Gemini models signify one of the most significant developing tendencies of healthcare education as they are multimodal in terms of their reasonings and larger contextual comprehension. Gemini models are becoming known in their capability to process text, images, audio, and video in parallel thus making them quite applicable in medical education, radiology education, pathology training, and anatomy training [68,69]. Med-Gemini builds on these with medical specific fine-tuning covering the radiology, dermatology, ophthalmology, genomics, and histopathology fields. The models have proven to be highly effective in multimodal medical tasks, frequently achieving better performance on tasks designing clinical image analyzing, medical question responding, and long-context retrieval of health records than GPT-4. Gemini and Med-Gemini models have particularly come into use in healthcare education in the context of simulation-based learning, image interpretation, diagnostic reasoning and training in the use of a virtual patient. Their capabilities in integrating various modalities of data also enable integrated learning experiences that are a better simulation of real-world healthcare practice.

Claude and Claude Opus Models

Claude and Claude opus models have gained more and more relevance in healthcare education due to their focus on reasoning, safety, long-context processing, and response generation in detail. Claude models are common to the study of literature, the support of academic writing, the reasoning of ethics and the discussion of complex clinical cases. Their text windows are particularly helpful in processes of reviewing long patient histories, analyzing long-form educational texts, and facilitating reflective learning work. The Claude Opus models have been strongly competitive in multimodal medical benchmarking and have been found to remain fairly stable in reasoning in a broad variety of medical specialties. Claude finds its application in healthcare education, specifically, in assisting students to

make synthesis of multiple sources of information, discover the ethical dilemmas, and learn in detail by using the case as the basis of learning. The focus on safer outputs and improved contextual perception also makes Claude appealing to the institutions that are worried about hallucinations and the risk of academic dishonesty.

Med-PaLM and Domain-Specific Medical Models

The use of Med-PaLM and other domain specific medical models is becoming more popular due to its explicit optimization in health care terms, clinical reasoning and biomedical knowledge. Compared to the general-purpose large language models, domain-specific medical models are trained on clinical notes, medical textbooks, medical journals, and health records [20,70-72]. This enables them to generate better and culturally suited responses when it comes to healthcare education. Med-PaLM has been showing good results in medical exams, diagnostic assignments, and evidence-based question answering. Based on the same concept, other types of healthcare-specific models are also forthcoming under the education of nursing, pharmaceutical education, and dental education due to the increasing demand of specialized educational resources. DSSM models Domain-specific models are, in particular, useful in facilitating clinical decision-making, virtual patient treatment and professional communication training due to their reduced risk of creating generic or erroneous results. Nonetheless, cautious supervision of these models is necessary as objectivity, transparency, and ethical AI are still the prominent issues in the sphere of healthcare education.

Llama and Open-Source Models

Llama, Llama 3 and Mistral, Mixtral and other open-source large language models are gaining more and more relevance in healthcare education due to their increased flexibility, affordability and their institute-level control. It is possible to use open source models and deploy them on-site, train them to understand the unique data related to healthcare and integrate into university services without fully depending on commercial options. This is in particular to institutions that are sensitive on the privacy and confidentiality of their data and the sustainability in the long run. Virtual patient system, educational chatbots, intelligent tutoring systems and automated assessment tools increasingly use llamabased models. Even though the input of open-source models may not always be comparable to the performance of the most dominant proprietary models, including GPT-4 or Gemini, they are significant in terms of personalization, openness, and cheapness. Their increased popularity can be seen as a wider move in decentralized and privacy-sensitive AI systems in medical education.

Multimodal Large Language Models.

One of the most rapidly emerging classes of Generative Artificial Intelligence models in healthcare education is multimodal large language models since they are capable of patently processing text, images, audio, and video at once. Such models are particularly useful in healthcare since a variety of educational activities require decoding various types of information [73-75]. Radiology training, pathology education, dermatology training, anatomy learning, and verbal communication skills can be delivered with the help of multimodal models which will be based on visual and textual input. Multimodal models are also becoming common in the production of radiology reports in healthcare education, interpretation of medical images, responding to questions regarding pathology slides and analysis of patient interactions. More recent findings indicate that multimodal models like GPT-4o, Gemini 2.5 Pro, Claude 4 Opus, and OpenAI o4-mini-high are highly diagnostic when the texts are used in combination with images. Such trends suggest that multimodal models can be seen as instruments of future healthcare training.

Retrieval-Augmented Generation Models

Models that utilize retrieval-augmented generation are gaining significant importance in healthcare education since they integrate generative ability and knowledge retrieval systems. Such models scan text books, clinical guidelines, biomedical databases and institutional repositories and then produce responses. This minimizes hallucinations, enhances factuality and facilitates evidenced based learning. RA-based generation models have particular applicability in medical education, nursing education, and

pharmacy education since they enable students to pose questions and answer them based on the current knowledge. Intelligent tutoring systems, virtual patient systems, and adaptive learning environments are becoming more integrated into these models. The increased attention on retrieval-augmented generation can be attributed to the increased interest in trustworthy and explainable AI in healthcare education.

