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REVIEW

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Training future physicians with artificial intelligence: Enhancing clinical decision-making abilities through AI-driven simulations and real-world data analysis

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ABSTRACT

Artificial Intelligence (AI) is transforming healthcare and medical education by reshaping clinical reasoning, diagnostics, and treatment planning. In medical training, AI-enabled simulations and real-time data analytics allow students and physicians to practice decision-making in controlled, risk-free environments. AI technologies including Machine Learning (ML), Deep Learning (DL), and Natural Language Processing (NLP) are widely applied across medical disciplines. In surgical education, AI-powered virtual 3D models enable trainees to rehearse complex procedures, while computer vision systems analyze surgical videos to identify errors and inefficiencies. In diagnostics, AI systems integrate imaging data, genomic profiles, and clinical histories to improve early detection of diseases such as cancer and cardiovascular disorders. Despite these advancements, significant barriers limit AI adoption, particularly in Low and Middle-Income Countries (LMICs). Challenges include limited infrastructure, insufficient trained personnel, data privacy concerns, financial constraints, and unclear regulatory frameworks. Ethical considerations such as algorithmic bias, transparency, accountability, and equitable access must also be addressed to ensure responsible AI deployment. To effectively integrate AI into healthcare, physicians and educators must develop competencies in data literacy, AI fundamentals, ethics, and interdisciplinary collaboration. Medical curricula should incorporate structured AI training to prepare future healthcare professionals for technology-enhanced clinical environments. While high-income countries are rapidly advancing AI integration, LMICs face systemic constraints. However, emerging national AI strategies and global collaboration initiatives offer promising pathways toward equitable adoption. Integrating AI into health professions education is essential for preparing the next generation of clinicians to operate within increasingly data-driven healthcare systems.

KEY WORDS

AI in healthcare; Medical education AI; Clinical decision-making; AI simulations; NLP in medicine

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Introduction

Mathematical modeling

There have been some remarkable advances with AI over the preceding two decades, and its disruptive potential for healthcare is now more evident than ever before. AI refers broadly to computer systems that can do tasks which, when done by people, require intelligent things like perceiving information in images, recognizing sounds, making decisions and solving problems. AI is applied to treatment design and the diagnosis of diseases. It has been a very useful application for providers and educator's alike as it can process large amounts of data both quickly and accurately [1].

And these are some ways it could potentially help improve healthcare: Automating accurate diagnoses making treatment decisions achievable with better accuracy Equipping doctors to deliver evidence-based care and practice personalized medicine. Specifically, AI algorithms can analyze patient data - including medical history, lab tests and images-to recommend courses of treatment [2]. For example, AI systems like IBM's Watson for Oncology can read through vast quantities of clinical papers and suggest individual treatment plans based on the most recent evidence from the field [3]. AI can also assist with diagnosing, spotting patterns in images generated from medical scans that might be hard for a human to identify. Medical Imaging AI algorithms have been demonstrated to identify early signs of cancer in mammograms more accurately than Rads what did you wish you knew about this process [4]?

Medical education is already utilizing AI by giving students access to a body of real world patient diagnosis and treatment patterns with which they may compare themselves in a standardized pre-licensure benchmark experience that can bias one in the direction of focusing away from being reactive [2].

AI may contribute to addressing the imbalances in access to good medical education for students studying in impoverished areas. AI simulations can provide a range of patient cases, some of which may be rare or complex and so not seen as regularly in traditional medical education [1].

Evolution of medical education

Classical medical education is based on an organized set of lectures, clinical rotations and case study learning. These approaches have been a mainstay of medical education for hundreds of years, stressing the value of learning, patient interaction, and diagnosis. Through clinical rotations, learners are exposed to healthcare delivery in hospitals and have the opportunity observe and interact with actual patients while learning from experienced physicians. To supplement this, case-based learning gives students the opportunity of examining complex medical cases and formulate diagnostic and therapeutic procedures [5].

However, conventional medical education also has some drawbacks. Students are exposed to few and complex cases

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during their clinical rotations and get focused on common disease management. Thereby, a lot of students come out of the med school without having seen some crucial low-frequency cases they may encounter in clinical practice. Furthermore, in traditional clinical rotations, the time given to students for hands-on practice is usually short and practical training falls far short. This discrepancy is especially troubling in high-stakes medical decisions, where time sensitive and accurate judgment is critical (e.g., emergency care, neurosurgery and oncology) [6].

A further limitation of conventional medical education is the uneven access to high-quality training opportunities. When students in highly resourced medical schools may have exposure to the latest technology, as well as a variety of patient populations, those in low-resourced settings might not see much cases and they might be using many obsolete tools. Consequently, these students may have increased challenges securing the relevant clinical experience and decision-making skills needed to succeed in the profession [7].

AI-driven solutions have presented themselves as a powerful instrument in revolutionizing medical education. AI-enabled platforms, like virtual patient simulators and AI-based diagnostic instruments help the medical students to engage with virtual patients, take clinical decisions and also get real time feed-back. These platform provide a comprehensive and uniform approach to clinical education allowing students to practice their diagnostic as well as treatment skills with a wide-spectrum of cases encompassing rare and complicated patients that might be hard-to-find during their clerkship training (Figure 1) [1].

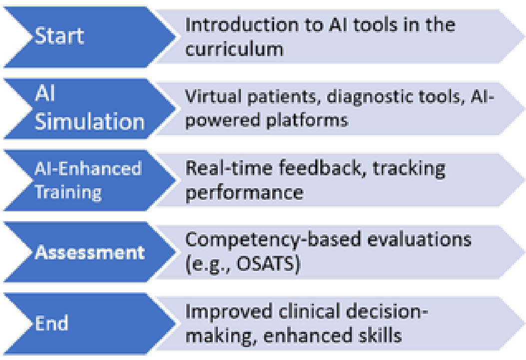

Figure 1. AI Integration in medical education.

Motivation for integrating AI in medical education

The use of AI in medical education therefore has potential to supplement the traditional teaching and address the shortcoming in clinical training. AI can resolve several issues such as lack of rare cases exposure, and shortage of time for practical training problems, access inequities to medical education resources. Simulating unusual variations of diseases when offering simulations of unusual medical conditions overcomplicated scenes in simulation these AI tools would provoke being diagnosed increases decision making for students, indicating them the tool therefore provides a broad clinical experience [8].

The skills framework related to AI is important for future physicians to properly use AI tools in clinical decision-making. There are five essential areas into which AI education should be incorporated at medical schools:

- **AI fundamentals:** Baseline knowledge of-ML/DL concepts and their applications such as medical decision making.
- **Ethical and legal issues:** Maintaining patient privacy, securing the data, ethical implications of AI in health care including bias in algorithms and transparency [9].
- **Data analysis and management:** Teach students the principles of data management, analysis and interpretation with big datasets such as Electronic Health Records (EHR), medical imaging and genomics.
- **Communication and teamwork:** Development of students' ability to communicate AI-based decision-making with patients/ partners and work collaboratively within multi-disciplinary teams including data scientists, clinicians and AI experts.
- **Assessment of the AI tool:** Training students to critically assess how well the AI tool works and whether it is fair, accurate, will be there for generalizable in making judgments or treatment recommendations.

Medical education is a key area that AI is applied to provide ubiquitous access to quality healthcare training. If the shortcomings of traditional medical education are met, AI-based solutions can offer students a more complete, varied and real-time clinical training so they can be better equipped to face today's healthcare issues. In the new era of AI, educators in medical education need to see that our trainees develop abilities to be able to use technologies that incorporate AI efficiently in their clinical practice. AI in the medical curriculum will result in better prepared physicians who are able to address changing clinical landscapes, improve patient outcomes, and meet the needs of inequities associated with access to medical training globally.

Methodology

Study design

This study employed a narrative integrative review approach to examine the evolving role of AI in healthcare and medical education. The review aimed to synthesize evidence regarding AI applications in clinical training, diagnostics, drug discovery, educator competency development, and implementation challenges while identifying implications for future medical education.

An integrative review methodology was selected because of the multidisciplinary nature of the topic and the diversity of available evidence, including empirical studies, systematic reviews, educational frameworks, policy reports, and technology assessments.

Literature search strategy

A structured literature search was conducted across multiple electronic databases, including :

- PubMed/MEDLINE
- Scopus
- Web of Science
- Google Scholar

The search focused on publications related to AI, healthcare education, medical training, clinical decision support, cancer diagnostics, drug discovery, competency frameworks, and AI governance.

Representative search terms included:

- "AI" AND "Medical Education"

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- "AI" AND "Healthcare Training"
- "ML" AND "Medical Curriculum"
- "Clinical Simulation" AND "AI"
- "Cancer Diagnosis" AND "Deep Learning"
- "AI Competencies" AND "Medical Educators"
- "Large Language Models" AND "Medical Education"

Reference lists of relevant articles were also manually screened to identify additional sources.

