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Medical Education in the Age of Digital Transformation

*Edited by Michael S. Firstenberg,
Stanislaw P. Stawicki and Julie M. Aultman*



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Aims and Scope of the Series

Education and Human Development is an interdisciplinary research area that aims to shed light on topics related to both learning and development. This Series is intended for researchers, practitioners, and students who are interested in understanding more about these fields and their applications.

Meet the Series Editor



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Preface

This Edited Volume is a collection of reviewed and relevant research chapters on developments in medical education. The book includes scholarly contributions from various authors and is edited by a group of experts in the field. Each contribution comes as a separate chapter complete in itself but directly related to the book's topics and objectives.

The book includes the following chapters:

1. Perspective Chapter: Teaching Pharmacology through a Global Health Lens - A Resource for Educators
2. Perspective Chapter: The Spark of Digital Integration ? Student Experiences in the Age of Digital Medical Education
3. Educating Future Leaders in Drug Development about AI
4. Seeing the Future: AI-Driven Visual Learning and Curriculum Innovation in Image-Rich Medical Specialties
5. Perspective Chapter: The Role of Artificial Intelligence in Medical Curriculum Design
6. Perspective Chapter: Integrating Interactive Learning and AI-Generated Assessment in Medical Education ? From Non-Technical Skills to Video-Based CBT Content
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8. From Expert Systems to Ambient and Augmented Care: AI in Internal Medicine, Dermatology, Neurology and Neurosurgery
9. Pedagogy of ECG Interpretation
10. Perspective Chapter: Digital Accessories and Online Platforms in Medical Education

The target audience comprises scholars and specialists in the field.

Chapter 1

Perspective Chapter: Teaching Pharmacology through A Global Health Lens – A Resource for Educators

Gudine Neijens, Roos de Jonge, Roma van Dijkhuizen and Rahul Pandit

Abstract

In times of rapid digital transformation, it is crucial to remember that creating the future of medical education requires us to also look to the past. Understanding historical and structural inequities is key to ensuring that advances in medical education do not inadvertently reinforce existing disparities in healthcare. Pharmacological treatment remains an important pillar of medicine and plays a central role within the medical curriculum. As the historical development and contemporary application of pharmacology have been shaped by complex global influences, recognizing these influences is important. It allows students, educators and practitioners to better understand why certain knowledge systems became dominant while others were marginalized.

This chapter explores how shared histories and cross-cultural exchanges have contributed to modern pharmacological knowledge and examines areas where legacy structures continue to influence research, clinical trials, and prescribing practices. We outline historical contributions from multiple medical traditions, discuss how sociocultural constructs such as race have been used inappropriately in clinical contexts, and highlight implications for drug development and access across global populations. The chapter offers a framework for educators to incorporate these insights into pharmacology curricula, supporting students in developing a more comprehensive understanding of the discipline's history, context, and relevance to equitable healthcare. By situating pharmacology within these broader narratives, the chapter encourages a more critical and inclusive approach to teaching and practice.

Keywords: pharmacology education, history of medicine, global health, equity, curriculum development

1. Introduction

Medicines form a cornerstone of modern healthcare, underpinning prevention, diagnosis, and treatment across virtually all medical specialties. Accordingly, the

ability to prescribe safely and effectively is a core competency in undergraduate medical education, developed primarily through the study of pharmacology. The discipline, derived from the Greek word *pharmakon* (“drug” or “poison”), investigates the interactions between living systems and chemical compounds, linking molecular mechanisms to therapeutic practice. Through this discipline, students learn about disease mechanisms, therapeutic strategies, and the vital role medications play in maintaining health and managing illness.

While pharmacology is often presented as a neutral and purely scientific field, its historical development has been shaped by broader social, cultural, and political contexts. Colonial expansion, global trade, and intercultural exchanges have influenced both the discovery of medicinal substances and the construction of pharmacological knowledge. At the same time, structural inequities, such as the underrepresentation of certain populations in clinical research or the unequal global distribution of medications, have persisted into the present. These disparities begin much earlier in the drug development pipeline, from initial research and clinical trials through to prescription practices, and include racial and ethnic bias among healthcare providers, barriers to medication access, and exclusionary practices in research and clinical trials [1]. While disciplines within medical education such as anatomy [2], psychiatry [3] and global health [4] have begun to confront structural biases, pharmacology remains a relatively late entrant to this critical discourse. The disproportionate influence of the Global North over the Global South has shaped the content and philosophy of pharmacology education, resulting in a narrow, often one-dimensional curriculum [5]. This limits student’s understanding of the field’s multicultural roots and perpetuates biases that educators may unknowingly pass on to future health professionals. Furthermore, the overcrowded medical curricula often sideline these vital discussions, maintaining the status quo and continuing inequalities [6]. It is therefore important to emphasize that the current state of pharmacology education is not inherently flawed; rather, it reflects historical influences and systemic structures that have shaped its development over time. A deeper understanding of these influences is crucial for implementing structural changes in how pharmacology is taught and how prescribing is approached. As Tucker & Zecharia argue, addressing global inequalities and the influence of dominant power structures is essential for developing a more inclusive and socially conscious pharmacology curriculum [7]. By embracing this critical perspective, educators can create a more inclusive, socially conscious curriculum that better prepares physicians to address diverse patient needs.

This chapter aims to synthesize historical and contemporary literature to (1) trace the evolution of pharmacology within a global and cross-cultural context, (2) identify areas where colonial legacies continue to shape pharmacological research and practice, and (3) suggest ways educators can integrate these insights into curricula to promote contextual understanding and equitable care.

1.1 Going beyond eurocentrism, acknowledging non-western roots of modern pharmacology

To understand the current position of modern pharmacology, it is helpful to first look at its history, which for a large part is intertwined with that of western medicine and science. Modern pharmacology (**Figure 1**), often traced to the establishment of Rudolf Buchheim’s pharmacological institute in 1847 [8] is frequently presented as emerging from Western scientific traditions. However, this narrative oversimplifies the field’s origins and underrepresents contributions from other medical systems.

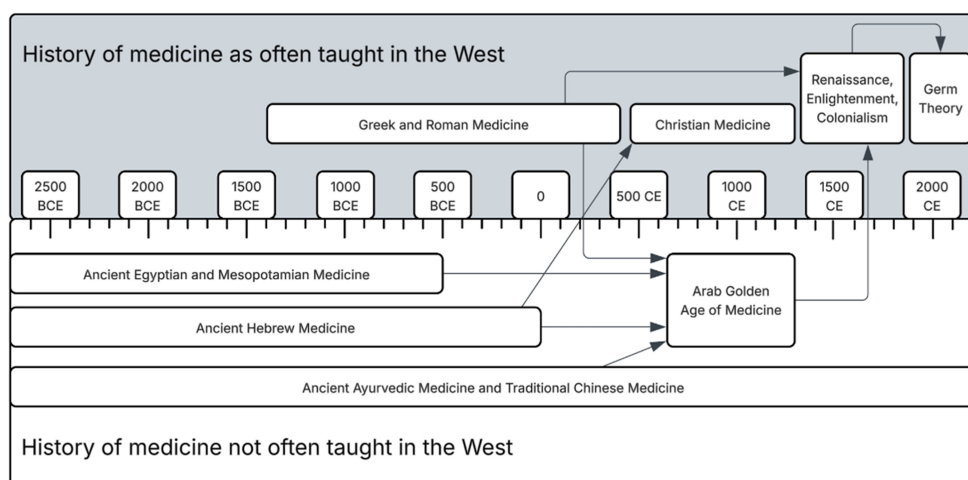


Figure 1.
The evolution of modern medicine as outlined by western textbooks. Top half of the figure shows the evolution of medicine as often outlined by western textbooks. The bottom half of the figure shows important parts of medicine often emitted. Arrows indicate influence. The systems highlighted here may have become more visible due to historical trade routes and intercultural exchanges that facilitated the flow of ideas, commodities, and techniques across regions. Information adapted from [9–11] and [12].

Multiple sources [13–15] place the origin of western medicine (and civilization) at the time of the Ancient Greeks and Romans. It is important to note however, although this period is often defaulted to as the cradle of culture, these are not the only and not the first societies that shaped medical systems and that they were greatly influenced by non-western cultures [16]. Ancient civilizations including those of Egypt, Mesopotamia, India, China, and the Islamic world developed sophisticated frameworks for understanding disease and therapeutics. Many of these ideas informed, and were later incorporated into, Western medical thought through processes of cultural exchange facilitated by trade, migration, and colonial expansion [9, 10]. For example, Ayurvedic medicine in India characterized by holistic concepts such as the three doshas (vata, pitta, kapha), shares conceptual parallels with the Greek humoral theory that dominated Western medicine for centuries (**Figure 2**) [10]. Rooted in a holistic understanding of physical and mental well-being, Ayurveda emphasizes balance by herbal remedies, animal-derived substances such as milk products, minerals, dietary practices, and physical activity [10]. While Ayurveda remains a widely practiced form of medicine in India today, it has also gained recognition in Western societies in recent times, often categorized as a form of “alternative medicine” [17]. Substances used in Ayurveda have been investigated in modern pharmacological research as well [18]. Similarly, Traditional Chinese Medicine, centered on Qi and the balance of Yin and Yang, offers another integrative framework [13, 19, 20]. Qi means the life energy or vital breath that flows through the body, while Yin and Yang symbolize complementary opposites such as cold and hot or passive and active; their biomedical counterparts can be seen in physiological processes like energy metabolism, autonomic nervous system balance, and homeostasis [19–21]. Islamic scholars of the medieval period, building on Greek, Persian, and Indian sources, contributed significantly to pharmacology, including the development of early pharmacies and systematic drug compendia [22].

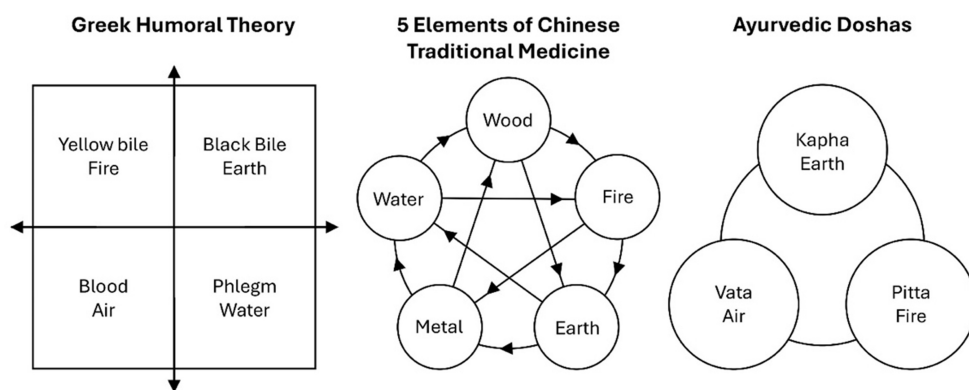


Figure 2.

Similarities between Greek, Chinese and ayurvedic holistic view of medicine. Greek humoral theory, chinese traditional medicine and ayurvedic doshas each view the body holistically and as composed of different elements. Information adapted from zebroski [9].

The Renaissance and subsequent colonial expansion facilitated the global circulation of medicinal plants and knowledge but also introduced asymmetries in ownership and recognition. Indigenous botanical knowledge, for instance, was frequently appropriated without acknowledgment or equitable benefit-sharing [23]. Recognizing these diverse historical contributions allows for a fuller understanding of pharmacology's evolution and highlights the importance of cultural context in contemporary education.

Despite major advances in pharmacological science, several enduring challenges reflect historical and structural dynamics. This highlights five key areas relevant to pharmacology education and practice.

1.2 Interplay between science and religious thought in western medicine

Although often perceived as distinct domains, the development of Western medicine and pharmacology was historically intertwined with religious thought. During the medieval and early modern periods, Christian theological concepts influenced emerging ideas about the natural world and human physiology [24, 25]. Early notions of European and Christian supersessionism and universalism contributed to frameworks that categorized other belief systems and knowledge traditions as less advanced, shaping social hierarchies that later intersected with colonial expansion. These ideological foundations informed aspects of racial classification in medicine. For example, 18th- and 19th-century theories of human difference, including cranial measurements used to infer intelligence [26] emerged within a broader intellectual context that combined theological, philosophical, and scientific reasoning. While such concepts have since been discredited, their legacy persists in certain medical practices, such as the uncritical use of race as a biological proxy in pharmacotherapy. Recognizing this historical interplay between science and religious thought does not diminish pharmacology's scientific achievements but provides context for understanding how cultural and ideological assumptions shaped its evolution.

2. Contemporary challenges and legacy issues

Pharmacology today benefits from sophisticated laboratory methods, rigorous regulatory frameworks, and globalized research networks. Yet several enduring challenges reflect historical legacies and sociocultural dynamics rather than purely scientific considerations. Addressing these challenges is vital for equitable pharmacological practice and offers rich opportunities for medical education. Five interrelated areas are examined below.

2.1 Use of race in pharmacotherapy

Race has long been used as a proxy for biological difference in medicine, dating back to 18th- and 19th-century racial classifications that attempted to link physical traits to disease susceptibility [26]. These frameworks persisted into the 20th century, influencing diagnostic algorithms, clinical guidelines, and drug prescribing patterns. Genetic research has demonstrated that all humans currently inhabiting the planet are approximately 99.9% genetically identical [27]. Furthermore, about 94% of genetic variation exists within populations, while only around 6% occurs between populations [28]. These findings highlight the limitations of using race as a biological category. Race is, in fact, a social construct and a colonial legacy and has often been used to reinforce social inequalities and exclusion [27]. Traits commonly associated with race – such as skin color or hair texture are genetically determined, they are polygenic and do not reliably indicate disease susceptibility. Human traits are furthermore non-concordant in inheritance, meaning that the genes responsible for racialized features do not necessarily influence health outcomes [29]. Nevertheless, race continues to be used uncritically in medicine and pharmacology, often leading to biased practices and assumptions [30].

One prominent example is the estimated glomerular filtration rate (eGFR) equation, historically adjusted for Black patients under the assumption of higher muscle mass and creatinine production. While intended to improve accuracy, this adjustment often delayed referral for kidney transplantation and treatment initiation [31, 32]. In recent years, major institutions, including the National Kidney Foundation and American Society of Nephrology have recommended removing race from eGFR calculations, advocating race-neutral equations that better reflect individual variation.

Similarly, race has influenced hypertension management, with guidelines historically recommending thiazide diuretics or calcium channel blockers as first-line therapy for Black patients. While based on observed differences in treatment response, critics argue these recommendations risk oversimplification and overlook socioeconomic and environmental determinants of hypertension [32].

Similarly, race has influenced hypertension management, with guidelines historically recommending thiazide diuretics or calcium channel blockers as first-line therapy for Black patients. While based on observed differences in treatment response, critics argue these recommendations risk oversimplification and overlook socioeconomic and environmental determinants of hypertension [32].

Physician bias is another major problem in healthcare. For example, pain assessed in patients belonging to minority groups are often diagnosed as less severe, leading to sub-optimal dosage of analgesics and unnecessary suffering [33]. Alarming, medical students, but also graduates, endorse false beliefs that differences in skin thickness between racial groups, could underlie difference in pain perception [34]. Similar

disparities are noted in treatment of opiate addiction [35]. Facing these problems further aggravates the mistrust of ethnic minorities in the health care system affecting drug adherence and resulting in a vicious cycle [36]. However, Sharma et al. [37] argue that differences in gene expression among individuals from diverse backgrounds do exist and may contribute to adverse drug reactions, warranting consideration rather than outright dismissal [37]. While race and ethnicity are poor proxies for broad patterns of human genetic diversity shaped by demographic and migratory histories, genetic variation within specific ethnic or racial groups can hold clinical significance in localized populations. This implies that genetic findings within one racial or ethnic category should not be generalized to all individuals within that group [38, 37]. To better identify clinically relevant genetic markers in pharmacogenomics, expanding clinical trials to include ethnically diverse populations worldwide is essential [38].

For educators, this debate provides a valuable teaching moment. Students can explore how well-intentioned clinical practices may perpetuate inequities and learn to critically evaluate the use of demographic variables in therapeutic decision-making.

2.2 Problem 2: Lack of trial inclusivity and underrepresentation of ethnic minorities in clinical trials

Clinical research has historically underrepresented women, ethnic minorities, and populations from low- and middle-income countries (LMICs). This lack of diversity limits the generalizability of trial findings and can obscure differences in drug metabolism, efficacy, or adverse effects [39].

Promoting inclusivity in medical trials may also enhance trust among minority populations towards medical research and healthcare overall [40]. Various reasons could underlie the underrepresentation of ethnic minorities in clinical research. These could include lack of medical literacy of prospective subjects, which is often coupled with lower socioeconomic status of minorities [41]. Alternatively, physician bias [42], could also play a role where minorities are deemed to be less suitable as research subjects [43]. The most important factor preventing trial inclusivity however is mistrust in medical research precipitated by research misconduct in the colonial past. Distrust of research among minority communities partly stems from unethical studies such as the Tuskegee Syphilis Study (1932–1972), in which African American men were misled and denied treatment to observe disease progression [44]. Similar abuses in colonial contexts, such as unconsented drug testing [25, 45], further deepened skepticism toward biomedical research. Other medicine related trials include clinical trials on sleeping sickness and malaria [46, 45] but also testing the effectivity of medications, their side effects or effects of withdrawal [44].

For pharmacology teaching, trial representation highlights the importance of critically appraising evidence. Students should ask who was studied, what populations were excluded, and how this affects applicability to their future patients.

2.3 Problem 3: Continued imbalances in research and policy making in pharmacology in the global setting

Pharmaceutical innovation is heavily concentrated in high-income countries (HICs), yet clinical trials are increasingly outsourced to LMICs. Drivers

include lower costs, faster recruitment, and regulatory flexibility [47]. While this globalization can foster technology transfer and capacity building, it raises ethical concerns regarding exploitation and post-trial access to therapies [48]. In spite of efforts to promote bidirectional knowledge transfer, in practice it is mostly people from HICs who set the research agenda [49], who have the best access to newly published research [50], whose research is most likely to be published [51] and for whom new research is most applicable [52].

Over the past few decades, the conducting of clinical trials has globalized. Trials led by researchers from HICs are increasingly being executed in LMICs [47]. The positive side of this is that new medicines and therapies might become more accessible to people from LMICs and that it might help build capacity to lead their own research in the future [53]. It appears “offshoring” of clinical trials is largely driven by a lack of availability of suitable patients in the home country [54]. Drug companies are also driven by lower cost and lower regulatory barriers in LMICs [55]. Besides, many of the drugs that have been trialed in LMICs eventually never are made available in these countries or for prices that are exorbitant for people of LMIC countries to afford [55].

Students should understand not only the scientific design of trials but also their geopolitical context, how funding sources, site selection, and intellectual property rights shape global drug availability.

2.4 Problem 4: Drug access and drug adherence remain persisting challenges in the pharmacotherapeutic continuum

In the trajectory of pharmacological treatment, fair access and adherence to medications are other hurdles to equitable healthcare. Disparities in access to medications persist across racial and socioeconomic lines, significantly impacting contentment and health outcomes for various populations. Costs of medicines and their availability remains an issue, which eventually leads to a decrease in medication intake [56]. This is additionally aggravated by the reduced availability of pharmacies attributed, among other factors, to the “pharmacy deserts” in minority neighborhoods [57]. Over the study period, fewer pharmacies opened in these areas compared to predominantly white neighborhoods, while pharmacy closures were more frequent [57]. The affordability of medicines has multiple contributing factors, including the fact that independent pharmacies, which are more common in minority neighborhoods, often have higher drug prices than large chain pharmacies [58]. Additionally, financial barriers in accessing medications are significant in particularly for those with lower incomes. These individuals are less likely to fill in their prescriptions or take less medications [56] or switch to herbal remedies [59]. This signifies that even when physical access to pharmacies is available, the financial burden remains a significant barrier, further disadvantaging populations in lower-income and minority neighborhoods.

2.5 Problem 5: Biocolonialism and knowledge appropriation

Looking at drug sources, currently, roughly 40–50% of all Western medicines originate directly or indirectly from plants [60, 61]. Although the majority of global plant biodiversity is concentrated in the Global South, the technological infrastructure required to convert these resources into pharmaceuticals is

predominantly located in industrialized nations [62]. Due to the immense and still largely unexplored diversity of biological species, pharmaceutical companies and researchers increasingly turn to the biodiversity and traditional knowledge of indigenous cultures to discover new opportunities for drug development [23]. In this process, the knowledge of medicinal plants held by indigenous peoples is often appropriated without adequate acknowledgment or compensation, a practice referred to as biocolonialism or biopiracy [23]. A historical example of biocolonialism is evident in the case of the Guajajara people, native to the Maranhão region of Brazil, and their traditional use of *Pilocarpus jaborandi*. The plant was introduced to Western medicine in 1873 with the isolation of the alkaloid pilocarpine [63], which remains a source for several modern cholinergic drugs used to treat conditions such as glaucoma and xerostomia. The large-scale commercial exploitation of *P. jaborandi* has contributed to concerns about its conservation status [63, 64]. While significant profits have been generated from this trade, the Guajajara and other indigenous communities have experienced adverse social and economic impacts, including forms of labor exploitation linked to resource extraction [65].

Biocolonialism is not merely a historical phenomenon linked to colonialism; it continues to persist in contemporary contexts. A prominent example is the patenting of turmeric (*Curcuma longa*), a plant used for millennia in the Ayurvedic system of medicine in India [18]. In 1995, researchers at the Mississippi Medical Center secured a patent for the use of turmeric in the treatment of surgical wounds. This patent was subsequently challenged by the Indian government, which presented ancient Sanskrit texts documenting the medicinal applications of turmeric. As a result, the patent was revoked [66, 67]. These examples represent only a fraction of the many instances where biocolonialism continues to affect countries in the Global South [23]. Although the Nagoya Protocol, established in 2006, seeks to address biopiracy by promoting the equitable sharing of benefits arising from the use of traditional knowledge and genetic [68], its implementation faces significant challenges, including legal loopholes and interpretative ambiguities [62].

3. Discussion: What does this mean for pharmacology educators?

Pharmacology teaching has traditionally centered on drug mechanisms, therapeutic indications, and pharmacokinetics. While this focus is indispensable for safe prescribing, it can unintentionally convey the impression of pharmacology as an ahistorical and culturally neutral science. The historical and sociocultural perspectives reviewed earlier demonstrate that pharmacology has been shaped by multiple medical traditions, colonial encounters, and persistent inequities in research and access. Incorporating these dimensions into curricula offers opportunities to deepen students' understanding of the discipline, enhance critical thinking, and prepare graduates for diverse clinical contexts. This paper elaborates on the previous work of Tucker and Zecharia [7] for incorporating critical analyses of colonialism and its lasting influence on pharmacology into the curriculum. Efforts by Bakkum and colleagues partially address this issue [32]. By integrating these insights, educators can create more reflective, culturally sensitive pharmacologists who are better prepared to address health disparities and ethical

issues in their future careers. In support of support this, few practical recommendations are offered.

3.1 Broadening the conceptual framework of pharmacology

In Western medicine it is the biomedical model of disease that is used to interpret a state of illness or health. In the biomedical model of disease, disease is caused by the dysfunction of pathophysiological components of the body, which follows the philosophy of reductionism [69]. Reductionism, introduced initially by Thales (636 BC) and later reintroduced by Descartes (1637), deconstructs a complex phenomenon into smaller components for enhanced comprehension. Zooming in and understanding the detailed biomolecular aspects of a disease has helped in the development of many medicines, a pitfall however, remains the oversimplification of the problem [69]. However, this philosophy is proving to be too narrow as it fails to adequately address disease when it comes to noncommunicable and mental disease and it overlooks social determinants of health, the origin of health inequities and the existence of scarcity [70].

Introducing students to the global and historical evolution of pharmacology can counteract the perception of Western medicine as the sole source of scientific authority. Historical examples, such as Ayurvedic concepts of doshas, Chinese Qi, and Islamic pharmacopeias, illustrate that sophisticated pharmacological thinking existed across civilizations. Framing pharmacology within this pluralistic history can encourage students to appreciate diverse knowledge systems and critically examine how scientific ideas evolve through cultural exchange and contestation. When entering clinical practice, students will encounter patients who use herbal remedies, osteopathy or homeopathy as (adjuvant) treatment strategies. Disparaging patients from using such remedies will trigger mistrust between healthcare professionals and their patients, resulting in patients' unwillingness to mention the use of such therapeutic strategies. This could in fact affect pharmacotherapy, as clinically relevant interactions between herbs and western medicine are not uncommon [71]. This broadened perspective aligns with current trends toward inclusive curricula and resonates with students' increasing interest in global health.

3.2 Including the value of patient perspectives as limbs of evidence-based medicine (EBM)

Evidence-based medicine is the foundational philosophy which drives current biomedical research and its clinical application. Although the initial concept of EBM embraced three components: *"patients" circumstances and patients' preferences and actions, and best research evidence, with a central role for clinical expertise to integrate these components* [72], the modern interpretation has been predominantly limited to research evidence, thus compromising on patient values [73]. While catering to the "average" patient, individual requirements are often abandoned. These could range from restricting financial reimbursements for treatments which are not evidence-based [74, 73], but which might be beneficial to the patient. Furthermore, the price of this averaging, would be even higher for minority and ethnic groups, as most EBM protocols devised for white race [75, 76]. Embedding these considerations into pharmacology teaching can help students develop a more nuanced understanding of trial data and its applicability.

3.3 Linking pharmacology to social determinants of health

Pharmacology curricula often emphasize molecular targets, dosing regimens, and adverse effects, with limited attention to how social determinants such as income, geography, cultural beliefs, influence real-world drug use. Yet disparities in pharmacy access, affordability of medicines, and patient adherence profoundly affect therapeutic outcomes. Integrating social context into pharmacology can enhance students' ability to anticipate barriers to adherence and develop patient-centered solutions.

Teaching strategies could include patient scenarios that require students to identify and address non-biological factors affecting medication use, such as limited access to pharmacies, reliance on traditional remedies, or financial constraints. Interprofessional case discussions with pharmacy and public health students can further highlight system-level approaches, such as mobile pharmacy initiatives or subsidy programs. Such learning experiences foster both clinical and advocacy skills, equipping students to navigate real-world prescribing challenges beyond the clinic.

3.4 Discussing ethics in pharmacology

Within this broader historical and cultural framework, ethical considerations remain central to pharmacological research and education. Cases of exploitation in clinical trials and biocolonial appropriation of indigenous knowledge underscore the importance of benefit-sharing, informed consent, and equitable representation in both research and drug development. Bringing these issues into pharmacology teaching fosters critical reflection, helping students to connect scientific knowledge with questions of justice and responsibility. Such integration equips future clinicians to approach prescribing not only as a technical task but as an ethically informed practice that acknowledges the complex interplay of science, society, and culture.

3.5 Final words

The resurgence of interest of this topic, ensuing geopolitical dynamics provides an opportunity for medical educators to understand the effect of colonization, empire and racism within their field of teaching, in this case pharmacology and thereby contribute towards an inclusive curriculum [77]. As pharmacologists, embracing this responsibility is essential to educate a generation of practitioners who are not only scientifically competent but also socially conscious and committed to addressing systemic health inequities. Within the ongoing digital transformation of medical education, these perspectives also open up new possibilities to integrate diverse sources of knowledge and pedagogical approaches, supporting curricula that are both scientifically robust and contextually responsive.

Author contributions

Conceptualization- RP, RdJ; methodology: RP, GN; writing: GN, RP, RvD; visualization: GN, RvD; supervision: RP, RdJ.

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Perspective Chapter: The Spark of Digital Integration – Student Experiences in the Age of Digital Medical Education

Amna Ikhlmaq and Sameet Hassan

Abstract

Much like Prometheus bringing fire to the darkened world of humans and lighting the way to civilization, digitalization of learning practices serves as a spark for integrating contemporary ideologies with conventional andragogical structures, providing the opportunity to construct a curriculum that is both innovative and responsive to the evolving needs of medical students. The COVID-19 pandemic accelerated the evolution of traditional, in-person curricula into hybrid models, as social limitations necessitated the blending of different instructional approaches. In Pakistan, the Pakistan Medical & Dental Council (PM&DC) has implemented the Integrated Modular Curriculum (IMC). Faculty and students at Aziz Fatimah Medical and Dental College, Faisalabad, recently conducted a phenomenological study aimed at exploring both the perceived benefits and challenges encountered by students navigating this newly adopted framework. Following the initial study's publication, a supplementary investigation was conducted to explore participants' perspectives on technology-enhanced learning in the modular system. The participants largely agreed that the IMC has integrated digital methods as one of its core educational elements. Key benefits identified by students included increased curricular engagement, blending of educational and administrative functions, and compatibility with international educational standards. Conversely, students faced systemic challenges with navigating between different management systems, lack of cohesion between institutional curriculum and external digital resources, and pitfalls in the orientation of faculty with newly introduced digital approaches. These findings offer valuable, student-centered insights for institutions to address gaps in digital integration in the field of medical education so that they may build a sustained system of digital innovation and academic progress.

Keywords: medical education, digital integration, digital literacy, Integrated Modular Curriculum, student perspectives, digital education tools

1. Introduction- digital andragogy

Digital literacy has become a hallmark of receiving education in recent years. Gaining fame as a viable method during the COVID-19 pandemic, the World Economic Forum has dubbed digital literacy an essential element of a learner's toolkit in the modern age [1]. Tools used to assess digital literacy usually explore the domains of cognitive, technical, and communication skills. The Digital Literacy Scale (DLS), developed by Ng (2012), is the most cited in educational research and involves mapping student experiences with platform use, navigation, and ethical collaboration across social media sites [2]. The Digital Health Literacy Instrument (DHLI) and the more recently designed European Health Literacy Survey 2019–2020 digital instrument (HLS19-DIGI) further evaluate medical students' ability to critically judge the relevancy of online resources and their application in content generation or clinical decision-making [3, 4].

These domains align with traditional theories of adult learning – behaviorism, cognitivism, constructivism, and humanism [5]. Behaviorism measures learning as a change in behavior in response to learning a new concept. In cognitivism, the emphasis is on how knowledge is assimilated. Constructivism highlights the role of the learner in applying learned knowledge. Humanism suggests that learners are in charge of their own learning by aligning learned concepts with their needs, while instructors play a more supportive role. Andragogy, introduced by Malcolm Knowles as the theory of adult learning, builds on these humanistic assumptions [6]. Knowles' principles serve as a model for operationalizing these ideals and offer educators a framework for integrating self-directed learning opportunities into their curricula.

Digital andragogy is defined by Blackley and Sheffield as “the practice of educators to equip and encourage adult learners to choose and use the affordances of accessible digital technologies to personalise their learning and facilitate their interactions with peers and tutors” [7]. This definition extends the previously discussed theoretical frameworks by synthesizing their key dimensions and offering a foundation for the integration of digital platforms in contemporary curricula. Much like Prometheus bringing fire to the darkened world of humans and lighting the way to civilization, digitalization of learning practices serves as a spark for integrating contemporary ideologies with conventional andragogical structures, providing the opportunity to construct a curriculum that is both innovative and responsive to the evolving needs of medical students.

2. Existing curricula

2.1 Traditional curricula

Traditional advancements in medical education are credited to Abraham Flexner, who proposed changes in medical education through his report in 1909. Emphasis was placed on learning the basic sciences, such as anatomy, biochemistry, and physiology, and connecting disease pathology to these foundational elements [8]. He also proposed the importance of setting aside protected time for faculty to hone their research skills to ensure ongoing learning and cultivate advancements in the medical field. Flexner addressed the importance of testing medical knowledge, leading to the development of various assessment tools, improving the

problem-solving abilities of students as it allowed for bridging clinical knowledge with situational logic. In recent years, however, the focus has regressed from the cultivation of clinical skills to paper-stamping exercises regulated by private practice ideals [8].

2.2 Clinical integration

Curricula integrating clinical learning have been developed to address these issues, promoting concurrent learning of basic and clinical sciences. The syllabus is organized by organ system and allows the student to be exposed to the mechanisms of disease development and the resulting pathological processes at the same time, enabling them to connect the dots between organ function and decline [9].

Integrated curricula have also been shown to strengthen students' academic outcomes while supporting problem-solving, critical thinking skills, and self-efficacy. In light of these attributes, many medical schools are adopting integrated models, with students generally responding positively. To fully realize the potential of a clinically integrated system, it is essential to complement classroom-based instruction with structured clinical exposure, enabling students to translate theoretical knowledge into practical skills at an earlier stage. In addition, equipping learners with time management strategies can help them balance the demands of clinical duties with self-directed study [9, 10].

2.3 Curriculum organization

Furthermore, learning is also impacted by the way the curriculum is organized. Since the midtwentieth century, medical education has evolved to introduce various structural approaches, namely annual and modular systems. Annual systems teach each subject in isolation – anatomy, physiology, and pathology are delivered as separate courses throughout the academic year. However, students in these programs have reported experiencing a disconnect between theoretical knowledge and its clinical application [11, 12].

In response to these limitations, modular systems emerged as an attempt to bridge this divide. These systems organize curricula around body systems (e.g., cardiovascular, respiratory, neurological), integrating basic sciences with clinical skills within each module [13]. For example, when studying the cardiovascular system, students simultaneously learn anatomy, physiology, pathology, pharmacology, and related clinical examination skills. This integrated approach aims to help students understand how foundational knowledge directly relates to clinical practice.

Several institutions have pioneered innovative approaches to modular integrated curriculum development. McMaster University pioneered problem-based learning (PBL) in the late 1960s and, in 2005, inaugurated the current COMPASS curriculum to produce medical professionals with better medical expertise, communication skills, and a passion for continued learning [14]. Similarly, institutions like University College London and the National University of Singapore offer system-based modules that integrate educational gain with clinical and professional development [15, 16].

More recently, Charité University Berlin demonstrated the ongoing evolution of integrated modular curricula. In the 1980s, a student strike led to major educational

reform, which resulted in a curriculum structured into blocks by theme and integrated with early patient contact. A comparison of traditional and reformed cohorts indicated that future physicians felt more prepared after the changes were implemented [17]. This reform also led to the formulation of competency-based learning objectives, revolutionizing curriculum design.

2.4 Pakistani context

In Pakistan, currently, the main medical education regulatory body, the Pakistan Medical & Dental Council (PM&DC), has implemented the Integrated Modular Curriculum (IMC). It defines this curriculum as one in which evaluation is aligned with modular teaching, ensuring that both horizontal and vertical integration are reflected in the way students are tested. Instead of separate subject-based examinations, assessments are organized around modules and themes, requiring students to demonstrate synthesis of knowledge across basic sciences and clinical applications. The PM&DC emphasizes formative assessments, such as frequent quizzes and objective structured clinical examinations (OSCEs), alongside summative modular exams, to encourage continuous learning, early identification of gaps, and the development of higher-order reasoning [18, 19].

2.5 Digital integration

These integrated modular curricula have continued to evolve, particularly through the incorporation of digital technologies. The COVID-19 pandemic accelerated this evolution, as social limitations necessitated the rapid adoption of hybrid models that blend different instructional approaches. Most commonly, these hybrid systems integrate both online (digital, remote) and traditional face-to-face (in-person) teaching, while also combining synchronous (real-time) and asynchronous (self-paced) learning [20]. This shift toward digital integration not only addressed immediate pandemic needs but also opened new possibilities for enhancing medical education.

Recent empirical evidence supports the effectiveness of these hybrid approaches in medical education. Zhao et al. (2024) conducted a longitudinal study tracking 240 third-year medical students from three Chinese universities as they transitioned through online/distance learning (May, 2021), hybrid learning (May, 2022), and in-person learning (May, 2023). Findings revealed the greatest student satisfaction for hybrid learning due to its combination of digital flexibility and face-to-face interaction, which allowed students to benefit from online resources while maintaining the social engagement and direct contact with instructors characteristic of traditional education [21].

2.6 Digital literacy

As such, digital literacy among medical students must be systematically assessed and developed to enhance their capacity to effectively utilize digital tools within hybrid learning frameworks. According to the Museum and Library Services Act of 2010, these skills comprise the ability to “find, evaluate, organize, create, and communicate information” through technological means, while also encompassing “digital citizenship and responsible technology use” [22]. Within the medical

context, such competencies extend specifically to the application of digital tools for clinical learning and decision-making processes.