Multimodal Diagnostic Models

Multimodal diagnostic models are becoming one of the key types of AI models as they are able to use a mix of text, images, and structured data to enhance the diagnostic reasoning. There has been an evaluation of models like OpenAI o4-mini-high, Gemini 2.5 Pro, Claude 4 Opus, and Qwen 3 on multimodal clinical tasks that required the reading and understanding of text, as well as reading and understanding of images [38,76-78]. The OpenAI o4-mini-high model has performed better than any of these models on the hardest cases, as well as ontopics like cardiology, ophthalmology, pediatrics, infectious diseases and dermatology. Gemini 2.5 Pro, Claude 4 Opus also exhibit a high diagnostic accuracy but both perform poorly once image data has been presented only. These results are significant to healthcare education since they indicate that multimodal diagnostic models could be a helpful resource that can be employed to teach radiology, pathology, and clinical reasoning. Nevertheless, they underscore the need to supplement various data sources since most models do not perform well when free of the textual context.

Conversational and Virtual Patient Models

Virtual patient models and conversational models are taking centre stage in healthcare education since they embrace the use of realistic learning experiences based on dialogue. These models are meant to act like people and cause emotions as well as the development of adaptive situations that change based on the actions of the students [79-81]. The models of conversational AI are employed in the practice of patient interviewing, communication skills training, counseling practice and in clinical documentation exercises. Virtual patient models prove particularly useful as they subject students to a variety of patients and unusual conditions and complicated ethical scenarios that might not be taught during the placement. Recent studies also describe growing attention to benchmark systems, including MedPI, that assess large language models in a number of dimensions of patient communication, treatment effects, and competencies based on accreditation. The results of these developments indicate that conversational and virtual patient models will continue to rise in simulation-based (learning) and competency-based learning.

Explainable and Ethical AI Models

Describable AI models are gaining more and more significance in the field of healthcare education as teachers and learners must get to know how AI-based outputs are created. Most giant language models are black boxes, and it is challenging to ascertain what rationales result in the creation of a given suggestion, explanation, or critique. Explainable AI models aim to address this issue by revealing evidence trails, as well as reasoning steps, confidence numbers, and readily available explanations. These models have particular significance in the sphere of healthcare as students should not passively use the outputs suggested by the auto recommender but be able to see the logic behind clinical reasoning and treatment suggestions. Other issues that AI models find solutions to in their ethical aspects include bias mitigation, fairness, data privacy, and transparency. The rise in explainability is indicative of larger issues regarding academic integrity, trust, and accountability in health care education. The question of explainability will emerge as a vital prerequisite of responsible AI implementation since AI models will continue to be progressively more involved in assessments, clinical reasoning, and personalised learning.

Future Trends in AI Models for Healthcare Education

The future of AI models in healthcare education would probably entail the use of increased specialization, multi-modal, trying out thereof, and the capacity to know the context. Newer models are started to be structured in a way that unites text, images, audio, genomic information and real-time information retrieval into a single type of education [82,83]. Increased attention is also paid to agentic

AI models, Model-Context Protocol frameworks and systems that can be integrated with external tools, electronic health records, and institutional databases. The models in the future will become more individualized, comprehensible and adaptive, facilitating competency-based education, predictive analytics, and future workforce preparedness. Nevertheless, the fast growth of the AI models also brings onto the issues of academic dishonesty, plagiarism detectors, ethical AI, and critical thinking skills maintenance. This means that education systems in the future of healthcare must strike a balance between technological change and robust governance, faculty preparedness, and responsible human-AI partnership.

3.5 Artificial intelligence applications

Personalized Learning and Adaptive Learning Applications

Personalized learning and adaptive learning is one of the most popular topics on the uses of Generative Artificial Intelligence in healthcare education. Big language models like ChatGPT and GPT-4 are capable of explaining in specific ways, creating custom study plans, breaking down understanding of difficult biomedical terms, and customizing learning materials based on their level of learner knowledge. GenAI systems are also increasingly applied to provide students with tailored feedback, practice questions, and revision summaries based on their learning gaps in medical education, nursing education, pharmacy education, and dental education. The adaptive learning technologies prove especially handy since the students of healthcare tend to join the programs with varying levels of academic preparation and diverse backgrounds. In addition to enhancing student engagement, self-directed learning, and knowledge retention, AI systems have the capacity to track progress, detect deficiencies and modify content difficulty, thus supporting learning. These applications are also compatible with competency based learning since a learner is able to build pace and invest in areas where his or her skills need a boost. One-on-one tutoring and adaptive learning strategies are now considered as significant factors leading to improved learning and more efficient healthcare education.