Eligibility criteria

Studies were included if they:

- Examined applications of AI in healthcare or medical education.
- Discussed AI-enabled clinical training, diagnostics, drug discovery, or educational innovation.
- Addressed educator competencies, AI literacy, governance, ethics, or implementation challenges.
- Were published in peer-reviewed journals, conference proceedings, or recognized institutional reports.
- Were available in English.

Studies were excluded if they :

- Focused exclusively on technical algorithm development without healthcare or educational relevance.
- Lacked sufficient methodological information.
- Were duplicate publications.
- Were non-English publications.

Study selection and data extraction

Titles and abstracts identified through database searches were screened for relevance. Potentially eligible articles underwent full-text review. Information extracted from included sources included:

- Study objectives.
- AI technologies examined.
- Healthcare or educational applications.
- Reported outcomes and findings.
- Ethical, regulatory, and implementation considerations.
- Recommendations for future practice and research.

Data were organized thematically to facilitate synthesis across multiple domains of AI application.

Data synthesis

A thematic synthesis approach was employed to identify recurring concepts and emerging trends across the literature. Findings were grouped into major thematic areas:

1. AI in clinical simulation and healthcare training.
2. AI-assisted diagnostics and cancer detection.
3. AI in drug discovery and biomedical research.
4. Competencies required for medical educators.
5. Global implementation considerations.
6. Ethical, regulatory, and governance challenges.

These themes informed the development of the conceptual framework proposed in this review.

Development of the competency framework

The proposed competency framework was developed through synthesis of recurring concepts identified within the reviewed literature. Competencies described by healthcare education organizations, digital health initiatives, and AI education frameworks were examined and categorized into common domains.

Five competency areas emerged consistently across the literature:

- Foundational AI Literacy
- Ethics and Responsible AI
- Data and Digital Health Literacy
- Interdisciplinary Collaboration
- Critical Evaluation of AI Systems

The framework should be regarded as a conceptual model intended to guide future curriculum development and research rather than a formally validated assessment instrument.

Limitations of the review methodology

Several methodological limitations should be acknowledged. First, the review did not employ a formal systematic-review protocol such as PRISMA and therefore may not have captured all relevant publications. Second, the rapidly evolving nature of AI means that new evidence may emerge after completion of the search process. Third, included studies varied considerably in design, scope, and quality, which may influence interpretation of findings.

Despite these limitations, the review provides a comprehensive synthesis of current evidence regarding AI in healthcare and medical education and identifies priorities for future research and practice.

AI-Driven Simulations and Clinical Decision-Making

Artificial intelligence (AI) is changing the landscape of medical education, particularly in clinical decision making. AI-driven simulations provide the possibility to interact with virtual, interactive clinical patients mirroring cases in real life and allow students to practice diagnostic and treatment decisions without risk for harm of real-life patients. In this review, we describe the use of AI-based platforms in clinical training, provide an overview of existing evidence on their efficacy and discuss the AI methods that have been applied for CPSS.

AI in simulations for clinical training

AI-based platforms are now an essential part of contemporary medical training and education through hands-on, high-fidelity simulations. Students practice and hone their clinical decision making in these artificial (virtual) environments. Some AI tools, like those offered by Surgical Theater, Touch Surgery and Osso VR, offer virtual reality that simulate complex surgeries and other clinical situations in 3D. By leveraging ML and DL algorithms, such devices analyze medical data and provide real-time feedback to students.

Surgical Theater is a top AI-driven simulation platform that generates 3D models of an individual patient's anatomy, helping students practice surgical procedures before they treat actual patients. Surgical Theater uses ML techniques to process preoperative imaging and patient information to

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mold simulations of procedures. This enables students to practice neurosurgeries and cardiac-operations in an even more accurate way – without the risks live operations bring along.

Touch Surgery also has high-fidelity simulations for various sorts of surgery, even minimally invasive procedures like laparoscopy and robotic surgery. The platform leverages DL to assess how well students complete different stages of surgery, in turn giving them immediate feedback to hone their abilities. A study of Kelley et al., Touch Surgery has been found to enhance students' technical proficiency, including the motion economy and bimanual dexterity (Key components of successful surgical practice).

Use Cases in Surgical Training:

- **Neurosurgery:** In neurosurgery, AI simulations enable students to practice on 3D models of patients' brains, performing dry runs of procedures such as tumor removal or cranial surgery. This allows students to practice difficult skills before applying them with real people.
- **Cardiac procedures:** Cardiac interventions e.g. coronary artery bypass grafting (CABG) and valve replacements require exactness. With AI simulations in cardiac surgery, students can learn how to plan for the surgery, make decisions and perform before they go into high-pressure situations. With the help of DL, these platforms can produce effects of a range of heart conditions for students to learn from [2].
- **Minimally invasive procedure:** Minimally invasive procedures, such as laparoscopy are performed by skilled professionals. AI powered platforms are critical for students to learn these skills, in that they give them real-time feedback on their suturing technique amongst other modalities like manipulation of a tool, dissection and handling tissue. The use of virtual simulations enables students to rehearse the skills prior to using them in actual clinical situations [4].

Comparison with traditional training methods

Conventional methods used to teach surgery are predominantly through supervised clinical rotations, where students watch and assist in few surgeries under an experienced specialist surgeon. This provides hands-on experience, though it has its flaws as well like unavailability of rare/complicated conditions, a limited time to practice and the risk of causing harm to the patient [1].

AI-powered simulations can help solve these problems by giving students additional, personalized training sessions with instant feedback. These virtual-training platforms improve technical skills, such as motion economy, bimanual dexterity and tissue handling as students have the opportunities to repeat each simulation multiple times without needing live operating time.

Measuring effectiveness: Outcomes and improvements

The effectiveness of AI-based simulation in medical education has been evaluated through various outcome measures, including technical skill acquisition, procedural accuracy, learning efficiency, and time to competency. Recent studies suggest that AI-enhanced simulation environments can facilitate deliberate practice by providing individualized feedback and objective performance assessment.

AI-driven simulation platforms use motion tracking, performance analytics, and automated feedback mechanisms to identify technical deficiencies during training. These systems allow learners to repeatedly practice procedures in a risk-free environment while receiving immediate guidance on instrument handling, hand movements, procedural sequencing, and error correction. Such feedback has been associated with improvements in technical performance and procedural confidence among medical trainees.

Several studies have demonstrated that learners trained using AI-assisted simulation achieve improved scores on standardized surgical assessment tools such as the Objective Structured Assessment of Technical Skills (OSATS). These improvements have been observed in domains including tissue handling, instrument use, flow of operation, and overall technical performance. Furthermore, AI-supported simulation systems provide objective metrics such as motion economy, path length, instrument smoothness, and task completion time, enabling a more comprehensive evaluation of learner competence than traditional subjective assessment methods.

Advanced simulation platforms increasingly incorporate motion tracking and kinematic analysis to quantify surgical performance. By analyzing hand movements and instrument trajectories, these technologies can distinguish between novice and expert performance patterns and generate personalized recommendations for skill improvement. Such objective performance measures support competency-based medical education and may contribute to more efficient progression toward clinical proficiency.

Overall, current evidence suggests that AI-enhanced simulation represents a valuable adjunct to traditional clinical training by improving feedback quality, enabling personalized learning, and facilitating objective assessment of procedural skills.

Types of AI techniques used in clinical simulations

AI-based clinical simulation platforms employ a range of computational techniques to enhance learning, provide personalized feedback, and support clinical decision-making. The most commonly applied approaches include ML, DL, computer vision, NLP, and reinforcement learning.

Machine learning

ML algorithms analyze learner performance data to identify patterns, assess competency levels, and generate individualized feedback. Supervised learning models can classify trainee performance based on predefined benchmarks, while unsupervised approaches can identify hidden patterns in learner behavior. In surgical education, ML techniques have been used to analyze motion-tracking and kinematic data to distinguish novice from expert performance and support competency assessment.

Deep Learning and Convolutional Neural Networks (CNNs)

DL methods, particularly convolutional neural networks (CNNs), are widely used in simulation systems involving medical imaging and surgical video analysis. CNNs can evaluate procedural recordings, identify technical errors, monitor instrument trajectories, and assess task performance. In image-based training environments, these models help learners recognize anatomical structures, pathological findings, and procedural landmarks. Real-time feedback generated by CNN-based systems can improve procedural accuracy and enhance learner engagement.

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Natural Language Processing (NLP)

NLP enables AI systems to understand and generate human language. In medical education, NLP supports intelligent tutoring systems, virtual patients, and conversational learning platforms. These tools can evaluate student responses, provide automated feedback, simulate patient interactions, and facilitate clinical reasoning exercises. Recent advances in large language models (LLMs) have further expanded the educational applications of NLP by enabling more sophisticated dialogue-based learning experiences.