The concept of digital health literacy, alternatively termed eHealth literacy, represents a specialized domain within this broader framework. As outlined by the eHealth literacy framework, this construct encompasses “the capabilities and resources required for individuals to use and benefit from digital health resources” [23]. This definition underscores the importance of future health professionals developing digital competencies necessary for effective engagement with health-related technologies and information systems, to better serve the needs of an increasingly digitized patient population.

3. Student insights

During the 2024–2025 academic year, the lead author, in collaboration with a group of MBBS student representatives, conducted a phenomenological investigation examining student perceptions of the IMC – also referred to as the Integrated Modular System (IMS) – as implemented at their institute under the umbrella of the University of Health Sciences, Lahore [10]. This qualitative study aimed to explore both the perceived benefits and challenges encountered by students navigating this newly adopted framework. The study sample consisted of first- and second-year students, representing the initial cohorts exposed to this curricular reform at the institute. Given its focus on early-stage implementation experiences, this research provides critical insights into the adoption of integrated curricula within Punjab’s higher education institutions.

Key benefits identified by students included enhanced clinical integration, compatibility with international examination standards, and increased curricular engagement. Conversely, students faced systemic challenges with transitioning to a new curriculum, reporting limited guidance from previous batches that had studied under the annual examination system, as well as pitfalls in the orientation of faculty with newly introduced content. These findings offer valuable, student-centered insights for institutions looking to revamp their traditional curricula and highlight critical factors that would need to be addressed to bring about change at regional and national scales to ensure smooth implementation.

Following the initial study’s publication, a supplementary investigation was conducted to explore participants’ perspectives on digital integration within the IMC framework. Interviewees were invited to provide feedback through a follow-up questionnaire, examining their experiences with technology-enhanced learning in the modular system. The participants largely agreed that the IMC had incorporated digital delivery methods as one of its core educational elements.

3.1 Learning and assessment

The distribution of digitally recorded lectures emerged as a primary mode of content delivery. Moodle and Google Classroom were identified by participants as the principal platforms employed for lecture delivery. This digitization extended to evaluative methods as well, with both multiple choice questions (MCQs) and short essay questions (SEQs) being administered through online platforms. In fact, the institution has recently deployed a new, comprehensively designed learning

management system (LMS) interface equipped with standardized templates for structured assessments and assignments. This marks a significant departure from traditional paper-based evaluation systems and demonstrates the institution's commitment to incorporating digital tools to support novel learning practices.

Of particular significance is the integration of technology in subject-specific teaching. The introduction of digital simulation models in anatomy represents a notable advancement in traditionally hands-on disciplines. Students can now utilize specialized applications such as Complete Anatomy Atlas and VH Dissector, which facilitate interactive engagement with anatomical content and improve comprehension of complex structures and spatial relationships. These experiences complement traditional dissection-based instruction, creating a unique blend of clinical and digital modalities.

Digitizing the delivery of educational materials has significantly enhanced learning flexibility, according to the participants. Unrestricted access to lectures allows students to revisit the content and engage with it regardless of time or location. Participants particularly value the immediate feedback provided through digital quizzes and assignments, as it facilitates the timely identification of learning gaps. This asynchronous model supports the principle of self-learning and has fostered a more student-centered approach, accommodating individual learning preferences and schedules while maintaining academic rigor.

Despite these technological innovations, students have expressed that certain aspects of in-person teaching remain irreplaceable, particularly in clinical settings where hands-on experience is the most valuable teacher, as well as in classroom settings where peer interaction drives critical thinking. Rather than viewing digital and traditional methods as competing approaches, learners advocate for a hybrid model where both modalities complement each other, creating a more comprehensive educational experience. Concerns about reduced cognitive stimulation also arose around the use of generative artificial intelligence (AI) platforms such as ChatGPT or Grammarly for writing assignments or content summarization, particularly regarding the loss of opportunities for creative problem-solving. As identified by students, the challenge lies in striking a balance between efficiency and academic integrity.

3.2 Administrative and communication infrastructure

The digital transformation extends beyond andragogical applications to involve administrative functions as well. Through its announcements and tailored class features, the new LMS also provides a platform for timetable management and dissemination of real-time updates. This integration of administrative processes within the digital ecosystem streamlines the accessibility of essential administrative information for students and faculty alike, promoting a culture of “peer-to-peer collaboration,” as one student identified. Multiple students also stated that these centralized features proved beneficial for time management and organizational skills, allowing them to better structure their academic schedules.

At the same time, contrasting perspectives emerged regarding information management, with some students expressing that the fragmentation of information across multiple platforms – including WhatsApp, Google Classroom, and the LMS – created challenges in navigation, which could be overwhelming to manage. This finding suggests that while digital tools offer organizational benefits, the

proliferation of communication channels may inadvertently complicate information access for some learners.

Some of these challenges may stem from insufficient formal training. Students reported receiving only basic orientation for the LMS and Google Classroom, with no training provided for simulator applications. This lack of structured guidance forced them to rely on trial-and-error methods or peer assistance, which impacted their learning pace. Furthermore, students indicated that while faculty often assume they are “digital natives,” this assumption overlooks their actual need for hands-on training. Students specifically requested that such training be incorporated into introductory modules to better support their transition to digital learning environments.

3.3 Resource effectiveness

Students described simulation applications – particularly three-dimensional atlases for anatomy and physiology – as especially valuable in comprehending difficult concepts such as neural pathways, musculoskeletal structures, and even reviewing clinical case studies. Constant access also allowed them to revisit material and reinforce their understanding outside scheduled sessions. At the same time, several noted that technical problems, such as mislabeled specimens or incorrect answer keys, sometimes caused confusion and temporarily reduced their trust in these resources.

Reliance on digital tools beyond the prescribed curriculum also emerged. Popular choices included YouTube channels such as Osmosis, AMBOSS, and Ninja Nerd, alongside tools like Anki decks to address missed topics during revision. Students praised these resources for their visually engaging formats, approachable design, and inclusion of current clinical information with practical examples. However, they also noted that inconsistent alignment with UHS learning objectives disrupted their study planning. Some recommended incorporating selected external tools into the curriculum to improve coherence and reduce study load, given their widespread informal use.

Overall, these insights reveal both the benefits and limitations students encounter when using digital tools, and they highlight the opportunities to align institutional strategies with student-driven learning practices.

4. Digital tools

Digital integration in medical education has been made possible largely through the quality and accessibility of innovative tools available to students. Simulation-based training, online learning platforms, and AI – driven resources now encourage learners to develop and test clinical skills in realistic but risk-free settings, ensuring patient safety while strengthening competence.

For the purposes of this chapter, these tools are categorized as internal resources, assigned within the formal curriculum, and external resources, independently selected by students to support their own learning.

Internal resources:

LMS: An LMS is a digital platform designed to organize, deliver, and monitor educational content. It is most commonly used to organize lecture schedules,

monitor attendance, and track students' performance grades [24]. In this way, it allows students to remain organized and up to date with changes in coursework. For faculty, it facilitates course management, real time evaluation of class performance and identifies gaps in student learning. It serves as a cohesive platform for integrating teaching materials, communication, and assessment, thereby streamlining academic processes and improving overall course delivery.

Google Classroom: Google Workspace is a cloud-based suite of tools that can support diverse educational needs. Among these, Google Classroom is the most widely adopted in educational settings and can function as a freely available LMS, particularly in low- and middle-income contexts where institutions may lack the resources to implement dedicated platforms [25]. It enables educators to create classes, distribute materials, assign and collect coursework, and provide feedback in a structured online environment. It facilitates communication and collaboration through announcements, discussions, and integration with Google tools such as Drive and Meet. Its mobile accessibility and analytic features support flexible learning and allow educators to monitor student progress effectively.

Kahoot!: Kahoot! is a game-based platform that enables educators to design and administer user-generated quizzes. These quizzes can be integrated into online environments such as Google Classroom, providing interactive formative assessment and feedback. Research indicates that, when used in medical education, Kahoot! increases student engagement, improves retention of knowledge, and correlates positively with exam performance [26].

WhatsApp: WhatsApp, a free instant messaging application owned by Meta, is widely used as an informal communication tool between learners and educators due to its accessibility and user-friendly interface. Official class groups – often administered by faculty or student affairs – are commonly deployed to maintain real-time connectivity between students and instructors [27].

External resources:

Anki: Anki is a free flashcard app that uses spaced repetition and active recall to help students retain complex information more effectively. Medical students often use it to create or use premade decks covering various subjects such as anatomy, physiology, pathology, etc., and review material repeatedly over time. According to a recent study in Pakistan, students using Anki for spaced repetition in pediatrics achieved significantly greater improvements in test scores compared to peer groups using traditional learning methods [28].

VH Dissector and Complete Anatomy: VH Dissector and Complete Anatomy are 3D simulation platforms that provide interactive visualization of human structures. VH Dissector uses segmented cadaver images from the Visible Human Project, allowing students to explore anatomy layer by layer and strengthen their spatial understanding [29]. Complete Anatomy offers high-resolution models, customizable dissections, and interactive features such as quizzes and clinical videos, helping learners connect anatomical knowledge with clinical practice [30]. Together, these tools serve as accessible, engaging complements to traditional dissection labs.

Osmosis: Developed by Elsevier – a leading global provider of medical and educational resources – Osmosis is a multimedia learning platform offering concise, animated videos, flashcards, and practice questions. Its visually engaging format and curriculum-aligned content help medical students master complex concepts efficiently, while mobile access and integrated study tools support flexible, self-directed learning [31].

ChatGPT: Chat Generative Pre-trained Transformer, or ChatGPT, is a generative AI tool that uses prediction models to produce human-like text responses in response to a prompt query. Faculty and students alike use it for clarifying difficult concepts, drafting academic content, and reviewing learning material. Recent updates even offer a dedicated study mode for learners. Additionally, evidence suggests that while ChatGPT shows promise, there are limitations related to misinformation, ethical concerns, and variability in how well its outputs align with curriculum requirements [32].

5. Gaps in digital integration

Digital integration in medical education has acted as a Promethean spark – much like fire, it has illuminated new pathways for learning and ignited creativity among learners and educators alike. Yet, as with fire, its brilliance also casts shadows, exposing vulnerabilities within our systems. Unmanaged or under-supported, the same tools that empower may reveal weaknesses in institutional preparedness, gaps in faculty training, and inconsistencies in curricular cohesion. To harness this spark effectively, institutions must approach digital innovation not as a temporary flare of progress but as a sustained catalyst for andragogical growth.

Student insights revealed the following commonly observed gaps:

Platform fragmentation: institutions use multiple uncoordinated platforms for managing lectures, assessments, and communication. This fragmentation can lead to inconsistent workflows, duplicated efforts, and confusion for both students and faculty, reducing the overall efficiency of digital integration.

Andragogical cohesion: while external resources such as Osmosis and Anki are highly valued by students, their content does not always correspond with formal curricular objectives. Learners emphasized the importance of better alignment or formal integration of these tools within the curriculum to ensure consistent learning goals and reduce unnecessary study burdens.

Faculty preparedness: uneven levels of digital literacy and limited training among educators can hinder the effective use of platforms. Some students noted that technical errors, such as mislabeled answer keys, were not promptly addressed, reflecting gaps in faculty oversight.

Student orientation and training: limited or inconsistent orientation on using digital platforms leaves many students underprepared to navigate assigned tools effectively. This gap can reduce the benefits of digital integration and increase reliance on informal peer guidance, which may lead to uneven results.

Students' proactive use of tools such as Osmosis, Anki, and ChatGPT reflects the principles of adult learning theory – particularly Knowles' concept of andragogy, which emphasizes self-directed learning and readiness to learn. By independently seeking out resources that address their perceived gaps, learners are demonstrating motivational autonomy. Without curricular alignment, however, it may empower some learners to construct deeper understanding, while others are left feeling misaligned with program objectives. Grounding digital integration in adult learning principles can ensure that student agency is supported rather than discouraged.

Similarly, without training, faculty may default to directive teaching, which can undermine humanistic principles that value students' self-direction, and intrinsic motivation. Moreover, insufficient guidance in navigating diverse digital

tools – combined with the introduction of multiple, uncoordinated platforms – can leave students without the structured scaffolding required to construct their own understanding effectively, as emphasized by constructivist theory. Such disorganization hampers understanding and risks cognitive overload, as uncoordinated resources and frequent platform-switching can exceed working memory and reduce knowledge retention.

6. Conclusion - sustaining the spark of digital integration

A clear understanding of how digital tools shape learning outcomes provides the groundwork for targeted recommendations. Institutions should equip both faculty and students with structured training, invest in user-friendly infrastructure, and provide students with guidance on the use of external resources, which align commonly with their curricular objectives, to ensure coherent learning experiences. By introducing early orientation sessions for students, fostering digital literacy across all stakeholders, and developing clear ethical guidelines for the use of data-sharing and AI tools, medical schools can transform digital innovation from a fragmented experiment into a sustained, strategic approach that enhances student autonomy. By embedding these measures within broader planning, institutions can fan the Promethean spark of digital integration and nurture its light to advance educational quality, cultivating innovation in learning practices that remain andragogically cohesive and responsive to the evolving demands of digital healthcare.

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Chapter 3

Educating Future Leaders in Drug Development about AI

Monika Graff, Annette Mollet and Thomas Szucs

Abstract

Artificial intelligence (AI) is transforming pharmaceutical development, from discovering new molecules to expediting product development and monitoring drug safety in real-world use. This shift calls for leaders who understand both AI's capabilities and its limitations, while navigating ethical complexities and regulatory uncertainties. This chapter explores how AI is being integrated across the drug development lifecycle and examines what skills future pharmaceutical leaders should have to guide this transformation responsibly. Using the European Center of Pharmaceutical Medicine (ECPM) program as an example, we discuss effective educational approaches that blend technical knowledge with ethical awareness and collaborative skills. Key challenges include keeping pace with fast-evolving technology, lack of standardized training and experiential learning tools, complex ethical considerations, and the need for new interprofessional collaboration models. We recommend adaptive curricula, interdisciplinary learning environments, global knowledge sharing, and hands-on experience with real-world cases. Ultimately, preparing leaders for AI-driven drug development means more than teaching technical skills because it requires fostering critical thinking, ethical judgment, and the ability to balance innovation with patient safety. Innovation in pharmaceutical medicine depends on leaders who can utilize AI's potential while remaining grounded in the realities of clinical practice and regulatory responsibility.

Keywords: artificial intelligence, drug development, pharmaceutical education, medical education, leadership training, digital transformation, machine learning, regulatory science, AI ethics, clinical trials, drug discovery, pharmacovigilance, curriculum design, postgraduate training, ECPM, healthcare innovation, interdisciplinary collaboration, technical literacy

1. Introduction

The rapid progress of artificial intelligence (AI) has begun to transform nearly every aspect of healthcare and the life sciences. In the pharmaceutical sector, in particular, AI applications are moving from experimental proofs of concept to tools that support and accelerate the development of new therapies. From molecule

discovery and clinical trial optimization to real-world monitoring of drug safety, AI has the potential to fundamentally change the ways in which medicines are researched, developed, and delivered [1].

Drug development is uniquely affected by this technological shift. It is one of the most complex, resource-intensive, and highly regulated areas of healthcare [2]. Each stage of the pipeline generates and depends on large amounts of data. AI-driven methods, such as machine learning, generative chemistry, and natural language processing, offer unprecedented opportunities to analyze this data, reduce inefficiencies, and accelerate the different phases of developing new medicines in a cost-effective way (see **Figure 1**).

At the same time, AI introduces a range of critical challenges and limitations. Data quality, representativeness, and bias remain significant concerns: models trained on incomplete or skewed datasets may produce misleading predictions, potentially compromising patient safety or reproducing health inequities. The “black-box” nature of many AI algorithms raises questions, making it difficult for regulators, clinicians, and patients to trust AI-informed decisions [3]. Moreover, regulations are evolving but often lag behind technological innovation, leaving gaps in oversight and creating uncertainty. Ethical and social dimensions, like informed consent, privacy protection, and equitable access to AI-enabled therapies, also require careful consideration, as the rush toward technological adoption can overshadow patient-centered values.

As AI becomes increasingly embedded in drug development, the need for well-prepared leaders who can navigate these developments grows more urgent [4]. Such leaders must not only understand the scientific and technological background of AI but also be able to critically evaluate its limitations, anticipate unintended consequences, and weigh the ethical and regulatory implications of its use. Education, therefore, plays a crucial role in equipping future decision-makers with the skills required to use AI responsibly and effectively.

This chapter aims to explore strategies, challenges, and opportunities in preparing future leaders in drug development to engage with AI. Drawing on examples from current initiatives like the European Center of Pharmaceutical Medicine (ECPM) postgraduate diploma program, we highlight how medical education can evolve to develop competencies relating to technical literacy, ethical awareness, and critical judgment, which are necessary for this new era [5]. We argue that governing AI-driven drug development will depend not only on technological innovation but also on cultivating a generation of professionals who are ready to lead with vision, responsibility, and collaboration.

2. The evolving role of AI in drug development

In the past few years, AI has rapidly evolved from an idea into a suite of tools impacting drug development across its entire lifecycle. Increasingly, AI not only streamlines tasks but also enables scientific discoveries that were previously out of reach, spanning early discovery, clinical development, post-marketing surveillance, and even adjacent areas such as medical devices and digital therapeutics [6]. Its potential, however, must be considered alongside significant limitations, including data quality issues, model transparency, and ethical and regulatory challenges.

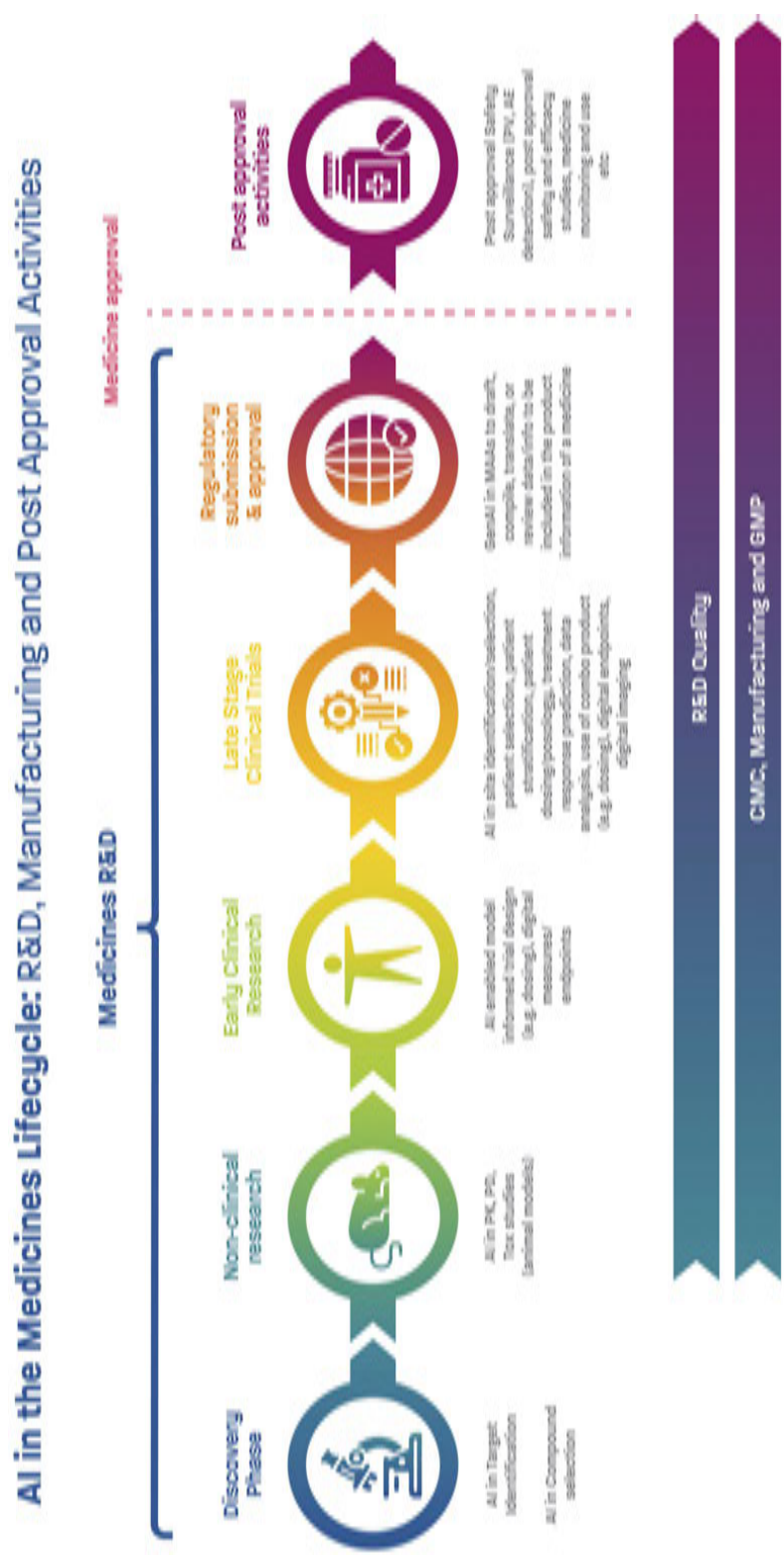


Figure 1.
The use of AI in the medicinal product lifecycle (Credit: Thomas Brookland, EFPIA).

Important considerations include the need for robust data-sharing mechanisms and the establishment of more comprehensive intellectual property protections for algorithms [7].

In early discovery, AI-based methods are transforming the traditionally slow and resource-heavy processes of target identification and drug candidate generation. Machine learning models enable faster biomarker discovery, molecular modeling, and structure-based drug design. Generative chemistry has already demonstrated remarkable promise [8]. For instance, in 2020, Insilico Medicine announced an AI-designed preclinical candidate targeting fibrosis that advanced from concept to validation in under 18 months. Similarly, DeepMind's AlphaFold has revolutionized protein science by predicting the structures of nearly all known proteins, accelerating therapeutic target discovery [9]. Yet, these successes need to be critically assessed. AI-designed compounds still require extensive experimental validation, and early-stage promise does not guarantee clinical success. Overreliance on computational predictions may bias research toward targets that are easiest to model rather than those of greatest clinical relevance, and reproducibility remains a challenge given the novelty of many AI methods [10].

In preclinical development, AI supports *in silico* testing and toxicity prediction, helping to reduce animal experimentation and filter out compounds unlikely to succeed in clinical trials. Companies such as Atomwise have pioneered AI-driven molecular screening, rapidly evaluating billions of potential compounds for activity and safety [11]. These approaches can improve resource allocation and reduce late-stage attrition. However, predictive accuracy depends heavily on the quality and representativeness of training data. Biases, poorly annotated datasets, or underrepresentation of patient populations can lead to misleading predictions, and integrating AI into preclinical workflows requires infrastructure, expertise, and cross-disciplinary collaboration that not all institutions possess [12].

During clinical development, AI offers tools to reduce cost and time by streamlining patient recruitment and enhancing patient monitoring and retention. It also improves trial design and efficiency, data analysis, and enhances precision in patient stratification. Algorithms analyzing electronic health records (EHRs) can match patients to studies more efficiently, and adaptive trial designs informed by AI allow real-time protocol adjustments. In oncology, for example, AI-driven imaging analyses help ensure that therapies are tested in the most relevant populations [13]. Nonetheless, risks remain: patient-matching algorithms may inadvertently reinforce disparities if training data reflect historical biases, adaptive trials require careful statistical oversight, and regulatory guidance for AI-informed designs is still evolving. Missteps in these areas could compromise data privacy, trial integrity, or ethical standards.

In regulatory submission and market authorization, AI integration is accelerating rapidly due to its potential to reduce document generation timelines and expedite market access. Agentic AI systems can analyze clinical data and feed results to generative AI tools that draft regulatory dossiers, creating continuity in AI-assisted data handling across the product development pipeline. However, this efficiency brings its own challenges; regulatory agencies and law makers are still developing frameworks for the use of AI in drug development, and quality assurance processes must adapt to ensure accuracy and completeness. The balance between automation and human oversight remains critical. In post-marketing surveillance, AI enhances pharmacovigilance by automating the detection of adverse events across large and

heterogeneous datasets [14]. This can significantly improve the efficiency and accuracy of adverse event detection and analysis, enabling a more proactive approach to enhancing patient safety [15]. Natural language processing tools can screen EHRs, insurance claims, and even social media to identify safety signals more rapidly than traditional reporting systems. Integration of AI into surveillance raises critical questions about data privacy, signal interpretability, and trustworthiness. Misinterpretation of AI-generated alerts could result in unnecessary alarm or overlooked risks, highlighting the need for rigorous validation and transparent processes [16].

The scope of AI in healthcare also extends to medical devices, clinical decision-support tools, and digital therapeutics. The US Food and Drug Administration (FDA)-approved AI-enabled imaging devices can autonomously detect conditions such as diabetic retinopathy, demonstrating the regulatory recognition of software as an intervention [17]. This blurs conventional boundaries between drugs, devices, and data-driven healthcare solutions but also introduces additional layers of regulatory and ethical complexity, including issues of explainability, accountability, and interoperability across systems.

Taken together, AI is becoming integral to drug development, offering unprecedented opportunities to accelerate discovery, optimize clinical trials, and monitor real-world safety. At the same time, technical limitations, data challenges, ethical considerations, and regulatory uncertainties show that its adoption must be approached critically [18]. Understanding both the promise and the limitations of AI is therefore essential for preparing the next generation of leaders who will guide drug development in an increasingly digital future.

3. Competencies required for future leaders

Leaders in drug development are entering a landscape where biomedical knowledge alone is no longer sufficient. Major pharmaceutical companies (including but not limited to AstraZeneca, Bayer, Novartis, Roche, and Sanofi) are investing heavily in the application of AI in drug development. The rise of AI requires a new blend of skills and perspectives, bringing together technical insight, ethical sensitivity, and the ability to collaborate across disciplines. With the rise of agentic AI, the role of the human will keep shifting since the AI systems will make decisions and take actions with minimal human oversight. While the potential of AI is substantial, overestimating its capabilities or underestimating its risks can lead to misguided strategies, wasted resources, and ethical problems.

One central expectation is that future leaders develop a baseline of technical literacy. They do not need to be able to program complex models themselves, but they should understand the principles of machine learning, data analytics, and generative AI well enough to ask the right questions, evaluate technological claims, and interact confidently with specialists [19]. At the same time, leaders must remain cautious of the limitations inherent in AI outputs. Predictive models can fail in unseen ways if trained on biased, incomplete, or unrepresentative datasets, and leaders must be able to critically assess both the assumptions underlying these tools and their real-world applicability. Misinterpretation or overreliance on AI-driven results can undermine decision-making, particularly when patient safety is at stake.

The integration of AI into drug development also demands professionals who can move fluidly between different fields. Drug discovery projects often bring together

clinicians, pharmacologists, statisticians, and computer scientists, each with their own language and priorities. Leaders must act as translators and bridge-builders, ensuring that these diverse perspectives align around common goals [20]. Yet, this is not without challenges: communication breakdowns, conflicting priorities, or misaligned incentives can result in AI systems being underused, misapplied, or even generating unintended consequences. Leaders must be aware that interdisciplinary collaboration is a skill that requires cultivation and continuous effort.

Beyond technical and organizational considerations, ethical responsibility is a crucial aspect of AI in drug development [21]. Issues such as bias in training datasets, patient privacy, and the opacity of algorithmic decision-making cannot simply be left to technical teams. Decision-makers must foster a culture where questions of fairness, accountability, and transparency are openly addressed, both to comply with regulations and to maintain public trust. Failure to adequately address these ethical dimensions can lead to public backlash, regulatory penalties, or inequitable healthcare outcomes, highlighting that ethical literacy is not optional but a core leadership competency.

Managing interdisciplinary projects also requires a distinct style of leadership. The capacity to guide cross-functional teams, mediate between commercial and scientific priorities, and adapt to the uncertainties of evolving regulations will be critical [22]. However, this adaptive style of leadership is challenging. In rapidly changing technological and regulatory environments, leaders may face conflicts between the speed and safety of innovations or between organizational priorities and societal expectations. Balancing these pressures requires judgment, humility, and the ability to navigate ambiguity. These are qualities that must be nurtured through experiential learning and mentorship.

Finally, the rapid pace of technological change makes lifelong learning an essential part of professional identity. Continuous engagement with new research, training programs, and professional networks will be necessary for leaders to keep pace with developments in AI and its implications for drug development [23]. Importantly, these learning needs vary across professional backgrounds: clinicians may seek to deepen their understanding of data science, researchers may focus on incorporating computational tools into laboratory workflows, while developers must learn to navigate the clinical and regulatory contexts in which their algorithms will be applied. Leaders must also recognize the risk of knowledge gaps emerging over time if continuous learning is neglected, potentially compromising decision-making quality in high-stakes contexts.

Taken together, these competencies form a holistic profile that balances scientific expertise with technological awareness, ethical judgment, and adaptive leadership. At the same time, they underscore the complexity and fragility of AI integration: without critical assessment, vigilance, and reflective leadership, even the most sophisticated tools may fail to deliver on their promise. Preparing future leaders in this way will ensure that the opportunities of AI are realized responsibly and sustainably in the service of patients, while also mitigating risks associated with overconfidence, ethical oversights, or misapplication.

4. Educational frameworks and pedagogical approaches

Preparing future leaders for the integration of AI into drug development requires educational strategies that go beyond the transfer of technical knowledge. It involves cultivating critical thinking, ethical awareness, and the

ability to work across disciplinary boundaries. The ECPM postgraduate diploma program at the University of Basel offers a particularly relevant example of how such competencies can be nurtured within a structured educational framework [5].

The ECPM program, long established for over 30 years as a leading postgraduate training initiative in pharmaceutical medicine, has begun to integrate digital health and AI-related content into its curriculum. This integration shows the recognition that tomorrow's professionals will be asked not only to understand the biological and regulatory foundations of drug development but also to critically evaluate the opportunities, limitations, and risks posed by emerging technologies. By embedding AI within a broader program of pharmaceutical medicine, clinical research, and pharmaceutical leadership, ECPM ensures that participants encounter these tools in context rather than as isolated technical modules. Pedagogically, the program also emphasizes interactive learning methods that are particularly well-suited to exploring the evolving drug development landscape [24].

Real-world examples embedded in lectures from industry professionals expose participants to cutting-edge AI applications, such as drug discovery platforms or AI-assisted pharmacovigilance systems [25]. However, classroom examples often focus on success stories, which may inadvertently bias learners toward perceiving AI as infallible. Incorporating critical analysis of failed projects, unintended consequences, or regulatory setbacks can help mitigate this risk and cultivate a realistic perspective.

Simulation-based case studies allow participants to experiment with project prioritization in early drug development in a safe classroom environment. The future will involve observing how AI may alter timelines, resource allocation, or patient outcomes [26]. Yet even simulations will be limited by assumptions built into the models, and learners must be made aware that real-world applications often involve unpredictable complexities, stakeholder conflicts, and ethical dilemmas that cannot be fully replicated in a classroom setting.

Assessment strategies within ECPM are aligned with these pedagogical goals. Evaluations focus on participants' ability to critically assess scientific publications, stakeholder landscapes, and frontiers in drug development. Group presentations and interdisciplinary case studies allow faculty to observe how participants communicate complex concepts to non-specialists. This is an essential skill for leadership in AI-enabled drug development. Nevertheless, assessing critical thinking remains inherently subjective, and programs must continually refine assessment frameworks to ensure consistency, fairness, and meaningful feedback.

By embedding AI literacy within an already interdisciplinary and practice-oriented curriculum, ECPM provides a model for how postgraduate education can adapt to digital transformation [27]. The program does not aim to turn physicians into data scientists or programmers into pharmacologists; instead, it equips participants with the language, frameworks, and critical perspective needed to lead in an environment where collaboration across domains is indispensable. At the same time, educators must remain vigilant to the risk of overestimating learners' AI competence or inadvertently conveying a sense of certainty that does not reflect the complex, evolving, and often uncertain reality of AI in drug development.

5. State of the art: Current educational initiatives

Educational responses to the rise of AI in drug development are still evolving and often fragmented. Universities, professional societies, and industry groups have launched a variety of initiatives, ranging from short workshops to fully-fledged postgraduate programs [28]. Yet approaches differ widely in depth, scope, and integration, leaving no universally standardized path for professionals seeking to build competencies at the intersection of pharmaceutical medicine and AI. This variability presents a challenge: learners may encounter gaps in technical, regulatory, or ethical training, and the absence of standardized curricula can hinder the comparability of skills across programs and institutions.

Across universities, digital health and biomedical data science are increasingly appearing as core elements in curricula. In the United States, institutions such as Stanford and MIT offer master's-level programs that combine computational sciences with biomedical applications, often including modules on AI-driven drug discovery. The University of Cambridge and Imperial College London in the United Kingdom have established dedicated institutes for health data innovation, embedding AI within broader training in translational medicine. In Asia, initiatives such as the National University of Singapore's master's program in biomedical informatics emphasize interdisciplinary training that prepares graduates to apply AI across healthcare and life sciences.

Despite these advances, critical gaps remain. Many programs focus heavily on computational or clinical aspects, with less emphasis on the regulatory, ethical, or translational challenges that are unique to drug development [29]. Graduates may emerge with strong technical knowledge but lack an understanding of the practical limitations, risk management requirements, or societal implications of AI implementation in pharmaceutical contexts. Additionally, programs often differ in accessibility and cost, limiting opportunities for a globally diverse cohort of learners to gain exposure to AI-driven drug development practices.

Professional societies have also taken an active role. Organizations such as DIA and EFPIA regularly offer workshops, webinars, and position papers on AI in the pharmaceutical sector. These initiatives are agile and closely tied to industry practice, providing timely updates on fast-moving developments. However, their short format often limits depth and continuity, and they generally serve as supplements rather than substitutes for structured educational programs. Similarly, massive open online courses (MOOCs) have expanded access globally, offering introductory training in machine learning and health data science [30]. While useful for foundational knowledge, MOOCs are typically generic, lack pharmaceutical focus, and do not provide the sustained, interactive learning environment required to translate knowledge into practice.

Within this diverse landscape, the ECPM postgraduate diploma with onsite teaching and learning occupies a distinctive position. Established over 30 years ago, ECPM provides a comprehensive, postgraduate-level education in pharmaceutical medicine and has systematically incorporated AI-related content into its curriculum. What differentiates ECPM from many other initiatives is its integrative perspective. While a MOOC may cover the technical basics of neural networks and a workshop may illustrate regulatory case studies, ECPM brings together scientific, clinical, regulatory, and managerial dimensions within a single framework. Its long-standing partnerships with academia, industry, and regulatory authorities allow participants

to engage directly with multiple stakeholders, situating AI not as a standalone subject but as part of the broader system of drug development.

Nevertheless, even ECPM faces challenges. Maintaining curriculum currency in the face of rapidly evolving AI technologies, ensuring faculty preparedness, and balancing technical depth with ethical and regulatory literacy are ongoing tasks. Programs must continuously evaluate content relevance, integrate emerging case studies, and provide opportunities for experiential learning that reflect real-world complexities.

Taken together, current educational initiatives demonstrate that the importance of AI in pharmaceutical medicine is widely recognized, yet approaches remain uneven and unstandardized. ECPM shows how established programs can evolve to meet this challenge, offering not just knowledge transfer but also a platform for dialog, reflection, and cross-disciplinary engagement. By connecting otherwise isolated perspectives, it provides a benchmark and illustrates how postgraduate education can act as an accelerator for preparing leaders to responsibly govern the digital transformation of drug development, while remaining mindful of the limitations and uncertainties inherent in AI technologies.

6. Challenges in educating leaders

While the need to prepare future leaders in drug development for the age of AI is widely acknowledged, the path to building effective educational programs has various challenges [31]. These difficulties reflect both the novelty of the field and the rapid pace of technological change (see **Table 1**). They are not unique to any one institution but are systemic, affecting universities, professional societies, and industry alike.