Intelligent Tutoring Systems and Virtual Classroom Assistants

The most prominent uses of GenAI in healthcare education have included intelligent tutoring Systems and virtual classroom assistant since this will offer round-the-clock assistance that is absent in the real classroom. These systems may provide responses to questions, exposit tricky concepts, create exemplified ones, and provide formative evaluation in real-time [28,84-86]. Intelligent tutoring systems are found in healthcare programs typically in the education of anatomy, physiology, pharmacology, pathology and in clinical reasoning. The virtual classroom assistants are particularly useful when the students require extra assistance once the lectures take place, as they can still access clarifications and instructions when required. The faculty members are also in favor of it as AI-powered tutors could unload faculty personnel by automating routine teaching assignments, producing learning materials, and answer routine queries posed by students. These are applications that have gained significance in large health care programs in which individual faculty support might be sparse. Nonetheless, it is also becoming disturbing that too much engagement with AI tutoring tools will suppress independent problem-solving and stop the deeper engagement with the learning material.

Virtual Patients and Simulation-Based Learning Applications

Virtual patients and simulation-based education are among the most significant GenAI applications in educational healthcare practice since they offer safe and realistic/real-world settings to practice clinical skills. AI-based virtual patient systems are able to recreate patient history, emotional reactions, symptoms, physical observations, and disease processes. These systems allow the students to communicate in an interactive manner, pose questions, order tests, and make decisions on treatment and give instant feedback. They are notably applicable in medical education, nursing education, and allied health education since they subject the learners to diverse patients, unique diseases, and high-risk scenarios that might not otherwise be experienced in clinical placements. Repeated practice can also be made possible through simulation-based learning without affecting patient safety. More recent developments in multimodal artificial intelligence have resulted in more realistic and interactive virtual

patients using a combination of text and voice data with visual evidence. Improvement in clinical reasoning, accuracy in diagnosis, communication and confidence among healthcare students is increasingly being applied by use of these developments.

Clinical Reasoning and Decision Support Applications

The incorporation of Generative Artificial Intelligence in clinical reasoning and decision support is being considered in the health care education scene more and more to provide support in this area. Large language models are able to generate differential diagnosis, disease mechanism explanations, treatment options, and can guide learners through the process of clinical decision-making [87,88]. Such applications come in extremely handy as clinical reasoning is among the most complex competences that otherwise a healthcare student can attain. The AI systems will be able to give step-by-step instructions, outline the reasons that justify an incorrect scenario, and propose other versions of how to interpret patient data. GenAI tools are currently being employed to educate in medical education, pharmacy education, on evidence-based medicine, diagnostic reasoning, medication safety, and treatment planning. Reflective learning can be promoted through these systems as well since learners will be able to compare their own choices with AI-generated recommendations, and find out their weak points. Nevertheless, there is a fear of concerns about hallucinations, overconfidence, and the fact that students will accept the AI-generated responses and not properly consider their validity. This means that human supervision should not be neglected in any AI-assisted clinical reasoning venture.

Academic Writing and Research Support Applications.

GenAI support in academic writing has emerged as one of the most widespread healthcare education application areas due to students often applying AI-supported systems to enhance grammar, summarize articles, structure ideas, and write academic papers. Tasks of literature reviews, reflective essays, research proposals, and writing scientific literature are frequently performed with the assistance of ChatGPT and other applications. In the postpartum care, these applications come in particularly handy since in nursing, students are typically asked to write a significant amount of work, such as patient case studies, treatment plans, journal entries, and evidence-based projects. GenAI is capable of enhancing the clarity, coherence and legibility of a written work and decreasing the time used to draft it and revise it. Nonetheless, the application of AI to academic writing also attracts the issues of plagiarism, authorship ambiguity, originality and misconduct in academia. The extent to which AI aid should be allowed in academic work is debated and institutions are required to draw the line between the acceptable assistance and unethical content generation. To maintain academic integrity, many universities are currently promoting open discussion of AI usage and the development of reflective writing, oral defense, and genuine assessment activities.

Automated Feedback and Assessment Applications

The use of automated feedback and assessment tools is common in health care education as they help decrease the amount of work required of a faculty and grant students quick access to the feedback on their performance. The quiz answers, reflective writing, SOAP notes, patient counseling scripts, and case-based assignments can be evaluated using GenAI [89-90]. These systems are able to detect mistakes, give suggestions to improve, and give individual comments in real time. Automated assessment applications are especially useful in healthcare programs since students need to practice a lot and get prompt feedback to enhance their clinical reasoning, communication, and documentation skills. GenAI can also be used by faculty to generate more efficiently examination questions, grading rubrics, and formative assessment tasks. Nonetheless, there have been worries that students can present AI-generated work in any assignment that will undergo evaluation by another AI system, forming a cycle of decreased authenticity and poor learning. This has raised the curiosity on assessment redesign, oral testing, process evaluation assessment and reflective assignments that entail the depiction of self-reliant thought and comprehension by pupils.

Conversational AI for Communication Skills Training

Conversational AI apps are finding their way into the healthcare education sector since any person who can communicate is capable of beneficially attending to a patient. Chatbots and virtual assistants based on AI can even imitate interviewing a patient, consultations, triage discussions, and awkward conversations on sensitive subjects. Such applications find their applications especially in nursing education, medical education and allied health education since the students can be given the opportunity to exercise empathy, active listening, professionalism and communication in realistic environments. Feedback on tone, clarity, empathy and language use can also be offered by conversational AI systems to help the student to develop his or her interpersonal skills. The recent advances in conversational AI involved emotionally reactive chatbots, multilingual support, and multi-turn dialogue systems, capable of maintaining an honest conversation over an extended period. Such applications are increasingly being considered as significant in equipping students to effectively communicate with different groups of patients.