Reinforcement Learning (RL)

Reinforcement learning is a branch of ML in which an agent learns optimal actions through interaction with an environment using rewards and penalties. In healthcare simulations, RL can support dynamic clinical decision-making scenarios such as emergency medicine, critical care management, and triage training. By adapting simulation complexity and feedback based on learner actions, RL-based systems create realistic educational environments that encourage problem-solving and decision-making under uncertainty.

Computer vision

Computer vision techniques enable AI systems to interpret visual information from images and videos. In clinical simulations, computer vision is used for gesture recognition, instrument tracking, procedural assessment, and performance monitoring. These technologies allow automated evaluation of technical skills and provide objective metrics that support competency-based medical education.

Collectively, these AI techniques contribute to more adaptive, personalized, and data-driven learning environments, enhancing both technical and non-technical competencies among healthcare professionals.

AI in Cancer Detection and Diagnosis

AI applied to the detection of cancer has demonstrated an impressive potential for early identification, accuracy and aiding treatment approach planning. AI technologies, such as ML and DL, have been increasingly used for medical data analyses of medical images, genomics, and patient histories to assist with early identification of cancers. In this part, we review AI for early cancer detection, Explainable AI (XAI) methods and chest imaging case studies in practice/the wild and the promise of AI for personalized cancer therapy.

AI's role in early cancer detection

Early detection remains one of the most important determinants of cancer survival and treatment success. AI has emerged as a valuable tool for improving cancer screening and diagnostic accuracy through the analysis of medical images, pathological specimens, genomic information, and electronic health records. By identifying subtle patterns that may be difficult for human observers to recognize, AI systems can support earlier diagnosis and assist clinicians in making evidence-based decisions.

Multimodal diagnostics

A major advantage of AI in oncology is its ability to integrate multiple sources of clinical information. Multimodal diagnostic systems combine radiological imaging, genomic profiles, laboratory findings, and patient history to generate more comprehensive assessments of cancer risk and disease progression. Such integration has the potential to improve diagnostic accuracy and support personalized treatment planning.

Recent advances in ML have enabled the development of models capable of analyzing heterogeneous datasets simultaneously. These approaches may provide more robust predictions than systems relying on a single diagnostic modality and are increasingly being explored across several cancer types, including breast, lung, colorectal, and ovarian cancers.

AI Applications in cancer screening

Breast cancer

Breast cancer screening is among the most extensively studied applications of AI in oncology. DL models trained on mammographic images have demonstrated performance comparable to, and in some settings exceeding, that of expert radiologists. In a landmark study, McKinney et al. (2020) reported that a DL system developed by Google Health reduced both false-positive and false-negative rates when compared with radiologist interpretation across multiple screening datasets.

Ovarian cancer

AI has also shown promise in ovarian cancer detection through the integration of imaging findings and biomarker information. ML models incorporating biomarkers such as CA-125 and HE4 alongside radiological features have demonstrated improved predictive performance compared with traditional risk assessment approaches. Although promising, further multicenter validation studies are required before widespread clinical adoption.

Lung cancer

Lung cancer screening has benefited substantially from advances in AI-assisted image analysis. DL algorithms have been developed to evaluate low-dose computed tomography (LDCT) scans and identify suspicious pulmonary nodules at earlier stages. Several studies have demonstrated that AI systems can achieve diagnostic performance comparable to experienced radiologists while reducing interpretation time and assisting with risk stratification.

Clinical significance

The growing body of evidence suggests that AI can enhance cancer screening workflows by improving efficiency, supporting clinical decision-making, and reducing diagnostic variability. However, AI systems should be viewed as decision-support tools rather than replacements for clinicians. Human oversight remains essential to ensure appropriate interpretation of findings, particularly in complex clinical scenarios where contextual judgment and patient-specific factors influence diagnostic decisions.

Explainable AI (XAI) in cancer diagnostics

Despite the impressive performance of AI systems in cancer detection and diagnosis, concerns regarding transparency and interpretability remain major barriers to clinical adoption. Many advanced DL models operate as "black-box" systems, generating predictions without providing clear explanations of how decisions are reached. In healthcare, where diagnostic decisions directly affect patient outcomes, clinicians must be able to understand, evaluate, and justify AI-generated recommendations.

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Importance of explainability in clinical practice

Explainability refers to the ability of an AI system to provide understandable reasons for its predictions or recommendations. In oncology, explainability is particularly important because diagnostic decisions often involve complex clinical considerations and high-risk consequences. Transparent AI systems can improve clinician trust, facilitate regulatory approval, support shared decision-making, and enhance patient confidence in AI-assisted care.

Furthermore, explainable models may assist clinicians in identifying potential errors, biases, or unexpected model behavior before these affect patient management. Consequently, explainability has become a central requirement for the safe and ethical deployment of AI in healthcare.

Major explainable AI techniques

Several methods have been developed to improve the interpretability of AI systems used in cancer diagnostics.

Gradient-weighted class activation mapping (Grad-CAM)

Grad-CAM is a visualization technique that highlights image regions contributing most strongly to a model's prediction. In cancer imaging applications, Grad-CAM can identify specific areas within mammograms, computed tomography (CT) scans, or histopathological images that influence diagnostic classifications. These visual explanations enable clinicians to compare AI reasoning with their own interpretations and improve confidence in model outputs.

Shapley additive explanations (SHAP)

SHAP is a model-agnostic interpretability framework that quantifies the contribution of individual variables to a prediction. In cancer diagnostics, SHAP can demonstrate how factors such as age, genetic markers, laboratory values, imaging features, and clinical history influence diagnostic outcomes. By providing feature-level explanations, SHAP improves transparency and facilitates clinical validation of AI recommendations.

Attention mechanisms

Attention-based neural networks identify and prioritize the most relevant information within complex datasets. In medical imaging applications, attention mechanisms can highlight clinically significant regions such as tumor boundaries, abnormal tissue patterns, or suspicious lesions. These visual cues allow clinicians to better understand the model's focus during decision-making and assess whether predictions are clinically reasonable.

Trust, transparency, and clinical acceptance

Trust remains one of the most significant challenges in AI adoption. Healthcare professionals are often reluctant to rely on recommendations generated by systems that cannot adequately explain their reasoning. Explainable AI techniques address this concern by providing interpretable outputs that support clinical judgment rather than replacing it.

However, explainability alone does not guarantee reliability. AI models may still be affected by dataset bias, poor generalizability, incomplete clinical data, or algorithmic errors. Therefore, explainability should be viewed as one component of a broader framework that includes rigorous validation, continuous monitoring, ethical oversight, and human supervision.

Limitations of explainable AI

Although XAI improves transparency, several limitations remain. Some explanation methods provide only approximate representations of model behavior and may not fully capture underlying decision processes. Additionally, different explanation techniques may generate varying interpretations for the same prediction. Future research should focus on developing standardized evaluation methods and clinically meaningful explanations that enhance both interpretability and patient safety.

Overall, explainable AI represents a critical step toward responsible integration of AI into oncology by improving transparency, supporting clinical decision-making, and fostering trust among healthcare professionals and patients.

Case studies: AI in cancer detection

Case studies provide valuable insights into the practical implementation of AI technologies in oncology. Although numerous AI systems have demonstrated promising performance in research settings, their translation into routine clinical practice requires careful evaluation of effectiveness, reliability, and clinical utility.

Deep learning for breast cancer screening

One of the most widely cited examples of AI in oncology is the application of DL to breast cancer screening. McKinney et al. (2020) developed a DL model capable of analyzing mammographic images and assisting radiologists in detecting breast cancer. The system demonstrated strong performance across multiple datasets and highlighted the potential of AI to reduce diagnostic workload while improving consistency in image interpretation.

The study emphasized that AI should function as a decision-support tool rather than a replacement for radiologists. Human oversight remained essential for interpreting findings, resolving ambiguous cases, and integrating imaging results with broader clinical information.

AI-supported clinical decision systems

AI-based clinical decision-support systems have been developed to assist oncologists in selecting treatment options based on patient characteristics, clinical guidelines, and scientific literature. These systems aim to synthesize large volumes of information and provide evidence-based recommendations that support clinical decision-making.

IBM Watson for Oncology is frequently cited as an early example of this approach. The platform was designed to analyze clinical data and generate treatment recommendations for various cancers. While some studies reported substantial agreement between Watson-generated recommendations and expert opinions, performance varied considerably across healthcare settings, cancer types, and patient populations. These experiences highlighted the challenges of implementing AI systems in complex clinical environments and underscored the importance of local validation before deployment.

Lessons learned from clinical applications

Several important lessons have emerged from AI implementation in oncology:

1. High algorithmic performance in research settings does not always translate directly into clinical effectiveness.
2. External validation across diverse patient populations is essential to ensure generalizability.

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3. Clinician oversight remains necessary to contextualize AI recommendations and address unusual clinical scenarios.
4. Transparency, explainability, and regulatory compliance are critical factors influencing clinical adoption.
5. Successful implementation requires integration with existing healthcare workflows and continuous performance monitoring.