Challenges in educating leaders for AI-driven drug development	Possible solutions
Absence of standardized curricula	Harmonize AI education by adapting existing curricula and sharing best practices. Remain innovative and adaptable.
Speed of AI technologies and applications	Curricula should be equipped to cope with rapid developments. Incorporate regular seminars to reflect advancements in AI methodologies, regulatory guidance, and clinical applications.
Regulatory uncertainty and missing guidance	Use experiential learning tools like sandbox projects and simulation platforms. Leverage open-access resources and anonymized clinical trial datasets to anticipate or contribute to evolving norms.
Ethical considerations	Integrate ethics into technical and clinical curricula. Bring real-world dilemmas into classroom discussions using skillful facilitation.
Resource limitations in IT infrastructure	Utilize open-access resources and shared datasets, and embed real-world examples into lectures to bridge the gap between theory and practice.
Interdisciplinary collaboration of specialists in drug development using AI	Actively encourage interprofessional learning through collaborative projects that bring together diverse specialists (e.g., clinicians, researchers, data scientists, and regulatory experts).

Table 1.
Challenges and solutions in educating leaders for AI-driven drug development.

One of the most pressing obstacles is the absence of standardized curricula [32]. Programs that address AI in drug development vary widely in focus, depth, and scope. Some emphasize technical concepts, such as machine learning algorithms, while others concentrate on clinical applications or regulatory perspectives. This heterogeneity makes it difficult to define what “AI literacy” should mean for pharmaceutical leaders and results in uneven competencies among graduates of different programs. Unlike traditional areas of pharmaceutical medicine, where competencies are relatively well-established, AI lacks a unified educational framework that could guide institutions globally. The absence of consensus also creates the risk that learners may graduate with an incomplete understanding, overestimating the capabilities of AI or underestimating its limitations.

Compounding this challenge is the extraordinary speed at which AI evolves. A lecture prepared one year may be outdated the next, as new models, methods, and regulatory guidelines emerge. Educational providers face the constant risk of content lagging behind the state of the art. This volatility places pressure on faculty, who must not only be experts in their domains but also continuously update their knowledge in ways that few traditional disciplines demand. Faculty preparedness is therefore a recurring concern [33]. Many instructors in pharmaceutical medicine were trained before the digital transformation gained momentum, and developing the confidence to teach AI-related topics often requires additional training, collaboration with data scientists, or joint teaching formats. If faculty is not appropriately prepared, there is a real risk of conveying oversimplified or inaccurate perspectives on AI, which can undermine learners’ ability to make informed decisions in practice.

Regulatory uncertainty adds another layer of difficulty. While agencies such as the FDA and the European Medicines Agency (EMA) have issued initial guidance on AI in drug development and medical devices, comprehensive frameworks remain incomplete and vary across jurisdictions [34]. Educators must, therefore, teach students to operate in an environment of ambiguity, preparing them to anticipate rather than simply follow regulatory norms. However, conveying this uncertainty in a structured curriculum is challenging, as traditional teaching tends to rely on stable knowledge bases rather than shifting regulatory landscapes. There is also a risk that students may either overemphasize regulatory challenges, becoming overly cautious, or underestimate them, thereby risking compliance issues in practice.

Ethical considerations represent another major frontier. Issues such as algorithmic bias, patient privacy, and the transparency of black-box models are not purely technical problems but deeply societal questions that require careful discussion. An entire CAS course is dedicated to the ethical and legal aspects of clinical trials at ECPM. Integrating ethics into technical and clinical curricula is complex; abstract principles alone are insufficient, and bringing real-world dilemmas into classroom discussions requires skillful facilitation [35]. Cultural diversity further complicates ethical education, as expectations about fairness, transparency, and responsibility may differ across regions, making global harmonization particularly difficult. Failing to address these nuances risks producing leaders who are technically competent but ill-prepared to navigate ethical controversies in real-world contexts.

Resource limitations also hinder progress. Training professionals to use AI requires access to computational infrastructure, representative datasets, and

specialized expertise [36]. Not all institutions can provide these resources, especially in regions where funding for digital health and AI initiatives is limited. Even in well-funded contexts, access to high-quality biomedical data is constrained by legal, technical, and privacy barriers. Without such access, teaching about AI risks becoming only theoretical, leaving learners without practical experience handling real-world data. This gap can impede the translation of AI literacy into meaningful contributions in drug development settings. Real-world examples embedded into lectures can help to bridge this gap.

Finally, the interdisciplinary nature of AI in drug development is itself a source of challenge [31]. Bringing together clinicians, pharmacologists, computer scientists, and regulators within a single educational framework demands careful balancing of language, expectations, and priorities. Participants often arrive with very different backgrounds, leading to asymmetries in engagement; for instance, a physician may struggle with mathematical concepts, while a computer scientist may lack familiarity with clinical trial design. Designing pedagogical approaches that engage diverse learners without oversimplifying or alienating participants is demanding and requires highly skilled faculty and innovative teaching formats. Failure to manage these dynamics can result in superficial learning, miscommunication, or underutilization of AI insights in collaborative settings.

These challenges illustrate that educating leaders for AI-driven drug development is not merely a matter of adding new content to existing programs. It requires a rethinking of educational design, institutional processes, and long-term strategies for faculty development and resource allocation. Addressing these obstacles will be critical if programs such as ECPM and its global counterparts are to equip professionals with the competencies needed to guide the pharmaceutical sector through digital transformation, balancing innovation with responsibility, safety, and ethical integrity.

7. Recommendations and future directions

The challenges of educating future leaders in AI-driven drug development underscore the need for innovative and adaptable strategies. As the field evolves rapidly, educational programs must anticipate change, integrate interdisciplinary perspectives, and create structures that allow learners to engage with both technical and regulatory complexities in a meaningful way. Several key recommendations emerge from the current landscape, each addressing specific limitations and risks identified in previous chapters.

First, curricula should be adaptive. Rather than relying on static course content, programs can incorporate seminars that are regularly updated to reflect advances in AI methodologies, regulatory guidance, and clinical applications. This design also allows learners from diverse professional backgrounds, such as physicians, researchers, and data scientists, to supplement core competencies with the latest knowledge by returning for seminars and continuing professional development courses. Educational providers should be wary of leaning too much into modular curricula, which carry the risk of fragmentation or uneven learning experiences if not carefully coordinated. A core program and faculty oversight are needed to ensure that all participants achieve foundational competencies, for example, as defined in the PharmaTrain syllabus.

Second, the establishment of multidisciplinary centers of excellence at universities and academic medical centers can support sustained innovation in teaching [37]. Such centers can bring together expertise from pharmaceutical medicine, computer science, regulatory science, and ethics, providing a platform for collaboration, joint research, and knowledge sharing. They can also facilitate faculty development, offering instructors opportunities to stay current with AI advancements and integrate new approaches into their teaching. Yet, building and maintaining these centers requires substantial investment, institutional commitment, and coordination across departments.

Third, global collaboration should be promoted to harmonize AI education in drug development. By sharing curricula, case studies, and best practices, institutions can reduce duplication of effort, benchmark competencies, and support consistency in professional standards across regions. International networks also create opportunities for cross-border workshops, joint projects, and exchange programs, exposing learners to diverse regulatory frameworks, healthcare systems, and cultural perspectives on ethics and data governance. At the same time, differences in regional regulatory regimes, data privacy laws, and cultural expectations pose potential barriers to harmonization, and programs must navigate these tensions carefully to avoid creating misleading assumptions about the universality of AI applications [38].

Fourth, open-access resources and shared datasets should be leveraged to enhance learning. Publicly available AI tools, anonymized clinical trial datasets, and simulation platforms could allow learners to gain hands-on experience. These resources foster reproducibility, transparency, and collaborative problem-solving – skills that are increasingly critical in AI-driven drug development. However, reliance on open-access datasets also carries limitations: data may be incomplete, non-representative, or lack sufficient context, potentially giving learners an oversimplified view of real-world challenges. Educators must ensure that exercises based on such resources are supplemented with critical discussion of their limitations.

Fifth, interprofessional learning should be actively encouraged. Collaborative projects that bring together clinicians, researchers, data scientists, and regulatory experts allow learners to practice communication, negotiation, and decision-making in realistic, interdisciplinary contexts [39]. Such experiences cultivate the collaborative leadership skills needed to guide teams and organizations through the complexities of AI integration, balancing innovation with safety and ethical responsibility. Nonetheless, managing interdisciplinary teams within educational settings can be challenging: differences in terminology, assumptions, and priorities may lead to miscommunication or unequal participation, requiring skilled facilitation and carefully designed activities to ensure equitable engagement. This is something that ECPM has been practicing for the past 30 years by welcoming participants from diverse backgrounds (see **Figure 2**).

Finally, continuous evaluation and feedback should be built into educational programs [29]. The rapid pace of AI innovation requires that programs monitor their own effectiveness, gather insights from alumni and industry partners, and iteratively improve content, teaching methods, and learning outcomes. By embedding evaluation into program design, institutions can remain responsive to the evolving needs of learners and the pharmaceutical sector alike. Yet, evaluation itself is complex due to human factors and the era of ChatGPT. Furthermore, assessing competencies in leadership or critical thinking is inherently subjective. Programs

Educational Background

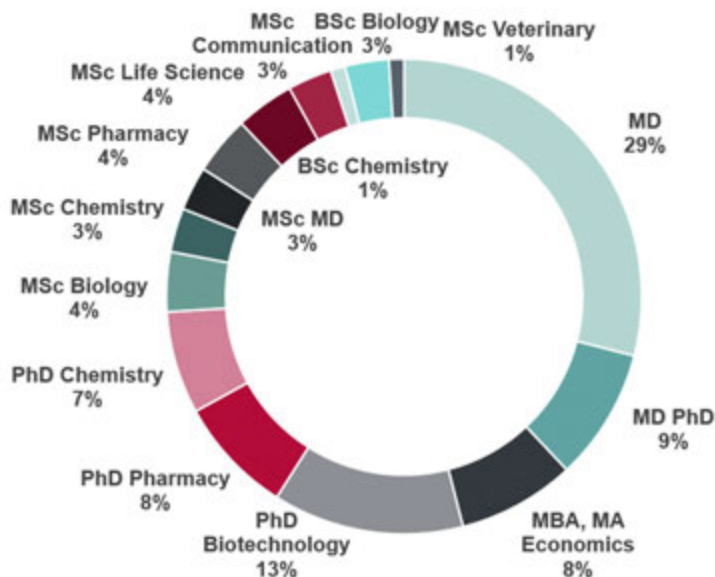


Figure 2.
ECPM' educational backgrounds.

must develop robust, transparent, and adaptable metrics to ensure meaningful feedback.

Taken together, these recommendations provide a guide for institutions seeking to prepare future leaders for the digital transformation of drug development. Adaptive curricula, multidisciplinary programs, global collaboration, open-access resources, interprofessional learning, and continuous evaluation collectively ensure that education not only keeps pace with technological change but also equips professionals to navigate it responsibly, ethically, and strategically. At the same time, these strategies require ongoing attention to potential pitfalls, resource constraints, and systemic complexities. This underscores that building effective AI education is as much a challenge of design, governance, and critical reflection as it is of content delivery.

8. Conclusion

The rapid integration of AI into drug development is redefining the pharmaceutical landscape. Preparing leaders who can responsibly guide this transformation is an urgent priority. As demonstrated throughout this chapter, AI presents opportunities to accelerate discovery, optimize clinical trials, and enhance post-marketing surveillance, but it also introduces technical, ethical, and regulatory complexities that demand informed, thoughtful leadership. Its transformative potential is tempered by limitations in data quality, model transparency, and the uneven pace of regulatory harmonization, reminding us that progress must be managed carefully to avoid unintended consequences.

Education is central to addressing this dual challenge of innovation and responsibility. By providing life-long learning, equipping professionals with the technical literacy to understand AI, the ethical awareness to evaluate its societal impact, and the collaborative skills to bridge interdisciplinary teams, educational programs provide the foundation for leadership that is both effective and principled. Structured initiatives, such as the ECPM diploma program, illustrate how curricula can integrate emerging technologies into broader pharmaceutical medicine training, fostering a new generation of leaders capable of navigating complexity and uncertainty. At the same time, the critical perspective highlights that even well-designed programs face challenges: faculty preparedness, ambiguous definitions of AI literacy, and the rapid evolution of AI demand continuous adaptation and robust assessment frameworks.

Yet education alone is not sufficient. The balance between innovation, safety, and ethics requires ongoing dialog and collaboration among academia, industry, and regulatory authorities. Institutions must work together to harmonize standards, share best practices, and provide platforms for continuous learning that reflect the evolving state of AI in drug development. Programs must also acknowledge and address real-world constraints, including data availability and interdisciplinary expertise. By fostering an environment that critically examines AI's limitations as well as its capabilities, the pharmaceutical community can prepare leaders who are both visionary and grounded.

Ultimately, the responsibility to govern AI-driven drug development lies with those who understand its potential and its limits. The call to action is clear: through concerted educational efforts, collaboration, and interdisciplinary engagement, the pharmaceutical community can cultivate leaders capable of guiding this transformation. Only by pairing technical proficiency with critical reflection, ethical sensitivity, and adaptive leadership can the next generation ensure that AI serves patients effectively, maintains public trust, and advances medicine sustainably. Innovative healthcare, and with that, the real-world impact of AI on patient outcomes, depends on the thoughtful decisions made by these well-prepared leaders today.

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Seeing the Future: AI-Driven Visual Learning and Curriculum Innovation in Image-Rich Medical Specialties

Jonah W. Perlmutter and Marissa Joseph

Abstract

Artificial intelligence (AI) has rapidly emerged as a transformative force in medical education, particularly in image-rich specialties such as dermatology, radiology, and pathology. These disciplines rely heavily on visual pattern recognition, yet medical curricula often provide insufficient exposure for trainees to develop these skills. AI offers scalable, adaptive, and cost-effective solutions through three primary roles: direct teaching via intelligent tutoring systems, collaborative teaching through natural language processing-enabled chatbots, and empowerment of multiple learners using virtual patient simulations. These tools can enhance diagnostic accuracy, procedural skills, and clinical reasoning while providing personalized feedback and broadening exposure to rare and diverse presentations, including underrepresented skin tones. Advances in generative AI allow the creation of photorealistic clinical images to supplement training datasets, reduce bias, and preserve patient privacy. Despite these benefits, risks include the perpetuation of bias from unrepresentative datasets, overreliance on algorithmic outputs, and limited access to large, high-quality multimodal data. Ethical integration requires diverse dataset development, transparency, bias mitigation strategies, faculty training, and preservation of human oversight. Future directions include incorporating AI into formal curricula, leveraging federated learning to enable collaborative dataset expansion, and conducting longitudinal studies to assess real-world impact on clinical competence and patient outcomes. With thoughtful implementation, AI can augment, not replace, educators, enhance visual diagnostic training, and improve equity in access to high-quality image-rich specialty education.

Keywords: artificial intelligence, medical education, image-rich specialties, dermatology, radiology, pathology, intelligent tutoring systems, virtual patient simulation, generative AI

1. Introduction

Artificial intelligence (AI) refers to a domain of computer science that develops programs capable of performing tasks that typically require human intelligence [1]. Through machine learning (ML), AI models are able to train using input data and self-generate predictive or analytical algorithms [1, 2]. In supervised learning, ML models are trained using labeled data points to analyze unlabeled data. In unsupervised learning, ML models are trained using unlabeled data, where the goal is to identify patterns or complex nonlinear relationships between data points. The latter technique may employ multiple levels of complexity and analysis in what is referred to as deep learning [1].

The process of identifying complex relationships between data points can be employed to store, modify, and respond to real-world situations in a meaningful fashion [3, 4]. Through rule-based modeling and decision-making, ML models employ “IF-THEN” statements to respond to input data according to predefined rules [1]. While these rules may be written by humans and used to train AI algorithms, many ML models may generate rules themselves, informed by complex data relationships [5]. For instance, Borah and Nath developed an ML model capable of scanning medical records and generating a rule set that can predict risk factors for disease [6]. In real-world situations where uncertainty clouds whether a rule may be appropriately applied, ML models may employ a fuzzy logic-based approach [1, 7]. Fuzzy logic quantifies a concept’s degree of truth and applies the appropriate rule sets accordingly. For example, fuzzy logic has been used to navigate complex clinical interactions, grading the degree of truth associated with different clinical parameters to assist with Parkinson’s diagnosis [8].

The corpus of knowledge readily accessible online allows ML models to selectively mine through vast amounts of data relevant to a given query [1, 9]. This enables case-based reasoning, where an ML program analyses scenarios and makes decisions informed by related information in reference data [1]. Similarly, it allows ML models to interpret written text through text mining and human speech through natural language processing (NLP). The models may then compare language input to existing knowledge to infer information, such as the emotional state or sentiment of the speaker [10]. Recently, AI data mining has become advanced enough to analyze and even generate images [11].

As the algorithms used by ML models have become more complex, AI has become more prevalent in industries ranging from finance to medicine. In 2018, the American Medical Association first supported the notion of AI integration into medical education, citing several studies reporting its successful use [12]. Since then, AI has grown increasingly impactful in medical education, contributing to three primary domains [4].

Firstly, AI can serve as a direct teacher through intelligent tutoring systems (ITSs). These systems are trained based on the student’s past performance and learning style to ensure that course content is taught to maximize long-term retention [13]. Initially, this may be achieved through adaptive learning systems, which assess a student’s current knowledge level and cater the complexity of information presented accordingly [4]. In medical education, students may begin by learning simple anatomy and terminology while eventually progressing to complex and realistic clinical scenarios [14]. Once information is taught, quizzing may be facilitated across a plethora of domains, including diagnostic skills, lab or image

interpretation, emergency response, and prescription writing [15–17]. These systems also gauge the pace at which a student is learning to determine how quickly the difficulty and complexity of lessons should be increased. Some ITSs implement gamification principles, where points, badges, and leaderboards are integrated into lessons to maximize student enjoyment and engagement [4]. After being quizzed, students are provided with detailed performance reports, where they can identify strengths and areas for improvement in their clinical reasoning. A recent review identified six studies with Kirkpatrick level 1 or 2b evidence supporting the use of ITSs in medical education [13]. Amongst these studies, ITSs were used to evaluate post-OSCE encounter notes, clinical reasoning assignments, and resident admission notes [13].

Secondly, AI can act as a supportive teacher to students, serving in a collaborative role during learning, primarily through chatbots. Chatbots are programmed to respond to human queries by mining information from external databases and communicating in human language using their advanced NLP models [4, 18]. Popular chatbots, such as OpenAI's ChatGPT, Microsoft's Copilot, and Google's Gemini, are accessible through any device with Wi-Fi connectivity [4]. Chatbots may be used to improve the efficiency of time-intensive tasks, such as summarizing scientific articles, responding to specific clinical queries, conducting research, and aiding health advocacy [19]. Chatbots have become prevalent in medical schools; one recent survey of 131 medical students identified that 45.3% were more likely to use ChatGPT to respond to clinical queries than consult with their professor or attending physician [20]. A scoping review similarly identified that quick access to reference data was the most common reason (28%) for chatbot use among medical students, in addition to assistance with research (28%) [21].

Finally, AI may serve to empower multiple learners by facilitating complex problem-solving [4]. This is primarily achieved through a virtual patient model, which exhibits symptoms and guides a student through a dynamic and responsive clinical encounter. The student may be prompted to provide a differential diagnosis, propose a management plan, and collaborate with peers [4, 19]. Virtual patient models allow students to be evaluated on their medical knowledge in addition to their communication and collaboration skills. One recent study identified that a virtual patient model enhanced the individual learning effectiveness of over 75% of students and promoted positive collaborative opportunities in 82.2% of cases [18]. Future projects aim to further improve the realism of these clinical encounters by incorporating virtual reality, particularly when simulating procedures [22, 23].

Although AI's incorporation into medical education is a relatively recent phenomenon, this textbook chapter aims to explain its importance and describe its current use in image-rich medical education, with a focus on dermatology. It will also comment on the limitations of AI and describe how, with careful implementation, AI may serve as a transformative tool for the future landscape of medical trainees in image-rich specialties. **Table 1** can be referenced as a summary of key AI-related concepts.

2. The need for AI in image-rich medical education

Dermatology, radiology, and pathology education are conducive to AI implementation due to the insufficient integration of these image-rich subject areas

Concept/role of AI	Definition/description	Key mechanisms and subtypes	Examples in medical education
Artificial intelligence (AI)	Field of computer science developing software to perform tasks requiring human intelligence.	Learns from data to create predictive/analytical algorithms.	Image analysis, diagnostic decision support.
Machine learning (ML)	AI models are trained on input data to self-generate algorithms.	Supervised learning (labeled data); Unsupervised learning (unlabeled data to detect patterns); Deep learning (multi-layered analysis).	Pattern recognition in clinical images; predictive analytics.
Rule-based modeling	Uses “IF–THEN” statements to make decisions based on predefined or learned rules.	Human-defined or model-generated rules.	Predicting disease risk factors from medical records.
Fuzzy logic	Evaluates concepts by degree of truth, applying rules accordingly.	Manages uncertainty in clinical data.	Parkinson’s disease diagnosis support.
Case-based reasoning	Decision-making based on the analysis of similar past cases.	Data mining from large corpora.	Clinical decision support, differential diagnosis.
Natural language processing (NLP)	Interprets written and spoken language.	Text mining, sentiment analysis.	Inferring emotional state in patient interviews.
Image analysis and generation	Interprets or creates images from reference data.	Computer vision techniques.	Generating medical images for training.
Role 1: Direct teacher (intelligent tutoring systems)	AI adapts teaching based on learner profile.	Adaptive learning, quizzing, gamification.	OSCE note evaluation, anatomy teaching, clinical reasoning feedback.
Role 2: Supportive teacher (chatbots)	Collaborative AI responding to student queries.	NLP-based retrieval from databases.	Article summaries, clinical Q&A, research assistance.
Role 3: Multi-learner empowerment (virtual patients)	AI simulates dynamic patient encounters.	Differential diagnosis, management planning, collaborative learning.	Virtual reality-enhanced procedural training.

Table 1.
Summary of AI concepts, mechanisms, and applications in medical education.

into medical school curricula [24, 25]. This is not necessarily an intentional lack of emphasis; rather, it relates to the way in which our brains learn to recognize common skin conditions, radiographic signs, or pathology findings.

Much like ML algorithms, the human brain facilitates pattern recognition by retrieving information that it was previously exposed to [26, 27]. Through complex hippocampal and cortical interactions, the retrieval and manipulation of information become increasingly succinct after repeated exposures [27]. Medical schools have mechanized this phenomenon by implementing “spiral curricula,” where students repeatedly revisit previously learned information to solidify knowledge and aid

clinical reasoning [28]. Similarly, medical students endorse the use of flashcard applications, such as Anki, which repeatedly expose them to course content at a frequency optimal for maximizing long-term retention [29]. For most medical subject areas, where a patient's clinical history, signs, and symptoms coalesce into a differential diagnosis, this method of learning is effective. Medical students are constantly learning new associations between clinical findings through (often text-centered) case-based learning modules, didactic lectures, and significant direct exposure during clerkship [30, 31]. However, image-rich specialties differ from other medical subject areas due to the necessity of visual pattern recognition in forming a differential diagnosis. A prospective study identified that a trained dermatologist typically requires only 70 seconds for a complete skin assessment, underscoring the importance of pattern recognition and repeated exposure to images during training [32].

Unfortunately, medical schools are failing to expose students sufficiently to image-rich specialties to allow them to develop this essential skill of pattern recognition [25]. In pre-clerkship, little time is devoted toward image-rich specialties, and clerks are rarely consulted to see patients in these fields [25]. A Canadian survey study of 89 medical students revealed that only 17.1% felt their dermatology education was sufficient, and 10.2% were comfortable managing patients with skin conditions [25]. Another cross-sectional study identified that, amongst 1,411 students, approximately half had only 1–4 hours of total dermatology course content, while less than half were required to rotate through dermatology during clerkship [33]. Similar findings have been reported for radiology and pathology, the latter of which is facing a concerning decline in applicants [34, 35].

While medical school is designed to teach a diverse array of fundamental content to trainees, it does not aim to produce expert dermatologists, radiologists, or pathologists after four years. However, there are health system-level benefits of medical trainees graduating with even basic competencies in image-rich specialties. In primary care, skin conditions are the most common complaints, and unnecessary referrals are commonly made to dermatologists for benign or uncomplicated conditions [36]. These delays in care worsen outcomes, particularly among the nearly half of Americans living in an area with limited access to a dermatologist [37]. Similarly, while non-dermatologist physicians should be equipped to confidently recognize common skin emergencies, a cross-sectional study revealed that only 25.3% were able to do so [38]. Primary care physicians (PCPs) must also be able to communicate using appropriate terminology when referring cases to image-rich specialists. This is particularly important in dermatology, where appropriately described morphology (the “language of dermatology”) in a referral letter may expedite and improve care [39, 40]. Likewise, 80% of emergency departments in rural areas lack CT access and rely on the interpretation of basic imaging, such as X-rays, by PCPs and trainees [41]. By training medical students in image-rich specialties, decreased downstream burden on the healthcare system and better patient care can be achieved.

One potential solution to a lack of image-rich specialty exposure is curriculum reform to ensure increased time spent on these specialties. One study showed that by introducing a 15-hour dermatology course, students demonstrated a significantly improved ability to diagnose fungal infections, malignant lesions, and dermatologic emergencies [42]. Another study revealed improved student confidence in conducting skin checks after only one hour of additional lecture content [37].

However, due to a lack of available qualified professors and funding, increasing dedicated class time to image-rich specialties may not be realistic, particularly in resource-limited settings [43, 44]. Despite repeated attempts at curriculum reform, Canadian national surveys have demonstrated consistently disproportionately low levels of dermatology education in medical schools since the early 1980s [25]. Ironically, the misplaced notion that AI will replace, rather than assist, image-based specialties may further disincentivize their emphasis in medical training [45, 46]. Beyond the practical challenges of increasing exposure time to image-rich specialties, this would not address flaws in the way these topics are currently taught. Notably, skin of color remains underrepresented in dermatology training materials during both medical school and residency [47–49]. Studies report that only 16% of skin pathologies in undergraduate dermatology are taught in at least three skin tones, while nearly half of dermatology residents report insufficient knowledge of conditions primarily seen in skin of color. Despite recent initiatives to ameliorate this disparity, patients with skin of color still experience poorer dermatologic care and worse outcomes, emphasizing the need for educational reform [50].

By utilizing intelligent tutoring systems adaptive to student needs, virtual patient models, and advanced image-generation algorithms, AI may overcome many of the current barriers preventing adequate teaching of image-rich specialties. AI can serve as a cost-effective direct teacher, collaborative teacher, and empowering agent that allows students to maximize their exposure to these specialties throughout medical school and residency.

3. AI's present implementation in image-rich medical education

Integrating AI into image-rich specialty training is widely endorsed by both faculty and trainees, in contrast with other methods of curriculum reform. In a survey of Australian dermatologists, the majority suggested implementing learning modules devoted to effectively using AI for learning [51]. An international survey of 1,271 dermatologists similarly revealed that 79.8% supported AI as an essential part of medical education [52]. Trainees also support formally incorporating AI into dermatology education; a survey of 60 clerks revealed that 90% supported AI-related dermatology content being implemented in their curriculum [53].

Since many AI tools, such as ChatGPT, are available at minimal cost or even free, with plans starting at approximately US \$20 per month for access to the latest models, integrating these technologies is financially feasible for most training programs. Given their accessibility, credibility, and high acceptance among both educators and learners, AI-assisted training is well-positioned to become a foundational component of future image-rich specialty education. **Figure 1** summarizes the available tools that have been employed to assist with image-rich specialty training, which the remainder of this chapter will explore in further detail.

3.1 AI as a direct teacher

Intelligent tutoring systems have been successfully used to teach several image-rich specialties. In dermatology, AI-engineered platforms such as DeepDerm and HAM10000 can generate virtual training modules containing clinical and dermoscopic images, enabling medical students to gain exposure to a wide range of

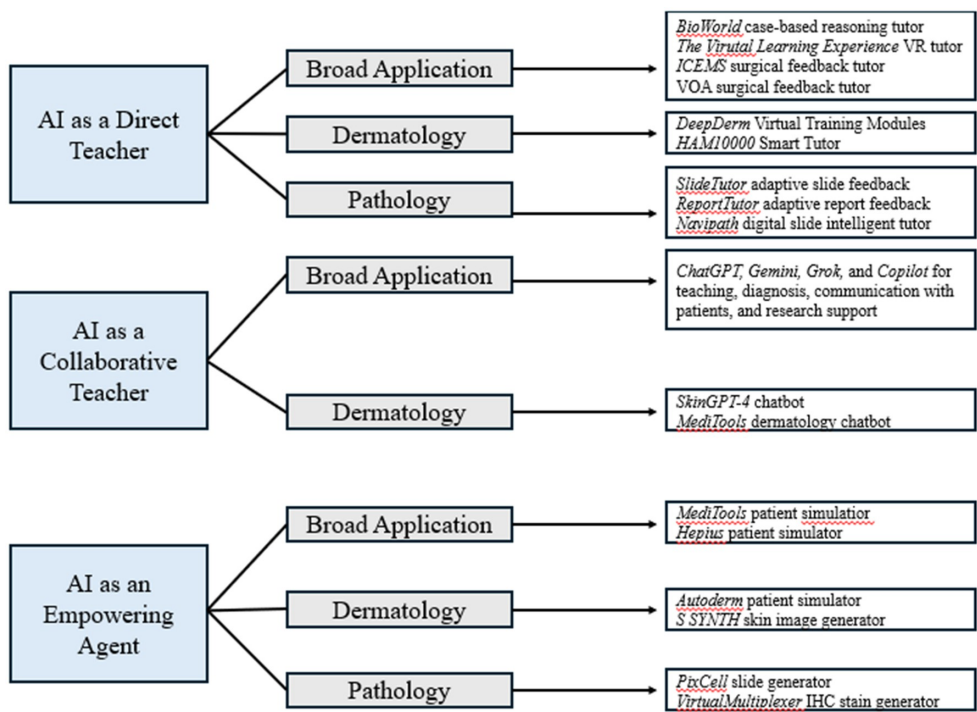


Figure 1.
Summary of available AI tools for education in image-rich specialties.

skin pathologies [54]. In radiology, AI-powered tutoring platforms use large annotated imaging datasets to create case-based learning modules for modalities such as X-ray, CT, and MRI, providing trainees with guided interpretation practice and real-time feedback on accuracy [55]. In pathology, SlideTutor employs model-tracing to monitor learner actions on virtual whole-slide images, offering immediate, context-specific hints when errors occur, while ReportTutor provides feedback on structured pathology reports to align them with clinical standards [56–59]. Evaluation of these systems has shown substantial educational impact; SlideTutor users demonstrated up to a fourfold improvement in diagnostic accuracy (from 11.7% to 50.2%) after a single session, with performance gains persisting at a one-week follow-up [58]. The AI-enhanced digital slide platform NaviPath can also be used to direct a learner’s attention to salient histological features, improving recognition rates and diagnostic agreement compared with unguided review [60, 61].

In addition to specialty-specific systems, several intelligent tutors in general medical education have features that translate well to image-rich fields. BioWorld is a case-based reasoning tutor that continuously logs a learner’s diagnostic hypotheses, information-gathering actions, and management decisions, maintaining a dynamic learner model to adapt scaffolding in real time [62–64]. In controlled studies, BioWorld use was associated with measurable gains in diagnostic efficiency and metacognitive monitoring, with learners demonstrating improved accuracy in final

diagnoses and more efficient problem-solving pathways compared to unguided case review [62–64].

The Virtual Learning Experience platform is an AI-enabled intelligent tutoring system integrating virtual reality simulation and machine learning to deliver adaptive pharmacology tutoring for medical students. The platform assesses baseline knowledge and adjusts difficulty dynamically, providing immediate, individualized feedback on both factual and applied problem-solving [65]. In a randomized trial of 100 students over six weeks, both AI and expert groups covered identical content, but the AI group achieved significantly higher final test scores (mean 96.04 vs. 79.18; $p < 0.0001$) [65]. The AI group also outperformed on image-based clinical questions and demonstrated stronger long-term retention, likely due to spaced repetition, targeted remediation, and reduced cognitive load. Students rated instructions as clear and found the AI video tutorials and practice tests most useful, highlighting the platform's effectiveness for enhancing complex medical knowledge acquisition [65].

Intelligent tutoring systems also assist with teaching and supervising procedures. The Intelligent Continuous Expertise Monitoring System (ICEMS) is an AI-driven surgical tutoring tool that analyzes performance metrics every 0.2 seconds and provides real-time auditory feedback along with targeted video reviews [66]. In a randomized trial of 97 medical students on simulated brain tumor resections, ICEMS outperformed post-hoc feedback and in-person expert instruction by the fifth repetition, achieving higher composite scores and demonstrating superior hemostasis, tissue respect, flow, and instrument handling [66]. Similarly, the Virtual Operative Assistant (VOA) is an AI tutoring system that analyzes surgical simulator data and provides personalized, metric-based feedback [67]. In a randomized trial of 70 medical students, the VOA produced higher quantitative performance scores than both remote expert instruction and no feedback, while eliciting comparable cognitive and emotional responses among trainees [68]. The precision feedback of these models could translate well to the procedural aspects of image-rich specialties, such as Mohs surgery, where fine tissue control and dexterity are essential.

3.2 AI as a collaborative teacher

Chatbots are the most common form of AI used in medical education [51]. Several AI chatbots have been designed specifically to respond to queries related to dermatology. SkinGPT-4 is an interactive dermatology diagnostic system built on a multimodal large language model, integrating image analysis with natural language output [54, 69]. Trained on over 52,000 annotated dermatologic images, it enables learners to upload clinical photographs, receive automated descriptions of morphological features, propose differential diagnoses, and discuss management in a conversational format [69]. In a study of 150 real-world cases, board-certified dermatologists rated 80.6% of its diagnoses as correct or relevant, and over 85% of its treatment recommendations as useful, highlighting its potential as a self-directed learning tool to strengthen pattern recognition, diagnostic reasoning, and familiarity with dermatologic terminology [69]. Similarly, MediTools' Dermatology Case Simulation Tool uses real patient images and large language model-powered virtual patient interactions to let learners practice history-taking, diagnostic workflows, and clinical decision-making with optional live or end-of-case feedback [70]. In pilot

testing with 10 healthcare professionals and students, 80% rated the LLM's responses as "good" or "excellent" in accuracy. Additionally, MediTools features an AI-enhanced PubMed tool for querying full-text research articles and a Google News tool for AI-generated medical news summaries, providing an integrated hub for both clinical skill rehearsal and staying current with the literature [70].

In addition to chatbots designed for specialty-specific applications, multipurpose chatbots are commonly used among medical trainees, with ChatGPT being the most common [71]. Due to the plethora of tasks for which multipurpose chatbots are used – ranging from quickly referencing information, summarizing text, assisting with writing, or responding to clinical scenarios – it is difficult to quantify their exact impact on education. The accuracy and reliability of chatbot output are, however, essential to ensure their utility and have been well-reported [72, 73]. To investigate the accuracy of Open AI's ChatGPT-4 in teaching dermatology content, Rao et al. prompted it to generate 20 clinical vignettes with explanations for skin and soft tissue diseases tested on the USMLE [72]. Three attending physicians rated the vignettes highly for scientific accuracy (4.45/5), comprehensiveness (4.3/5), and overall quality (4.28/5), with low scores for potential clinical harm (1.6/5) and demographic bias (1.52/5). A strong correlation ($r = 0.83$) was found between comprehensiveness and overall quality, though demographic representation was limited, with most patients depicted as male and few non-White cases. The authors concluded that large language models can provide scalable, customizable, and accessible dermatology education materials but require intentional inclusion of diverse patient demographics and expert review to ensure accuracy [72]. Several studies have also investigated the ability of Chat-GPT to answer dermatology board exam-style questions, revealing its ability to score a passing mark and an improvement in performance as new models are released [74, 75].

Medical trainees may also use AI chatbots to assist with patient interactions. The performance of AI in diagnosing skin lesions, interpreting medical imaging, and analyzing tissue slides is well-reported and improving. In dermatology, there is hope that AI will evolve into a diagnostic tool capable of accurately detecting skin cancer. A recent meta-analysis of AI's ability to detect skin cancer reported a pooled sensitivity of 87.0% and specificity of 77.1%, outperforming the abilities of overall clinicians (79.8% sensitivity and 73.6% specificity) [76]. Performance was markedly superior when AI was compared with generalists, while results were comparable to expert dermatologists, and AI assistance improved diagnostic accuracy, particularly among less-experienced clinicians [76]. Beyond skin cancer, deep learning models have demonstrated high accuracy for a range of common skin diseases, including acne (94%), rosacea (94%), atopic dermatitis (93%), and psoriasis (89%), with some systems also capable of grading disease severity [77].