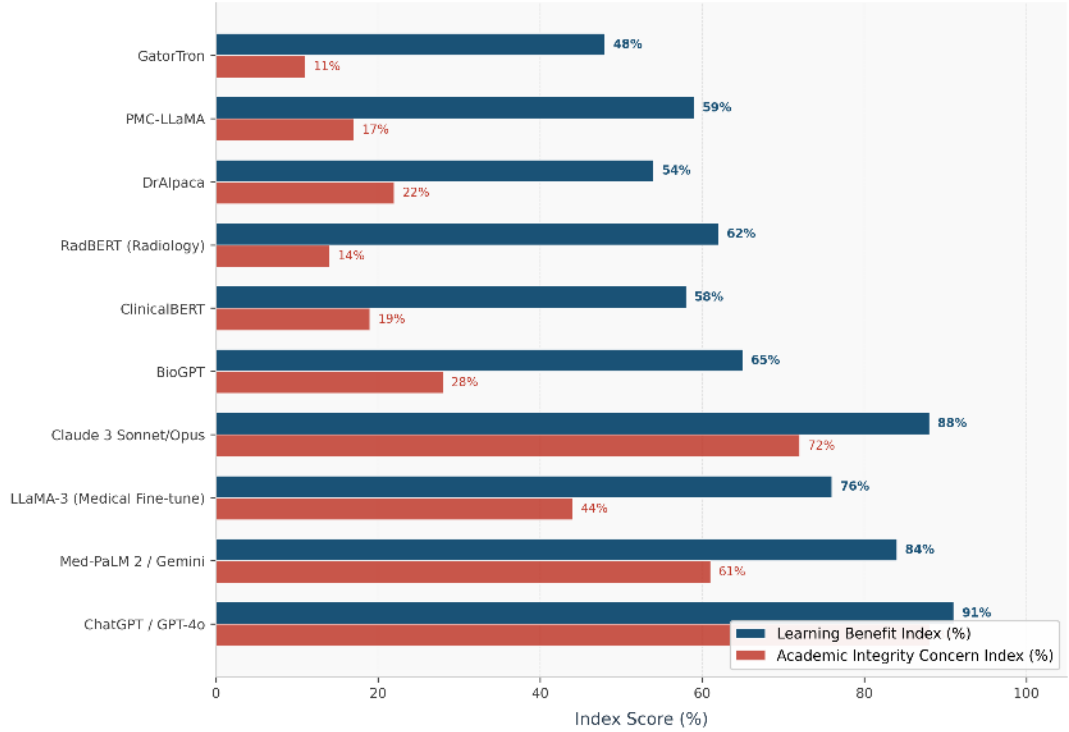

Fig. 5 Horizontal Bar Chart - Learning Benefit Index vs. Academic Integrity Concern Index by AI Model

Fig 5 visualizes horizontal bar chart presents a dual-index comparison across ten prominent AI models evaluated in the healthcare education literature, juxtaposing each model's Learning Benefit Index against its Academic Integrity Concern Index. Both indices are expressed as percentages derived from aggregated expert survey and empirical study data. ChatGPT and GPT-4o exhibit the highest scores on both indices simultaneously, reflecting their exceptional instructional utility and their disproportionate association with contract cheating, unauthorized examination assistance, and AI-generated assignment submission concerns. Specialty models such as GatorTron, PMC-LLaMA, and RadBERT show substantially lower integrity concern scores but correspondingly lower learning benefit scores, as their narrower domain focus restricts both their educational versatility and their susceptibility to academic misuse. Claude 3 Sonnet and Opus present an interesting profile of high learning benefit with moderate-to-high integrity concern, suggesting that reasoning-optimized architectures carry dual-use risks that educators must proactively address through assessment redesign and policy development. The chart reveals a pattern that informs institutional decision-making: generalist high-capability models offer the greatest pedagogical value but demand the most rigorous integrity governance frameworks.

Curriculum Innovation and Faculty Support Applications

Curriculum innovation and productivity of faculty in healthcare education are also commonly supported with the use of Generative Artificial Intelligence. The faculty members are relying more on AI systems in order to generate lesson plans, create examination questions, design case studies, summarize research literature and prepare educational materials [30-32]. GenAI may also be used in curriculum mapping, competency alignment, as well as in the creation of cross-disciplinary educational resources. Effectively, in the healthcare programs where faculty tend to work a lot, these applications could enhance productivity and provide more time to interact with the students directly. The need to innovate curriculum in particular is critical since healthcare education is evolving quite fast, and corresponding institutions have to keep changing material according to new technologies, emerging illnesses, and alterations in clinical practice. Digital literacy, AI literacy, and future workforce readiness can also be promoted through AI- facilitated curriculum design by making topics related to GenAI a part of the learning experience. Nevertheless, the institutions should make sure that the faculty is well trained in the responsible and ethical use of AI tools.