These case studies demonstrate that while AI has considerable potential to enhance cancer detection and clinical decision-making, successful adoption depends on rigorous validation, multidisciplinary collaboration, and responsible governance.

AI and personalized cancer treatment

AI-driven treatment recommendations

AI contributes indispensable role in prescribing personalized treatment strategies for cancer patients utilizing data such as cancer subtypes, genetic mutations, patient overall health and medical history. Trained on large datasets, such as genomic profiles, details of previous clinical trials and the results obtained from different patients subjected to those therapies, AI algorithms learn how to comprehensively analyze these data in order to recommend the most suitable therapy [2]. That enable "precision oncology" — treatments tailored to the specific nature of the patient's disease and genetic profile.

Optimization of chemoradiation

AI is used to model optimal combinations of chemotherapy and radiation therapy. AI systems can process dosage and timing of medicines, changing them in real time to achieve maximum benefit with minimum side effects. For instance, AI algorithms can predict the best radiation dose for patients with head and neck cancers to lower the chance of damaging healthy surrounding tissues [4].

Prediction of treatment outcomes and minimization of side effects

AI systems can also be used to forecast the outcome of treatment, helping clinicians modify treatments based on individual outcomes. By crunching historical health data and treatment response rates, AI can even forecast how patients will likely respond to particular treatments. This predictive capacity empowers physicians to develop a treatment plan more intelligently, even early in disease course, thus decreasing chances of treatment failure and side effects.

AI in Personalized Medicine and Drug Discovery

The convergence of AI and personalized medicine is a new, promising, field in healthcare that has the ability to significantly improve medications discovery, disease diagnosis and treatment. AI-based tools such as DL and ML have shown great promise in predicting protein structures, drug targets and designing personalized patient treatment plans." Here is what today's installment will be about this chapter discusses how AI helps in drug discovery, specifically focusing on AlphaFold 3, it's improvements and applications in the real-life examples and also how its implications affect drug repurposing, target identification and personalized treatment plans (Table 1).

Table 1. Comparison of AI tools in healthcare.

AI Tool	Field	Application	Key Benefits
Surgical Theater	Surgical Training	Virtual surgery simulations on 3D models	Enhances precision, reduces error
CHEXpert	Diagnostics (Radiology)	Lung cancer, TB, pneumonia diagnosis	Offline diagnostic tool, reduces errors
IBM Watson for Oncology	Cancer Treatment	Personalized treatment plans for cancer	Improves treatment accuracy, personalized care
MedMinder	Drug Safety	Medication interaction alerts	Prevents adverse drug reactions

AlphaFold 3 and drug discovery

AI has significantly transformed drug discovery through advances in protein structure prediction, molecular modeling, and target identification. Among the most influential developments is AlphaFold, an AI system developed by DeepMind that predicts three-dimensional protein structures from amino acid sequences. Accurate prediction of protein structures is essential for understanding biological mechanisms, identifying therapeutic targets, and accelerating drug development.

Evolution from AlphaFold 2 to AlphaFold 3

AlphaFold 2 represented a major breakthrough in computational biology by achieving near-experimental accuracy in protein structure prediction. Building upon this achievement, AlphaFold 3 introduced substantial improvements in modeling biologically relevant molecular interactions. Unlike previous versions, AlphaFold 3 can predict interactions among proteins, DNA, RNA, ligands, and other biomolecules, providing a more comprehensive representation of cellular processes.

These advances enable researchers to investigate complex molecular systems that were previously difficult to characterize using computational approaches alone.

Protein structure prediction and drug discovery

Understanding protein structure is fundamental to modern drug discovery because protein shape determines biological function and influences interactions with therapeutic compounds. Traditional experimental techniques such as X-ray crystallography, nuclear magnetic resonance spectroscopy, and cryo-electron microscopy provide highly accurate structural information but are often time-consuming and resource-intensive.

AI-based prediction systems such as AlphaFold have dramatically accelerated this process by generating accurate structural models within hours rather than months or years. The availability of large-scale protein structure databases has expanded opportunities for researchers to identify novel drug targets and better understand disease mechanisms.

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Molecular interaction prediction

A major advancement introduced by AlphaFold 3 is its enhanced ability to model molecular interactions. Drug discovery depends heavily on understanding how proteins interact with small molecules, nucleic acids, and other biological structures. By accurately predicting these interactions, AlphaFold 3 can assist researchers in identifying promising therapeutic candidates and prioritizing experimental investigations.

Improved modeling of protein–ligand interactions may facilitate more efficient drug screening, optimization of lead compounds, and rational drug design strategies.

Applications in biomedical research

AlphaFold-derived structural predictions have already contributed to research in oncology, neurodegenerative disorders, infectious diseases, and rare genetic conditions. Structural insights generated through AI-assisted modeling have supported investigations of disease-associated proteins and accelerated hypothesis generation for potential therapeutic interventions.

In cancer research, structural prediction tools have aided the characterization of proteins involved in tumor growth and signaling pathways. In neurodegenerative diseases, researchers have used computational models to better understand protein aggregation processes associated with disorders such as Alzheimer's and Parkinson's disease.

Limitations and future directions

Despite its transformative impact, AlphaFold does not eliminate the need for experimental validation. Predicted structures must still be confirmed through laboratory studies before clinical application. Furthermore, biological systems are dynamic and influenced by environmental factors that may not be fully captured by computational models.

Future developments are expected to further improve prediction accuracy, model complex cellular interactions, and integrate multi-omics data, thereby strengthening the role of AI in precision medicine and drug discovery.

Overall, AlphaFold 3 represents a significant advancement in AI-enabled biomedical research and illustrates how computational innovations can accelerate scientific discovery while complementing traditional experimental methods.

AI in drug repurposing and target identification

AI is increasingly being used to accelerate drug discovery by supporting target identification, biomarker discovery, and drug repurposing. Traditional drug development is often costly, time-consuming, and associated with high failure rates. AI-based approaches can assist researchers by analyzing large-scale biological and clinical datasets to identify promising therapeutic opportunities more efficiently.

AI in target identification

Target identification is a critical early stage of drug discovery that involves determining biological molecules associated with disease processes. ML algorithms can analyze genomic, proteomic, transcriptomic, and clinical datasets to identify genes, proteins, and signaling pathways that may serve as therapeutic targets.

By integrating diverse biological data sources, AI systems can reveal previously unrecognized relationships between molecular pathways and disease mechanisms. These approaches have been applied in oncology, cardiovascular disease, infectious diseases, and neurological disorders to support the discovery of potential intervention points.

Network-based ML methods are particularly useful for identifying disease-associated pathways and prioritizing candidate targets for further experimental investigation. However, computational predictions must undergo rigorous laboratory validation before they can inform clinical development.

AI-driven drug repurposing

Drug repurposing refers to the identification of new therapeutic uses for existing medications. Because repurposed drugs often have established safety profiles, this strategy may reduce development costs and shorten the time required for clinical translation.

AI can facilitate drug repurposing by analyzing biomedical literature, electronic health records, molecular interaction networks, and clinical datasets to identify potential drug–disease relationships. ML models can detect patterns that may not be readily apparent through conventional analytical methods and generate hypotheses for further investigation.

During the COVID-19 pandemic, AI-based approaches were widely used to screen existing drug libraries and prioritize compounds for evaluation against SARS-CoV-2. Although many AI-generated candidates required subsequent experimental verification, these efforts demonstrated the potential of computational approaches to accelerate early-stage drug discovery workflows.

Integration of multi-omics data

Recent advances in AI have enabled the integration of multi-omics datasets, including genomics, transcriptomics, proteomics, and metabolomics. Such integration provides a more comprehensive understanding of disease biology and may improve the identification of therapeutic targets and biomarkers.

AI models can uncover complex interactions among biological systems that would be difficult to detect using traditional statistical approaches alone. These capabilities support precision medicine initiatives aimed at developing more individualized treatment strategies.

Challenges and limitations

Despite its promise, AI-assisted drug discovery faces several challenges. Many models depend on large, high-quality datasets that may be incomplete, biased, or unavailable for certain diseases. Reproducibility and generalizability remain important concerns, particularly when models are applied across different populations or healthcare settings.

Furthermore, computational predictions do not constitute proof of efficacy. Candidate targets and repurposed drugs identified through AI must undergo extensive experimental validation, preclinical testing, and clinical trials before they can be adopted in routine clinical practice.

Future directions

Future research is expected to focus on combining AI with systems biology, molecular simulation, and real-world clinical data to improve predictive performance and translational

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relevance. As datasets become more comprehensive and algorithms more sophisticated, AI is likely to play an increasingly important role in supporting but not replacing the scientific processes underlying drug discovery and development.