In radiology, deep learning models have shown significantly higher diagnostic sensitivity when compared to radiologists (93% vs. 83%), while maintaining comparable specificity (91% vs. 90%) [78]. Additionally, AI tools are widely integrated into radiology clinical practice, with hundreds of approved systems assisting with detecting brain tumors, strokes, and breast cancer [79].

In pathology, AI-augmented augmented-reality microscopes overlay diagnostic annotations in real time during slide examination, improving detection efficiency in cases such as breast and prostate cancer, while deep learning-based virtual staining enables label-free tissue imaging by converting intrinsic fluorescence into diagnostically equivalent histology slides, streamlining workflows and expediting

diagnosis [80, 81]. AI applied to whole-slide images across diverse diseases has been reported to achieve a pooled diagnostic sensitivity of 96.3% and specificity of 93.3% [82]. AI assistance has also markedly improved the performance of pathologists. For instance, in Gleason grading of prostate biopsies, AI support increased clinician agreement with expert reference standards (Cohen's kappa from 0.799 to 0.872; $p = 0.018$) [83]. Altogether, these advances suggest that AI chatbots can serve as powerful educational and diagnostic support tools for medical trainees across image-rich specialties, enhancing accuracy, confidence, and learning opportunities while fostering human-AI collaboration.

Medical trainees are also regularly tasked with communicating clinical findings to patients and their families [84]. AI may serve as an effective tool to help facilitate medical communication in a comprehensible and sensitive fashion, as reported by several studies. Yan et al. reported that for rosacea, ChatGPT achieved 92.22–97.78% accuracy and 98.61–100.00% clinical applicability, closely aligning with guideline-based care [85]. Ferreira et al. revealed that when ChatGPT was tasked with explaining six common skin conditions (acne, atopic dermatitis, alopecia, psoriasis, rosacea, and skin cancer) to patients, 88% of its responses were deemed appropriate, with perfect performance for acne and rosacea but up to 25% inappropriate answers for alopecia and atopic dermatitis [86]. When ChatGPT was prompted to communicate with patients about melanoma, accuracy was high (4.88/5), yet only 64% of responses contained the level of detail needed for clinical applicability [87]. In basal cell carcinoma, 84% of explanations were appropriate, although some contained notable inaccuracies [88]. In acne education, ChatGPT produced materials readable at a high school to early college level, but review was recommended to ensure originality [89]. Collectively, these findings suggest that ChatGPT can support trainee–patient communication, particularly for common conditions, while underscoring the need for clinician oversight in complex or high-stakes scenarios. This aligns with findings from Reynolds et al., who compared dermatologist and ChatGPT-generated responses to real patient messages in the electronic medical record. Physician responses were preferred for overall quality, readability, accuracy, and empathy, though ChatGPT outputs contained no harmful misinformation and could serve as time-saving first drafts for trainees preparing patient communication materials [90].

Chatbots also have significant potential to support trainees with research tasks by producing robust first drafts of academic articles, theses, and assignments [91, 92]. ChatGPT is already capable of generating case reports that over half of expert reviewers fail to differentiate from human-written reports [93]. Additionally, chatbots have been shown to save significant amounts of time while writing review articles, and some speculate they may replace reviews altogether [94, 95]. In dermatology, ChatGPT has been described as a versatile writing assistant, able to revise language, extract data from electronic medical records, assist with literature searches, provide style and formatting guidance, suggest statistical approaches, and even generate complete manuscripts [96]. While these capabilities can increase efficiency, human expertise remains essential for creativity, interpretation, ethical oversight, and nuanced communication, suggesting that collaboration, rather than replacement, is the optimal model [73]. These capabilities can streamline the time-intensive process of medical writing, allowing trainees and clinicians to focus more on content development and interpretation rather than mechanics. However, comparative studies show that

while ChatGPT can produce coherent and well-structured text, the quality often falls short of experienced dermatologists' work, particularly in terms of readability, empathy, and thoroughness [73, 97]. Ethical considerations also arise regarding authorship, originality, and the integrity of the research process, with a scoping review noting that AI is rarely credited as an author despite its growing role in manuscript preparation [98]. While AI models have been investigated as tools for manuscript peer review, they remain limited in handling complex, subjective assessments compared to human reviewers [97]. As such, experts recommend a collaborative approach, leveraging AI to enhance efficiency while preserving the creativity, interpretation, and ethical oversight provided by human expertise.

3.3 AI as an empowering agent

AI-driven simulated patients, perhaps the most promising of current applications, enable trainees to practice collaborative problem-solving, history-taking, examination, diagnostic reasoning, and communication in safe and adaptive environments [99]. In pilot testing of MediTools' large language model-powered virtual patient tool, which uses real patient images and enables interactive dialogue with AI acting as a patient, medical trainees reported high satisfaction and usability [70]. In a non-randomized controlled trial, students who practiced with AI-simulated patients achieved significantly higher OSCE interview scores than peers relying on standard preparation alone. Hepius is another virtual patient simulator that interprets free-text clinical inputs, such as patient history, examination findings, and differential diagnoses, and delivers real-time, step-by-step feedback to guide clinical reasoning [100]. In a study of 15 undergraduate medical students, pre-/post-simulation testing showed statistically significant gains in both overall scores and core diagnostic question performance ($P < 0.001$), demonstrating measurable improvements in knowledge retention and diagnostic ability.

AI patient modeling adds considerable value in specifically image-rich specialties. In dermatology, AI-assisted platforms can pair clinical imagery, such as photos of eczema, psoriasis, or melanoma, with interactive simulated patient dialogues. Autoderm v2.2, a virtual patient simulation presenting history, lesion images, and AI-generated ranked differential diagnoses, improved fourth-year medical students' diagnostic accuracy in 70–75% of cases, enhanced management accuracy by 80%, and reduced case completion time by 40% compared to controls [101].

The next evolution of AI patient modeling lies in image generative models, which can algorithmically create novel, photorealistic clinical images under controlled parameters. They function using generative adversarial networks or diffusion architectures, learning statistical patterns from large, curated datasets to synthesize clinically realistic images with user-specified variations in features such as morphology, location, and background anatomy [19, 102]. These models can augment virtual patient simulations with rare, subtle, or demographically diverse presentations while mitigating concerns over patient privacy [103, 104]. In dermatology, synthetic datasets such as S-SYNTH enable large-scale generation of skin images across a spectrum of conditions, lesion morphologies, and Fitzpatrick skin types, allowing trainees and algorithms to encounter underrepresented



Figure 2.

Demonstration of OpenAI's ChatGPT-5's ability to generate images of patients with atopic dermatitis (top left), psoriasis (top right), acne (bottom left), and skin cancer (bottom right). To generate these images, the prompt "generate a photorealistic image of a patient with (insert skin disease)" was input into GPT-5. The first images generated were compiled to create this figure. Note the lack of diversity with respect to patient phenotype and sex.

presentations, such as melanoma in darker skin, that are often missing from clinical archives [105]. Early evaluations have shown that augmenting training datasets with S-SYNTH images has the potential to reduce misclassification rates for skin-of-color cases [105, 106]. **Figure 2** demonstrates the current state of image generative AI's output quality in dermatology. In radiology, AI-generated CT and MRI scans have been used to simulate rare pathologies and augment case-based learning in areas such as lung nodule detection and neuroimaging, with studies reporting improved trainee sensitivity without increasing false-positive rates [107]. In pathology, diffusion-based generative models like PixCell, trained on over 69,000 whole-slide H&E images, can synthesize high-fidelity histology slides that effectively substitute for real images in training self-supervised models and can even generate realistic IHC-like patterns from H&E alone [108]. Similarly, the VirtualMultiplexer system creates multiplexed IHC stains directly from H&E slides without needing paired training images, improving cancer prediction capabilities [109].

Taken together, these studies highlight how AI-simulated and image-enabled virtual patients, especially when embedded with visual diagnostic tools, offer powerful, customizable, and scalable learning environments. They enable learners to build confidence, improve diagnostic accuracy, and refine communication skills specific to dermatology in preparation for real clinical encounters.

4. The risks and limitations of AI in medical education

AI in medical education offers the potential to enhance diagnostic accuracy, streamline workflows, and expand access to care; however, its integration also presents significant risks. Across specialties, AI systems can amplify existing biases, introduce new errors, and degrade in performance over time if not continuously monitored [110]. Biases embedded in training datasets and model feedback loops can perpetuate inequities in education, research, and patient care. In dermatology, for instance, AI is known to perform worse when diagnosing lesions in skin of color across several models [110]. **Figure 2** demonstrates that when ChatGPT-5 was prompted to create images of patients with skin conditions, four depicted male-presenting individuals, and one depicted an individual with skin of color. Strategies to mitigate bias include training AI with large and diverse datasets, prompt-engineering clinical scenarios to present diverse patient populations, and implementing bias appraisal tools [111, 112].

Both ML and deep learning also require enormous, high-quality datasets to produce complex yet accurate algorithms [113]. However, publicly available datasets that are clinically validated remain small and unimodal, with most progress being made in radiology [114–117]. Expansion into specialties such as dermatology is constrained by the high cost and proprietary nature of large, multimodal datasets, as well as institutional resistance, legal and privacy barriers, and security concerns [113–117]. Federated learning offers one potential solution by enabling collaborative model training without centralized data sharing but introduces its own transparency and governance challenges [118, 119]. Addressing these issues will require deliberate trust-building between institutions, accountability for data stewardship, and strong commitments to ethical AI use, as defined by institutions collaboratively [113, 118, 119].

Finally, organizational apprehension that AI-based tools may replace educators or administrative staff can foster resistance to adoption [4]. Such fears often overlook the fact that effective medical education relies on human judgment, mentorship, and contextual decision-making – elements that current AI systems cannot replicate [4, 120]. Rather than framing AI as a substitute for faculty and support staff, its role should be understood as augmentative: re-engineering workflows, automating routine administrative tasks, and providing decision support to allow educators to focus on higher-value teaching and mentorship [121]. This principle is equally important to convey to students, ensuring they view AI as a supportive tool rather than a definitive authority, thereby avoiding overreliance on algorithmic outputs at the expense of critical thinking. Proactive engagement, transparent communication, and inclusive planning are critical to building institutional trust and ensuring that AI integration strengthens rather than undermines the human elements essential to medical education [4].

5. Future directions and conclusions

The future of AI in image-rich medical education lies in its integration into curricula while maintaining the irreplaceable role of human educators [113]. AI applications, such as ITSs, virtual patient simulations, and generative image models,

should be incorporated gradually, with specialty-specific validation to ensure their accuracy, relevance, and equity across diverse populations [122]. Institutions should prioritize developing large, representative, and multimodal datasets for training AI systems, with deliberate inclusion of underrepresented demographics and rare disease presentations to reduce bias and improve generalizability [111, 112].

Faculty development will be essential, as educators must be trained not only in using AI tools but also in evaluating their outputs, identifying errors, and integrating them into pedagogically sound lesson plans [123]. Similarly, students must be educated on AI's limitations to avoid overreliance and to cultivate the skills required to challenge algorithmic recommendations when necessary [119].

From a technological standpoint, federated learning and privacy-preserving AI architectures offer a path toward collaborative dataset development without compromising patient confidentiality [124, 125]. Alongside this, establishing robust regulatory frameworks and transparent governance structures will be vital for ensuring patient data security, ethical model training, and accountability for AI-generated outputs [119, 124, 125].

Research should also focus on longitudinal impact studies that measure not only short-term knowledge gains but also the effect of AI-assisted learning on clinical performance, diagnostic accuracy, and patient outcomes over time [126]. This includes evaluating AI's potential to reduce diagnostic errors, improve access to care in underserved areas, and enhance interprofessional communication in real-world healthcare settings [127].

Envisioning the next decade, AI-enhanced medical classrooms may become commonplace, where students wear immersive augmented or virtual reality headsets, allowing them to examine photorealistic, AI-generated skin lesions of varying morphologies and skin tones in three dimensions. Virtual patients will respond dynamically to questions, modifying their histories and physical findings based on learners' decisions. Intelligent tutoring systems track each student's diagnostic reasoning, instantly adjusting case difficulty and providing targeted remediation. Global federated learning networks ensure these simulations are powered by continually updated, demographically diverse datasets, while built-in bias detection algorithms flag potentially inequitable outputs in real time. Such a future would not only democratize access to high-quality, image-rich specialty training but also ensure that every learner, regardless of geography or resources, can repeatedly encounter and learn from the full spectrum of clinical presentations.

In conclusion, AI has the potential to transform education in dermatology, radiology, pathology, and other image-rich specialties by addressing long-standing barriers to exposure and training. However, this potential will only be realized with thoughtful implementation that prioritizes diversity, accuracy, data security, and the preservation of human oversight. By leveraging AI as an augmentative, not replacement, tool, educators can enhance pattern recognition, clinical reasoning, and communication skills for the next generation of medical professionals, ultimately improving patient care and outcomes.

Abbreviation

AI	artificial intelligence
Anki	a digital flashcard-based spaced repetition software

COP	coefficient of performance
CT	computed tomography
EMF	enhanced metafile (image format)
EPS	Encapsulated PostScript (image format)
GAN	generative adversarial network
GIF	graphics interchange format (image format)
GPU	graphics processing unit
HAM10000	Human Against Machine with 10000 training images dataset
H&E	hematoxylin and eosin stain
IHC	immunohistochemistry
ICEMS	intelligent continuous expertise monitoring system
ITS	intelligent tutoring system
JPEG	Joint Photographic Experts Group (image format)
LLM	large language model
ML	machine learning
MRI	magnetic resonance imaging
MPG/MPEG	Moving Picture Experts Group video file format
MS	microsoft
NLP	natural language processing
NPV	negative predictive value
OSATS	objective structured assessment of technical skill
OSCE	objective structured clinical examination
PCP	primary care physician
PDF	Portable Document Format
PNG	Portable Network Graphics (image format)
PPTX	PowerPoint Open XML Presentation file format
S SYNTH	synthetic skin dataset for diverse dermatological image generation
TIFF	Tagged Image File Format
USMLE	United States Medical Licensing Examination
VOA	virtual operative assistant
VR	virtual reality

Conflict of Interest

Dr. Marissa Joseph has received consulting fees from AbbVie, Amgen, Bausch Health, Bristol Myers Squibb, Fresenius Kabi, Galderma, Incyte, Janssen, Kenvue, Leo Pharma, Novartis, Pfizer, Sandoz, and Sanofi. Mr. Jonah Perlmutter declares no conflicts of interest.

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Perspective Chapter: The Role of Artificial Intelligence in Medical Curriculum Design

Mahdi Naeim

Abstract

This chapter explores how artificial intelligence (AI) is transforming the design and delivery of medical education. AI technologies facilitate personalized learning by tailoring content and pacing to individual students' needs, while adaptive assessments provide real-time feedback that supports competency-based education. Virtual simulations, AI-driven tutoring systems, and predictive analytics enable students to practice clinical decision-making in safe, controlled environments, enhancing both knowledge retention and practical skill development. The chapter reviews current applications of AI in medical curricula, highlighting how machine learning algorithms can identify knowledge gaps, optimize study plans, and support evidence-based instructional strategies. Ethical considerations are also addressed, including algorithmic bias, data privacy, and the need for transparency in AI-assisted educational tools. Additionally, the chapter discusses the integration of AI into interprofessional education and lifelong learning frameworks, emphasizing how these technologies can complement human instruction rather than replace it. By providing data-driven insights and supporting individualized learning pathways, AI offers significant potential to improve educational outcomes, increase student engagement, and better prepare future healthcare professionals for the complexities of modern clinical practice. Finally, the chapter outlines practical recommendations for implementing AI in medical education responsibly, highlighting the importance of faculty training, institutional policies, and continuous evaluation to ensure that AI enhances, rather than undermines, the quality and equity of medical training.

Keywords: artificial intelligence, medical education, curriculum design, digital transformation, personalized learning

1. Introduction

Medical education is undergoing a profound transformation, driven by rapid advancements in technology and evolving healthcare demands. The integration of digital tools into educational frameworks has reshaped how future physicians are trained, emphasizing efficiency, accessibility, and adaptability. Artificial intelligence (AI) stands out as a pivotal technology, offering innovative solutions to enhance

curriculum design and delivery. This chapter explores AI's transformative role in medical education, focusing on its applications, challenges, and future potential.

1.1 Background of digital transformation in medical education

The shift toward digital transformation in medical education began with the adoption of e-learning platforms and virtual tools, accelerated by global events like the COVID-19 pandemic. Digital technologies have enabled remote learning, interactive simulations, and data-driven assessments, addressing the need for scalable and flexible education systems. Studies highlight that digital tools improve access to education and support diverse learning needs [1]. For instance, online platforms have expanded opportunities for medical training in resource-limited settings, ensuring broader reach and inclusivity [2].

This transformation aligns with the growing complexity of healthcare, where physicians must master vast knowledge and skills. Digital tools, such as learning management systems and virtual reality (VR), have become integral to modern curricula, enabling students to practice clinical scenarios in controlled environments [3]. However, the integration of these technologies requires careful planning to ensure effectiveness and equity, setting the stage for AI to play a transformative role.

1.2 Role of AI in educational innovation

AI is redefining educational innovation by enabling data-driven, personalized learning experiences. AI systems analyze student performance to identify learning gaps and recommend tailored content, enhancing competency-based education (CBE). For example, machine learning algorithms can adapt curricula to individual needs, improving outcomes in skills such as diagnostics and clinical reasoning [4]. Systematic reviews confirm that AI-driven tools increase student engagement and knowledge retention, particularly in undergraduate medical programs [1, 5].

AI also supports educators by automating tasks like assessment design and feedback delivery, allowing them to focus more on teaching. Its ability to process large datasets enables the creation of dynamic curricula that evolve with medical advancements. However, challenges such as algorithmic bias and the lack of standardized guidelines must be addressed to maximize AI's benefits [2]. The potential of AI lies in its capacity to complement human expertise, making education more efficient and effective.

1.3 Objectives and scope of the chapter

This chapter aims to examine AI's role in medical curriculum design, focusing on its applications in personalized learning, virtual simulations, and assessments. It explores ethical and practical challenges, such as data privacy and faculty readiness, to provide a balanced perspective. The scope includes current AI applications, supported by evidence from recent studies, and future directions for integration. Written for a broad audience, including those unfamiliar with AI, the chapter ensures clarity while maintaining academic rigor. It draws on systematic reviews and empirical studies to offer a comprehensive overview of AI's transformative potential in medical education [3–5].

2. Applications of AI in medical curriculum design

AI is revolutionizing medical curriculum design by enabling data-driven, efficient, and targeted learning experiences. By analyzing large datasets, AI identifies learning gaps, customizes content, and supports CBE, addressing the diverse needs of medical students. This section focuses on personalized learning pathways, a key application of AI, and examines how adaptive systems, competency-based approaches, and improved student outcomes contribute to transforming medical education. Subsequent sections will explore virtual simulations, assessments, and ethical challenges.

2.1 Personalized learning pathways

Personalized learning pathways leverage AI to tailor educational content to individual student needs, enhancing efficiency and effectiveness. Unlike traditional one-size-fits-all curricula, AI-driven systems adapt content dynamically, ensuring students progress at their own pace while mastering essential competencies. This approach is particularly valuable in medical education, where students enter with varied backgrounds and skill levels. AI's ability to analyze performance data and recommend targeted interventions is transforming how curricula are designed and delivered [1, 3, 6].

2.1.1 Adaptive learning systems and machine learning algorithms

Adaptive learning systems use machine learning algorithms to analyze student performance and customize educational content. These systems track metrics such as test scores, response times, and error patterns to identify strengths and weaknesses. Based on this analysis, AI recommends specific modules, readings, or exercises to address individual needs. For example, in medical education, an AI system might detect a student's difficulty with diagnostic reasoning and suggest additional case studies or tutorials to improve this skill [4].

Research highlights the effectiveness of adaptive systems. A systematic review found that AI-driven adaptive learning improved knowledge retention and clinical skills in disciplines like radiology and surgery [7]. These systems employ algorithms such as neural networks or decision trees to predict learning needs, ensuring content aligns with students' progress (**Table 1**).

For instance, platforms like AMBOSS use AI to adapt question banks for medical students, enhancing preparation for licensing exams [5]. However, the success of these systems depends on high-quality, diverse datasets. Biased or incomplete data can lead to inaccurate recommendations, potentially disadvantaging certain student groups [3].

Figure 1 illustrates the architecture of an adaptive learning system leveraging machine learning algorithms. Student data is collected and processed by a learning analytics engine, which applies machine learning models to analyze performance, predict learning needs, and recommend personalized content. The system then provides targeted feedback to learners, supporting individualized learning paths and enhancing engagement. This architecture demonstrates how AI can be integrated into educational platforms to optimize both learning efficiency and the development of clinical competencies in medical education.

Algorithm	Key features	Applications in medical education	Strengths	Limitations
Decision trees	Rule-based structure, interpretable	Identifying student learning paths and providing decision support in quizzes.	Easy to interpret, fast execution	Prone to overfitting
Neural networks	Layered architecture, models complex patterns	Predicting student weaknesses, customizing clinical scenarios.	High accuracy with large data	Requires large datasets, less interpretable
Support vector machines (SVM)	Maximizes margin between data classes	Classifying student performance categories	Effective in high-dimensional data	Less efficient on large datasets
Random forest	Ensemble of decision trees	Personalized content recommendation	Reduces overfitting, handles missing data	Slower training time
K-nearest neighbors (KNN)	Instance-based learning	Suggesting similar learning paths to peer groups.	Simple to implement; no training phase.	Sensitive to noisy data; computationally heavy.

Table 1.
Comparison of machine learning algorithms used in adaptive learning systems in medical education.

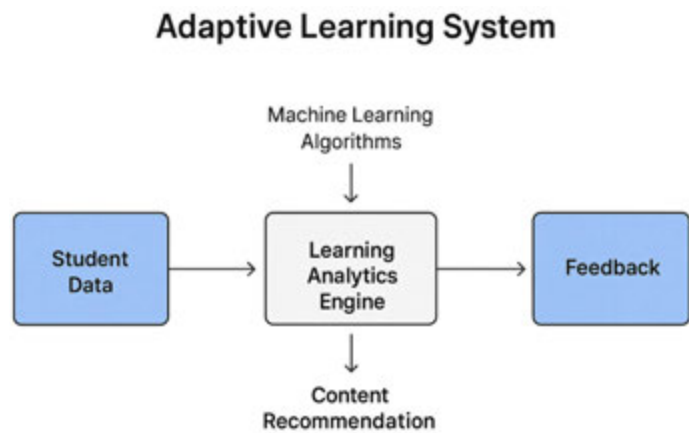


Figure 1.
Architecture of an adaptive learning system using machine learning algorithms.

2.1.2 Competency-based education and AI-driven customization

CBE focuses on ensuring students achieve specific skills rather than adhering to fixed timelines. AI enhances CBE by providing real-time feedback and customizing learning paths to meet competency goals. For example, AI can monitor a student’s progress in clinical decision-making and adjust coursework to focus on areas needing improvement, such as interpreting lab results or analyzing patient history [4].

Studies demonstrate that AI-driven CBE improves outcomes. A scoping review reported that AI-supported curricula enable students to achieve competencies faster, particularly in procedural skills like suturing or imaging interpretation [1]. AI tools also allow educators to set individualized benchmarks, ensuring students meet standards without unnecessary repetition. For instance, AI platforms can generate personalized learning plans for each student, aligning with accreditation requirements such as those of the Liaison Committee on Medical Education [7]. This customization ensures efficiency and relevance, especially in resource-constrained settings where tailored education is critical [6].

However, implementing AI-driven CBE requires robust infrastructure and faculty training. Without these, institutions may struggle to integrate AI effectively, limiting its impact [5]. Despite these challenges, AI's ability to align curricula with competency goals makes it a powerful tool for modern medical education.

2.1.3 Impact on student engagement and learning outcomes

AI-driven personalized learning significantly enhances student engagement and learning outcomes. By tailoring content to individual needs, AI reduces frustration and increases motivation. For example, students struggling with pharmacology can receive targeted tutorials, while advanced learners are challenged with complex case studies, maintaining engagement across skill levels [4]. A systematic review found that AI-enhanced curricula increased student satisfaction and engagement by 20–30% compared to traditional methods [7].

Learning outcomes also improve with AI. Research shows that students using AI-driven systems perform better on standardized exams and clinical assessments, particularly in diagnostics and patient management [1]. As shown in **Table 2**, AI-enhanced education demonstrates notably higher improvements in exam scores, knowledge retention, and student satisfaction compared with traditional methods. For instance, a study on AI-supported medical training reported a 15% improvement in diagnostic accuracy among students using adaptive platforms [5]. These systems also foster self-directed learning, as students receive immediate feedback and can track their progress, thereby building confidence and autonomy.

Global institutions, such as those in the USA and Europe, have piloted AI-driven curricula with promising results. For example, Stanford University's use of AI to personalize clerkship training has led to higher student satisfaction and better clinical performance [3]. However, ensuring equitable access to these technologies is critical, as disparities in resources can limit their benefits for underrepresented

Aspect	Traditional education	AI-enhanced education
Improvement in exam scores	5–10%	15–25%
Student satisfaction	Moderate	High (20–30% increase)
Knowledge retention rate	~60% after 1 month	~80–85% after 1 month
Self-directed learning	Limited	Strongly supported
Feedback speed	Delayed (manual grading)	Instant (automated)

Table 2.
Comparative outcomes of traditional versus AI-enhanced medical education.

groups [6]. Future advancements, such as integrating AI with VR, could further enhance engagement by offering immersive, personalized learning experiences.

2.2 Virtual simulations and AI-driven assessments

AI is transforming medical education by enabling virtual simulations and automated assessments that enhance practical training and evaluation. These tools allow students to practice complex clinical scenarios in risk-free environments and provide educators with efficient, data-driven assessment methods. By integrating AI with advanced technologies, medical curricula can offer realistic, scalable, and adaptive learning experiences. This section explores AI-powered clinical simulations, automated assessment tools, and the integration of AI with emerging technologies like augmented reality (AR), highlighting their impact on medical education.

2.2.1 AI-powered clinical simulations for practical training

AI-powered clinical simulations replicate real-world medical scenarios, allowing students to practice skills such as surgery, diagnosis, and patient management without risk to actual patients. These simulations use AI to generate dynamic, realistic patient responses based on large datasets, mimicking the variability of clinical practice. For example, AI-driven surgical simulators can replicate patient-specific conditions, such as varying anatomical structures, enabling students to develop precision and decision-making skills (see **Figure 2**) [3].

Research highlights the effectiveness of AI in simulation-based training. A scoping review found that AI-enhanced simulations improved procedural skills in surgery and emergency medicine by 20–30% compared to traditional methods [1]. Platforms like Touch Surgery use AI to create interactive surgical simulations,

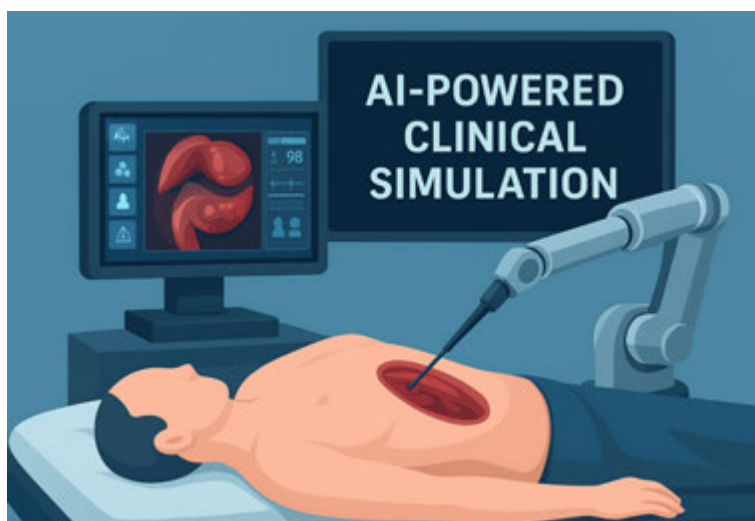


Figure 2.
AI-powered surgical simulation environment.

allowing students to practice procedures step-by-step [6]. These tools adapt scenarios based on user performance, increasing complexity as skills improve, which enhances learning efficiency.

However, the quality of simulations depends on robust datasets. Incomplete or biased data can lead to unrealistic scenarios, reducing training effectiveness [3]. Institutions must invest in high-quality data collection and validation to ensure simulations accurately reflect clinical realities. Despite these challenges, AI-powered simulations are becoming integral to medical curricula, offering scalable solutions for hands-on training.

2.2.2 Automated assessment tools and adaptive testing

AI-driven automated assessment tools streamline the evaluation process by generating, administering, and grading assessments with high accuracy. These tools create case-based questions tailored to specific learning objectives, ensuring relevance and fairness. For instance, in pharmacology education, AI systems generate questions based on clinical cases, adjusting difficulty to match student proficiency [4]. This approach reduces educators' workload and provides students with immediate feedback, enabling rapid improvement.

Studies confirm the precision of AI assessments. A systematic review reported that AI-driven testing in surgical training achieved 95% accuracy in evaluating technical skills, surpassing traditional human grading in consistency [1]. As shown in **Table 3**, AI-based assessments outperform human-based evaluations in accuracy, speed, adaptability, and scalability. Adaptive testing, where question difficulty adjusts based on student responses, further enhances assessment effectiveness. For example, AI platforms like MedEdAI use adaptive algorithms to test clinical reasoning, ensuring that students are challenged at an appropriate level [7].

Automated assessments also support CBE by aligning evaluations with specific learning outcomes. However, challenges include ensuring question diversity and avoiding algorithmic bias, which can skew results if the training data is not representative [3]. Regular updates to AI models and the use of diverse datasets are essential to maintain fairness and accuracy in assessments.

Criteria	Human-based assessment	AI-based assessment
Accuracy	Moderate (subjective variability)	High (up to 95% in technical skill evaluation).
Speed	Slow (manual grading; delays in feedback)	Instant (automated feedback delivery)
Adaptability to student level	Limited (fixed question sets)	High (adaptive testing based on performance).
Faculty workload	High (requires time for design and grading).	Low (automation reduces faculty burden)
Scalability	Limited (resource-intensive)	High (can efficiently assess large groups)

Table 3.
Comparison between human-based and AI-based assessment in medical education.

2.2.3 Integration with emerging technologies

The integration of AI with emerging technologies, such as AR, is revolutionizing medical education by creating immersive training environments. AI enhances AR by providing real-time data analysis and feedback during simulations. For example, AR headsets combined with AI can overlay patient data onto virtual models, allowing students to practice procedures like catheter insertion in a 3D environment [5].

The integration of augmented reality (AR) and artificial intelligence (AI) has transformed anatomy education by allowing students to visualize and interact with 3D models of the human body in real time. As shown in **Figure 3**, medical students can use AR headsets to explore holographic anatomy models, enhancing spatial understanding and engagement. AI algorithms further personalize the experience by adjusting the complexity of visualizations and highlighting key anatomical structures based on learner progress.

Research indicates that AI-AR integration improves learning outcomes. A study found that medical students using AI-powered AR simulations for anatomy training achieved 25% higher retention rates compared to traditional methods [6]. These systems allow students to interact with virtual patients and receive AI-driven feedback on their performance, which enhances both technical and cognitive skills.

The potential of AI-AR integration extends to continuous medical education, where professionals can practice complex procedures in virtual settings. However, challenges include high costs and the technical expertise required for implementation [7]. Smaller institutions may face barriers in adopting these technologies, potentially widening educational disparities. Collaboration between academic institutions and technology developers is needed to make AI-AR solutions accessible and cost-effective.



Figure 3.
Integration of augmented reality and AI in anatomy education. Medical students interacting with holographic 3D anatomy models using AR headsets in an AI-supported classroom environment.

2.3 Ethical and practical challenges

While AI offers significant benefits for medical curriculum design, it introduces complex ethical and practical challenges. These include algorithmic bias, data privacy concerns, and the need for faculty training and institutional readiness. Addressing these challenges is critical to ensuring AI enhances medical education equitably and responsibly. This section examines these issues, drawing on recent studies to highlight their implications and propose strategies for mitigation.

2.3.1 Algorithmic bias and its implications for equity

Algorithmic bias is a major ethical concern in AI-driven medical education. Bias occurs when training data is incomplete, unrepresentative, or skewed, leading to unfair outcomes. For example, if AI systems are trained on datasets predominantly representing certain demographics, they may generate learning recommendations that disadvantage minority students, such as those from underrepresented ethnic or socioeconomic groups [3]. A systematic review found that biased algorithms in medical education could reinforce inequalities, with up to 20% of AI-driven assessments showing disparities in performance across student groups [1].

Such biases can undermine equity in education. As shown in **Figure 4**, disparities in success rates among different student groups highlight the influence of algorithmic bias on minority and gendered populations in AI-driven medical assessments. For instance, an AI system recommending learning modules based on biased data might prioritize content irrelevant to certain students' needs, hindering

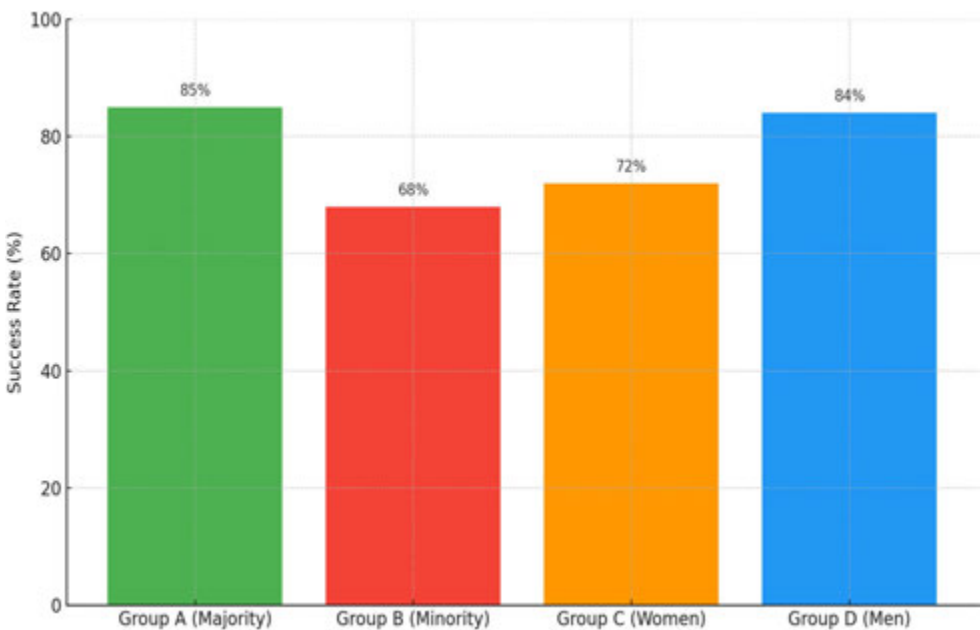


Figure 4. Performance disparities in AI-based assessments across student groups. This chart illustrates differing success rates among student groups, emphasizing the impact of algorithmic bias on minority and gendered populations in AI-driven medical assessments.

their progress [6]. To mitigate this, institutions must use diverse, inclusive datasets and implement regular algorithm audits. Research suggests that involving multidisciplinary teams, including ethicists and educators, can help identify and address biases effectively [8]. Ensuring equitable AI applications is essential to maintain fairness and support all students in achieving competency-based learning goals.

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2.3.2 Data privacy and security concerns in AI systems

AI systems in medical education rely on large datasets, often including sensitive student information such as performance metrics, health records, or personal details. This raises significant data privacy and security concerns. Unauthorized access or data breaches could compromise student confidentiality, violating regulations such as the General Data Protection Regulation (GDPR) [3]. A study highlighted that 30% of educational institutions using AI lacked robust data security protocols, increasing the risk of breaches [5].

Protecting student data requires stringent measures, such as encryption, anonymization, and secure storage systems. Additionally, students and faculty must be informed about data usage and must provide explicit consent [8]. Ethical AI implementation demands transparency in how data is collected, processed, and stored. Institutions should adopt frameworks like the FAIR principles (Findable, Accessible, Interoperable, Reusable) to ensure responsible data management [6]. Failure to address these concerns could erode trust in AI systems and hinder their adoption in medical education.