Table 1. Summary of Generative Artificial Intelligence Applications, Benefits, and Challenges in Healthcare Education

Sr. No.	Application	Techniques / Technologies / Models	Key Benefits	Major Challenges
1	Personalized learning	Adaptive learning, ChatGPT, GPT-4	Tailored study support	Overdependence on AI
2	Intelligent tutoring systems	Conversational AI, large language models	Continuous academic support	Reduced independent learning
3	Virtual patients	Simulation-based learning, multimodal AI	Safe clinical practice	Limited realism
4	Clinical reasoning support	Decision support systems, prompt engineering	Improved diagnostic thinking	Automation bias
5	Academic writing support	Natural language processing, ChatGPT	Improved writing efficiency	Plagiarism risk
6	Literature summarization	Retrieval-augmented generation	Faster review of evidence	Superficial understanding
7	Assessment generation	Automated feedback, question generation	Reduced faculty workload	Assessment validity concerns
8	Communication training	Conversational AI, speech recognition	Improved empathy and communication	Artificial interaction quality
9	Curriculum design	Generative AI, learning analytics	Faster curriculum innovation	Faculty skill gaps
10	Reflective learning	ChatGPT, virtual mentors	Better self-awareness	Generic reflections
11	Diagnostic image interpretation	Multimodal AI, computer vision	Enhanced radiology learning	Misinterpretation risk
12	Pharmacology support	Retrieval-augmented generation	Faster medication learning	Outdated drug information
13	Anatomy education	3D simulation, multimodal AI	Better spatial understanding	High technological cost
14	Predictive analytics	Learning analytics, machine learning	Early identification of at-risk students	Bias and fairness concerns
15	Competency tracking	Competency-based education platforms	Better monitoring of skill development	Privacy issues
16	Faculty productivity	Automated content generation	Reduced administrative burden	Reduced originality
17	Oral communication assessment	Speech recognition, sentiment analysis	Real-time communication feedback	Limited contextual understanding

18	AI literacy training	Prompt engineering, digital literacy	Better responsible AI use	Unequal student readiness
19	Academic integrity monitoring	AI detection tools, stylometric analysis	Misconduct detection	False positives
20	Professional identity formation	Reflective AI tools	Improved self-evaluation	Reduced authenticity
21	Interprofessional education	Collaborative AI simulations	Better team-based learning	Lack of standardization
22	Mental health support	AI chatbots, conversational agents	Increased student support	Ethical and privacy concerns
23	Research assistance	Literature synthesis, idea generation	Faster research planning	Authorship ambiguity
24	Examination preparation	Personalized revision tools	Better retention and confidence	Memorization over reasoning
25	Clinical documentation practice	SOAP note generators	Improved documentation skills	Risk of copy-paste behavior

Predictive Analytics and Learning Analytics Applications

GenAI applications in the fields of education are relevant to predictive analytics and learning analytics, which finds more and more applications in healthcare education as it provides the institutions with an idea of the students at risk and advance the academic performance. This is based on the analysis of examination outcomes, attendance, engagement and online learning behavior to recognize students who could be in need of further assistance. Faculty can also use predictive analytics to predict performance during clinical placement, licensure examination, and performance evaluation. These applications are especially useful in the education of healthcare as the programs are rather demanding academically, and the turnover rates are high. The increment of learning analytics can also give comprehensive information about the most effective teaching strategies, curriculum elements, and types of assessments. Nevertheless, there are still issues of privacy of data, transparency, bias, and fairness since predictive models can misclassify students or support existing inequalities. Careful human governance and governance is therefore needed to enact ethical implementation.

AI Literacy and Digital Literacy Applications

With the increased use of Generative Artificial Intelligence in healthcare education, the use of AI literacy and digital literacy becomes more popular. Numerous institutions will start educating students on understanding AI systems and how to assess AI-generated knowledge and apply prompt engineering in practice. The future of AI literacy education is rising due to the fact that medical workers are going to have to deal with AI-based systems throughout the course of their career. The learners will be required to comprehend the advantages and constraints of large language models, identify hallucinations, assess bias, and utilize ethical concepts when utilizing AI resources. AI literacy is also regarded as a component of professional competency frameworks in nursing education and medical education since the readiness of the future workforce is becoming conditional on the opportunity to use AI in a responsible manner. Academic integrity is another aspect that is supported by digital literacy training since it allows the student to learn the correct and incorrect applications of GenAI in assessments and assignments.

Academic Integrity and Plagiarism Detection Applications

Among the most sensitive uses of GenAI in healthcare education, the effect it has on academic integrity and plagiarism detection could be mentioned. Although AI systems can serve the purpose of learning and writing, they can also be used to create essays, solve assignments, and avoid the use of classic plagiarism detection software. The AI detection software, stylometric analysis and linguistic pattern recognition are now used to identify AI written content at many universities. These technologies are however not reliable and are likely to give false positives. It is increasingly appreciated that it is not enough to detect rather institutions needs to restructuring assessments to minimise avenue of

misconduct. More specifically, oral examinations, authentic clinical work, reflexive writing, and process based testing are becoming increasingly popular since it becomes harder to make students totally depend on AI-generated knowledge. The high rate of GenAI usage among students has propelled a more decisive approach to policies, disclosure practices, and ethical AI in healthcare education.