Clinical applications of AI in medicine

Case studies on AI for personalized medicine

AI has been taking on a growing role in personalized medicine, an approach to treatment that customizes medical care for patients based on their individual disease gene characteristics. The integration of genomic data with clinical histories in order to devise personalized treatment plans for patients is one of the main uses of AI in personalised medicine. AI mechanisms are taught to interpret a patient's genetic profile, such as particular types of mutation, and gene expression patterns in order to inform treatment responses [2].

IBM Watson for Oncology, is one that uses AI to analyze a patient's genetic information and medical records along with the latest clinical trial findings to suggest personalized treatments for cancer. This system have been proved to accurately align treatment recommendations with expert oncologists' choices in cancer diseases, such as breast cancer and colon cancer.

AI in the context of precision medicine for chronic diseases

AI has also been heavily implemented in precision medicine for chronic diseases such as diabetes and cardiovascular disease. AI models are predictive of hyperglycemia or hypoglycemia by considering various biological determinants like genetic data, nutrition and life style factors in diabetes. By tracking all these factors into AI can recommend medications and lifestyle changes that allow patients to control the condition in a more effective way [2].

And while AI is analyzing genomic markers, blood pressure and cholesterol levels in cardiovascular disease to develop personalized treatment regimens. AI models can predict an individual's risk of heart attack, stroke or another cardiovascular event and thus help doctors to deliver timely interventions that might save lives [2].

Physician Competencies for AI Integration

With the ongoing transformational impact of AI within health care, it is important that next-generation physicians can competently incorporate AI-based tools into their daily clinical work. The increasing use of AI in diagnosis, treatment planning, and decision-making has made it necessary for medical professionals to have a general knowledge of not only the technical side of AI but also its ethical-legal aspects and related data problems. This section discusses a 5-domain competency model as a proposed framework for physician competencies, in relation to the specialized skills under medical education that should be developed to support AI integration into practice. The section will also examine how to educate these competencies, in curricula at medical schools, as well as the need for AI training that is specialized according to specialty.

Development of the proposed AI competency framework

The competency framework proposed in this paper was developed through synthesis of themes identified across contemporary literature on AI in healthcare education, physician competency development, digital health literacy, and AI governance. Rather than presenting a completely novel framework, the model represents an integrative adaptation of competencies described by organizations such as the Association of American Medical Colleges (AAMC), the World Health Organization (WHO), the Royal College of Physicians and Surgeons of Canada, and emerging AI education frameworks reported in the literature [9].

The framework was designed to address the evolving role of medical educators in preparing healthcare professionals for AI-enabled clinical environments. Five competency domains were identified based on their recurring presence across educational, clinical, ethical, and technological discussions within the reviewed literature. These domains encompass foundational AI knowledge, ethical and regulatory awareness, data literacy, interdisciplinary collaboration, and critical evaluation of AI systems.

As a conceptual framework, the model has not yet undergone formal empirical validation. Future studies should evaluate its reliability, content validity, and educational effectiveness through expert consensus methods, Delphi studies, and implementation across diverse medical education settings.

Competency framework for physicians using AI

The deployment of AI on the clinical floor involves a wide array of skills from technical and ethical to interaction-based factors. Suggested 5-domain Physician Competency Framework The proposed framework enumerates domains thought to be necessary for the proper deployment of AI tools in clinical settings. These domains are intended to allow a physician not just to use AI tools but understand when they can and cannot be relied upon, assess reliability, communicate findings with both patients and care teams.

AI fundamentals

Medical educators should possess a fundamental understanding of AI concepts, including ML, DL, NLP, computer vision, and clinical decision-support systems. Educators are not expected to become AI developers; however, they should understand the capabilities, limitations, and clinical applications of AI technologies sufficiently to teach these concepts within healthcare curricula.

Key competencies include:

- Understanding core AI terminology and principles.
- Recognizing major healthcare applications of AI.
- Interpreting AI-generated outputs within clinical contexts.
- Appreciating the strengths and limitations of AI systems.

Ethics, governance, and responsible AI

Medical educators should be capable of teaching ethical and regulatory considerations surrounding AI implementation in healthcare. This includes issues related to patient privacy, informed consent, algorithmic bias, transparency, accountability, and equity.

Key competencies include:

- Understanding ethical principles governing AI use.
- Recognizing sources of algorithmic bias.
- Promoting responsible and equitable AI deployment.
- Interpreting relevant regulatory and governance frameworks.

Data and digital health literacy

AI-enabled healthcare depends on high-quality data. Medical

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educators should understand the principles of data quality, electronic health records, clinical datasets, and data stewardship. Such knowledge enables educators to teach learners how data influence AI performance and clinical reliability.

Key competencies include:

- Understanding healthcare data sources.
- Appreciating data quality and bias issues.
- Interpreting AI performance metrics.
- Promoting evidence-based use of digital health technologies.

Interdisciplinary collaboration

Effective AI implementation requires collaboration among clinicians, educators, data scientists, engineers, informaticians, and policymakers. Medical educators should prepare learners to work within multidisciplinary teams and communicate effectively across professional boundaries.

Key competencies include:

- Collaborating with technical specialists.
- Participating in AI implementation initiatives.
- Facilitating team-based problem solving.
- Supporting innovation within healthcare systems.

Critical evaluation of AI systems

Medical educators should develop the ability to critically evaluate AI technologies before recommending or adopting them in educational or clinical settings. Learners must understand that AI outputs should not be accepted uncritically and must always be interpreted within clinical context.

Key competencies include:

- Assessing AI performance and validity.
- Identifying limitations and potential risks.
- Evaluating explainability and transparency.
- Applying evidence-based judgment to AI-assisted decisions.

Limitations of the proposed framework

The proposed framework is conceptual and derived from synthesis of existing literature rather than empirical testing. Although it incorporates themes consistently identified across published competency frameworks, formal validation has not yet been conducted. Future research should evaluate the framework through expert consensus processes, multicenter implementation studies, and assessment of educational outcomes among faculty and learners.

Developing physician competencies in AI

Training physicians in AI is particularly important to make sure AI tools will be well integrated into clinical practice. Curricula celebrating and integrating the 5 domains of competency into medical education should be created so that graduates are not only competent, but remain relevant in the challenges they must face. AI Fundamentals, ethics and practices Data management and clinical application of AI And the need to promote an interdisciplinary approach for integrating AI into medical research [9].

Physicians' proficiency in AI needs to be evaluated by competency-based measures. Such tests can be practical tests (where test-takers reproduce code using AI-enabled simulation platforms), as well as written exams and discussions based on real case studies. Through a structured evaluation of AI proficiency, medical programs can ensure that their learners possess the ability to optimally utilize AI tools to enhance patient care [10].

Educator Competencies in AI-Enhanced Education

The proper training of medical educators with respect to teaching AI concepts is an important need considering increasing widespread use of AI in medical education. This review discusses the AI-related competencies of medical educators, emphasizing to the frameworks by AAMC and RSNA, approaches on how to develop AIA-competent medical educators, and assessments for measuring the success of incorporating AI in teaching [11].

Core competencies for medical educators in the AI era

The integration of AI into healthcare requires medical educators to develop competencies that extend beyond traditional teaching responsibilities. Educators must be prepared not only to explain AI concepts but also to guide learners in critically evaluating, ethically applying, and safely integrating AI technologies into clinical practice.

AI Literacy and clinical applications

Medical educators should possess foundational knowledge of AI concepts, including ML, DL, NLP, computer vision, and clinical decision-support systems. This knowledge enables educators to explain how AI technologies are applied in areas such as medical imaging, diagnostics, risk prediction, treatment planning, and healthcare operations.

Critical evaluation of AI systems

Educators should be capable of teaching learners how to assess the strengths, limitations, and potential risks of AI systems. This includes understanding model performance metrics, sources of bias, generalizability concerns, and the importance of external validation before clinical implementation.

Ethical and regulatory competence

AI education should include ethical considerations such as patient privacy, algorithmic bias, transparency, accountability, fairness, and informed consent. Educators must help learners understand the ethical responsibilities associated with AI-assisted healthcare and the evolving regulatory landscape governing AI technologies.

Interdisciplinary collaboration

Successful AI implementation requires collaboration among clinicians, educators, data scientists, engineers, and healthcare administrators. Medical educators should promote interdisciplinary teamwork and prepare learners to work effectively within technology-enabled healthcare environments.

AI-enhanced teaching and assessment

Educators should understand how AI-powered educational technologies can support personalized learning, adaptive assessment, virtual patient simulations, and competency-based education. Effective integration of these tools can enhance learning experiences while maintaining educational rigor and human oversight.

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Large language models in medical education

Recent advances in LLMs have introduced new opportunities and challenges for medical education. Systems such as generative AI chatbots can support learning by providing explanations, generating clinical scenarios, assisting with literature review, and facilitating self-directed study [12].

Potential educational applications include:

- Clinical reasoning exercises.
- Generation of case-based learning scenarios.
- Drafting educational content and assessment materials.
- Summarization of scientific literature.
- Support for reflective learning and feedback.