2.3.3 Faculty training and institutional readiness

The successful integration of AI in medical curricula depends on faculty training and institutional readiness. Many educators lack the technical expertise to implement AI tools effectively, limiting their ability to leverage these technologies [5]. A scoping review found that 60% of medical faculty reported insufficient training in AI applications, leading to the underutilization of tools like adaptive learning systems or simulation platforms [1].

Training programs are essential to equip faculty with the skills to use AI tools, interpret their outputs, and integrate them into teaching. For example, workshops on AI-driven assessment tools can help educators design fair and effective evaluations [8]. Institutions must also invest in infrastructure, such as high-performance computing systems and secure data platforms, to support AI implementation [3]. Smaller institutions may face resource constraints, potentially widening disparities in AI adoption.

Collaboration between academic institutions, technology developers, and policymakers is crucial for developing standardized training protocols and guidelines [6]. By fostering AI literacy among faculty and ensuring institutional preparedness, medical schools can maximize the benefits of AI while minimizing implementation challenges.

3. Future directions for AI in medical education

As AI continues to reshape medical education, its future potential lies in deeper integration with advanced technologies, fostering AI literacy, and establishing robust policies and standards. These directions aim to maximize AI's benefits while addressing current limitations, ensuring equitable and effective education for future physicians. This section explores these pathways, emphasizing their role in preparing medical professionals for a dynamic healthcare landscape.

3.1 Integration of AI with advanced technologies

The integration of AI with emerging technologies, such as VR and AR, holds immense promise for medical education. AI can enhance VR/AR simulations by providing real-time feedback and adapting scenarios to individual learners' needs. For example, AI-driven VR platforms could simulate complex surgical procedures, allowing students to practice in immersive environments that mimic real-world conditions [3]. A study found that VR-based training combined with AI improved surgical skill retention by 25% compared to traditional methods [1].

Beyond VR/AR, AI can integrate with wearable devices and Internet of Things (IoT) technologies to monitor student performance during clinical training. For instance, AI-powered wearables can track a student's decision-making process during patient interactions, offering personalized coaching [6]. These advancements require significant investment in infrastructure and collaboration with technology developers to ensure accessibility, particularly for resource-limited institutions [8]. Future curricula should prioritize such integrations to create scalable, interactive training environments (**Figure 5**).

3.2 Development of AI literacy in medical curricula

AI literacy is essential for preparing students and educators to use AI responsibly. This involves understanding AI's capabilities, limitations, and ethical implications, such as algorithmic bias and data privacy. Incorporating AI literacy into medical curricula ensures that future physicians can critically evaluate AI tools and integrate them into practice without overreliance [8]. A systematic review emphasized that AI literacy programs improve students' confidence in using technology, with 80% of participants reporting a better understanding of AI applications [1].

The integration of artificial intelligence (AI) with advanced technologies such as augmented reality (AR), virtual reality (VR), the Internet of Things (IoT), and robotics has revolutionized medical education. As shown in **Figure 5**, these technologies collectively create immersive, data-driven learning environments that enhance student engagement and skill acquisition. By combining AI's analytical capabilities with real-time interactivity from AR and IoT devices, institutions can provide adaptive, personalized learning experiences that mirror real clinical contexts.

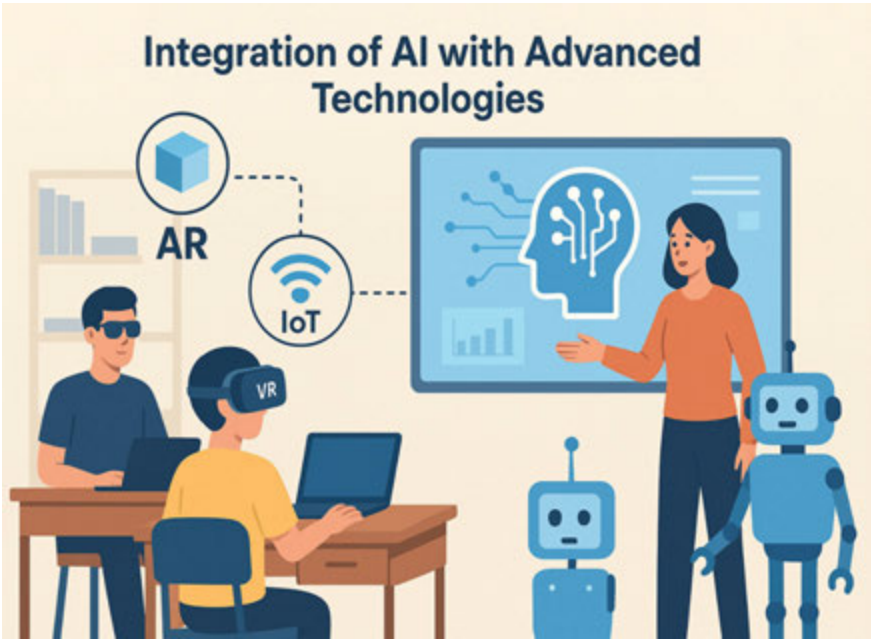


Figure 5.
Integration of AI with advanced technologies in medical education.

Curricula should include modules on AI ethics, data interpretation, and algorithmic transparency. As shown in **Table 4**, a structured AI literacy course for medical students can cover essential topics such as ethics, data analysis, and clinical decision support through a mix of theoretical and practical components. For example, workshops on identifying bias in AI-driven assessments can empower students to advocate for fair practices [5]. Faculty training is equally critical, as educators need the skills to teach AI concepts effectively. Pilot programs in USA and European medical schools have shown that AI literacy courses enhance both teaching and learning outcomes [3]. In the long term, AI literacy will equip medical professionals to navigate a technology-driven healthcare system.

Module/topic	Duration	Assessment method
Introduction to AI in healthcare	2 hours	Quiz + reflection report
Ethics of AI (Bias, Privacy, Equity)	3 hours	Case study + group discussion
Data interpretation and algorithm basics	4 hours	Practical exercises (datasets)
AI tools for clinical decision support	3 hours	Hands-on workshop + OSCE-style test
Critical appraisal of AI applications	2 hours	Short essay + presentation
Future trends and responsible use	2 hours	Open-book exam + peer Review

Table 4.
Proposed AI literacy course structure for medical students.

3.3 Policy and standardization needs

The widespread adoption of AI in medical education requires clear policies and standards to ensure ethical and equitable use. Current guidelines are often inconsistent, leading to variations in AI implementation across institutions [6]. Standardized frameworks should address data privacy, algorithmic fairness, and quality assurance for AI tools. For instance, policies aligned with GDPR or HIPAA can protect student data while promoting trust in AI systems [8].

Collaboration between academic institutions, regulatory bodies, and technology developers is essential to developing these standards. A review highlighted that standardized protocols could reduce implementation barriers by 30%, particularly for smaller institutions [5]. Policies should also mandate regular audits of AI systems to prevent bias and ensure alignment with educational goals. By establishing robust standards, medical education can leverage AI's potential while minimizing risks.

4. Conclusions

AI is transforming medical curriculum design through personalized learning, virtual simulations, and automated assessments. Its integration enhances educational efficiency and prepares physicians for modern healthcare challenges. However, ethical issues, such as algorithmic bias, and practical challenges, such as faculty training, must be addressed. Future directions, including integration with advanced technologies, AI literacy development, and standardized policies, will ensure AI's responsible use. By balancing AI with human expertise, medical education can achieve equitable and effective outcomes, equipping future physicians for a digital healthcare era.

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Conflict of interest

The author declares no conflicts of interest.

Notes, thanks, and other declarations

Notes.

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Perspective Chapter: Integrating Interactive Learning and AI-Generated Assessment in Medical Education – From Non-Technical Skills to Video-Based CBT Content

Hiroshi Mihara

Abstract

This chapter presents a comprehensive approach to integrating interactive learning opportunities and artificial intelligence (AI)-generated assessment in undergraduate medical education. It addresses the challenge of teaching non-technical skills – such as professionalism, communication, and ethical behavior – by utilizing video-based scenarios and structured feedback mechanisms, including the analysis of unprofessional conduct. The chapter further explores the development of AI-assisted, computer-based testing (CBT) materials enriched with video and audio content. It introduces methods for generating examination items and providing formative feedback on free-text responses using large language models (LLMs). Real-world case studies from Japan demonstrate how scalable and reflective learning experiences can be enhanced using digital tools.

Keywords: generative AI, hybrid feedback model, clinical note assessment, human–AI collaboration, feedback

1. Introduction

Medical education is experiencing a profound transformation driven by technological innovation, evolving pedagogical models, and increasing demand for efficiency and authenticity in clinical training. Traditionally, assessments focused on factual recall through multiple-choice questions (MCQs), but this approach is being complemented by scenario-based formats that aim to evaluate clinical reasoning, communication, and ethical judgment [1].

Computer-based testing (CBT) has become a cornerstone in this shift, enabling scalable and standardized assessments. Yet CBT is no longer confined to static text-based formats. Advances in technology now allow integration of multimedia – such as images, audio clips, and clinical videos – into CBT platforms, enabling more

nuanced assessment of decision-making under realistic conditions. Also, a cross-sectional study of medical students revealed that most students were aware of the growing impact of AI in medicine and perceived it positively, though some concerns remained [2].

Parallel to these developments, artificial intelligence (AI), especially large language models (LLMs) such as GPT-4, has emerged as a transformative tool in medical education. AI is being employed not only to support the creation of MCQs [3] and clinical cases but also to provide real-time feedback and automated scoring [4, 5]. These tools significantly reduce faculty workload and turnaround time, while maintaining acceptable levels of accuracy and reliability.

A particularly promising application of AI lies in the support of non-technical skill (NTS) development. Skills such as professionalism, empathy, communication, and ethical decision-making are essential for safe and effective clinical practice. However, they are difficult to teach and assess using traditional methods. Longitudinal studies show that unprofessional behavior during undergraduate training is strongly associated with future disciplinary action [6].

To address this, many programs have turned to scenario-based learning (SBL) approaches using real-world dilemmas, standardized patients, and video cases [7, 8]. These experiences promote reflective practice and ethical awareness, especially when combined with structured debriefing models such as Holmes' reflection approach [9].

At the same time, simulation-based education remains a valuable tool for NTS training. Pre-simulation briefing and psychological safety are critical for creating a safe learning environment [10]. New systems like MedSimAI now extend the simulation space into the digital domain, allowing for AI-powered patient interactions and feedback [11]. These innovations increase access, support self-regulated learning, and facilitate deliberate practice without exhausting faculty resources.

Beyond individual interventions, the shift toward integrated, multimodal learning environments requires curricular restructuring. Efforts to define core AI competencies for health professionals [12] and to ensure equitable access to digital resources [13] are also underway. Scoping reviews reveal a growing global interest in harmonizing these efforts and promoting ethical implementation strategies [14, 15].

This chapter presents a cohesive framework for integrating AI-supported educational interventions into medical curricula, with a specific focus on the following components:

- SBL for cultivating NTS,
- AI-assisted multimedia CBT content creation and implementation,
- Formative feedback using GPT–human hybrid models, and
- Scalability and multilingual adaptation for regional and global dissemination.

Each section will provide examples from Japanese and international educational contexts, along with original visuals, videos, and AI-generated content. This work aims to contribute to the ongoing dialogue on how to responsibly and effectively blend AI with human-centered medical education.

2. SBL for NTS

In recent years, the importance of NTS in medical education has gained widespread recognition. These skills – including professionalism, communication, empathy, teamwork, and ethical reasoning – are essential for ensuring patient safety and high-quality care. Yet, unlike technical knowledge or procedural expertise, NTS are often subtle, context-dependent, and difficult to teach through traditional lectures or assessments.

3. Reflective learning from unprofessional behavior

Unprofessional behavior during medical training is a strong predictor of later professional misconduct. A landmark study demonstrated that students flagged for professionalism issues were significantly more likely to receive disciplinary actions after licensure [6]. In response, educational frameworks have evolved to include reflective learning approaches specifically designed to address such behavior. One notable model is Holmes' reflection approach, which encourages learners to analyze their own behavior, motivations, and the consequences of their actions. In a randomized controlled trial, this approach was shown to improve students' insight into unprofessional conduct [9].

A systematic review by Mak-van der Vossen et al. [16] categorized descriptors of unprofessional behavior in medical students and emphasized the importance of early intervention and feedback. These studies support the use of structured, guided reflection on real or simulated unprofessional behaviors to build professional identity.

4. Implementation of scenario-based workshops

SBL has emerged as a powerful method to promote NTS development. Unlike didactic instruction, SBL immerses learners in realistic clinical situations that require communication, empathy, and ethical decision-making. One such implementation used structured small-group workshops where medical students analyzed and role-played clinical professionalism scenarios. The course showed high learner satisfaction and significant improvements in ethical reasoning [7].

Another study explored how faculty members and students perceive professional and unprofessional behavior differently, underscoring the value of open dialogue and shared reflections within the learning environment [8]. These findings reinforce the need for scenario-based discussions that bridge generational and hierarchical gaps in understanding professionalism.

We have developed video-based teaching materials that depict problematic behaviors related to patient safety – such as patient neglect, disrespectful communication, and boundary violations in nuanced clinical settings. These videos are shared via unlisted YouTube links. Workshops utilizing these videos have been conducted at multiple medical schools in Japan to confirm the ease of material dissemination and to evaluate their educational effectiveness.

5. Tools for structured feedback and learning management

The integration of structured feedback templates and Learning Management Systems (LMS) enhances the effectiveness and sustainability of SBL. Feedback tools aligned with reflective models such as “Describe-Analyze-Reflect” or Holmes’ four-phase approach can provide consistency across facilitators. Templates also help educators provide timely, specific, and non-judgmental input to guide learners through their own reflection process [9].

Workshops are typically delivered in hybrid formats combining:

- Live scenario analysis and discussion;
- Structured role-play activities;
- Reflection writing;
- Peer and facilitator feedback via LMS.

These modalities not only scaffold deep learning but also enable longitudinal tracking of learners’ professional identity formation.

6. Psychological safety and pre-briefing

Creating a psychologically safe environment is a critical precondition for effective SBL. Learners must feel secure enough to express uncertainty, admit mistakes, and explore ethical dilemmas. Pre-simulation briefing is one effective strategy for establishing this safe container [10]. It includes setting expectations, clarifying learning goals, and encouraging honest participation.

Without such briefing, learners may remain guarded or disengaged, especially when reflecting on emotionally charged or socially sensitive topics such as discrimination, bias, or patient trust breaches.

7. AI-powered scenario design and augmentation

Recent advances in generative AI have opened new possibilities for expanding SBL. Tools such as ChatGPT and Gemini can now generate dynamic, realistic clinical scenarios based on user-defined parameters [11]. These tools have been used to create branching narratives, patient dialogue, and even communication breakdowns, which educators can then edit and integrate into their sessions.

AI tools can also assist in translating workshop materials into multiple languages, facilitating cross-cultural adaptation and broader implementation in multilingual environments [15].

This conceptual diagram (see **Figure 1**) illustrates a video-based experiential learning model inspired by Kolb’s learning cycle. The process begins with the Experience phase, where learners watch scenario-based videos depicting complex clinical situations such as patient neglect or boundary violations. This is followed by Reflective Observation, in which learners engage in individual reflection and group

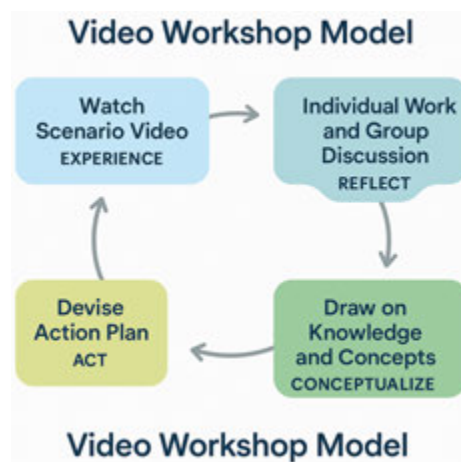


Figure 1.
Experiential learning cycle in a video-based medical ethics workshop.

discussion to explore their thoughts and reactions. During the Conceptualization phase, they derive key insights, connect them to relevant theories or ethical frameworks, and consolidate new understanding. Finally, the Active Experimentation phase encourages learners to develop actionable plans to apply these insights in future clinical encounters, reinforcing a continuous learning loop.

This AI-generated video illustrates five typical unprofessional behaviors observed among medical learners. The dramatized scenes include:

- Playing mobile games during lectures, disregarding academic focus;
- Discussing identifiable patient details in public hospital corridors, blocking passageways;
- Displaying a disengaged, uncooperative attitude during group assignments;
- Reacting dismissively to constructive feedback from faculty;
- Showing impatience and inattentiveness during clinical teaching sessions.

These behaviors highlight subtle yet frequent professionalism issues that are often absent from formal curricula. This video serves as a springboard for ethics education and professionalism workshops, helping learners reflect on real-world gray-zone challenges in healthcare education.

 Video Link

-  [English Version](#)



-  [Japanese Version](#)



Video 1.
"Crossing the line: five unprofessional behaviors in medical education".

AI-generated content for CBT

The implementation of CBT in medical education has traditionally relied on text-based, static formats such as MCQs.

However, with recent advances in generative AI, there is growing potential for transformative changes in the design, delivery, and assessment methods in competency-based training (such as CBT). With the introduction of LLMs like ChatGPT and multimodal generation tools such as LTX Studio (see **Video 1**), educators can now create complex, context-rich, interactive examination content with unprecedented efficiency.

Emergence of AI in educational content generation

The rise of generative AI tools has allowed for the scalable creation of clinical vignettes, patient narratives, and decision-making scenarios. These models can simulate real-world complexity, ambiguity, and communication nuances that conventional CBT formats fail to capture. As Hersh outlines, generative AI has the potential to fundamentally reshape how we prepare, assess, and credential future health professionals [1].

Scoping reviews and needs assessments have echoed the same trend, highlighting the demand for AI-enhanced learning materials among both students and faculty [2]. These tools not only increase the volume and variety of questions but also enable adaptive content that matches learner proficiency.

Building AI-generated clinical scenarios

In our implementation, generative AI models like ChatGPT (OpenAI) and Gemini (Google) are prompted using clinical guidelines, standardized case formats, and competency frameworks. By tuning the prompts and evaluating the outputs through expert review, educators have been able to generate high-quality scenarios for use in both classroom and assessment settings.

Key features of this process include:

- Automatic generation of differential diagnoses and distractor options;
- Consistency in terminology and cognitive load;
- Inclusion of ethical dilemmas or uncertainty for advanced learners.

Cheung et al. [3] demonstrated that ChatGPT-generated internal medicine MCQs achieved psychometric properties comparable to those written by faculty experts. The process, however, still requires human-in-the-loop validation to mitigate factual inaccuracies and biases.

Multimodal Content and Video-Based CBT

Beyond text, AI now enables the creation of multimodal CBT items that incorporate voice, image, and video. LTX Studio and similar platforms allow educators to generate animated or actor-based clinical scenes using textual descriptions. These can be used to test not only factual recall but also observational skills, empathy, and decision-making under uncertainty. A typical video-based CBT item (see **Figure 2**) may include:

- A simulated patient interview showing subtle nonverbal cues;
- A diagnostic reasoning task based on a video vignette;
- A free-text response section analyzed by LLMs.

As shown in pilot implementations, learners find these video-based tasks more engaging and reflective of real-world situations. Krumsvik et al. [4] explored video-based summative assessments and found them to be valid, reliable, and well-received by students.

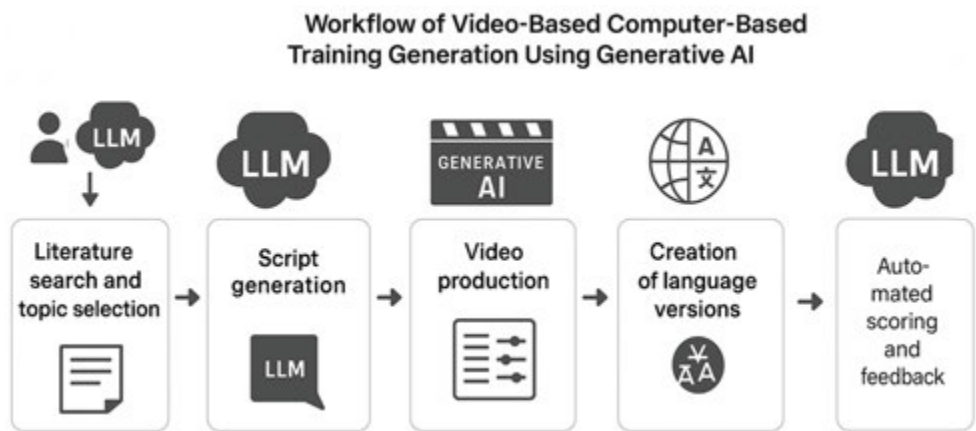


Figure 2. Workflow for AI-assisted development of video-based computer-based training (CBT). This schematic illustrates a step-by-step workflow for developing scenario-based computer-based training (CBT) modules using generative AI in collaboration with human experts. The process begins with literature search and topic selection, followed by script generation using large language models (LLMs). Generated scripts are then converted into educational videos using generative video tools. These videos are adapted into multiple languages to enhance accessibility. Finally, LLMs are employed again to provide automated scoring and formative feedback, completing a cycle of scalable, multilingual, and feedback-driven CBT creation.

Custom GPT for unprofessional behavior feedback



Custom GPT for unprofessional behavior feedback: Chat interaction example is as follows.

This example demonstrates a typical conversation flow between the custom GPT (acting as the medical education expert) and a user (a medical student or educator) after the user has watched the video of unprofessional behaviors.

Thank you for sharing the document on inappropriate behavior among healthcare professionals – it’s an excellent, evidence-rich foundation. You’ve chosen a crucial topic, as the document powerfully connects unprofessional behaviors to compromised learning, patient safety, and public trust.

To start, let’s go with Step 1: Identify unprofessional behavior.

Prompt:

“Thank you for watching the videos. Please detail specific unprofessional behaviors you observed in each scene, as thoroughly as possible.”
Once you describe what you saw in each scene of the video, I’ll guide you through analyzing their impact and explore appropriate, professional alternatives with evidence-based support.
Looking forward to your observations.

You:

It is undesirable to play games during group discussions in class. Talking about a patient's personal information while walking around is undesirable from the perspective of personal information leakage. During group discussions, not cooperating and doing other things alone is undesirable due to low cooperativeness. Not submitting reports is also undesirable, and not accepting feedback honestly when pointed out is undesirable. Even when receiving guidance, a lack of enthusiasm for learning and constantly checking the time, waiting for the session to end, is an inappropriate attitude for a learner.

ChatGPT:

Excellent – thank you for your thoughtful summary. You've successfully identified key unprofessional behaviors across all the video scenes. Let's now analyze each one using the structure below:

Scene 1: Playing games during class discussions

Problem & Impact:

Engaging in non-academic activities (like gaming) during class discussions:

- *Shows disregard for learning.*
- *Disrespects peers and instructors.*
- *Creates external cognitive load, impairing retention and attention.*
- *Reduces "time on task," which is essential for long-term competence.*

Appropriate Action:

Active engagement and presence during academic discussions. Use of devices should be limited to educational purposes only.

Literature Support:

Gaming during lectures has been shown to significantly impair academic performance and knowledge acquisition by increasing distraction and reducing study focus (e.g., smartphone addiction among med students is associated with lower academic performance).

Scene 2: Discussing patient information while walking

Problem & Impact:

This is a direct violation of patient confidentiality:

- *Public discussion of PHI (Protected Health Information) violates HIPAA (or equivalent laws globally).*
- *Erodes patient trust.*
- *Legally and ethically indefensible.*

Appropriate Action:

All patient-related discussions must occur in private, controlled environments. Learners must understand and uphold the "minimum necessary information" principle.

Literature Support:

Careless disclosure of PHI is not only unethical but often illegal, and even minor breaches in public can cause significant harm and loss of public trust.

Scene 3: Not cooperating during group work/doing own thing

Problem & Impact:

Non-participation and disengagement during team activities:

- *Disrupts collective learning.*
- *Imbalances workload distribution.*
- *Demonstrates poor teamwork and accountability.*
- *Undermines safety culture in clinical settings.*

Appropriate Action:

Contribute actively and collaboratively. Effective medical care demands teamwork and mutual responsibility.

Literature Support:

Team dysfunction is a well-documented root cause of clinical errors and adverse outcomes. Interprofessional education (IPE) explicitly aims to prevent such deficits.

Scene 4: Failing to submit reports/rejecting feedback

Problem & Impact:

Failing to meet deadlines shows lack of responsibility.

Rejecting feedback indicates poor self-reflection and hinders growth.

Both behaviors are signs of professional immaturity.

Appropriate Action:

Honor academic obligations and view feedback as a gift, not criticism.

- *Self-reflection enables development of ethical awareness, critical thinking, and clinical reasoning.*

Literature Support:

Disregard for feedback limits personal and professional development. Reflection is pivotal for lifelong competence and professionalism.

Scene 5: Clock-watching/lack of focus during guidance

Problem & Impact:

Checking the time repeatedly or showing disinterest suggests lack of motivation.

Reduces attentiveness during crucial learning moments.

- *In clinical settings, such distraction increases error rates and compromises patient safety.*

Appropriate Action:
Demonstrate active interest and attention. Adopt habits of preparedness and mental presence.

Literature Support:
Cognitive fatigue and distraction are major causes of preventable medical errors. A single interruption increases error risk by 12.7%; repeated ones exponentially more.

Summary table of behaviors & impact

Scene	Unprofessional behavior	Impact	Professional alternative
1	Playing games in class	Reduces focus, distracts others	Engage in active learning
2	Discussing PHI publicly	Breach of privacy, trust loss	Private, secure discussions only
3	Not cooperating in group	Team dysfunction, learning loss	Participate collaboratively
4	Ignoring feedback	Stunts growth, accountability failure	Accept and reflect constructively
5	Lack of focus during session	Patient safety risk, poor learning	Stay engaged, minimize distractions

Reflection prompt:
Do you agree with these assessments of inappropriate behaviors and appropriate responses? Are there any different perspectives or additional points you'd like to add?

You:
None

ChatGPT:
Thank you! Since you're aligned with the assessments, I'll now provide constructive feedback based on your observations, with evidence from literature.

Feedback summary by behavior

1. Playing games during discussions

Problem & impact:
This behavior distracts from academic engagement, reduces learning efficiency, and can disrupt group dynamics.

Appropriate action:
Prioritize attention during sessions. Use digital tools only if they directly support learning goals.

Evidence:
A study on medical students showed smartphone addiction (including gaming) correlated with poor academic performance. Gaming creates external cognitive load that detracts from meaningful learning (Kim HJ et al., BMC Med Educ. 2021).

2. Discussing patient information in public

Problem & impact:
Violates confidentiality, undermines legal compliance, and erodes patient trust.

Appropriate action:

All PHI discussions must occur in private, secure settings with those directly involved in care.

Evidence:

The HIPAA framework and similar global laws emphasize the severe consequences of even inadvertent data exposure. Trust erosion leads to underreporting by patients and decreased treatment effectiveness.

3. Lack of cooperation in group work

Problem & impact:

Harms teamwork, reduces efficiency, and can lead to unsafe care in real-world settings.

Appropriate action:

Engage constructively with peers, complete assigned roles, and communicate clearly.

Evidence:

Uncooperative attitudes undermine interprofessional synergy and have been tied to increased medical error rates (Reeves S et al., J Interprof Care. 2016).

4. Not accepting feedback/skipping reports

Problem & impact:

Demonstrates avoidance of responsibility and a fixed mindset. Missed feedback loops hinder clinical and ethical development.

Appropriate action:

Welcome feedback as a tool for growth. Submit all reports to practice accountability and time management.

Evidence:

Reflective learning is a core component of professional identity formation. Avoidance leads to stagnation in skills and ethics (Sandars J, Med Teach. 2009).

5. Lack of focus during clinical sessions

Problem & impact:

Yawning, looking at the clock, and appearing disengaged signals disrespect and mental absence. These can lead to increased clinical errors.

Appropriate action:

Maintain presence, show curiosity, and manage fatigue through healthy routines.

Evidence:

Each distraction increases medication error risks significantly (Westbrook JI et al., BMJ Qual Saf. 2010). The impact on patient safety is quantifiable and severe.

Next steps for your professional growth

Consider focusing on:

- Active reflection and feedback engagement.
- Practicing discretion and privacy awareness.
- Team communication skills.

- *Developing consistent attention strategies during patient interactions and lectures.*

Self-reflection prompt:

“What aspect of professionalism do you feel you still need to work on the most, and what support or resources would help you grow further?”

I’m here to guide you – let’s continue building your professional foundation!

The content above was generated by the custom feedback GPT up to this point.

Validation and challenges in AI-based test generation

While generative AI offers significant advantages in content creation, it also presents challenges in content validation, psychometric reliability, and fairness. Evaluation studies show variability in output depending on prompt construction, model version, and update cycles [17].

Moreover, concerns remain regarding:

- Reproducibility of AI outputs;
- Cultural and linguistic neutrality;
- Legal and ethical risks associated with automated content delivery.

Ali et al. [18] compared AI feedback with human tutor assessments and noted differences in empathy expression and context comprehension, emphasizing the need for hybrid systems.

Therefore, a human–AI collaborative model is currently the best practice. Educators define the pedagogical goal and rubric, while AI accelerates the drafting process. Final content must still undergo expert review before deployment.

Future directions and integration with LMS

As AI-generated CBT matures, integration with LMS is critical. Dynamic delivery, real-time learner adaptation, and automated scoring can greatly reduce educator burden while personalizing learner experience. Projects like MedSimAI demonstrate how LLMs can be embedded within interactive simulation environments for deliberate practice and CBT-aligned evaluation [11].

Furthermore, these platforms can log learner behavior, generate analytics, and suggest individualized remediation strategies.

AI-generated content represents a major leap forward in medical assessment design. When properly guided, these tools can produce complex, authentic scenarios that better reflect clinical reasoning, communication, and decision-making than traditional MCQs alone.

However, the success of AI-assisted CBT depends on thoughtful design, continuous evaluation, and responsible implementation. It is not the technology alone but its integration into an educational strategy that will determine its value.

8. Formative feedback using LLMs

The assessment of free-text responses in medical education has long posed a challenge due to the high demand for expert review, variation in subjective

interpretation, and limited scalability. The advent of LLMs such as GPT-4 presents an opportunity to deliver formative feedback efficiently and at scale, especially for open-ended tasks that simulate real-world clinical reasoning and communication.

9. The case for feedback in medical education

Formative feedback plays a pivotal role in developing self-reflective and competent clinicians. It fosters metacognition, clarifies performance expectations, and encourages continuous improvement. However, traditional feedback systems often fall short due to time constraints, limited faculty availability, and inconsistent quality.

Integrating LLMs into the feedback loop can help bridge this gap. GPT-based systems can analyze free-text responses, identify strengths and areas for improvement, and provide structured, criterion-based feedback. These capabilities are aligned with the core principles of effective medical education feedback – timeliness, specificity, and learner-centeredness [4].

10. Architecture of GPT-powered feedback systems

In our implementation model, learner responses are first collected through a scenario-based digital interface. Responses are then analyzed by a fine-tuned GPT model using a feedback template aligned with the assessment rubric. Feedback is categorized into:

- Content Accuracy: Correctness of clinical information.
- Communication Quality: Clarity, empathy, and structure.
- Clinical Reasoning: Justification and logic of diagnostic decisions.

GPT-generated ratings of student clinical notes were comparable to those made by trained evaluators, with moderate inter-rater agreement [17]. This suggests a viable role for AI as a first-line formative assessor.

This flowchart (see **Figure 3**) illustrates the collaborative process in which student-generated text submissions are first assessed by a GPT-based LLM. The model provides initial structured feedback, which is then reviewed and adjusted by educators. The final feedback, incorporating both AI-generated insights and expert judgment, is delivered to the student.

Despite the efficiency of AI tools, they often lack sensitivity to emotional nuance, cultural context, and pedagogical appropriateness. To address these gaps, a hybrid model is proposed:

- Step 1: Students submit written responses or assignments.
- Step 2: GPT performs a preliminary assessment and provides feedback.
- Step 3: Educators verify, modify, or enhance the feedback as needed.
- Step 4: Final feedback is returned to the student for reflection and improvement.

This method optimizes both educational quality and instructor workload. Research has shown that learners perceive hybrid feedback as more trustworthy and clear than feedback from AI or human tutors alone [18].

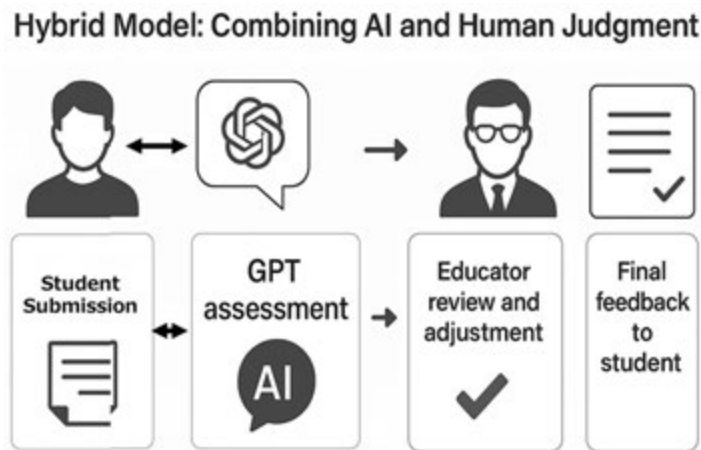


Figure 3.
Hybrid feedback model combining AI and human judgment.

Templates and integration with LMS

To streamline implementation, we developed a suite of GPT-compatible feedback templates aligned with our curriculum’s competencies. These templates guide the AI’s language and content structure, enabling consistent and high-quality responses.

Furthermore, integration with LMS platforms allows for:

- Automated logging of learner progress;
- Comparison across peer cohorts;
- Visualization of feedback trends over time.

Such integration is essential for fostering data-informed educational practices and continuous curriculum refinement [15].

Educational impact and learner reception

Initial feedback from learners has been overwhelmingly positive. Students report that AI-driven feedback is:

- Faster than traditional methods;
- Less intimidating than face-to-face critique;
- Useful for self-regulated learning and review.

In a pilot course where GPT-generated feedback was used across four modules, over 80% of students rated it as “clear and actionable,” with many appreciating the consistency and promptness of the input.

Importantly, the formative nature of these systems reduces the anxiety commonly associated with high-stakes assessments, thereby fostering a safer and more supportive learning environment.

Limitations and considerations

Despite promising results, several challenges remain:

- Bias and fairness: GPT may perpetuate biases present in training data.
- Transparency: Learners should be informed when feedback is AI-assisted.
- Customization: Templates must be tailored to specific learning contexts.

Moreover, faculty training is essential to ensure responsible use and meaningful moderation. Future iterations may benefit from multilingual capabilities and adaptive feedback structures, making the system more inclusive and versatile [19].

In summary, the integration of LLMs into formative feedback systems offers an innovative, scalable, and learner-friendly solution to long-standing assessment challenges. When used judiciously within a hybrid model, these tools can improve the quality, consistency, and timeliness of feedback while reducing educator burden.

By aligning AI-generated feedback with pedagogical goals, educators can support students in becoming more reflective, confident, and competent professionals.

Integration and scalability

While individual initiatives utilizing SBL, generative AI, and hybrid formative feedback have shown promise, the broader challenge lies in scaling these innovations across institutions, languages, and health professions. Educational technologies must not only prove their pedagogical value in controlled environments but also demonstrate flexibility and sustainability across diverse educational contexts.

From isolated pilots to institutional curricula

Initial implementations often begin as isolated workshops or elective modules. However, for maximal impact, these innovations must be integrated into the core medical curriculum. This requires:

- Alignment with national competency frameworks;
- Faculty development for digital content creation;
- Administrative support for infrastructure and assessment integration.

Our experience in Japan revealed that piloting AI-assisted scenario-based modules within general medicine clerkships paved the way for formal curriculum revisions. Cross-departmental collaboration and outcome documentation were key in gaining institutional approval [20].

Moreover, scenario-based tools focusing on professionalism and communication were incorporated into required preclinical courses, supported by structured rubrics and LMS integration [7].