Ethical AI, Data Privacy, and Responsible AI Applications

The use of responsible AI applications is emerging as one of the most important ethics matters in healthcare education since often AI systems handle sensitive educational and clinical data. The AI tools are frequently applied to patient cases, clinical notes, and other confidential data by healthcare students, bringing in the question of privacy and data security [7,13-16]. Ethical applications of AI are supposed to foster transparency and fairness, reduce biases, and responsible human-AI cooperation. Colleges will come up with more guidelines to make sure that the use of artificial intelligence devices is done properly and to make sure that the students are aware of their roles whenever using such devices. Responsible AI models also highlight the necessity to have human supervision, particularly and specifically in high-stakes educational processes, i.e., clinical decision-making, competency study, and professional evaluation. The further combination of GenAI into healthcare education is bound to render ethical governance and responsible use of AI more significant to safeguard academic integrity, patient confidentiality, and quality of education.

4. Discussion

The results concerning this systematic review demonstrate that Generative Artificial Intelligence is rapidly changing the sphere of healthcare education by affecting the results of learning and academic integrity in medical education and nursing education, pharmacy education, dental education, and allied health education. Large language models like ChatGPT and GPT-4 are also becoming integrated into the educational setting, whether as intelligent tutoring mirrors, adaptive learning interfaces, chat robots, virtual patients, or learning simulators [2,17-19]. The technologies have proved to be very valuable in promoting personalized learning, student engagement, self-directed learning and curriculum innovation. Immediate explanations, automated feedback, revision summaries, and case-based direction are beneficial to students, whereas simplified lesson preparation, assessment support, and less administrative work are beneficial to faculty members. It is also emerging that most higher education students use Generative Artificial Intelligence more frequently and on academic assignments like concept descriptions, literature summaries, research projects, and assignment writing, which is another indication that AI is no longer used experimentally as a tool in higher education.

The broad implementation of Generative Artificial Intelligence in healthcare education has also emphasized the increased significance of clinical reasoning; skill of problem-solving and competency-based learning, as well. The use of AI-assisted tools to simulate patient scenarios, think through the diagnostic process, and support evidence-based decision-making grows in popularity. Complex clinical situations can be presented to students through the use of virtual patients and multimodal AI systems, and students can train communication, diagnosis, and treatment planning under safe learning conditions. This is particularly important in the fields of healthcare, where direct contact with the patient can be sporadic or at a low level. Also, retrieval-augmented generation/prompt engineering is enhancing the quality of educational material by basing responses on evidence-based content and facilitating more questions-driven interaction with AI systems. Such developments indicate that Generative Artificial Intelligence can be used as a thought-provoking aid, instead of an automated source of information, especially with careful incorporation into pedagogic contexts by focusing on reflective learning and critical thinking.

The review, however, also reveals that accelerated growth of Generative Artificial Intelligence has raised significant issues regarding academic honesty, the potential to identify plagiarism, indistinct authorship, and validity in assessment. However, the obsolete plagiarism detection tools would fail to detect any genuine but AI-generated works, and it is becoming more and more difficult to allow an institution to recognize genuine work of a student and some machine-produced work. ChatGPT and similar assistance are now extensively used by many students when working on written assignments,

reflective essays, case analyses, and examination preparation. Whereas this can enhance productivity and ease of access, people are increasingly concerned that overdependence of AI-generated material might undermine intellectual capacity, writing skills, verbal capabilities, and the originality. According to current researches, the use of GenAI in evaluation by students has surged exponentially, and most universities have not established explicit policies and governance systems to control responsible usage. These findings imply that healthcare education is a transition whose period requires assessment redesign to maintain academic integrity and assure the continuation of exhibited understanding and professional competence among students.