Despite these benefits, LLMs may produce inaccurate, outdated, or fabricated information. Consequently, medical educators should teach learners to critically evaluate AI-generated content, verify information using authoritative sources, and recognize the limitations of generative AI systems [13].

The growing presence of LLMs in healthcare education highlights the need for AI literacy that extends beyond predictive algorithms to include responsible use of generative AI technologies [14].

Building educator competencies in AI

Developing AI competency among medical educators requires a structured and continuous professional development strategy. Faculty development initiatives should focus on foundational knowledge, practical applications, ethical considerations, and educational implementation.

Faculty development programs

Medical schools should establish dedicated faculty-development programs that introduce educators to AI concepts and healthcare applications. These initiatives may include workshops, online courses, certification programs, and hands-on training experiences involving clinical AI tools.

Communities of practice

AI competency development should be viewed as an ongoing process rather than a one-time training activity. Institutions should foster communities of practice that encourage collaboration, resource sharing, peer learning, and discussion of emerging developments in healthcare AI.

Experiential learning

Educators benefit from direct exposure to AI technologies used in clinical and educational settings. Examples include virtual patient platforms, AI-assisted diagnostic systems, adaptive learning environments, and educational analytics tools. Practical experience helps educators better understand both the opportunities and limitations of AI implementation.

Scholarship and continuous updating

Given the rapid pace of technological advancement, educators should engage in continuous professional development through conferences, scholarly publications, interdisciplinary collaborations, and professional societies focused on digital health and medical education.

Evaluation of educator competence in AI

Assessment of educator competence should align with the proposed competency framework and include multiple evaluation methods.

Key assessment domains include:

AI knowledge

- Understanding of foundational AI concepts and healthcare applications.
- Ability to explain AI capabilities and limitations.

Pedagogical integration

- Effective incorporation of AI-related content into teaching activities.
- Appropriate use of AI-enhanced educational technologies.

Ethical and regulatory awareness

- Ability to address ethical, legal, and governance issues associated with AI.

Learner feedback

- Student perceptions regarding clarity, relevance, and effectiveness of AI instruction.

Educational outcomes

- Evidence that learners can critically evaluate and appropriately apply AI concepts within clinical contexts.

A combination of self-assessment, peer review, learner feedback, teaching portfolios, and competency-based evaluation can provide a comprehensive assessment of educator readiness for AI-enabled medical education [15].

Global Implementation Landscape

The integration of AI into healthcare and medical education varies considerably across regions due to differences in infrastructure, regulatory maturity, workforce readiness, research capacity, and healthcare investment. While high-income countries (HICs) generally have greater access to digital resources and AI research ecosystems, low- and middle-income countries (LMICs) are increasingly exploring AI-enabled solutions to address workforce shortages, limited specialist access, and healthcare inequities [16].

Understanding these diverse implementation environments is essential for developing context-specific strategies for AI adoption in healthcare education and clinical practice.

AI readiness in high-income countries

Many high-income countries have established national AI strategies and invested substantially in digital health infrastructure, research, and workforce development. These investments have facilitated experimentation with AI applications in diagnostics, medical imaging, clinical decision support, and healthcare administration [17].

Medical education

Medical schools in several countries have begun introducing AI-related content into undergraduate and postgraduate curricula. Educational initiatives commonly include foundational AI literacy, digital health, data science, ethics, and clinical applications of ML. However, considerable variability remains regarding curriculum content, implementation approaches, and competency assessment.

Clinical implementation

AI technologies have been evaluated in a variety of clinical settings, including radiology, pathology, ophthalmology, and

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oncology. Clinical decision-support systems and AI-assisted diagnostic tools are increasingly being incorporated into healthcare workflows, although adoption remains uneven and often depends on local infrastructure, regulatory approval, and clinician acceptance.

Persistent challenges

Despite favorable conditions, several barriers continue to affect implementation:

- Integration with existing clinical workflows.
- Clinician trust and acceptance.
- Algorithmic bias and fairness concerns.
- Data governance and privacy requirements.
- Regulatory oversight and validation requirements.

These challenges demonstrate that successful AI adoption depends not only on technological capability but also on organizational readiness and governance structures.

AI adoption in low- and middle-income countries

AI has the potential to address several healthcare challenges in LMICs, including shortages of healthcare professionals, limited specialist availability, delayed diagnoses, and restricted access to educational resources. However, implementation is often constrained by infrastructure limitations and resource availability [18].

Common barriers

Key barriers reported in LMIC settings include:

- Limited digital infrastructure.
- Variable internet connectivity.
- Insufficient computational resources.
- Shortages of AI-trained personnel.
- Limited regulatory guidance.
- Restricted access to high-quality healthcare datasets.

These challenges may hinder both educational and clinical implementation of AI technologies.

Emerging opportunities

Despite these constraints, AI may provide important opportunities for strengthening healthcare delivery and medical education. Mobile-health platforms, telemedicine services, cloud-based educational resources, and AI-assisted diagnostic systems may help extend healthcare services to underserved populations.

Several initiatives have demonstrated the feasibility of deploying AI-supported healthcare solutions in resource-constrained environments, particularly when technologies are adapted to local needs and infrastructure realities.

Bridging the global AI divide

Reducing disparities in AI adoption requires collaborative approaches involving governments, educational institutions, healthcare organizations, industry partners, and international agencies [19].

Potential strategies include:

- Investment in digital infrastructure.
- Development of context-specific regulatory frameworks.
- Expansion of AI literacy and workforce training programs.
- Promotion of international research collaborations.
- Support for open-access educational resources.
- Encouragement of locally relevant AI innovation.

Such efforts may help ensure that the benefits of AI are distributed more equitably across healthcare systems worldwide.

Lessons for medical education

Experiences from both HICs and LMICs suggest that AI integration should be guided by educational needs rather than technological enthusiasm alone. Effective implementation requires attention to curriculum design, faculty development, ethical considerations, learner readiness, and institutional capacity.

Medical education programs should therefore adopt flexible, context-sensitive approaches that prepare future healthcare professionals to use AI responsibly while maintaining patient-centered care and professional judgment.

Critical perspective on global AI adoption

Although enthusiasm surrounding AI continues to grow, evidence regarding large-scale implementation remains mixed. Many AI systems demonstrate promising performance under controlled research conditions but encounter challenges during real-world deployment. Factors such as workflow integration, clinician acceptance, regulatory approval, data quality, and long-term sustainability frequently influence implementation success. Consequently, healthcare organizations should evaluate AI technologies critically and prioritize evidence-based adoption strategies.

Pakistan and South Asia Context

AI is gaining increasing attention across South Asia as healthcare systems seek innovative approaches to address workforce shortages, unequal healthcare access, rising disease burdens, and resource constraints [20]. Countries including Pakistan, India, Bangladesh, and Sri Lanka have initiated digital health and AI-related programs; however, implementation remains uneven due to variations in infrastructure, workforce preparedness, regulatory development, and technological capacity.

In the context of medical education, AI presents opportunities to enhance learning, improve access to educational resources, and strengthen clinical decision-making skills. Nevertheless, successful integration requires attention to digital literacy, faculty development, ethical considerations, and local healthcare realities.

This section examines emerging AI initiatives in Pakistan and South Asia while highlighting key opportunities, challenges, and implications for healthcare education and practice.

Policy and institutional readiness

Several South Asian countries have recognized the potential importance of AI within national development strategies. These initiatives generally emphasize digital transformation, innovation, workforce development, and expansion of technology-enabled services.

In Pakistan, policy discussions increasingly acknowledge the potential role of AI in healthcare, education, agriculture, and public services. Similarly, neighboring countries such as India have launched national initiatives focused on digital health, health informatics, and AI-driven innovation. Despite these developments, implementation remains at an early stage, and substantial gaps persist between policy aspirations and operational deployment.

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Challenges affecting institutional readiness include limited digital infrastructure, variable internet access, shortages of trained personnel, fragmented healthcare data systems, and evolving regulatory frameworks [21]. Addressing these barriers will be essential for sustainable AI integration within healthcare and medical education.

Emerging applications of AI in healthcare

Although large-scale AI deployment remains limited in many South Asian healthcare systems, several emerging applications illustrate the potential value of AI-supported healthcare services (Figure 2).

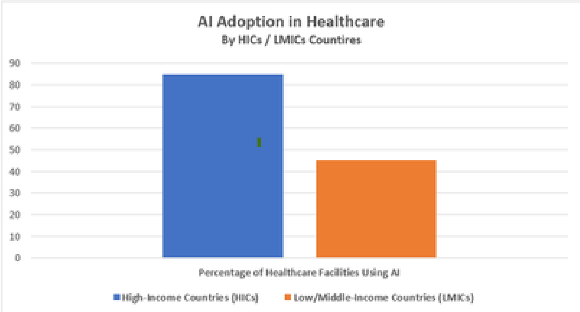

Figure 2. AI adoption in healthcare between HICs and LMICs.