Technological interoperability and customization

One of the critical enablers of scalability is interoperability. Tools developed with open standards (e.g., LTI, SCORM) can be embedded within various LMS platforms used worldwide. This allows local educators to customize content while retaining the underlying instructional design and AI functionalities.

Figure 4 provides direct access links to multilingual AI-simulated physician chatbots covering 33 Asian languages. These chatbots were built using custom (LLMs



Figure 4.
Access map to multilingual simulated physician chatbots across Asia.

with automatic translation capabilities. By enabling real-time dialogue in various languages – including Japanese, Mandarin, Thai, and Hindi – this system exemplifies how generative AI can facilitate cross-border educational tools for standardized patient training and clinical communication exercises in Asia [21].

This infrastructure supports scenario deployment across regional medical schools with shared cases but locally adapted dialogue and assessment features. Hernández Rincón et al. emphasize the importance of such culturally sensitive design in scaling medical AI tools globally [19].

Application across healthcare professions

While most AI implementations have targeted undergraduate medical education, their applicability extends to nursing, pharmacy, dentistry, and allied health fields. For example:

- Communication training for nurses using AI-simulated family interactions;
- Scenario-based medication counseling for pharmacy students;
- Ethical dilemma simulations for physical therapy trainees.

Cross-professional modules facilitate interprofessional education (IPE), promoting shared understanding and collaboration among health workers. Integrated AI tools can highlight connections and act as bridges between disciplines, fostering holistic care practices[15].

Language, equity, and accessibility

Scalability is also an equity issue. Digital tools must support multiple languages, offline usage in low-connectivity areas, and adaptive interfaces for different user abilities. Projects such as MedSimAI [11] demonstrate scalable cloud-based solutions but require localization for sustainable deployment.

It is underlined that, unless addressed explicitly, technological innovations may exacerbate existing disparities in medical education access [13]. Therefore, partnerships with regional institutions and end-user co-design are vital for inclusive implementation.

In sum, sustainable scalability in medical education depends not only on technological sophistication but also on institutional alignment, cultural adaptability, and a commitment to educational equity. By moving beyond pilot stages, we can build robust ecosystems where AI-enhanced learning becomes the norm rather than the exception.

11. Conclusion

The integration of generative AI, SBL, and hybrid feedback systems represents a transformative opportunity for health professions education. These tools, when thoughtfully implemented, can enhance the quality, interactivity, and scalability of educational experiences, particularly in fostering non-technical competencies such as professionalism, communication, and ethical reasoning.

CBT reform has provided the digital infrastructure necessary for this evolution, enabling video-based, multimodal assessments that better reflect the complexity of real-world clinical encounters. By leveraging AI-generated cases and simulations, educators can create dynamic content aligned with evolving clinical guidelines and learner needs.

Simultaneously, LLMs such as GPT-4 offer promising solutions for formative feedback, helping to close the feedback gap in resource-limited settings. These systems can provide instant, structured responses to free-text input, supporting learner reflection and self-regulation. When combined with faculty oversight, AI-human hybrid feedback models balance efficiency with trustworthiness.

However, the deployment of these technologies is not without challenges. Ethical concerns regarding bias, privacy, and academic integrity must be addressed proactively. Moreover, technological inequities – such as disparities in language access and digital literacy – can inadvertently widen educational gaps if not thoughtfully mitigated.

Scalability requires not only technological robustness but also institutional readiness. Faculty development, administrative support, and alignment with national and international accreditation standards are essential. Tools that support interoperability, cultural customization, and cross-professional applications will be most successful in moving from pilot projects to system-wide transformation.

Looking ahead, several areas warrant continued research and development:

- Longitudinal studies evaluating the impact of AI-generated content on clinical reasoning and empathy.
- Validation of AI feedback tools across diverse cultural and linguistic contexts.
- Development of governance frameworks to ensure ethical and pedagogically sound AI use.

In summary, the convergence of CBT platforms, AI innovations, and reflective practice pedagogy offers a blueprint for a more inclusive, interactive, and learner-centered future in medical education. The path forward lies not in replacing human educators but in empowering them – with data, dialogue, and digital tools – to elevate the learning experience for all health professionals.

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Conflict of Interest

The author declares no conflict of interest related to this work.

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Construction of a Psychological Resilience Cultivation System for Medical Students Based on Social Support and Positive Coping Implications for the Digital Transformation of Medical Education in the Post-COVID-19 Era

Hong-tao Song

Abstract

The COVID-19 pandemic has significantly impacted the mental health of medical students while also accelerating the digital transformation of medical education. Based on a summary of previous research, this chapter utilizes a large-sample cross-sectional online survey of Chinese medical students to reveal that positive coping can alleviate posttraumatic stress symptoms (PTSS) during the COVID-19 pandemic through the mediating role of social support. This chapter aims to move beyond mere phenomenological description and explore how, in the post-COVID-19 era, this empirical finding – combined with previous research – can be translated into concrete practices within the paradigm of digital medical education. We will elaborate on how to leverage online learning platforms, virtual simulation technologies, and digital mental health support systems to foster medical students' positive coping abilities and construct their social support networks in a standardized, personalized, and systematic manner. This will ultimately establish a future-oriented, integrated framework for cultivating psychological resilience in medical students, thereby providing theoretical foundations and practical pathways for medical humanities education in the digital era.

Keywords: medical student education, posttraumatic stress symptoms (PTSS), positive coping, social support, digital transformation, psychological resilience

1. Introduction

The digital transformation of medical education is often narrowly interpreted as a mere technological upgrade of teaching methods – such as the shift from offline to online instruction or the replacement of physical models with virtual simulations. However, the physical isolation necessitated by the COVID-19 pandemic forced a mass migration of students from traditional offline classrooms to online education platforms. This passive, large-scale transition – born from a global crisis – compelled a profound recontextualization of this abrupt transformation.

The COVID-19 pandemic, as a crisis, functions as a dual-prism. On one hand, as a public health emergency, it acted as an indiscriminate stress test. Multiple studies have confirmed a significant increase in the prevalence of mental health issues such as anxiety and depression among the postsecondary student population [1]. The psychological well-being of medical students was also threatened [2], further highlighting certain structural deficiencies in the previous educational models regarding their support for medical students' mental health. On the other hand, it appears to have served as an effective catalyst for the digital transformation of medical education, significantly accelerating the global adoption and application of digital technologies, thereby offering unprecedented possibilities for addressing the deeper challenges inherent in this transformation [3, 4]. As an emerging phenomenon of social development and progress, the digital transformation of medical education holds significant potential to enhance both the efficiency and quality of medical training. However, the abrupt and passive nature of its adoption may also lead to certain challenges in adaptation. In the post-COVID-19 era, as the wave of digital transformation continues, a critical question emerges for medical education: how can we move beyond the mere transmission of knowledge and skills to construct a resilient system capable of supporting future physicians in confronting extreme uncertainty, professional burnout, and psychological trauma? This represents a pressing issue that demands thorough contemplation, dedicated research, and concerted efforts toward viable solutions.

Against this backdrop, our previously published study [2] revealed that during the COVID-19 pandemic, the detection rate of posttraumatic stress symptoms (PTSS) among medical students engaged in online learning under home quarantine was 10.42%. Both positive coping and social support were identified as key protective factors for medical students against PTSS. Furthermore, the study uncovered a core mechanism: social support plays a crucial mediating role between positive coping and PTSS. This implies that positive coping strategies (such as positive reframing and problem-solving focus) not only directly buffer against PTSS but also, by enhancing an individual's ability to perceive, seek, and utilize social support networks, indirectly and more effectively reinforce psychological defenses, thereby alleviating PTSS. This chapter aims to use this empirical finding as a “compass” and digital transformation technologies as a “vessel” to conduct an in-depth exploration. We will move beyond merely identifying “what” the phenomena are and instead commit to elucidating the “why” and “how”.

2. Theoretical deepening of our research findings

2.1 Impact of the COVID-19 pandemic on medical students' mental health

A large-scale survey of over 740,000 Chinese college students revealed widespread mental health issues during the COVID-19 outbreak, with 45% exhibiting symptoms of acute stress, depression, or anxiety. Key risk factors included having infected family or friends, daily media exposure exceeding three hours, and low social support. Notably, individuals with low social support demonstrated 4.84–5.98 times higher risks of developing anxiety and depression. The study suggests that providing psychological services for high-risk students, strengthening social support systems, and regulating media exposure may serve as effective strategies for safeguarding university students' mental health [5]. A systematic review analyzing 64 studies across the Asia-Pacific region revealed significant mental health challenges among college students during the COVID-19 pandemic. High-risk groups identified included females, senior students, and medical students. The study demonstrated that social support, religious or spiritual activities, and physical exercise served as effective protective factors. Psychological stress could be mitigated through reducing screen time, strengthening support systems, and promoting proactive activities [6]. Healthcare workers are the primary frontline responders to the pandemic, enduring immense psychological pressure. As future medical professionals, medical students are by no means mere bystanders in such public health emergencies. Their sources of stress exhibit multidimensional characteristics – Health threats: fear of infection for themselves and their families, coupled with a sense of powerlessness when confronting the disease as quasi-physicians. Academic and career uncertainty: course interruptions, postponed examinations, and the suspension or transition to online formats for clinical rotations have triggered anxiety about future career development. – Social isolation: home quarantine and social distancing measures have weakened peer support systems, intensifying feelings of loneliness. Studies indicate that during the pandemic, medical students widely reported varying degrees of anxiety, depression, insomnia, and stress-related symptoms [7].

2.2 Positive coping: A key individual factor in stress management

Coping styles refer to the cognitive and behavioral strategies individuals employ to manage internal and external demands and the resulting emotional distress. They are generally categorized into positive coping (such as seeking support, problem-solving, and positive reappraisal) and negative coping (such as avoidance, self-blame, and fantasy). Numerous studies have confirmed that positive coping serves as a crucial protective factor for mental health, while negative coping is associated with higher levels of psychological distress [8]. In crisis situations, cultivating positive coping strategies is essential for enhancing an individual's adaptive capacity. A review analysis revealed that during the COVID-19 pandemic, depressive symptoms were prominent among Chinese university students. Students predominantly obtained mental health and pandemic-related information through social media platforms (such as WeChat and Weibo) and mental health applications. Notably, 59% of university students utilized mental health application services (Apps) as a positive coping mechanism to address their emotional challenges [9].

A study revealed that among international medical students studying in China, the prevalence of comorbidity of anxiety and depression (22.7%) was significantly higher than the rates of anxiety alone (5.8%) or depression alone (8.9%). Negative coping styles and perceived stress were identified as common predictive factors for anxiety, depression, and their comorbidity. Targeted interventions focusing on stress management, improving coping strategies, and promoting healthy lifestyles are needed to address the mental health challenges of international medical students [10]. Another study revealed significant mental health challenges among Saudi university students during the COVID-19 pandemic: 12.9% exhibited severe anxiety, 9.7% severe depression, 32% reported suicidal ideation, and 26.2% were diagnosed with posttraumatic stress disorder (PTSD). The students most frequently adopted positive coping strategies such as religious or spiritual coping and acceptance, while males showed a greater tendency to employ active coping. Targeted interventions through remote mental health services could effectively address these issues [11].

2.3 Social support: The “buffer” and “resource reservoir” for stress

Social support refers to the material, emotional, and informational assistance and support that individuals receive through their social networks. According to the “stress buffering model,” social support can buffer the relationship between stressful events and physical and mental health. It mitigates the negative effects of stress by providing resources for problem-solving, enhancing an individual’s sense of belonging and self-worth, or influencing the appraisal of stressful events [12]. Robust social support has been repeatedly demonstrated to be a critical positive predictor of PTSD/PTSS recovery outcomes following traumatic events [13]. A study investigating COVID-19-related PTSD risk groups among medical students in Daegu, South Korea, revealed that 10.4% of medical students belonged to the PTSD risk group. Key risk factors included being in lower grades (particularly first-year students), smoking, and indirect exposure to COVID-19. Conversely, higher psychological resilience, self-esteem, and social support served as protective factors. The study suggests that enhancing psychological resources and social support networks can effectively intervene in medical students’ PTSD risk [14]. A qualitative study conducted among university students in Dhaka, Bangladesh, revealed that during the pandemic lockdown, financial pressures, academic burdens, social disruption, and family relationship issues led to widespread anxiety, stress, and depression among students, with a minority even exhibiting self-harm or suicidal tendencies. Multiple sources of support at family and community levels, including family bonds and social networks, served as crucial social support systems that helped students cope with anxiety, stress, and depression [15]. A longitudinal study examined Chinese university students’ fear responses to COVID-19 during two distinct phases: the implementation of strict containment measures and the subsequent easing of these restrictions. The findings revealed that, counterintuitively, students’ fear of COVID-19 increased after the relaxation of control measures. Proactive seeking of social support was found to indirectly alleviate this heightened fear by enhancing perceived social support. This underscores the critical role of social support in mitigating pandemic-related psychological stress and highlights the need for public health policies to consider these psychological impacts while strengthening social support systems [16].

2.4 Coping styles, social support, and PTSS: A potential mediation model

Theoretically, individuals who adopt positive coping strategies may be more proactive in seeking and utilizing social support, thereby gaining more resources to deal with stress. Simultaneously, higher levels of social support may also enhance an individual's confidence and ability to employ positive coping strategies. Therefore, social support is likely to play a mediating role in the process through which positive coping influences PTSS. That is, positive coping not only directly alleviates PTSS but may also indirectly reduce the risk of PTSS by enhancing both perceived and actually received levels of social support [2]. A study revealed that among home-quarantined Chinese university students, COVID-19-related impacts influenced PTSD risk through three mediating pathways: past stressful events positively increased PTSD risk, while psychological resilience and social support served as protective factors with negative effects. The path model demonstrated that the pandemic's impact indirectly affected PTSD through the chain mediation pathway of "past stressful events→psychological resilience→social support." The study recommends focusing on students' stress experiences and mitigating the psychological harm of the pandemic by enhancing social support and psychological resilience [17]. A study focusing on nursing students revealed that during campus quarantine, the detection rate of PTSD among them reached 15.42%. Social support not only directly reduced PTSD symptoms but also indirectly alleviated PTSD through independent and chain mediation pathways by enhancing psychological resilience and reducing COVID-19 fear. The findings suggest that strengthening social support, fostering psychological resilience, and managing fear are effective approaches to mitigate psychological trauma among nursing students [18]. What specific roles do social support and coping styles play in the development and progression of posttraumatic stress, and what are their underlying mechanisms? The core research in this chapter aims to investigate these mechanisms through large-scale surveys and analytical studies. Clarifying this mechanism will provide highly precise targets for digital transformation interventions: the effectiveness of any digital intervention tool depends on its ability to effectively promote "the application of positive coping strategies" and/or "the perception and acquisition of high-quality social support." Our empirical study has been conducted to validate this pathway, confirming that social support serves as a critical mediating variable between positive coping and PTSS, which in turn offers concrete implementation pathways for the digital transformation of resilience cultivation.

3. Research case: Methods, results and conclusion

3.1 Overview of research methods

This study employed a cross-sectional survey design. Between February and March, 2020, a random cluster sampling method was used to conduct an online questionnaire survey via the Questionnaire Star platform among 2,280 Chinese medical students under home quarantine due to the pandemic. A total of 2,208 valid questionnaires were collected, yielding an effective response rate of 96.84%.

Measurement tools:

- 1 PTSS: assessed using the PTSD Checklist-Civilian Version (PCL-C), with a cutoff score of 38 points for PTSS screening.
- 2 Coping styles: evaluated using the Simplified Coping Style Questionnaire (SCSQ), which includes two dimensions: positive coping and negative coping.
- 3 Social support: measured using the Social Support Rating Scale (SSRS), which assesses objective support, subjective support, and utilization of support.

Following data collection and organization, SPSS statistical software was used for descriptive statistics, inter-group comparisons, correlation analysis, and regression analysis. AMOS software was employed to construct a structural equation model, and the bootstrap method was applied to test the mediating effect of social support.

3.2 Results

3.2.1 The PTSS of medical students

The study found PTSS scores of 26.47 ± 9.05 points. Among the participants, 230 medical students had PCL-C total scores exceeding 38 points, resulting in a PTSS detection rate of 10.42%. Further analysis revealed that female medical students showed significantly higher PCL-C total scores than males ($z = -3.57$, $p < 0.001$). However, no statistically significant differences in PTSS detection rates were observed across gender, age, single-child status, education level, or place of origin.

3.2.2 The relationship between PTSS, coping styles, and social support

This study revealed that medical students' PTSS showed a statistically significant negative correlation with coping styles, positive coping, as well as social support and its various dimensions ($p < 0.01$), while demonstrating a positive correlation with negative coping ($p < 0.01$). Additionally, medical students' coping styles and positive coping were positively correlated with social support and its dimensions ($p < 0.01$). However, no statistically significant correlation was observed between negative coping and social support or its dimensions ($p > 0.05$). Detailed results are presented in **Table 1**.

3.2.3 The social support and coping style status of the PTSS group and the non-PTSS group

The study found that, compared with the non-PTSS group, the PTSS group demonstrated significantly lower scores in total social support and all its dimensions, as well as in total coping style scores and positive coping scores, while showing significantly higher negative coping scores ($p < 0.01$). For detailed data, please refer to **Table 2**.

Using PTSS grouping (0 = non-PTSS group, 1 = PTSS group) as the dependent variable and various dimensions of social support and coping styles as independent variables, logistic regression analysis revealed that objective support (OR = 0.908,

Variables	PTSS	Coping style	Positive coping	Negative coping	Social support	Objective support	Subjective support
Coping style	-0.143*						
positive coping	-0.310*	0.892*					
Negative coping	0.198*	0.681*	0.277*				
Social support	-0.291*	0.366*	0.488*	0.054			
Objective support	-0.135*	0.219*	0.268*	0.031	0.632*		
Subjective support	-0.291*	0.260*	0.323*	0.030	0.892*	0.308*	
Availability of support	-0.248*	0.405*	0.481*	0.083	0.599*	0.307*	0.317*

N = 2208 observations; **P* < 0.01 (2-tailed)

Table 1.
The relationship between posttraumatic stress symptoms, coping styles, and social support.

Variables	Non-PTSS group (n = 1978)	PTSS group (n = 230)	t	p
Social support	37.18 ± 6.87	32.42 ± 6.23	-9.802	<0.001
Objective support	7.01 ± 2.29	6.03 ± 2.29	-6.231	<0.001
Subjective support	22.34 ± 4.84	19.51 ± 4.50	-8.246	<0.001
Availability of support	7.83 ± 1.91	6.88 ± 1.69	-7.286	<0.001
Coping style	34.22 ± 9.39	32.14 ± 8.77	-3.458	0.001
positive coping	24.62 ± 7.07	20.19 ± 6.25	-9.420	<0.001
Negative coping	9.61 ± 4.37	11.95 ± 4.13	-8.603	<0.001

Table 2.
Social support, coping style status of the PTSS group and non-PTSS group.

p < 0.001) and positive coping (OR = 0.936, *p* < 0.001) were the two primary protective factors against PTSS, accounting for 7.4% and 3.6% of the variance explained, respectively.

3.2.4 The mediating role of social support between positive coping and PTSS

A structural equation model was constructed with social support as the mediating variable, positive coping as the independent variable, and PTSS as the dependent variable. Statistical analysis revealed that the constructed model demonstrated excellent fit ($\chi^2 = 18.927$, *df* = 2, GFI = 0.997, AGFI = 0.974, NFI = 0.988, RFI = 0.940, IFI = 0.989, TLI = 0.946, CFI = 0.989, RMSEA = 0.062, *p* < 0.07). Bootstrap testing indicated that social support played a partial mediating role between positive coping and PTSS, with a total effect of - 0.310, direct effect of - 0.128, and indirect effect of - 0.182. The mediating effect accounted for 58.81% of the total effect. The path model is shown in **Figure 1**.

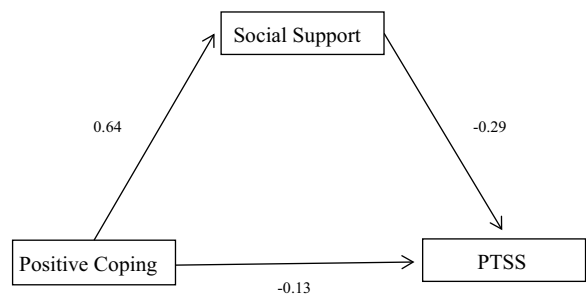


Figure 1.
The mediating role of social support between positive coping and PTSS.

3.3 Conclusions

This study investigated the relationships among positive coping, social support, and PTSS among 2,280 Chinese medical students during the COVID-19 pandemic through an online survey. The results showed a PTSS detection rate of 10.42%, with female students demonstrating significantly higher PTSS scores than males. Positive coping was positively correlated with social support, and both were negatively correlated with PTSS. Social support mediated the relationship between positive coping and PTSS, accounting for 58.81% of the total effect. The study indicates that objective support and positive coping serve as primary protective factors against PTSS, suggesting that psychological interventions targeting coping style improvement and social support enhancement can effectively alleviate PTSS.

4. Deep empowerment of digital transformation: From theory to targeted practice

The advent of the postpandemic era has brought unprecedented opportunities for digital transformation, significantly enhancing interpersonal connectivity while overcoming geographical limitations inherent in traditional education. This evolution has also created broader modalities and practical pathways for delivering social support [4, 19]. Within this transformative landscape, critical questions emerge: How should medical education evolve in the digital age, and how can robust mental health support systems for medical students be constructed? Based on the refined theoretical framework discussed above, digital technology is no longer merely a supplementary tool but an intervention instrument capable of performing precise “microsurgery” on psychological resilience mechanisms.

4.1 Online learning platforms: From content repositories to intelligent “resilience hubs”

The advent of the digital era necessitates a redefinition of the traditional learning management system (LMS), which should evolve into an intelligent ecosystem capable of assessment, personalized intervention, and early warning. This transformation shifts the paradigm from passive, compliance-driven learning to a multidimensional structure grounded in positive coping. For instance, developing

a series of targeted learning modules – such as a “Cognitive Reappraisal Workshop” VR module (emotion-focused) and interactive “Clinical Problem-Solving SOP” cases (problem-focused) – can effectively foster adaptive skills. Furthermore, integrating brief self-assessment tools into the teaching process through digital resources enables continuous monitoring and timely support. For instance, after watching a video on “how to handle medical errors,” a slider could pop up asking: “What is your current stress level?” or “How would you rate your ability to use positive coping strategies?” These high-frequency, low-burden formative assessment data points are valuable resources for gaining insight into students’ psychological states. By establishing a multisource data fusion system within online learning platforms – which moves beyond analyzing academic performance alone – it becomes possible to anonymously integrate behavioral data (login frequency, video pause points, sentiment analysis of forum posts), self-reported data (embedded assessments), and academic performance data. This synthesized multisource data can then be utilized within machine learning models to develop a “Psychological Risk Early Warning Index”. For example, a student might exhibit the following pattern: repeatedly watching a specific high-stress content segment, a sharp decline in participation frequency within relevant discussion forums, and consistently high scores on embedded self-assessments of stress. The system could automatically flag this student as “medium-risk,” prompting a course instructor or counselor to initiate a low-threshold, caring check-in. This enables early, precise, and nonstigmatizing intervention.

4.2 Virtual simulation (VR/AR) – creating an arena for “controlled failure” and skill internalization

The value of VR lies in its provision of the highest form of experiential learning, enabling students to safely fail, reflect, and grow in environments that closely approximate real-world scenarios [19, 20]. By leveraging VR technology, simulation modules targeting specific stressors can be designed, such as: “Communication Simulation with an Angry Family Member,” “Breaking Bad News to a Terminally Ill Patient Simulation,” and “Multi-tasking Under Pressure Simulation.” The VR system can embed coping prompts and biofeedback mechanisms; for instance, when a sharp increase in the student’s heart rate is detected (via hand controller sensors or wearable devices), the system can unobtrusively display preset coping strategy options in the corner of the visual field (e.g., “Try taking three deep breaths,” or “Choose cognitive reframing: This is a learning opportunity, not a personal failure”). After the student makes a choice, the system can simulate the positive consequences of employing that strategy (e.g., the family member’s emotions gradually calming down), thereby reinforcing the belief that “positive coping is effective.” Following the simulation, the system provides a detailed data report, including a timeline, stress peak points, the coping strategies employed, and changes in physiological indicators. Guided by a mentor, students can use this objective report for debriefing, transforming the vague feeling of “feeling very stressed” into a clear, actionable insight such as, “At the X-minute mark, when encountering situation Y, my coping method could be optimized to Z.”

4.3 Digital support system – building an “always-on” support ecosystem

This approach digitally enhances and expands the three dimensions of social support. An AI-powered chatbot, built on the principles of cognitive behavioral

therapy (CBT), serves as a key tool. It is not merely a simple chat program; its dialogue logic is embedded with CBT techniques, enabling it to guide users to identify automatic negative thoughts (e.g., “I will definitely fail this exam”) and help them through cognitive restructuring by asking questions (e.g., “What evidence supports this thought? What evidence contradicts it?”) [21]. The AI chatbot is also capable of identifying high-risk keywords related to suicide or self-harm through language analysis, immediately activating an emergency protocol: terminating the AI conversation, strongly recommending, and directly redirecting the user to a human-staffed psychological counseling hotline or crisis intervention platform.

Leveraging online social platforms to establish anonymous peer support communities, which can be subdivided into dedicated sections such as “Academic Stress Zone,” “Clinical Rotations Venting Corner,” and “Emotional Support Space.” These communities are guided by trained peer supporters or moderators to ensure a safe and positive atmosphere. Mental health professionals and senior physicians are regularly invited to host “AMA (Ask Me Anything)” online Q&A sessions, thereby infusing professional support into the peer network in a low-threshold and demystified manner. A unified “Seek Help” portal is designed so that students, with just one click, can view clear options based on their specific needs (e.g., academic difficulties, emotional distress, financial issues) and directly schedule appointments with corresponding online or offline services (such as academic tutors, psychological counselors, or the student financial aid office). This significantly reduces the decision-making complexity and psychological cost of seeking support.

5. Challenges and future directions

In the era of digital transformation, numerous opportunities coexist with significant challenges. The digital divide is multifaceted, extending beyond mere device access to include an “intention gap” (distrust of technology) and a “skills gap” (insufficient digital literacy). Addressing this dilemma requires providing complementary technical training and support, alongside designing user-friendly interfaces. Data privacy and security demand paramount consideration. Leveraging cutting-edge technologies to ensure anonymization at the algorithmic level is crucial, while simultaneously establishing extremely clear protocols for data ownership, usage rights, and informed consent. While AI brings convenience, we must remain vigilant about algorithmic bias that may cause unfair warnings or interventions for specific student groups (e.g., those from different cultural backgrounds or genders). Models require regular fairness audits, and their decision-making processes should be made as interpretable as possible. While fully utilizing AI, it is crucial to establish clear boundaries for human-computer collaboration and define an unequivocal ethical red line [21]. Digital tools should serve as channels for screening, support, supplementation, and referral, but must never replace human professional judgment and profound human empathy in significant decisions. The goal of AI is to augment, not replace, human educators and supporters.

6. Conclusions

A series of studies has unveiled a long-overlooked yet critical issue in medical education during the COVID-19 pandemic: the systematic cultivation of learners’

psychological resilience. Our research elucidates the core mechanism underlying this cultivation process – the mediating role of social support in the relationship between positive coping and stress symptoms. The digital transformation of medical education presents a historic opportunity to translate this mechanistic understanding into scalable, quantifiable, and personalized educational practices.

This chapter articulates not merely a set of technical solutions but a reconceptualization of the educational paradigm. It calls for elevating digital technology from its role as a “teaching tool” to a new stature as a “medium for fostering psychological resilience” in learners. Through a carefully designed digital ecosystem, we can weave an invisible yet resilient support network for every medical student – a simulated environment that allows them to fail safely and learn from mistakes, and a seamless pathway to professional help. A successful digital transformation represents a profound integration of technology and humanistic spirit. Its outcome will not only be technically proficient physicians but a generation of “whole persons” who understand how to care for themselves, support their peers, and maintain resilience and empathy in adversity – perhaps the most profound and urgent interpretation of “medical humanity” for our time.

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Conflict of interest

The author declares no conflict of interest.

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From Expert Systems to Ambient and Augmented Care: AI in Internal Medicine, Dermatology, Neurology and Neurosurgery

Khadeja Alrefaie, Basel Madlol and Oday Atallah

Abstract

Artificial intelligence (AI) is now woven into the everyday clinical practice of internal medicine, neurology, neurosurgery, and dermatology, transforming how clinicians triage, diagnose, document, and operate. From the early rule-based systems of the 1970s to today's deep-learning platforms and multimodal foundation models, the evolution of medical AI reflects simultaneous advances in data availability, computational power, and regulatory oversight. Contemporary tools – automated stroke triage, rapid-response EEG, seizure-detection wearables, dermatologic image classifiers, and augmented-reality surgical navigation – have accelerated clinical workflows while raising new questions about validation, safety, and equity. This chapter traces that trajectory and examines the distinction between regulatory clearance, technical accuracy, and true clinical benefit. It outlines evidence standards across specialties, highlights lessons from successful and unsuccessful deployments, and provides a practical governance and education framework for integrating AI responsibly into training programs. As AI moves from proof-of-concept to routine care, medical educators must prepare clinicians to critically appraise model outputs, interpret uncertainty, communicate transparently with patients, and engage in continuous monitoring within their institutions. The goal is not to replace clinical judgment but to strengthen it – ensuring that AI becomes a safe, reliable partner in decision-making across the spectrum of acute care, chronic disease management, and procedural practice.

Keywords: medical artificial intelligence, clinical decision support, neurology, neurosurgery, internal medicine, dermatology, augmented reality in surgery, rapid EEG, stroke triage

1. Introduction: From expert systems to ambient and augmented care

Artificial intelligence (AI) has moved from the margins of health care into the day-to-day fabric of clinical work. Neurosurgery and internal medicine, including its sub-specialties such as neurology and dermatology, feel this change

early and intensely. These specialties depend on rapid interpretation of imaging, continuous physiologic data, and high-stakes decisions where minutes matter. What was once experimental – automated CT analysis, bedside seizure triage, augmented-reality (AR) surgical guidance, and automated note generation – is now entering routine practice through U.S. Food and Drug Administration (FDA)-cleared systems and enterprise integrations. For clinicians and educators, the question is no longer whether AI will shape practice, but how to use it responsibly while maintaining the standards of judgment that define our professions.

A typical example unfolds in the emergency department. A patient arrives with sudden right-sided weakness. The CT scanner completes a non-contrast study, and before the resident loads the images, an automated alert fires to the neurologist's phone. A large-vessel occlusion (LVO) is detected with high confidence, the perfusion maps show a salvageable penumbra, and the thrombectomy team is mobilized. The workflow is not science fiction; it reflects systems such as Viz.ai and RapidAI that are already deployed across major stroke centers. Similar shifts appear elsewhere – a Ceribell headset at the bedside helping the team distinguish status epilepticus from metabolic encephalopathy, or an AR headset guiding the placement of pedicle screws in spine surgery. These tools do not replace clinicians, but they change how clinicians think, act, and teach.

This moment differs from earlier waves of digital innovation. The first generation of expert systems was limited by brittle rule sets and narrow use cases. Today's tools combine deep learning, cloud connectivity, multimodal inputs, and continuous quality monitoring. Ambient clinical documentation is reducing cognitive load, decision-support systems are being regulated as medical devices, and cross-specialty models are emerging that handle imaging, text, and biosignals together. This convergence makes AI more powerful but also more opaque, creating new responsibilities around validation, equity, accountability, and privacy.

This chapter traces that evolution and examines what it means for modern medical education. We begin with the historical arc from MYCIN to deep learning, then evaluate real tools in current clinical use across internal medicine, neurology, and neurosurgery. We discuss successful deployments, notable failures such as the Epic Sepsis Model (ESM), and the emerging regulatory landscape. We close with a realistic forecast of the next decade – multimodal foundation models at the bedside, closed-loop neurostimulation, and AR operating rooms – and offer a practical adoption framework for educators and clinical leaders. The goal is simple – to prepare clinicians to use these technologies with confidence, skepticism, and a grounded understanding of their impact on patient care.

2. Historical trajectories and early clinical adoption of medical AI

2.1 The early foundations of medical AI

Modern clinical AI did not appear suddenly. Its roots trace back to the early expert systems of the 1970s and 1980s, which attempted to translate the reasoning of clinicians into structured rule sets. The best-known example, MYCIN, used approximately 450 decision rules to recommend antibiotics for bacteremia and meningitis and performed at least as well as infectious-disease experts in controlled evaluations [1–5]. Although MYCIN never reached real clinical deployment due to

medicolegal and workflow barriers, it established the core idea that computational systems could assist with specialized reasoning in medicine. Other systems followed – Puff for pulmonary function interpretation, INTERNIST-1 for diagnostic support in internal medicine – and each contributed conceptual foundations for knowledge representation and probabilistic reasoning in clinical care [6–12].

These early systems ultimately struggled because their rule bases were brittle: small changes in patient data sometimes produced unrealistic outputs, and the maintenance burden grew rapidly. Nevertheless, the principles they established – structured knowledge, inference engines, and explicit representations of uncertainty – became essential for the next generation of AI in medicine. Many of the challenges described in contemporary AI ethics, such as accountability, transparency, and data provenance, were already articulated in the early expert-system literature [13].

These early limitations also exposed a recurring theme that persists today: AI performs best when its operational environment remains stable, well-defined, and predictable. Whenever clinical reality deviates from these conditions – through atypical presentations, new disease patterns, or heterogeneity across institutions – model fragility becomes visible. The expert-system era, therefore, provided not only technical foundations but also early cautionary lessons about over-reliance on algorithmic certainty.

2.2 The deep learning shift

The modern wave of AI was catalyzed by advances in deep learning, especially convolutional neural networks, which transformed medical imaging analysis. Landmark studies demonstrated high performance in diabetic retinopathy screening, dermatologic lesion classification, and radiologic interpretation across multiple modalities [14–16]. Many of these systems performed at levels comparable to specialists under controlled testing conditions. Although the gap between test-set performance and real-world deployment remains significant, these studies changed the trajectory of clinical AI and accelerated regulatory interest.

By 2022, the FDA had cleared more than 350 AI-enabled medical devices, with radiology accounting for over 70% of them [17–19]. Tools relevant to neurology and neurosurgery – stroke triage platforms, intracranial hemorrhage (ICH) detectors, CT perfusion analyzers, and postoperative hardware assessment – expanded rapidly during this period [20–27]. The move from rule-based reasoning to deep learning allowed models to leverage large-scale image datasets and uncover features not easily visible to the human eye, especially in time-critical workflows such as acute stroke care [20, 28–33].

This shift also marked the beginning of multimodal models – systems capable of integrating imaging with clinical text, laboratory data, or physiologic signals. Although still in its early stages, these architectures hint at a future in which AI tools support more holistic decision-making rather than single-task classification.

2.3 Why internal medicine, neurology, and neurosurgery became early adopters

These specialties adopted AI early for three reasons. First, they generate abundant high-quality digital data: imaging, electroencephalogram (EEG), electrocardiogram (EKG), laboratory time-series, and electronic notes. Second, they operate in

time-sensitive decision environments where early alerts can meaningfully affect outcomes. Stroke care is the clearest example, where every 15-minute delay in reperfusion is associated with higher mortality and functional disability [34]. Third, cognitive load in these disciplines is high; continuous EEG interpretation, neuroimaging backlogs, and documentation demands often exceed available personnel. AI systems that automate preliminary triage or summarize high-volume data offer pragmatic value.

At the same time, early adopters faced the consequences of model limitations.

The ESM, implemented across hundreds of US hospitals, was shown to have poor sensitivity and substantial false-alert rates when evaluated independently [35]. This reinforced the lesson that AI cannot be judged by internal validation alone and highlighted the importance of external auditing, calibration, and domain-specific education.

The experience in these high-acuity fields also demonstrated that the “human factors” component of AI – alert fatigue, trust calibration, workflow fit, and communication across teams – was just as important as algorithmic accuracy. AI tools that performed well in validation often underperformed when they disrupted established clinical rhythms or generated unprioritized alerts [36–44].