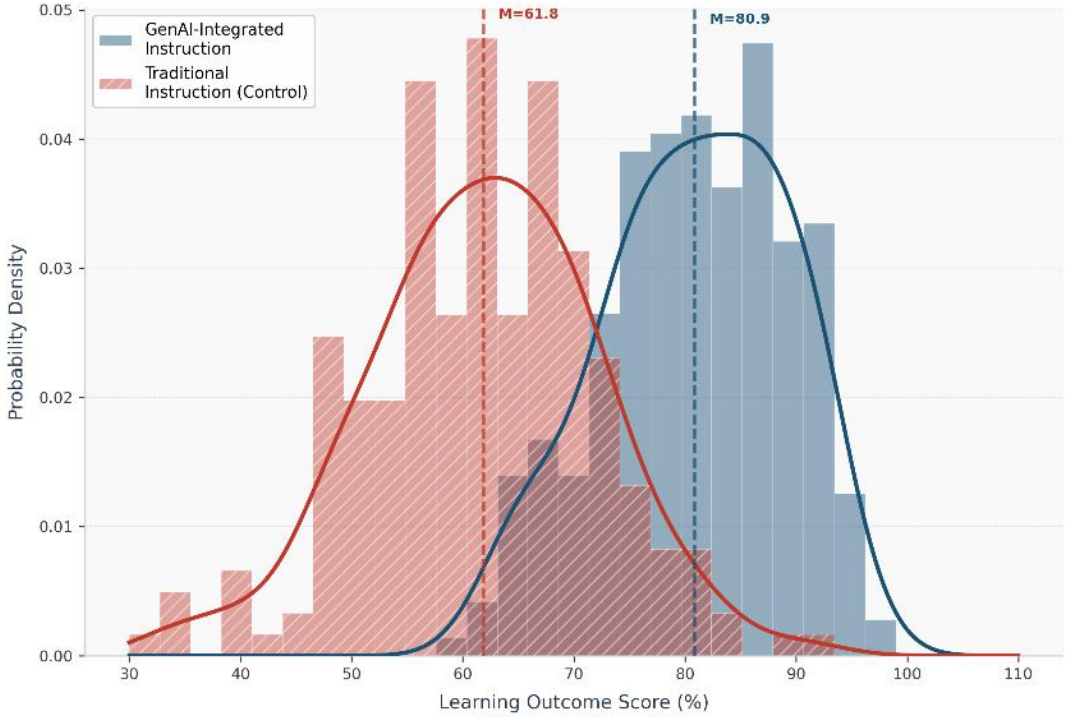

Fig. 6 Distribution of Learning Outcome Scores for GenAI-Integrated vs. Traditional Instruction

Fig. 6 shows histogram with overlaid kernel density estimation (KDE) curves illustrates the full distributional profiles of learning outcome scores for two groups of healthcare education students: those receiving GenAI-integrated instruction and those in traditional instructional control conditions. The GenAI-integrated group exhibits a distinctly bimodal distribution, with one peak centered around the mid-70s and a secondary peak near 88%, suggesting that GenAI tools produce differential benefits across learner subpopulations, possibly reflecting variability in prior digital literacy, self-regulation capacity, or institutional implementation quality. By contrast, the traditional instruction group follows a unimodal, approximately normal distribution centered near 63%, with a broader spread indicating greater within-group heterogeneity in conventional educational settings. Mean markers annotated with dashed vertical lines make the central tendency difference visually unambiguous. The partial overlap between the two distributions cautions against overgeneralizing the effectiveness of GenAI tools, as a subset of traditionally instructed learners performs comparably to or above the lower-performing segment of the GenAI group. This overlap underscores the importance of implementation fidelity, pedagogical design quality, and learner support structures in determining whether GenAI integration translates into measurable educational benefit across diverse healthcare training contexts.

It is also largely proven that the excessive use of Generative Artificial Intelligence can have an adverse impact on high-order cognitive abilities. According to recent reports, educators have raised concerns that students are becoming over reliant on AI tools to write, summarize, spell and even basic reasoning over time, which is raising concerns that over time, students will become less critical thinkers and may eventually lose the ability to solve problems independently. This is of importance especially in healthcare education whereby professional competence relies on clinical judgment, ethical reasoning, communication, and decision-making. It is not merely that students will cheat, but that they will not

acquire the intellectual habits and reflective skills that would enable them to operate safely in a clinical practice. Other educators currently refer to AI as a threat to professionalism, assessment validity, and formation of professional identity since it is capable of obscuring authorship, undermining accountability, and diminishing the authenticity of student learning.

Table 2. Summary of Future Directions, Opportunities, and Policy Priorities for Generative Artificial Intelligence in Healthcare Education

Sr. No.	Area	Opportunity	Future Direction
1	AI literacy	Improve responsible AI use	Integrate AI literacy into curricula
2	Prompt engineering	Better interaction with AI	Teach structured prompt design
3	Assessment redesign	Preserve academic integrity	Increase oral and authentic assessments
4	Faculty readiness	Enhance teaching effectiveness	Expand faculty training programs
5	Ethical AI	Reduce bias and misuse	Develop ethical governance frameworks
6	Transparency	Improve trust in AI outputs	Require AI disclosure statements
7	Data privacy	Protect student and patient information	Strengthen institutional safeguards
8	Bias mitigation	Promote equitable learning	Use diverse and inclusive datasets
9	Explainable AI	Improve understanding of AI decisions	Integrate transparent AI systems
10	Multimodal AI	Enhance simulation and diagnosis training	Expand image-text learning systems
11	Retrieval-augmented generation	Improve factual accuracy	Link AI tools to trusted databases
12	Virtual patients	Increase clinical exposure	Create emotionally responsive simulations
13	Learning analytics	Support at-risk students	Develop ethical predictive models
14	Competency-based education	Personalize progression	Align AI tools with competency frameworks
15	Interprofessional collaboration	Improve teamwork training	Use collaborative simulation platforms
16	Academic integrity	Strengthen authentic learning	Shift from punishment to prevention
17	Student engagement	Increase motivation and participation	Build interactive AI learning environments
18	Digital literacy	Improve technology adoption	Include digital competency modules
19	Human-AI collaboration	Balance AI use with human judgment	Promote reflective practice
20	Simulation-based learning	Expand risk-free training	Increase immersive virtual reality integration
21	Research support	Improve productivity	Encourage transparent AI-assisted research
22	Global access	Reduce educational disparities	Expand affordable AI platforms
23	Regulatory frameworks	Improve accountability	Establish international AI standards
24	Longitudinal research	Improve evidence quality	Conduct long-term outcome studies
25	Workforce readiness	Prepare students for AI-enabled healthcare	Integrate AI competencies into accreditation standards