Telemedicine and digital health

The rapid expansion of telemedicine platforms has demonstrated how digital technologies can improve access to healthcare, particularly in underserved and rural communities. AI-assisted triage systems, symptom assessment tools, and virtual consultation platforms may help optimize healthcare delivery where specialist resources are limited [22].

Medical imaging and diagnostic support

AI-assisted diagnostic systems have attracted considerable interest because of their potential to support interpretation of radiological and pathological data. Such technologies may be particularly valuable in regions experiencing shortages of radiologists and other specialists. However, successful implementation requires local validation, appropriate infrastructure, and regulatory oversight to ensure reliability and patient safety.

Public health applications

AI has also been explored for disease surveillance, outbreak monitoring, healthcare resource allocation, and population-health analytics [23]. These applications may contribute to more efficient healthcare planning and improved responses to emerging public health challenges.

Despite encouraging developments, most AI applications in South Asia remain in pilot, research, or early implementation phases. Additional evidence is required to establish long-term effectiveness, scalability, and sustainability.

Attitudes of medical students and healthcare professionals toward AI

Emerging studies from South Asia and other regions suggest that medical students generally express positive attitudes toward AI and recognize its potential role in future clinical practice [24]. Students commonly report interest in learning about AI applications in diagnostics, medical imaging, clinical decision support, and healthcare management.

At the same time, concerns frequently emerge regarding :

- Insufficient AI-related education.
- Limited understanding of underlying technologies.
- Ethical and legal implications.
- Data privacy and security.
- Potential effects on professional roles and employment.

These findings indicate a growing demand for structured AI education within medical curricula. Medical schools should therefore consider incorporating foundational AI literacy, digital health competencies, and critical appraisal skills to prepare graduates for AI-enabled healthcare environments.

Opportunities and challenges for medical education

The integration of AI into medical education in Pakistan and South Asia presents both opportunities and challenges.

Opportunities

- Enhanced access to educational resources.
- Personalized and adaptive learning systems.
- AI-supported clinical simulation.
- Improved assessment and feedback mechanisms.
- Greater exposure to digital health technologies.

Challenges

- Limited faculty expertise in AI.
- Inconsistent technological infrastructure.
- Resource constraints.
- Lack of standardized curricula.
- Ethical and regulatory uncertainties.

Addressing these challenges will require coordinated efforts among educational institutions, healthcare organizations, policymakers, and professional bodies. Faculty development programs, curriculum reform, and investment in digital infrastructure are likely to play important roles in supporting sustainable implementation.

Ethical, Regulatory, and Governance Frameworks

The growing integration of AI into healthcare and medical education offers substantial opportunities for improving clinical decision-making, operational efficiency, and educational effectiveness [25]. However, these benefits are accompanied by important ethical, legal, regulatory, and governance challenges. AI systems frequently rely on large volumes of sensitive data and may influence decisions with significant implications for patient outcomes, professional accountability, and public trust.

Responsible AI implementation therefore requires robust governance mechanisms that promote transparency, fairness, safety, accountability, privacy protection, and human oversight. Rather than viewing ethics and regulation as barriers to innovation, they should be considered essential components of sustainable and trustworthy AI adoption.

This section examines major considerations related to data governance, regulatory oversight, algorithmic bias, explainability, accountability, and responsible implementation in healthcare and medical education.

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Data privacy and security

Healthcare AI systems depend heavily on patient information, including electronic health records, medical images, laboratory results, genomic data, and clinical documentation. The collection and use of these data raise important concerns regarding privacy, confidentiality, security, and informed consent.

Protecting patient information is fundamental to maintaining trust in AI-enabled healthcare systems. Healthcare organizations must ensure that data are collected, stored, processed, and shared in accordance with applicable legal and ethical standards [26].

Privacy-preserving technologies

Several technological approaches have been proposed to enhance privacy protection while supporting AI development.

Federated learning

Federated learning enables multiple institutions to collaboratively train AI models without transferring raw patient data between organizations. Instead, model parameters are shared while data remain locally stored. This approach may reduce privacy risks and facilitate multi-institutional collaboration.

Homomorphic encryption

Homomorphic encryption allows computational operations to be performed on encrypted data without requiring decryption. Although computationally demanding, this approach offers potential benefits for secure AI applications involving sensitive healthcare information.

Data de-identification and anonymization

Techniques such as anonymization and pseudonymization reduce the risk of patient re-identification by removing or masking personally identifiable information. However, complete anonymity cannot always be guaranteed, particularly when datasets are linked with external sources.

Successful privacy protection therefore requires a combination of technical safeguards, organizational policies, and ethical governance practices.

Regulatory oversight and governance

As AI systems increasingly influence clinical and educational decisions, regulatory oversight has become essential to ensure safety, effectiveness, and public accountability.

Healthcare AI differs from many other technologies because its outputs may directly affect diagnosis, treatment, patient monitoring, and resource allocation [27]. Consequently, AI systems should undergo rigorous evaluation before implementation and continuous monitoring after deployment.

Key governance principles include:

- Transparency regarding model development and intended use.
- Independent validation prior to implementation.
- Ongoing performance monitoring.
- Documentation of limitations and risks.
- Mechanisms for reporting adverse events.
- Clear assignment of accountability and responsibility.

Regulatory frameworks continue to evolve internationally. Although specific legal requirements differ across jurisdictions, there is increasing consensus that AI systems should meet standards for safety, effectiveness, fairness, and transparency comparable to those applied to other healthcare technologies.

Algorithmic bias and health equity

Algorithmic bias represents one of the most significant ethical challenges associated with healthcare AI. Bias may arise from unrepresentative training datasets, measurement errors, historical inequities, or flawed model design.

When biased systems are deployed in clinical settings, they may produce unequal outcomes across demographic groups, potentially exacerbating existing healthcare disparities. Examples include reduced diagnostic accuracy in underrepresented populations and unequal access to AI-supported services [28].

Mitigating algorithmic bias requires:

- Diverse and representative datasets.
- Transparent reporting of model development.
- External validation across populations.
- Continuous monitoring after deployment.
- Inclusion of equity considerations during system design.

Healthcare organizations should recognize that algorithmic fairness is not solely a technical issue but also a social and ethical responsibility.

Explainability, accountability, and human oversight

AI systems should support not replace professional judgment. Clinicians and educators remain responsible for decisions affecting patient care and learner outcomes, even when AI tools are involved.

Explainability is particularly important in healthcare because clinicians must understand the rationale underlying AI-generated recommendations. Transparent systems facilitate trust, support informed decision-making, and enable identification of potential errors.

Accountability frameworks should clearly define:

- Who is responsible for AI deployment.
- How errors are investigated.
- How performance is monitored.
- How patient concerns are addressed.
- When human review is required.

Human oversight remains essential because AI systems may generate inaccurate, biased, or contextually inappropriate outputs. Final decisions should therefore remain under the supervision of qualified healthcare professionals.

A responsible AI governance framework

Based on the literature reviewed, a responsible AI governance framework for healthcare and medical education should incorporate five interconnected principles:

1. **Transparency:** Clear documentation of model development, intended use, and limitations.
2. **Fairness:** Continuous assessment and mitigation of algorithmic bias.

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3. **Privacy and Security :** Protection of sensitive healthcare information.
4. **Accountability:** Clearly defined responsibility for AI-assisted decisions.
5. **Human Oversight:** Maintenance of clinician and educator authority over final decisions.

Together, these principles provide a foundation for trustworthy and sustainable AI implementation across healthcare and educational settings.

Critical reflection

Although ethical principles and governance frameworks are increasingly discussed in the AI literature, practical implementation remains challenging. Many healthcare organizations continue to face difficulties related to data quality, interoperability, regulatory uncertainty, workforce preparedness, and resource constraints. Consequently, responsible AI adoption requires ongoing evaluation, stakeholder engagement, and adaptation as technologies evolve.

Limitations of this review

Several limitations should be considered when interpreting the findings of this review. First, the rapidly evolving nature of AI means that new technologies, regulatory developments, and educational initiatives may emerge after publication. Second, much of the available literature consists of reviews, conceptual papers, pilot studies, and technology evaluations rather than large-scale longitudinal investigations. Third, evidence regarding AI implementation in low- and middle-income countries remains relatively limited compared with high-income settings. Finally, the proposed competency framework is conceptual and has not yet undergone formal empirical validation.

These limitations highlight the need for continued research and ongoing evaluation of AI applications in healthcare and medical education.

Conclusion and Future Directions

AI is increasingly influencing healthcare delivery, biomedical research, and medical education. Applications ranging from clinical simulation and diagnostic support to drug discovery and personalized learning demonstrate the transformative potential of AI technologies. At the same time, the integration of AI into healthcare and education introduces important challenges related to ethics, governance, data quality, transparency, workforce preparedness, and equitable implementation.