2.4 Integrating AI into the clinical learning environment

For educators, the challenge is not only to teach how AI works but also how to reason with AI outputs. Learners must understand algorithmic uncertainty, dataset bias, thresholding, and human-AI teaming. Several professional societies have emphasized this shift as essential for modern medical curricula [45–47]. The American Medical Association has called for explicit training in augmented decision-making and algorithmic oversight [48–51]. Professional societies have begun highlighting the need for structured training as AI-driven imaging tools and AR navigation enter neurology and neurosurgery, with recent reviews emphasizing competency development, workflow integration, and safety standards for trainees using extended-reality systems [46, 47, 52]. As these systems become embedded in everyday workflows, teaching clinicians how to interpret, critique, and appropriately rely on them becomes as important as teaching them to read EKGs or CT scans.

Importantly, AI literacy does not require that trainees become programmers. Instead, it requires fluency in concepts such as false-positive tradeoffs, calibration drift, dataset shift, and the distinction between technical accuracy and clinical utility. Embedding these concepts early in training helps clinicians develop a balanced mindset – neither techno-optimistic nor reflexively skeptical, but capable of integrating AI responsibly into patient care.

3. What counts as ‘good evidence’ (and how to teach it)

If the first wave of clinical AI proved anything, it’s that regulatory status does not equal clinical benefit. Viz.ai’s LVO triage app received the FDA’s first *de novo* marketing authorization for stroke-alerting software in 2018, based on evidence that it can analyze CT angiography and notify specialists about suspected LVO strokes [53]. The same year, the DEFUSE 3 randomized trial extended thrombectomy to

6–16 hours after last-known-well using perfusion-based selection generated by the RAPID automated software; patients selected in this way had substantially better functional outcomes with endovascular therapy [54, 55]. These two facts are often conflated. In teaching, it's essential to show trainees the distinction: RAPID's automated perfusion criteria were part of a randomized efficacy trial (DEFUSE 3), whereas Viz.ai's LVO alert underwent device clearance for detection/notification, not randomized outcome testing [53–55].

It is also valuable to emphasize that FDA "*de novo*" authorization evaluates safety and technical performance, not patient-centered outcomes. This distinction mirrors other device categories, where regulatory pathways do not require randomized clinical trials. Clarifying this early helps trainees understand why workflow tools must still undergo local validation despite regulatory approval.

Comparative evidence is accumulating for the software students will actually see on call. Recent multicenter and single-center studies comparing CT-perfusion outputs from RAPID and Viz.ai report substantial agreement on volumes and eligibility under DEFUSE-3 rules, while noting clinically relevant discordances in a minority of cases – useful material for morbidity and improvement conferences and local protocol design [56, 57]. Importantly, such studies highlight the need to teach threshold literacy (e.g., how mismatch ratios, core limits, and Tmax maps translate into decisions) and site-level validation before adopting automated cut-points wholesale [56, 57].

Educators can use real perfusion cases – where automated core estimates differ from the neurointerventionalist's interpretation – to teach how imaging biomarkers behave under different scanners, reconstruction kernels, or motion artifacts. These examples demonstrate that even FDA-cleared software is sensitive to site-specific technical factors.

Not all triage AI improves workflow or outcomes. In ICH, one emergency-department implementation study associated Aidoc's triage tool with shorter report turnaround times, but a prospective evaluation in 2024 found no improvement in diagnostic performance or turnaround times with an ICH triage system, cautioning against assuming benefit from adoption alone [58, 59]. A separate "before-after" ICH project reported improved time metrics after deployment, but with typical nonrandomized limitations [60]. These mixed results are teachable moments: residents should learn to read study design labels (randomized vs. before-after), look for calibration and drift analyses, and ask whether endpoints (time stamps) are proximal surrogates or translate to patient-centered outcomes. These studies also offer an opportunity to illustrate the difference between "efficacy" and "effectiveness." A system may demonstrate accurate detection under test conditions yet fail to improve meaningful clinical endpoints due to bottlenecks elsewhere in the workflow, such as scanner availability or paging delays. Teaching this helps clinicians critically evaluate claims of "time saved."

Internal medicine offers an equally important counterexample. The ESM, widely deployed as a proprietary early-warning system, performed poorly on external validation at a large academic center – with suboptimal discrimination and calibration and substantial alert burden [35, 61]. It's a vivid case for the curriculum: require learners to inspect Area Under the Receiver Operating Characteristic/Precision-Recall (AUROC/PR) curves, calibration plots, and net benefit, and to understand how silent shifts in local practice or population case-mix can degrade performance after go-live. Because ESM is proprietary, hospitals cannot inspect its

features or retrain it, offering a real-world example of why transparency matters for safety. The case also allows instructors to discuss “model drift,” since sepsis definitions, workflows, and antibiotic protocols evolve over time – conditions under which static models underperform.

For bedside neurophysiology, evidence has matured enough to set expectations precisely. Rapid-Response EEG (Ceribell) reduces the time to diagnosis of status epilepticus compared with conventional EEG availability in pragmatic hospital studies and can alter management at the point of care [62–64]. Reviews and multicenter analyses now articulate where rapid 10-lead EEG is non-inferior for risk-stratification tools (e.g., 2HELPS2B) and where a full montage remains necessary [65]. Teaching point: Embed device-specific competencies (lead placement, artifact recognition, sonification use) alongside classic EEG interpretation. Using Ceribell cases in morning reports – especially those where continuous EEG later confirmed or ruled out subclinical seizures – helps trainees appreciate both the strengths and limitations of rapid EEG and prevents over-reliance on abbreviated montages.

For wearable seizure detection, the FDA-cleared Empatica Embrace watch detects generalized tonic-clonic seizures using accelerometry and electrodermal activity; peer-reviewed validation demonstrates high sensitivity with low false-alarm rates in supervised and at-home settings [66–68]. Here, educators should emphasize indications and limits (convulsive seizures only; adjunctive alerting), regulatory labeling, and how to counsel patients on false alarms and data privacy. In patient-safety teaching, this device provides an excellent case for discussing what constitutes “clinical-grade” wearables, how FDA clearance differs from consumer wellness claims, and why seizure-detection devices require specific counseling regarding nocturnal events, caretaker notification, and Sudden Unexpected Death in Epilepsy (SUDEP) risk frameworks.

Dermatology provides another high-value teaching case for evidence appraisal because it is one of the earliest specialties where deep-learning performance approached or exceeded that of clinicians under test conditions. The landmark study by Esteva et al. [15] demonstrated that a convolutional neural network could classify skin lesions at dermatologist-level performance using a large dataset of clinical and dermoscopic images. Subsequent prospective reader studies have reinforced this pattern: Haenssle et al. [69] showed that a deep-learning system outperformed most of 58 dermatologists in melanoma detection using dermoscopic images, and a randomized diagnostic study by Tschandl et al. [70] demonstrated that machine-learning systems performed comparably to international experts across multiple lesion types [70]. These studies allow educators to highlight critical distinctions between “test-set performance” and real-world applicability: the models were evaluated on curated dermoscopy datasets, under controlled conditions, and without the clinical context dermatologists normally use. They therefore illustrate why diagnostic AI cannot be adopted without examining dataset provenance, image acquisition differences, and whether the model has been validated on the skin-types and disease distributions represented in one’s own patient population. This makes dermatology an ideal platform for teaching dataset bias, domain shift, and the importance of local calibration before clinical use.

Finally, AR navigation in spine surgery – increasingly visible in neurosurgical theaters – has peer-reviewed early-experience cohorts with ~97%–98% Gertzbein-Robbins A/B pedicle-screw accuracy, including large series and cervical applications, plus systematic reviews summarizing accuracy and workflow considerations [71–75].

The teaching agenda should move past “AR is cool” toward how registration works, what error metrics mean, when fluoroscopy is still needed, and how to audit screw accuracy during adoption. Hands-on simulation using sawbones or cadaveric labs can meaningfully accelerate learners’ understanding of AR alignment, entry-point planning, and error propagation – skills that translate directly into safer use in the operating room.

Bottom line for educators and service leads: teach clinicians to separate regulatory clearance, technical accuracy, workflow impact, and patient outcomes; to demand external validation and calibration in their own population; and to treat AI the way we treat any new drug or device – with local protocols, auditing, and continuous quality improvement.

As institutions adopt AI more widely, integrating these discussions into morbidity and mortality conferences, quality-improvement curricula, and interdisciplinary rounds ensures that AI governance becomes part of routine clinical culture rather than a specialist niche.

4. A practical framework for safe, evidence-based AI adoption

As clinicians move from trial to routine use, governance, measurement, and education must all advance in parallel. The final two pages, therefore, organize practical next steps into three sections: (1) governance and validation for clinical services, (2) an educator’s adoption checklist and competency map, (3) realistic near-term directions (emerging) with their educational implications, and (4) practical expectations for educators.

4.1 Governance and continuous validation

Hospitals adopting AI-enabled tools must treat them as medical technologies with a lifecycle – not as one-off software installs. Key governance elements include vendor evaluation, local technical validation, deployment monitoring, and pre-defined mitigation plans for failure modes (e.g., silent degradation after model drift) [76]. The FDA’s AI/machine learning (ML) SaMD Action Plan and subsequent guidance emphasize total-product-lifecycle approaches and the need for predetermined change control plans when models are updated in the field; institutions should map these regulatory expectations to local procurement and risk-management processes before go-live [76]. A practical enhancement is for hospitals to formally align AI governance with existing structures such as Pharmacy and Therapeutics committees, device evaluation boards, or quality and safety councils, ensuring that AI oversight becomes part of the institution’s standard clinical governance fabric rather than a standalone experiment.

Validation must be both external and local. The ESM example illustrates the consequences of skipping rigorous external evaluation: an independently conducted external validation showed suboptimal discrimination and calibration when the model was applied at scale, with a high alert burden and limited clinical benefit in that cohort [35]. For imaging pipelines such as CT perfusion, the literature shows high overall concordance across commercial packages but clinically relevant discordances in a minority of cases (which can change patient eligibility for thrombectomy under DEFUSE-3/DAWN criteria); multicenter comparative work

therefore becomes a routine part of pre-adoption testing [54, 56]. Local validation should include (1) measurement of diagnostic accuracy against a local reference standard, (2) evaluation of workflow effects (time-to-notification, clinician response), (3) calibration checks across subpopulations, and (4) prospective monitoring of downstream clinical outcomes when feasible. Institutions should build audit dashboards that track model performance and alert rates and tie these to a clinical governance committee with the authority to tune thresholds or withdraw a tool if safety signals arise. An additional enhancement is to require structured “pre-mortem” sessions before deployment: multidisciplinary teams outline plausible failure scenarios (e.g., drift, incorrect thresholds, misrouted notifications) and agree in advance on monitoring triggers and contingency responses. Such planning mirrors established safety science practices and prepares organizations for the operational realities of AI in clinical environments.

4.2 An adoption checklist and competency map for educators

Below is a compact, implementable checklist designed for clinical leaders and educators who must introduce AI into training environments. Items are arranged as “deployable actions,” followed by the trainee competencies they map to.

(1) Pre-deployment: vendor dossier + local validation

- Action: Require vendor documentation (intended use, training data provenance, reported metrics, FDA clearance summary) and conduct a locally designed validation on a convenience sample before initiating live alerts.
- Competencies taught: “understand model intended use and limits”; “read and critique reported performance metrics (AUROC, calibration, PPV/ NPV)” [49, 76].
- Educators can include brief workshops where trainees manually compare AI outputs to ground truth on a small, curated validation set, fostering hands-on understanding of metrics such as false positives, calibration, and threshold effects.

(2) Threshold and workflow design

- Action: Define clinical thresholds, notification recipients, and escalation pathways in co-design sessions with frontline clinicians. Log response times and outcomes.
- Competencies taught: “workflow integration and human-AI teaming”; “situational judgment in responding to model alerts.”
- Simulation sessions – using de-identified case vignettes – can help learners practice escalation decisions and understand how model thresholds shape team activation patterns.

(3) Monitoring and governance

- Action: Set up automated dashboards for alert volume, positive predictive value, and user overrides; mandate quarterly review meetings with quality leaders.
- Competencies taught: “interpret monitoring dashboards”; “recognize model drift and when to escalate to governance.”
- Trainees could rotate through governance meetings as observers, gaining direct exposure to institutional oversight processes and real-world debates about safety and performance monitoring.

(4) Education and assessment

- Action: Create case-based modules where trainees review AI outputs paired with ground truth (e.g., CT angiography with RAPID/Viz.ai output and angiography results) and lead morbidity-and-mortality-style reviews of discordant cases.
- Competencies taught: “critical appraisal of AI outputs”, “safe reliance and suspicion – knowing when to override” [77].
- Programs can incorporate structured reflection templates, prompting learners to articulate why they overrode or accepted a given AI output, fostering the metacognitive habits needed for safe AI-assisted decision-making.

(5) Patient communication and consent

- Action: Develop scripts and patient-facing materials explaining the role of AI in decision-making and data use; integrate these into informed-consent workflows where AI materially affects care.
- Competencies taught: “Explain the role and limits of AI to patients” and “Address privacy and data-sharing questions.”
- Standardized patient encounters can be used to assess communication skills, allowing trainees to practice explanations that are technically accurate but accessible to lay audiences.

These items map to an assessment blueprint: Objective structured clinical examination (OSCE) stations that require learners to (1) interpret an AI-annotated study and explain its uncertainty to a simulated patient, (2) decide whether to accept or overrule an AI alert in a time-pressured vignette, and (3) critique a short vendor summary for gaps in provenance or validation. Programs may also introduce longitudinal portfolios where trainees document cases involving AI use, reflections on errors, and lessons learned – mirroring surgical logbooks or radiology case portfolios.

4.3 Near-term technical directions

We close by summarizing three near-term technologies and their educational implications. Each is explicitly framed as either established (sufficient evidence to change practice), supported but context-dependent (evidence for specific uses), or emerging (limited but plausible).

- (1) Multimodal bedside decision support – supported but context-dependent.

Systems that combine imaging, time-series vitals, and text (notes/labs) are beginning to appear as cleared devices, and research prototypes are increasingly multimodal. Regulators (FDA) and reviews of device approvals document rapid growth in AI/ML-enabled devices, especially in imaging, though evidence of improved patient-level outcomes is mixed and depends heavily on implementation. Education must therefore emphasize multimodal signal interpretation, calibration issues, and the difference between notification and demonstrated clinical benefit [78]. Educators may develop “modality-mapping” exercises where trainees trace how each data stream – imaging, labs, vitals, notes – contributes to a multimodal model’s prediction, helping them reason about strengths and weaknesses at the feature level without requiring technical knowledge of model internals.

- (2) Closed-loop neurostimulation – established for specific indications; educational needs are specialized.

Closed-loop responsive neurostimulation is an active clinical technology with rigorous randomized evidence in focal epilepsy (the RNS System), showing durable seizure reduction and a growing post-approval evidence base [79, 80]. As closed-loop paradigms expand (e.g., DBS research for Parkinson’s and other targets), trainees must learn neurophysiological biomarkers, device safety, and ethical issues surrounding automated stimulation [81, 82]. Cross-disciplinary teaching – pairing neurology and neurosurgery trainees with biomedical engineering faculty – can deepen understanding of signal acquisition, artifact handling, and device troubleshooting.

- (3) Augmented reality in the operating room – promising accuracy metrics; training must be competency-based.

Head-mounted AR systems for spine navigation and pedicle-screw placement report high early accuracy rates and favorable workflow metrics in early cohorts and systematic reviews; however, long-term comparative outcome and complication data are still developing [71, 72]. For surgical trainees, the practical curriculum should cover registration methods, sources of registration error, fluoroscopy fallback strategies, and intraoperative auditing of screw placement – taught in simulation before live cases. Programs can incorporate AR-enabled simulators or cadaver labs where trainees practice registration steps and error recognition before operating on patients.

4.4 Practical expectations for educators

AI in medicine has moved from academic proofs-of-concept into clinical operations. The right frame for educators is pragmatic: Teach the fundamentals of

model evaluation (design, training data, metrics), insist on local validation and monitoring, integrate AI scenarios into assessment, and develop governance that mirrors how devices and drugs are introduced – with independent oversight and outcomes monitoring [49, 76, 77]. Finally, treat “AI competency” as a longitudinal skill: it is not a single lecture but a set of practical literacies embedded across rotations – from emergency-stroke workflows to the neurosurgical OR and the bedside neurophysiology consult. If educators can produce clinicians who can read an AI output critically, explain it to patients, and decide when to act or override, we will have done the practical work that prepares medicine for this era – safely, skeptically, and effectively. Embedding these competencies across multiple years of training – rather than isolating AI content in elective courses – ensures that proficiency develops in parallel with clinical maturation, ultimately making AI literacy a routine component of medical professionalism.

5. Conclusion

AI in medicine has moved decisively from experimental promise to operational reality. Across internal medicine, neurology, neurosurgery, and dermatology, AI tools are now shaping diagnostic pathways, influencing workflows, and altering the cognitive demands placed on clinicians. The history of medical AI – from MYCIN to deep learning – demonstrates that technical innovation alone is insufficient; each generation of tools requires parallel evolution in validation methods, governance structures, and medical education.

The evidence reviewed in this chapter shows several consistent themes. First, regulatory authorization does not guarantee clinical benefit, making external validation, local calibration, and continuous monitoring essential components of safe deployment. Second, high test-set accuracy rarely predicts real-world performance without attention to workflow integration, dataset shifts, and human–AI teaming. Third, specialties such as neurology, dermatology, and neurosurgery offer powerful teaching platforms for cultivating AI literacy because they contain well-studied, FDA-cleared tools with both strengths and limitations. Finally, the next decade will demand clinicians who can interpret multimodal model outputs, evaluate uncertainty, communicate risks transparently, and know when to override automated recommendations.

In practical terms, “AI competency” must become a longitudinal skill woven across the training continuum – from emergency stroke response to dermatologic image interpretation to neurosurgical navigation. When educators create clinicians who can question, validate, communicate, and govern AI tools – not merely operate them – they ensure that technology augments rather than displaces the core principles of medical judgment. Through deliberate governance, evidence-based adoption, and thoughtful curriculum design, AI can become a safe and responsible force multiplier for modern clinical care.

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Conflict of Interest

The authors declare no conflict of interest.

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Chapter 9

Pedagogy of ECG Interpretation

Divyanshu Jain, James O'Neill and Michael J. Daly

Abstract

The recording of a 12-lead electrocardiogram (ECG) is widely regarded as a key clinical procedure that is utilised for patient care in a multitude of clinical settings. The ubiquitous use of the 12-lead ECG, and the plethora of clinical diagnoses that can be made by this simple procedure, necessitates a high degree of ECG interpretation mastery to mitigate adverse patient outcomes. From the diagnosis of life-threatening arrhythmias to the recognition of key ECG patterns that affect patient management and risk stratification, accurate ECG interpretation is a key skill for clinicians to cultivate in order to deliver high-quality patient care. Several studies have repeatedly highlighted the deficiencies in ECG interpretation skills amongst healthcare workers at various levels of experience and training. The pedagogy of ECG interpretation is variable from faculty to faculty due to a lack of standardisation. This chapter explores the range of pedagogical approaches that can be used to create comprehensive and effective instruction on this topic. We will also discuss the prevailing challenges that exist in the field and provide empirical guidance on strategies to address these challenges.

Keywords: electrocardiogram, pedagogy, digital learning, medical education, learning theory

1. Introduction

The electrocardiogram (ECG), a bedside medical investigation, is the cornerstone of non-invasive diagnostic tests in cardiac care. It is a key clinical investigation that can lead to the diagnosis of multiple life-threatening conditions, including, but not limited to, acute coronary syndromes and life-threatening arrhythmias. On the other hand, over-interpretation of pathology on an ECG can have life-changing implications for a patient. The importance of ECG interpretation is not only limited to cardiologists; it is ubiquitously important in a wide range of specialties, spanning the entire spectrum from general practice to critical care: A proper understanding of ECG interpretation is essential for safe and effective practice in emergency medical response teams, acute medicine, emergency medicine, cardiology, psychiatry, paediatric medicine, general practice, and intensive care. Current meta-analyses in the field highlight that medical students achieve only 42% accuracy in ECG interpretation, while residents achieve 55.8%, practicing physicians 68.5%, and even cardiologists reach only 74.9% [1]. This reveals a deficiency in ECG interpretation competency amongst medical students and healthcare professionals

and points to a potential fundamental failure in medical education that can directly impact patient safety. It highlights the potential pitfalls in the current pedagogy of ECG interpretation and raises the call for modification, research, and optimisation to impart this valuable skill to our healthcare students and staff alike.

2. Origin of ‘The Standard 12-Lead ECG’

In the nineteenth century, it was demonstrated that cardiac muscle activity could generate a non-invasively measurable electrical current [2]. Myocardial cells create electrical signals via a chain of depolarisation and repolarisation, the sum of which can be measured using electrodes on the skin. The standard 12-lead ECG involves multiple tracings that correspond to the electrical depolarisation and repolarisation of cardiac muscle, with different waveforms correlating to distinct parts of the cardiac cycle (**Figure 1**).

The Nobel Prize-winning discovery by Willem Einthoven in 1903 used a string galvanometer and led to the first instrument that could produce and record a clear 3-lead ECG tracing in humans. The nomenclature developed at the time – P, Q, R, S, and T for the waveforms – is still universally used to this day [3].

The electrodes themselves can be paired in various configurations, forming ‘leads’ that allow for more detailed evaluations (**Figure 2**). When the sum of electrical activity is moving towards the positive electrode, the ECG machine creates an upward or positive deflection. When the electrical activity is moving away from the positive electrode, it creates a negative or downward deflection. This allows us to interpret the cardiac electrical activity in various planes (**Figure 3**).

As medical professionals learned to use this technology, they discovered that the 3-lead system had deficiencies; that is, it was blind to some areas of the heart. Over the following three decades, innovation continued and culminated in the development of the precordial (chest) leads V1–V6 (Wolforth and Wood, Frank

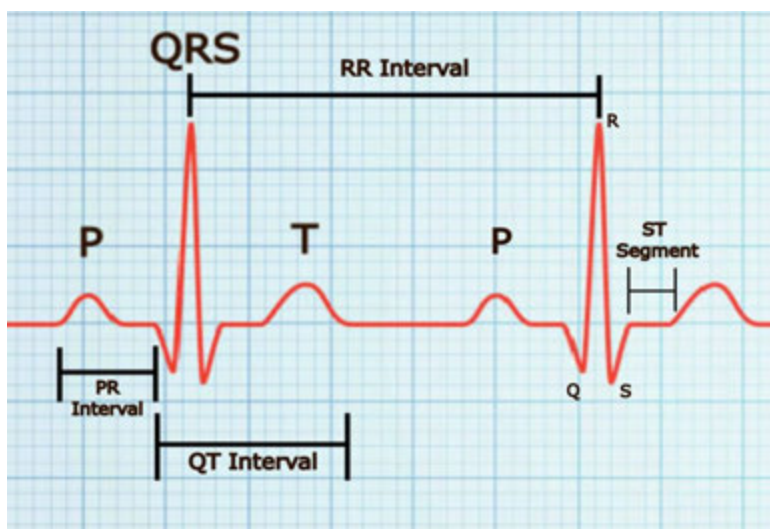


Figure 1.
The waveforms and intervals seen on an ECG.

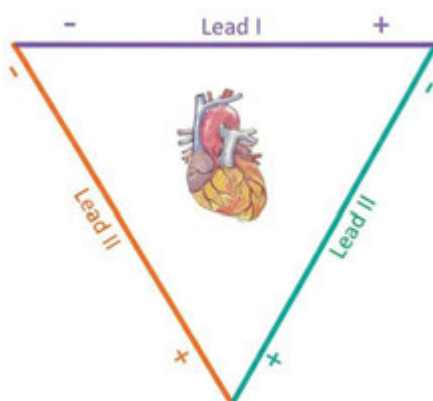


Figure 2.
 Einthoven's triangle.

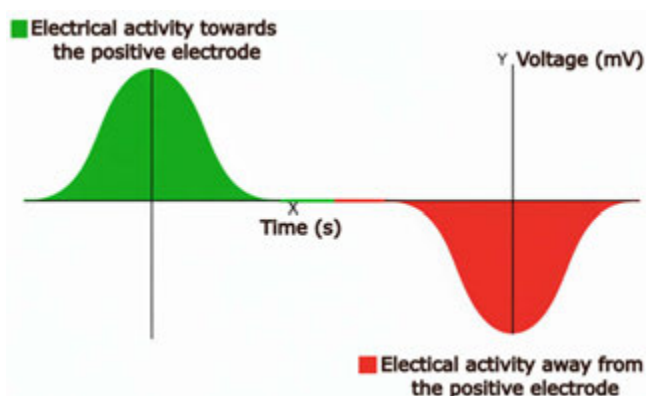


Figure 3.
 Deflections on an ECG.

Wilson) and the augmented leads aVR, aVL, and aVF (Emanuel Goldberger), completing the standard 12-lead ECG arrangement by 1942 [4, 5]. In 1954, the investigation was standardised and recommended by the American Heart Association and remains unchanged in contemporary practice [6].

3. The role of the ECG

The discovery of the ECG was instrumental in allowing clinicians and researchers to correlate cardiac anatomical discoveries, that is, Purkinje fibres, bundle of His, and AV node, with their electrical manifestations on the surface ECG [7–9].

3.1 Ischaemia detection

ECGs led to the recognition of myocardial infarction in the form of pathological Q waves, ST-segment electrical disturbances, and T-wave changes

[10–12]. This series of discoveries culminated in the WHO publishing the first standardised definition of myocardial infarction based on ischaemic pain and ECG changes [13]. Initially used to differentiate cardiac from non-cardiac chest pain, it has evolved to a point where the findings on the ECG by first responders, coupled with the patient’s presentation, decide whether the patient is triaged to a primary PCI centre. New patterns of ischaemia continue to be discovered over a century later, reinforcing the importance of continued research and scholarship in the field.

3.2 Arrhythmia detection

One of the earliest discoveries facilitated by ECG was atrial fibrillation by Sir Lewis, who described it as ‘delirium cordis’ [14]. Now, atrial fibrillation is the leading cardiac arrhythmia diagnosed in adults, with a global prevalence of 59 million in 2019, over a century after it was first described [15]. This was followed by a host of equally revolutionary discoveries, including, but not limited to, Wolff–Parkinson–White syndrome, long QT syndrome, Torsades de Pointes, and ventricular tachycardia classification and localisation [16–20]. Furthermore, the discovery of ECG has contributed to the birth of a major cardiac subspecialty, that is, electrophysiology (EP). EP is a rapidly growing field with an expanding array of procedures available to diagnose and treat electrical cardiac abnormalities such as supraventricular tachycardias, atrial fibrillation, atrial flutter, and ventricular tachycardia.

4. Challenges with ECG interpretation

Effective ECG interpretation remains a complex skill to transfer due to the multiple variables involved in generating a standardised trace, the complex and variable ECG findings, and the time constraints that educators face. Some other factors that contribute to the challenge include as follows (Table 1):

Challenges	Summary
Calibration	Standardised lead placement and calibration.
Normal variants	Requires strong knowledge base to recognise normal variants.
Abnormal variants	Abnormal findings range from subtle to dramatic; multiple abnormalities can co-exist.
Volume of components	Comprehensive ECG analysis warrants rate, rhythm, axis, P wave, PR interval, QRS morphology, QT interval, ST segment, and T wave assessment.
Clinical correlation	Interpretation must consider the clinical context for appropriate patient care.
Resource constraints	Increasing medical curricula limit the time and resources for ECG teaching.
Knowledge attrition	Complex skills such as ECG interpretation are prone to being forgotten without repetition.

Table 1.
Challenges with ECG interpretation.

4.1 Calibration

Arguably, the first step towards interpreting any ECG correctly is having the ECG recorded in a standardised fashion, with each electrode placed correctly, minimising motion artefact, and using standard calibration speed and magnitude (traditionally 25 mm/second sweep speed and 10 mm/mV voltage). If the learner is unaware of these factors as potential pitfalls, or is unable to recognise when they may be erroneously calibrated, it is easy to imagine a scenario where misinterpretation can occur.

4.2 Variation in normal

Effective ECG interpretation relies on the learner having an appreciation of the normal findings and normal variations before abnormal findings can be appreciated. There are numerous findings that constitute a normal finding, such as sinus bradycardia, sinus tachycardia, benign early repolarisation, premature atrial complex, and premature ventricular complex, to name but a few. This adds a significant cognitive load on the learner, and if they do not understand the variations, they will fail to appreciate their significance or lack thereof to a specific case.

4.3 Variation of abnormal

Abnormal ECG findings can range from subtle, such as a tall P wave suggesting right atrial enlargement, to tombstone ST-segment elevation portending an acute coronary occlusion and medical emergency. Additionally, there are various ECG findings, such as bundle branch block, evidence of abnormal electrical pathways in the form of delta waves, and particular patterns such as the Wellen's pattern, which usually require scrutiny from an expert to diagnose and differentiate. In addition, the definition of various pathological abnormalities can vary in different textbooks.

4.4 Large volume of components

The number of factors that the learner needs to evaluate in order to comprehensively read a 12-lead ECG is formidable. In an ideal scenario, an ECG will have its rate, rhythm, calibration, axis, P wave, PR interval, QRS duration and morphology, ST segment, T wave, QT interval, U wave, and R wave voltage all assessed. Sometimes, all of the above are evaluated via pattern recognition in a matter of seconds in a busy clinical setting, such as the emergency department, where hundreds are carried out and interpreted each day.

4.5 Clinical correlation

In the clinical setting, it is vital that the clinical vignette corresponding to the patient's ECG is available and given at least equal, if not more, importance. The same ECG, when interpreted in an asymptomatic individual, will lead to a very different management plan compared to the same ECG in an individual who has presented with syncope or chest pain.

4.6 Resource constraints

With an ever-growing medical syllabus, medical investigations, and increasing patient attendances to health services, the relative amount of time and resources available to teach ECG interpretation has become limited. The lack of standardisation of pedagogy across different institutes, even within the same city, results in a heterogeneously competent group of medical professionals interpreting ECGs in clinical settings.

4.7 Attrition

One of the biggest challenges in medical education, which is generalisable across the various specialties, is how to combat attrition. With an ever-growing syllabus, it is only natural that the more complex skills are susceptible to attrition unless a curriculum is tailored to promote repetition, learner engagement, and re-engagement.

5. Relevant learning theory

Learning theories can seem to have an ‘ivory tower’ reputation when it comes to their real-world application to learners; however, it is beneficial to explore the concepts and apply them to modern education in the digital age in an effort to establish a comprehensive pedagogy.

5.1 Andragogy

This theory was proposed by Knowles in the 1970s and is based on five core assumptions about adult learners [21]. These assumptions explore how adult learners prefer being in charge, use experience as a resource, prefer relevance to real life, and value the immediate application of knowledge. They are also more likely to be internally motivated (**Figure 4**). When applied to health professionals’ education, andragogy is highly relevant, as healthcare professionals are often engaged in lifelong scholarship and residency/training programs where the acquisition of new skills and knowledge is crucial for their own growth and for patient safety. Additionally, medical courses have a large component of postgraduate learners, for whom an understanding of adult learning theories will facilitate better alignment and achievement of the educators’ and learners’ goals.

5.2 Metacognition

The theory of metacognition was popularised by John Flavell in the 1970s [22] and refers to ‘cognitions about cognitions’, that is, thinking about thinking. Flavell’s model includes four components: metacognitive knowledge, metacognitive experiences, tasks and goals, and strategies or actions (**Figure 5**). This theory stresses the importance of developing clinical reasoning skills, evaluating one’s own learning process, planning, and monitoring one’s learning. It focuses on highlighting knowledge gaps and fostering understanding in the learner to enhance their motivation, attention, and retention. This theory supports case-based learning (CBL), small group facilitator-led sessions, and reflective practice.

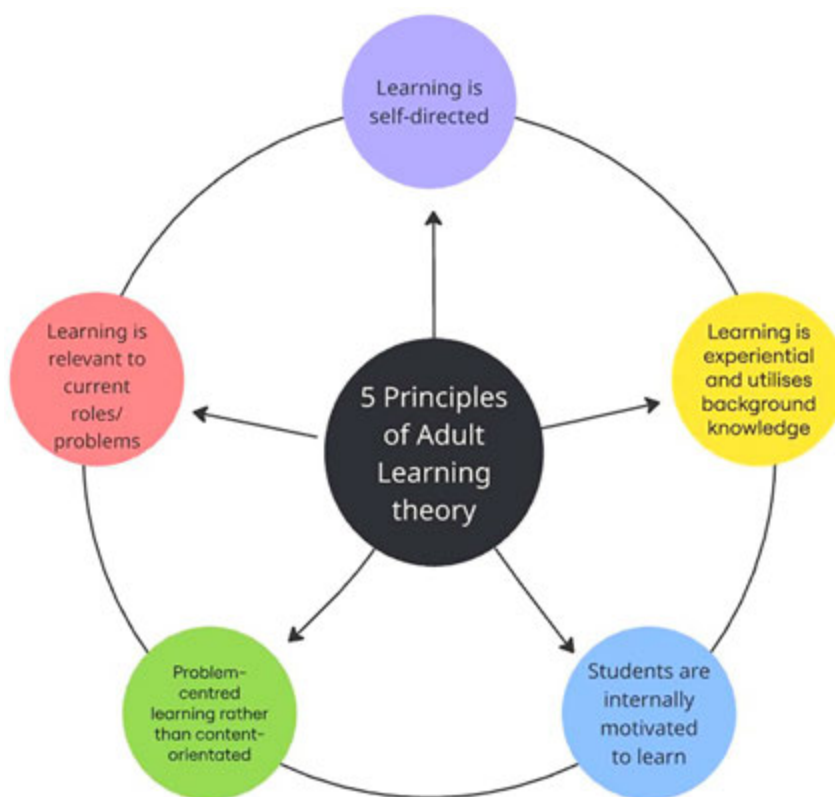


Figure 4.
Five principles of Knowles' adult learning theory.

5.3 Experiential learning

Rooted in John Dewey's philosophical work, experiential learning theory was formalised by David Kolb in 1976 and emphasises learning through direct experience and reflection [23]. Kolb highlighted a four-stage learning cycle, which includes concrete experience, reflective observation, abstract conceptualisation, and active experimentation. This cyclical process facilitates learners as they transform experience into knowledge through reflection. The core of this theory is based on Piaget's proposition that the construction of knowledge is an active process through experience rather than passive absorption [24].

Experiential learning is a key part of healthcare education through electives, clinical rotations, training programs, and hands-on patient care. The popular medical adage of 'see one, do one, teach one' has its roots firmly grounded in experiential learning theory. In modern education, simulation training and CBL represent educational methods that apply this theory.