The review also gives much emphasis to ethical AI, responsible AI, transparency, mitigation of bias, and privacy of data in healthcare education. Multimodal AI systems and large language models tend to be trained on incomplete (or intentionally biased) sets of data, potentially resulting in false, unfair, or misrepresentative results. It can also happen that students are sharing sensitive patient information with external AI platforms without knowing, which poses the problem of data privacy and confidentiality. Also, disparities in AI usage can increase the gap in education between less digitally literate and less technologically advantaged institutions and learners in institutions that can afford AI usage. These problems support the importance of more robust governance structures, faculty preparedness initiatives,

AI literacy educational efforts, and clear institutional guidance on what is and is not acceptable in the context of AI application in learning environments. Complete application of responsible implementation involves not just technological innovation but ethical stewardship, interdisciplinary cooperation, and the desire to exercise fairness and inclusivity.

A major message of this review is that healthcare education institutions should stop adopting reactive methods of plagiarism detection and instead implement proactive strategies of redesigning assessment methods. Oral tests, realistic clinical experiences, reflective writing, process-based examination, work-based examination, and face-to-face interviews are all the more suggested due to the fact that they make students apply logical inferences, create, and showcase applied knowledge in contrast to merely writing down outputs. Other institutions are also offering AI disclosure statements, AI literacy training, and timely engineering training as components of more comprehensive academic integrity models. The approaches acknowledge that Generative Artificial Intelligence is not going to fade away and that it requires proper governance that involves educating the students on how to use such tools in a responsible manner as opposed to banning them altogether. The learning of ethical AI, digital literacy, prompt engineering, transparency, and human-AI collaboration as vital competencies to future labor market will probably be incorporated in the future healthcare curriculum as formal knowledge.

5. Conclusions

This systematic review shows that Generative Artificial Intelligence has emerged as a paradigm shift in healthcare education and transformed teaching practice, the learning experience, assessment methods and academic culture in medical education, nursing education, pharmacy education, dental education and allied health education. The integration of the existing evidence indicates that the application of GenAI tools like ChatGPT and other large language models can substantially enhance the results of learning in the form of personalized learning, adaptive learning, intelligent tutoring system, virtual patient simulation, and self-directed learning environment. Such technologies assist in skills of clinical reasoning, problem-solving, critical thinking, digital literacy, and AI literacy, helping the students to work more actively with challenging concepts of healthcare and enhance their preparedness in the future professional practice. GenAI is also involved in the efficiency of education since it helps faculty through curriculum innovation, automated feedback, content generation, formative assessment and one-on-one student support.

Along with such positive aspects, the review also mentions significant risks connected with the extensive implementation of GenAI in healthcare training. The issue of plagiarism, academic dishonesty, excessive use of AI-created work, bias, transparency, data privacy, and diminished authenticity of student work are all major obstacles to responsible application. It has been indicated that current literature holds that the traditional assessment models are becoming more susceptible to abuse due to the fact that students can afford to use AI-generated responses without necessarily developing higher-order thinking and showing actual understanding. This has increased the necessity to redesign assessments by using oral assessments, reflective writing, simulated real-world clinical assignments, competency-based education, and process-based assessments that put greater focus on reasoning, communication, and practice as opposed to memorization. The review also shows the faculty preparedness and institutional policies to be inconsistent, leaving loopholes in the use of AI ethically, governance frameworks, and how to acceptably practice AI in academia.

The results indicate that the future of healthcare education will not be determined by the adoption of GenAI but rather by the degree to which it is successfully introduced into the teaching and learning systems. The collaboration between humans and AI should be at the core, with AI serving as the auxiliary learning device and not the alternative to autonomous thinking, clinical judgment and professionalism. Longitudinal studies, randomized controlled trials, and cross-disciplinary studies are the areas of future research to improve the understanding of the long-term impacts of GenAI on the learning outcomes, workforce readiness, cognitive development, and academic integrity. Further focus is required to investigate prompt engineering skills, ethical AI literacy, student perceptions, faculty readiness and creation of inclusive policies that are mindful of bias and equity issues. With the ongoing

development of healthcare education, the responsible integration of AI, evidence-based application, and robust ethical models will be required to achieve the full educational potential of GenAI without jeopardizing the credibility, authenticity, and integrity of healthcare training.

Conflict of interest

The authors declare no conflicts of interest.

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