This review examined the evolving role of AI across healthcare and medical education, highlighting its applications in clinical training, cancer diagnostics, drug discovery, competency development, and healthcare innovation. Particular attention was given to the competencies required of medical educators to prepare future healthcare professionals for AI-enabled clinical environments. Based on the synthesis of existing literature, a conceptual competency framework was proposed encompassing foundational AI literacy, ethical and regulatory awareness, data literacy, interdisciplinary collaboration, and critical evaluation of AI systems.

Although AI offers substantial opportunities to enhance educational effectiveness and clinical decision-making, current evidence also underscores important limitations. Many AI systems continue to face challenges related to generalizability, explainability, algorithmic bias, regulatory oversight, and real-world implementation. Furthermore, successful adoption depends not only on technological performance but also on institutional readiness, faculty development, infrastructure availability, and stakeholder trust.

For medical education, AI should be viewed as a tool that complements rather than replaces human educators. Similarly, within healthcare settings, AI functions most effectively as a decision-support technology operating under appropriate professional oversight. Maintaining human judgment, ethical responsibility, and patient-centered care remains essential as AI capabilities continue to evolve.

Future research should focus on validating AI competency frameworks, evaluating educational outcomes associated with AI integration, assessing long-term implementation strategies, and developing evidence-based approaches for responsible AI governance. Additional studies are also needed to examine AI adoption in low- and middle-income countries, where resource constraints and contextual factors may influence implementation pathways.

Ultimately, the future impact of AI in healthcare and medical education will depend not only on technological innovation but also on the ability of institutions, educators, clinicians, and policymakers to ensure that these technologies are deployed safely, ethically, and equitably.

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- Grammar correction
- Sentence restructuring
- Improving clarity and coherence
- Enhancing formal scholarly and academic language

Disclosure Statement

No potential conflict of interest was reported by the author.

References

1. Topol EJ. High-performance medicine: the convergence of human and artificial intelligence. Nat Med. 2019;25(1):44-56. https://doi.org/10.1038/s41591-018-0300-7
2. Esteva A, Kuprel B, Novoa RA, Ko J, Swetter SM, Blau HM, et al. Dermatologist-level classification of skin cancer with deep neural networks. nature. 2017;542(7639):115-118. https://doi.org/10.1038/nature21056
3. Petiwala FF, Shukla VK, Vyas S. IBM watson: redefining artificial intelligence through cognitive computing. InProceedings of international conference on machine intelligence and data science applications: MIDAS 2020. 2021:173-185. Singapore: Springer Singapore. https://doi.org/10.1007/978-981-33-4087-9_15
4. Liu C, Zhao Y, Okwan-Duodu D, Basho R, Cui X. COVID-19 in cancer patients: risk, clinical features, and management. Cancer Biol Med. 2020;17(3):519-527. https://doi.org/10.20892/j.issn.2095-3941.2020.0289

https://doi.org/10.61577/jaiar.2025.1000017

5. Benner SA, Bell EA, Biondi E, Brasser R, Carell T, Kim HJ, et al. When did life likely emerge on Earth in an RNA-first process?. ChemSystemsChem. 2020;2(2):e1900035. https://doi.org/10.1002/syst.201900035
6. Wilson NW, Bouhuijs PA, Conradie HH, Reuter H, Van Heerden BB, Marais B. Perceived educational value and enjoyment of a rural clinical rotation for medical students. Rural Remote Health. 2008;8(3):1-3.
7. Jahanpour F, Sharif F, Salsali M, Kaveh MH, Williams LM. Clinical decision-making in senior nursing students in Iran. Int J Nurs Pract. 2010;16(6):595-602. https://doi.org/10.1111/j.1440-172X.2010.01886.x
8. Barbara G, Scaioli E, Barbaro MR, Biagi E, Laghi L, Cremon C, et al. Gut microbiota, metabolome and immune signatures in patients with uncomplicated diverticular disease. Gut. 2017;66(7):1252-1261. https://doi.org/10.1136/gutjnl-2016-312377
9. AAMC. "AI Competencies for Medical Educators." Association of American Medical Colleges;2025. Retrieved from: https://www.aamc.org
10. Khakpaki A. Advancements in artificial intelligence transforming medical education: a comprehensive overview. Med Educ Online. 2025;30(1):2542807. https://doi.org/10.1080/10872981.2025.2542807
11. Pan H, Gong MC, Lu JH, Zeng ZR, Chen W, Wu H, et al. Expert Consensus on Artificial Intelligence Proficiency for Medical Educators (2025 Edition). Zhongguo yi xue ke xue Yuan xue bao. Acta Academiae Medicinae Sinicae. 2026. https://doi.org/10.3881/j.issn.1000-503x.17190
12. Benítez TM, Xu Y, Boudreau JD, Kow AW, Bello F, Van Phuoc L, et al. Harnessing the potential of large language models in medical education: promise and pitfalls. J Am Med Inform Assoc. 2024;31(3):776-783. https://doi.org/10.1093/jamia/ocad252
13. Rodger D, Mann SP, Earp B, Savulescu J, Bobier C, Blackshaw BP. Generative AI in healthcare education: How AI literacy gaps could compromise learning and patient safety. Nurse Educ Practice. 2025;87:104461. https://doi.org/10.1016/j.nepr.2025.104461
14. Preiksaitis C, Rose C. Opportunities, challenges, and future directions of generative artificial intelligence in medical education: scoping review. JMIR Med Educ. 2023;9(1):e48785. https://doi.org/10.2196/48785
15. Salem MA, Zakaria OM, Aldoughan EA, Khalil ZA, Zakaria HM. Bridging the AI gap in medical education: A study of competency, readiness, and ethical perspectives in developing nations. Computers. 2025;14(6):238. https://doi.org/10.3390/computers14060238
16. Rabiee P. Artificial Intelligence in Healthcare Systems of Low-and Middle. Artificial Intelligence in Healthcare and Biomedical Visualization.:157. https://doi.org/10.1007/978-3-032-06520-9_9
17. Hadley TD, Pettit RW, Malik T, Khoei AA, Salihu HM. Artificial intelligence in global health—A framework and strategy for adoption and sustainabilityInt. J Matern Child Health AIDS. 2020;9(1):121. https://doi.org/10.21106/ijma.296
18. Bello AB, Adepoju DA, Ahmed AA, Bello IS, Anjorin AO, Fatai O, et al. The potential role of AI improving health care delivery in low-and middle-income countries (LMICs). Niger J Fam Pract. 2024;15(1):1-6. https://doi.org/10.64052/hm3vmf65
20. Adhikari S, Ahmed I, Bajracharya D, Khanal B, Solomon C, Jayaratne K, et al. Transforming healthcare through just, equitable and quality driven artificial intelligence solutions in South Asia. NPJ Digit. 2025;8(1):139. https://doi.org/10.1038/s41746-025-01534-0
21. Gardner J, Herron D, McNally N, Williams B. Advancing the digital and computational capabilities of healthcare providers: A qualitative study of a hospital organisation in the NHS. Digital Health. 2023;9:20552076231186513. https://doi.org/10.1177/20552076231186513
22. Kawde D, Puri C. MediHealth AI: An Integrated Framework for Automated Health Report Analysis, Symptom Triage, and Conversational Assistance. In2025 7th International Conference on Innovative Data Communication Technologies and Application (ICIDCA); 2025; IEEE; p. 697-702. https://doi.org/10.1109/ICIDCA66325.2025.11280587
23. Ali H. AI for pandemic preparedness and infectious disease surveillance: predicting outbreaks, modeling transmission, and optimizing public health interventions. Int J Res Publ Rev. 2024;5(8):4605-4619.
24. Sharma S, Saboo N, Baig VN. Exploring undergraduate medical students' perspectives towards artificial intelligence in healthcare: a qualitative study from India. JMA journal. 2025;8(3):718-729. https://doi.org/10.31662/jmaj.2024-0402
25. Mir MM, Mir GM, Raina NT, Mir SM, Mir SM, Miskeen E, et al. Application of artificial intelligence in medical education: current scenario and future perspectives. J Adv Med Educ Prof. 2023;11(3):133. https://doi.org/10.30476/JAMP.2023.98655.1803
26. Dobson R, Stowell M, Whittaker R. Maintaining patient trust as artificial intelligence's role in healthcare grows. Inadequate resourcing for clinical science in New Zealand. 2022:94.
27. Bohr A, Memarzadeh K. The rise of artificial intelligence in healthcare applications. InArtificial Intelligence in healthcare 2020:25-60. Academic Press. https://doi.org/10.1016/B978-0-12-818438-7.00002-2
28. Cross JL, Choma MA, Onofrey JA. Bias in medical AI: implications for clinical decision-making. PLOS digital health. 2024;3(11):e0000651. https://doi.org/10.1371/journal.pdig.0000651

https://doi.org/10.61577/jaiar.2025.1000017