5.4 Scaffolded learning theory

Lev Vygotsky, in the 1970s, proposed his sociocultural theory, which built upon the works of others in the field. His theory highlighted 'higher mental functions' as originating on the social plane (referred to as interpsychological) before they are

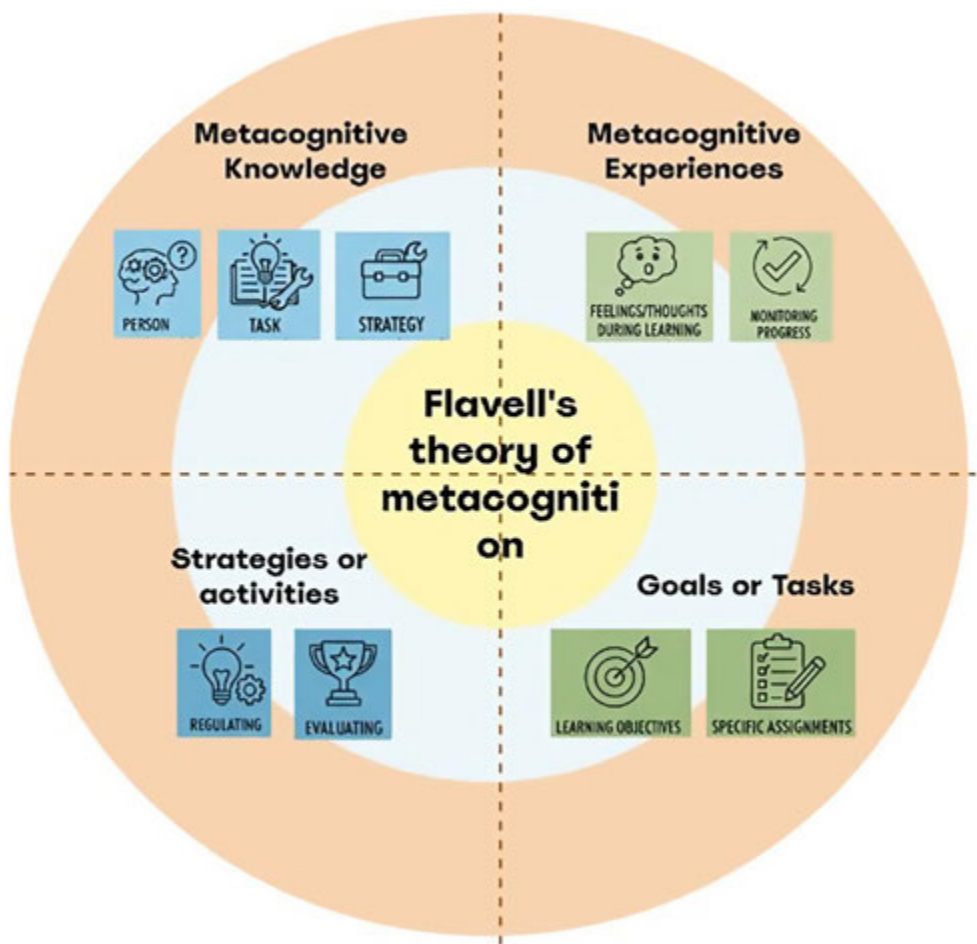


Figure 5.
Flavell's theory of metacognition.

internalised on the individual plane (referred to as intrapsychological). Arguably, his most referenced contribution was the zone of proximal development, which highlights the potential for knowledge development by interacting with a 'more knowledgeable other' or more capable peers. This concept was later termed 'scaffolding' by Wood *et al.* and involves temporary, adjustable support that fades as the learner's competence increases. It requires 'just-in-time' supports that are calibrated to the learner and progressively withdrawn. It functions very well in medical education, where medical professionals are often supervised by senior peers at the start of their careers and then progressively less so as competence develops. It also creates a foundation for peer-to-peer teaching and assessment, which can be a powerful resource in education.

5.5 Social cognitive theory

This theory was initially brought forward by Albert Bandura in 1977; it explores and emphasises that learning occurs through observation and imitation

of experienced role models and highlights the value of self-efficacy and self-regulation [25]. Bandura's observational learning involves four stages: attention, retention, reproduction, and motivation. Social cognitive theory has significant relevance to healthcare education, where both role modelling and mentorship relationships are common and make up a significant portion of the learners' education. In the university student population, the increasing use of small group tutorials and team-based tasks shows this theory in application. The model of healthcare 'teams', whether they are specialty-driven or ward-based, again reinforces the continued relevance of social learning theory in healthcare.

5.6 Reflective practice

Donald Schön was primarily responsible for developing reflective practice theory in his seminal work *The Reflective Practitioner* in 1983 [26]. He distinguishes between reflection-in-action, translating to reflecting while doing, and reflection-on-action, translating to retrospective analysis. The theory builds upon concepts focused on critical self-examination and emphasises professional development using reflection. Contemporary applications of reflective practice in medical education include portfolio reflection exercises, case-based discussions, and debriefing sessions. Reflective pieces particularly facilitate the integration of an artistic and creative aspect into learning and are valuable for processing challenging clinical experiences and developing professional resilience and self-awareness. This may be why the 'Father of Medicine, Hippocrates of Kos' himself was both a philosopher and a physician.

5.7 Cognitive load theory

In the 1980s, John Sweller developed cognitive load theory based on assumptions of human neurocognitive architecture, split into two core components: one being a limited working memory capacity, and the other being unlimited long-term memory with structured schemas [27]. He distinguishes three types of cognitive load: intrinsic load, being the complexity of the task that should be managed or reduced to simple steps; extraneous load, being the distractors which should be minimised; and germane load, correlating to the connections and schemas that should be optimised. Cognitive load theory is central to effective medical curriculum formation, given the complexity of some of the learning goals, and is a key reason why spiralled curricula are growing in popularity.

It should be noted that these learning theories should be evaluated as an interconnected whole when being applied to any specific learning outcome; they do not exist in isolation from each other. For example, there is significant overlap between metacognition theory and reflective theory. Educators benefit from developing an understanding of the different theories so they can facilitate learning in a variety of learners. In our case, when it comes to developing a pedagogy for ECG interpretation in healthcare professionals, we suggest an understanding of the above theories so they can be brought together to form a pedagogical framework that can benefit a wide array of learners. We have outlined the relevance of these different theories when applied to ECG interpretation in **Table 2**.

Learning theory	Application to ECG interpretation pedagogy
Andragogy	The target learners for ECG interpretation tend to have background experience and internal motivation. Harnessing this by providing real-life, relevant scenarios for teaching, such as clinical vignettes, will increase engagement.
Metacognition	A significant challenge in ECG interpretation is the unconsciously incompetent learner. Using metacognitive strategies to highlight knowledge gaps will aid effective, targeted education.
Experiential theory	A high number of repetitions is required to build a framework and pattern recognition in the learner. Curricula should emphasise finding ways to expose students to ECGs in a recurrent manner. A large bank of ECGs with detailed answers should be available, and their completion should be reinforced and/or rewarded.
Scaffolded learning theory	As a complicated learning task, ECG interpretation can be demystified for the learner by letting them interpret multiple ECGs for the basic components, such as rate and rhythm first, then move on to the interpretation of intervals, and then assess for ischaemia and arrhythmia as a way of scaffolding the information.
Social cognitive theory	ECG interpretation is often asked of the learner in clinical settings, such as ward rounds, clinics, and acute hospital settings. Displaying model behaviour and interpretation, and using small group workshops for learning, can help the learner develop a systematic framework for ECG interpretation.
Reflective practice	Utilising an ECG-of-the-week forum thread or asking students to do a 5-minute ECG presentation weekly can encourage both reflection-in-practice when they are in clinical placements or encountering ECGs in their curriculum. It will also encourage reflection-on-practice by ensuring they correlate the clinical scenario with the ECG findings.

Table 2.
Application of learning theory to ECG interpretation.

6. Methods of teaching

When we think of the traditional teaching of ECG interpretation, we usually imagine a musty classroom on a warm summer afternoon, full of dozing students and droning professors. Given the complexity of the topic at hand and the large volume of learners that need to be educated, it is easy to visualise a scenario where many learners' cognitive load, specifically working memory, might be overwhelmed very quickly. Thus, the SPICES model for curriculum development has been popularised in medical curricula (**Figure 6**).

There are various instructional methods that can be tailored to the topic at hand, depending on the resources available, the number of learners, the availability, and the expertise of the instructors. We will now highlight the various relevant methods that are commonly employed as discussed later.

6.1 Lecture-based learning

This alludes to the traditional lecture hall full of learners being passively taught by a lecturer delivering all the content, usually with one-way communication, clear learning outcomes, and a structured presentation. There are obvious advantages in terms of cost and resources in this method: One lecturer can simultaneously educate as many learners as a lecture theatre can hold, sometimes over 200; however, the disadvantages are numerous. Traditionally, lectures promote passive learning with minimal student engagement, and studies show poor retention – as little as 20% after

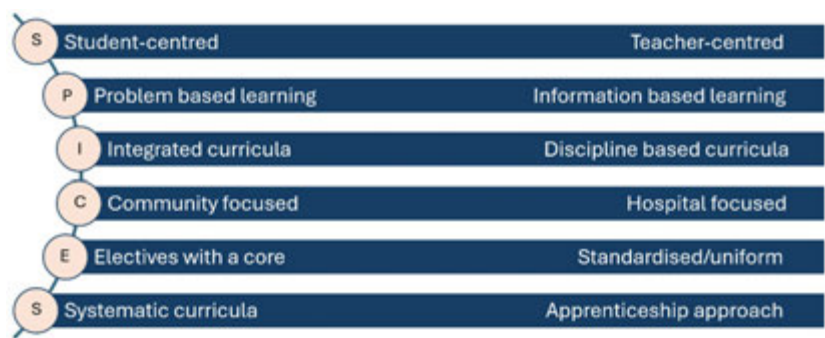


Figure 6.
SPICES model for curriculum design – features of a curriculum plotted on a continuum with traditional methods towards the right.

two weeks, based on commonly cited estimates [28] (**Figure 7**). There is little opportunity for the clarification of abstract concepts. Research shows that making lectures interactive, especially if timed when attention generally lapses, can help alleviate some of the drawbacks; however, this educational method remains primarily teacher-centred.

6.2 E-learning

Employing technology, online lectures, and webinars can be delivered to any number of learners. E-learning can facilitate the delivery of knowledge with unlimited scalability, making it highly cost-effective. The advantages: learners can access information without any geographical constraints, and they can repeat content or consume it at their own pace, at a time and place of their choosing.

Asynchronous learning benefits not only learners but can also ease the burden on educators. Experts can avoid having to make long-distance journeys to reach



Figure 7.
The learning pyramid, adapted from National Training Laboratories, Bethel, Maine.

a specific audience; they can also record their content on a flexible schedule. The disadvantages are reduced interpersonal interaction and communication, passive learning, and reliance on learner self-discipline and motivation for engagement. In addition, access to technological equipment and digital literacy is required.

6.3 Small group tutorials

A small group teaching approach is where 6–12 learners are encouraged by a tutor to have an engaging session about specific discussion topics. The advantages are that the learners generally actively participate by asking and answering questions on the topic, and the learners can identify and fill in knowledge gaps as they are given a degree of control over the discussion. The disadvantages include difficulty in standardising the learning outcomes reached by different groups. Furthermore, it can be difficult to source an adequate number of expert-level tutors on each topic. This can result in inconsistency in the quality of tutorials. Moreover, it is highly resource-intensive for faculty, especially when there are a large total number of learners.

6.4 Problem-based learning (PBL)

A well-adapted approach to moving towards the student-centred part of the SPICES model (**Figure 6**) involves the facilitator preparing problems or scenarios that the learners are encouraged to independently research and discuss in small groups, generally consisting of 6–12 learners. The benefits include self-directed learning in a small group setting, which promotes active learning, social learning, and critical thinking. These advantages are reflected in research comparing PBL with didactic lectures, resulting in higher levels of critical thinking [29]. One obvious disadvantage is the faculty resources required, as they necessitate significant faculty training, time-intensive preparation, and personnel-intensive facilitation. Other drawbacks include the variable learning outcomes and coverage of the curriculum, given the inconsistency introduced by different group dynamics.

6.5 Case-based learning

A commonly used educational method in healthcare education, case-based learning (CBL), promotes students connecting their theoretical knowledge with clinical scenarios, thus preparing them for their ultimate goal of patient-centred care. It generally consists of a small group of 6–12 learners focusing on specific clinical cases as a means of exploring learning outcomes. CBL also allows more control over the learning outcomes that will be explored by the group when compared to PBL. It promotes an active learning style and high levels of both interpersonal teamwork and communication. The drawbacks are akin to PBL, that is, it is faculty resource-intensive, and the discussion and resultant learning may be limited by group dynamics, case quality, and facilitator experience.

6.6 Flipped classroom

A relatively novel approach to education, where the learners have access to and have studied the discussion topic in advance of the class, allows self-paced learning

through the pre-class resources. The repetition of material, the pre-reading, and the higher student engagement result in better retention of information [29]. The higher knowledge floor amongst learners allows for more complex discussion, exploration, and clarification of higher-level ideas and concepts in the actual class. Lastly, it allows for flexible learning, catering to a wider range of learner styles. Disadvantages include requiring high levels of student motivation and discipline. There is an obvious increase in student time commitment, an increased burden on faculty to prepare pre-class resources, and a need to provide facilitators for the class. Technological literacy and access are also required.

6.7 Simulation-based learning

This educational approach aims to use realistic or immersive scenarios to enable a learner to actively engage in decision-making, teamwork, and skill development in a controlled environment. The scenario takes place in a safe environment where competencies can be practiced, and theory applied to clinical scenarios without any risk to patients. It is strongly based on experiential learning theory, allowing problem-solving and decision-making with the benefit of immediate feedback. Drawbacks of simulation include a significant amount of stress and anxiety for the learners, as they are asked to perform unfamiliar skills in a setting that is observed by peers and faculty. There is a significant time, resource, training, and faculty investment required to effectively run simulations, including a brief, scenario delivery, and debrief. There is also a financial burden associated with equipment purchase and maintenance.

6.8 Blended approach

It is plain to see that with such a variety of educational methods at our disposal and the various educational theories to consider, no single teaching method can be expected to achieve the educators' and learners' goals. Medical curricula are moving towards blended approaches that utilise a mixture of methods between large group teaching and small group teaching. Examples of incorporating these educational methods into a pedagogy for ECG interpretation are highlighted in **Table 3**.

Additionally, there has been an embrace of technological advances in the form of online lectures and asynchronous learning, with a significant role played by the COVID-19 pandemic. While the exact strain on health and education resources was different across individual countries, most educational systems had to adapt to a rapidly evolving situation that rendered their traditional teaching methods obsolete. Prior to the pandemic, medical education was heavily reliant on in-person lectures, attachments, tutorials, and placements. Social distancing restrictions due to the pandemic forced institutions to adapt to hybrid and remote learning models to preserve patient, educator, and learner safety.

Similarly, the explosion of public access to generative artificial intelligence (AI) is causing a significant transformation in how future healthcare professionals are trained and assessed. While still regarded with an appropriate degree of caution, there has been a wave of integration of AI-driven tools being tested and utilised in many medical colleges. The potential is clear: if utilised correctly, with caution and a deep understanding, medical education could be significantly enhanced by integrating AI into medical curricula. Examples of its use include AI-driven chatbots

Educational method	Application to ECG interpretation pedagogy
Lectures	Lectures remain the cornerstone of traditional and blended approaches. Methods that increase engagement, such as student participation via quizzes, are the most effective way to enhance the transfer of knowledge. Using clear slides and presentation techniques allows this method to remain low-resource yet affect a high volume of learners.
E-learning	E-learning ECG modules are already in widespread use, providing a platform that delivers background information to the learner, which can be consumed at their own pace and repeated or referenced when required, offering high value.
Small group tutorials	A tutorial format with an expert educator, who can manage group dynamics to optimise learning, clarify concepts, and pass on cognitive frameworks, is highly effective in ECG interpretation.
Problem/case-based learning	Clinical correlation of patient presentations with ECG findings helps embed the relevance and provides a reference for learners. Learning outcomes can be more clearly explored using appropriate cases and questions. Faculty have a role in fostering discussion and collaboration to achieve learning in a social setting.
Flipped classroom	ECG interpretation lends itself well to using the flipped classroom model, allowing students to explore background information such as ECG waveforms, normal findings, and calibration. Subsequently, the lesson serves as a method of exploring the depth of knowledge, giving cognitive frameworks, and providing clinical correlation to solidify mastery.
Simulation-based teaching	Simulation teaching provides an opportunity to teach the indications for performing an ECG, with learners demonstrating the correct technique for obtaining a 12-lead ECG and interpreting the results. Performing these tasks in a simulation setting allows for group collaboration, higher retention rates, and an opportunity for almost immediate feedback to enhance learning.

Table 3.
Application of educational methods to ECG interpretation.

to answer questions and clarify concepts around the clock. AI-driven assessments can help identify knowledge gaps individualised to the learner. AI-assisted cases, coupled with technological platforms such as virtual reality (VR) and augmented reality (AR), open a powerful door where clinical cases can be recreated with high fidelity, and the learner can experience an immersive, risk-free training environment that can be tailored to them. Some examples of these innovations are outlined in **Table 4**.

7. Pedagogical framework for ECG interpretation

There is no universal framework that can be generalised to every learner cohort, as the resources available, learner numbers, pre-existing knowledge, and instructor skills all contribute to the ideal framework.

One key aspect that should be addressed is the fear associated with ECG interpretation amongst learners. A study evaluating ‘ECG Phobia’ in medical students and doctors reported that up to 97.1% of learners felt they did not have enough supervised practice, and 62.5% felt they had received inadequate teaching [30]. When asked in this study what would reduce their fear, students suggested more clinical and practical exposure, more supervision during interpretation, and more interactive online resources. The adage ‘familiarity breeds contempt’ is completely inverted when it comes to complex task learning, where familiarity

Novel/future educational method	Application to ECG interpretation pedagogy
Computer-assisted teaching	Represented by online platforms that can track learning outcomes and create an algorithm to enforce frequent repetition until the learning outcome is achieved, there is an opportunity for explanations as to why certain answers may be correct or incorrect. It has the potential for instant feedback and unlimited practice.
VR-assisted teaching	Carrying out teaching in an emergency department setting with a simulated virtual patient would create a higher-fidelity simulation teaching session than is traditionally possible. Data exists that suggest that although VR methods did not show superiority in interpretation, the VR group demonstrated superior retention compared to traditional teaching methods.
AR-assisted teaching	AR headsets have the capability to provide reference ranges for intervals, algorithms for ECG interpretation, and allow comparison with reference tracings to identify abnormalities or even normal variants. They can also facilitate the teaching of electrode placement.
Generative AI-assisted teaching	Current AI models, such as the Queen of Hearts AI model, have shown a high degree of accuracy in diagnosing acute myocardial infarction. In the future, they may eventually be able to generate high-fidelity ECGs for clinical presentations, some of which may be rare and uncommonly encountered in routine clinical practice.

Table 4.
Future educational methods and potential applications for ECG interpretation.

breeds comfort, and peppering a curriculum with complex learning outcomes in different situations, contexts, and timelines is a reliable method of improving understanding and retention.

Some framework models that may be used include the SPICES model (**Figure 6**) and the 4-component instructional design (4CID) framework (**Figure 8**). The 4CID model was developed by Jeroen van Merriënboer and is grounded firmly in cognitive load theory and schema construction principles. It suggests teaching complex skills through four interconnected components: learning tasks, supportive information, procedural information, and part-task practice [31] (**Figure 8**). The learning tasks are the central pillar of the model, which suggests graduating from simple and extensively supported tasks to increasingly complex tasks with decreasing support. The supportive information is the background knowledge and theories that should be transferred to the learner to give them the conceptual knowledge needed to solve the task. Procedural information is a ‘just-in-time’ delivery of context-specific information to the learner. This decreases the cognitive load on the learner and reduces the risk of the learner being overwhelmed by complex tasks. Part-task practice is the repeated rehearsal of foundational or essential skills until the learner achieves expert-level proficiency and some degree of automaticity, again reducing their cognitive load.

When applying these models to ECG interpretation, one can theorise a spiral curriculum design where the basic physiology of the ECG is taught in the earlier pre-clinical years of a healthcare professional’s education via an interactive lecture, alongside when they are being taught about electrical potential and the pathology of myocardial necrosis. This will act as supportive background information, allowing the learner to form foundational frameworks around lead placement and the cardiac conduction pathway. Differential diagnosis and management could be

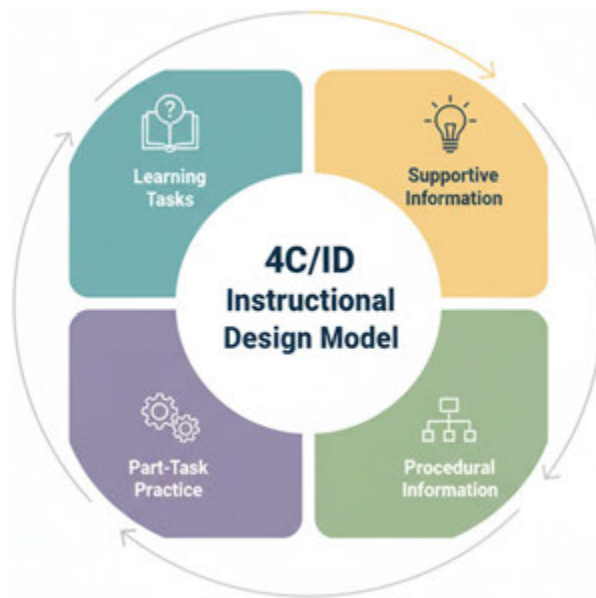


Figure 8.
Four-component instructional design model.

addressed in the future when ECG interpretation is taught in a later year, perhaps just prior to clinical contact with patients in a flipped classroom format. Learning tasks at this stage could include recognition of normal ECG patterns and recognition of the components of the ECG using a framework such as the HEARTS mnemonic developed by El Baba *et al.*, in a small group tutorial or CBL setup, where procedural information is provided in a just-in-time format to compound learning and manage cognitive load [32].

Learners would then get the opportunity for part-task practice when they encounter real patient ECGs in clinical practice. An ‘ECG of the week’ themed forum thread could be created to foster engagement among learners and encourage discussion. Given the need for a high number of repetitions to understand the variations in normal and abnormal, an online e-learning ECG question bank could be invaluable if the questions were in an MCQ format with a short clinical vignette, an explanation provided behind the correct option, and the rationale given for why certain answers were incorrect.

Educators could employ gamification of such a resource by fostering competition between the students to drive motivation through the use of leader boards, badges, or a points-based system for accuracy and completion. There is the possibility of providing metacognitive information (if you asked students about how confident they are in their answers) and just-in-time information (such as algorithms provided for bradycardia, tachycardia, and normal reference intervals like PR, QRS, and QT durations). There is a model that utilises some of this technology in the latest Acute Cardiac Life Support online pre-course work.

As for novel options, there has been research exploring the role of AR in teaching ECG electrode placement. In the future, this could be further improved upon so students can not only practice appropriate electrode placement, but they can also

evaluate the effect of their electrode placements on the ECG waveform in real time. One could also demonstrate the effect of changing the calibration to a slower sweep speed, giving the appearance of bradycardia.

The final goal in the future would be a VR platform where a student could take on the role of a first responder or medical staff member who must judge whether their AI-controlled simulated patient needs an ECG. They could then be asked to perform the electrode placement correctly to receive a case-specific AI-generated ECG. Subsequently, the learner will be expected to correctly interpret the ECG and carry out the next appropriate management steps. At any point, there could be reference information at hand that could be pulled up, such as normal interval ranges or arrhythmia management flowcharts.

Learners may be able to request a breakdown of their performance for feedback, for example, whether the ECG was correctly interpreted and the time taken to do so. They could clarify why an incorrect interpretation was the wrong answer in that particular clinical case and identify their personal knowledge gaps. Other benefits could include the possibility of pursuing multiple repetitions to reach competency.

While this seems like the 'Holy Grail', some of these aspects have already been created and researched. An AR HoloPatient has been created, which can describe the symptoms of a myocardial infarction [33]. Apps are available that allow electrode placement in VR for education [34]. Interestingly, the use of generative AI for ECG interpretation in acute myocardial infarction is already in clinical use and has early data supporting its superiority over 53 certified emergency and 42 cardiac consultant physicians. The Queen of Hearts algorithm boasts an impressive 2.5million ECGs in its training dataset [35]. There is a genuine argument regarding whether there will be a need for physicians to interpret ECGs at all in the future. We believe that healthcare professionals will need to independently have mastery over ECG interpretation despite any technological advances, as there will always be the possibility for AI to 'hallucinate' or misinterpret a variant, such as lead mispositioning, reversal, or artefact incorrectly. A fundamental understanding of the electro-physiological genesis of an ECG is essential to mitigate against the potential harm of hallucination and interpretation by AI. The future will more likely prove generative AI algorithms to be very useful adjuncts to the clinician in confirming their clinical diagnosis and avoiding poor patient outcomes due to human error (Figure 9).

Conflict of Interest

The authors declare no conflict of interest.

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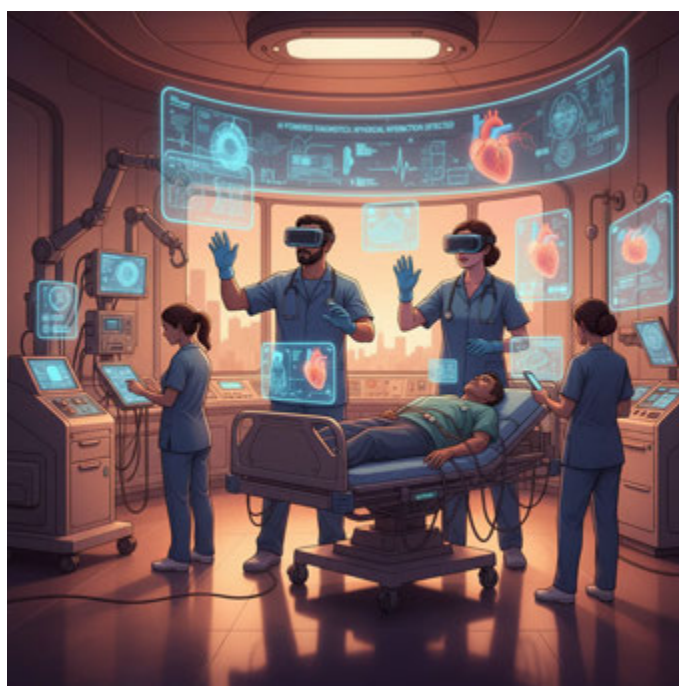


Figure 9.

A generative AI-generated image for demonstration purposes. Prompt: 'Create an image that shows AI and VR Technology being used in a clinical emergency department setting to diagnose a myocardial infarction. Make it an illustrated image with warm colours. Ensure there are 2 doctors, 2 nurses, and a patient in the image'.

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Perspective Chapter: Digital Accessories and Online Platforms in Medical Education

Musa Ibrahim

Abstract

With rapidly growing technology, digital transformations continue to shape the trajectory of many professions, especially educational systems. Medical education utilizes current technologies and plans to accommodate the future in all aspects of advancements, especially the transformations in the learning process. This chapter will explore the evolution of modern technology in medical education, focusing on the efficiency and effectiveness of computer systems and computer software in imparting knowledge. It will also examine the use of mobile devices, mobile apps, and online platforms in sharing information, knowledge resources, and facilitating virtual sessions and various forms of interaction. The benefits of these tools and the capabilities of harnessing emerging technologies are numerous. However, there are limitations regarding use, access, and credibility in some aspects. We must fully embrace digital technologies and prepare for the challenges that emerge with such advancements, adopting the best systems that support learning and addressing the weaknesses with caution.

Keywords: medical education, digital transformation, digital literacy, mobile devices, mobile apps, digital health, addition, tools, computer systems, computer software, technology, online sessions, resources, virtual sessions, services

1. Introduction

Medical education comprises Basic sciences, which include physics, chemistry, biology, and mathematics as a foundation. The basic medical sciences include medical biochemistry, human anatomy, and physiology. Basic clinical sciences include medical microbiology, anatomic pathology, forensic medicine, and clinical pharmacology.

Clinical science includes pediatrics, obstetrics and gynecology, medicine, surgery, and community medicine. This, with a few modifications and additions to preclinical and clinical dental curricula, also comprises dentistry. Postgraduate education continues in different paths, such as residency training or academic programs consisting of years of learning, practice, and research tailored to a particular specialty.

Digital accessories used in classrooms, laboratories, clinics, and libraries confer efficiency and flexibility in knowledge delivery and evolve from traditional methods

to continuously advancing technologies. From using chalk to write on chalkboards to using markers on whiteboards to PowerPoint presentations and the use of projectors, advancements in lecture organization and delivery, as well as enhanced systems and facilities in the learning environment, provide an avenue to access a vast amount of resources. These have shaped modern medical education through interactivity, efficiency, and flexibility, simplifying the learning processes and allowing the acquisition, storage, and access to knowledge resources anytime for continuous use by educators and students [1].

Computer-aided learning, digital case presentations, online pathology museums, mannequin simulations, and holographic dissection labs have enabled precise, ethical, and personalized medical education. These tools ensure uninterrupted learning, even during challenges like COVID-19, while reinforcing key concepts effectively. [2]

Mobile devices, including smartphones and tablets, present significant opportunities to enhance education within health professions. The integration of technologies such as augmented reality, virtual reality, and 3D printing has demonstrated effectiveness in both learning and practical applications [3]. In addition to enhancing communication efficiency, smartphones enable trainees to multitask effectively and provide immediate access to vital resources, including diagnostic references, medical guidelines, patient records, clinical calculations, and the latest research [4].

Digital transformation offers significant advantages and holds considerable promise for the advancement of new technologies. However, there are notable barriers that impact the development and implementation of online learning within medical education, along with challenges related to the adoption of digital tools [2].

This chapter will examine the evolution of modern technology in the field of medical education. It will analyze the efficiency and effectiveness of computer systems and software in enhancing knowledge acquisition. Furthermore, the discussion will encompass the utilization of mobile devices, applications, and online platforms for the dissemination of information, sharing of educational resources, and facilitating virtual sessions, along with various other forms of interaction.

2. Digital accessories in medical education

2.1 Use of computers in medical education

Traditional teaching methods use classrooms equipped with chalkboards and desks that support students in writing notes or jotting down important points using pen and paper, which gradually led to whiteboards with temporary markers to write on. Computers enable educators to access resources such as soft copies of textbooks, journals, websites, and other reference materials to prepare notes as PowerPoint presentations, PDFs, and other forms of documents as necessary. In a classroom setting, these materials can be displayed from the computer system of the teacher or instructor onto a large screen using a device called a projector, utilizing electric power, solar energy, or a rechargeable battery.

Knowledge of computers is essential for preparing learning materials and handling operations while giving lectures or academic presentations. The most common software useful in an academic setting includes Microsoft Word, Excel, and

PowerPoint [5]. These software programs come pre-installed on some computers, while others need to be downloaded, but at some point, they require updates based on the guidelines of the developers. The updates provide newer versions with enhanced or added features and changes to adapt to continuously advancing technologies [6]. Features offered for academic purposes include writing materials using text, multimedia like images and videos, and the design of infographics.

Medical courses require the use of images to fully explain the structures of the human body, the functioning of body systems, and a grasp of pathologies. Clinical scenarios, case simulations, and treatment modalities can be effectively presented on computers. The functionalities of hospital equipment can also be effectively presented on computers. These concepts are much better explained with videos and three-dimensional (3D) pictures, all of which can be prepared and incorporated into study materials created using computer software. Materials created for these purposes are saved as files, stored, and can be shared online or with other devices for access.

Compared to the traditional use of printed textbooks, computers can store and open the soft copies of these textbooks for quick access, with clear image quality and adjustable contrast to read anytime on demand. This saves a lot from carrying loads of printed textbooks that can be heavy for one to take many at a time; computer storage can take as much as one needs.

The implementation of computer-assisted learning, virtual case presentations, online clinicopathological correlation museums, mannequins, and hologram-based dissection laboratories has considerably advanced the capacity for precise learning and reinforcement of concepts within the medical education domain. These advanced methodologies facilitate personalized educational experiences while addressing ethical considerations, thereby ensuring the continuity of medical training, even amidst the challenges posed by the COVID-19 pandemic [2].

Educational institutions now use computers to test and examine students on certain parts of the examination, utilizing the system of computer-based tests (CBTs) in both entry exams, routine assessments, and professional examinations. The rapid expansion of CBTs in recent years is a testament to their significant advantages. These tests deliver real-time scoring and immediate feedback, support individualized testing methodologies, enhance test administration efficiency, and effectively reduce testing costs. It is essential to recognize the transformative impact CBTs bring to the assessment process. However, a study indicates that, despite Korean students having greater exposure to advanced information technologies such as computers, the Internet, and multimedia compared to students from other countries, they did not demonstrate higher scores on CBTs relative to paper-based tests (PBTs) [7].

Application of basic computer knowledge is important to both the teachers and students. E-learning has made computers a great tool in medical education, as will be discussed further in the chapter. It is now common for students to have personal computers to access learning materials shared, search for more information on the internet, and prepare assignments as well as projects, present and interpret data from one's research.

2.2 Mobile devices and newer technologies

Mobile devices, including smartphones and tablets, offer a range of functions, from communication in the form of calls and texts to the use of social media and the

internet. These basic functions, in one way or another, can help communicate arrangements for study schedules and the sharing of vital information among students. A study conducted at the Medical College of the University of Sharjah in the United Arab Emirates revealed that a vast majority (95.9%) of students possess at least one type of mobile handheld device. Most of these students (90.1%) used their handheld devices while learning. The majority of students (83.2%) use their handhelds when learning individually on their own time, whereas about half of them (48.3%) use them in learning with friends, i.e., collaboratively. Students utilized their devices mostly to complement and augment their learning in different contexts [8].

As with computer software, these devices have applications (apps). With the use of apps, materials or resources accessible on computers can be accessed via mobile devices. PDFs, PowerPoint presentations, and other documents can be stored, opened, and shared across peers with the use of mobile apps. Openly or secretly, the recordings of delivered lectures, snapping pictures of some book pages, and taking screenshots of important points from materials accessed via mobile are among the habits used by medical students to gather lots of information they find useful, especially when preparing for assessments and exams. Pictures, snapped pages, and screenshots can be saved and used for preparing another file, as with computers. The use of social media can be beneficial if students find some pages updating academic posts timely or providing links to knowledge resources of their institutions or journals.

Both computer and mobile devices have common applications to enhance learning and practice, provide ease of access, and improve the performance of students [9]. On the flip side, they come with a lot of limitations and disadvantages, as will be introduced later. Regardless, students need to be informed of the negative impacts and adopt a wise approach to use newer technologies positively.

The integration of digital stethoscopes into medical education significantly enhances the auscultation skills of students. These advanced tools enable real-time and pre-recorded playback of audio, allowing multiple listeners to engage with the sounds simultaneously, even at slower speeds without any loss of clarity. Additionally, they come equipped with external noise-filtering and sound amplification features to ensure clear auditory experiences. A key benefit is the visual display, which aids in pinpointing the location of sounds throughout the cardiac cycle, providing a comprehensive understanding of heart sounds [10].

Three-dimensional (3D) printing is increasingly recognized as a tool to enhance healthcare education and practice. Studies show its effectiveness in improving the understanding of human structures and functions, and it can also be utilized in educating patients. Virtual and augmented reality applications have proven effective in enhancing the learning experience in various health profession courses by creating synthetic environments that mimic the real world and provide interactive models [3].

An amazing tool of great wealth, knowledge, and experience that deserves mention is artificial intelligence (AI), which surfaces the global landscape with vast capacities and many implications. This powerful entity undoubtedly deserves a dedicated chapter to thoroughly explore its breadth and impact.

3. E-learning and online platforms

The use of the internet in search of knowledge from every discipline was found promising. Google appears to be a global resource center for students, educators, and

patients, linking to various medical education websites, journals, and pages of educational institutions.

Apart from access to a wealth of resources on the go, the current trend encapsulates virtual sessions, online platforms, and social media usage in learning.

E-learning offers an avenue to undertake programs online using learning management systems to facilitate virtual sessions such as Zoom, Google Meet, Microsoft Teams, Moodle, and many more. These platforms allow lectures to be delivered to a wide range of participants from different locations, with functionalities for sharing slides and other files, as well as interactive features such as enabling participants to raise their hands, display reactions, and speak while sharing their live video. Among these, some offer free access, either open or for a limited period, while others provide premium packages that require a subscription for unlimited use, offering more personalized and adaptive features.

The increased adoption of e-learning has surfaced in many institutions, especially during the COVID-19 pandemic. This served as a stimulus for many schools to augment physical programs with online sessions, an advantage that lasts beyond the COVID-19 pandemic by reducing geographic and time barriers to accessing knowledge in different locations [1]. Important educational events are held via these systems, such as conferences, workshops, seminars, and focus group discussions.

Massive open online courses (MOOCs) include the use of platforms such as Coursera, edX, Alison, Canvas, and many others that provide both free and paid courses, serving as tools for medical education, patient education, and for professionals seeking continuing medical education (CME). Utilizing mobile devices and internet services, these platforms offer a series of videos and files to access knowledge [11]. The systems are programmed to include various methods of user assessments, quizzes, and examinations, and to provide certificates of achievement upon completion.

Medical education platforms, known as learning management systems, continue to play a significant role in shaping students' performance in academic work, clinical practice, and preparation for board exams. Platforms such as Amboss, Lecturio, and Osmosis provide a wealth of content for medical education, structured in engaging formats, including videos, patient simulations, animations, games, texts, and podcasts, accessible to students, health professionals, and the general public. These platforms also provide explanations and patient education resources to support care. Web pages are designed for access via computer or mobile devices through browsers, and a mobile app is available for learning anytime, anywhere. Depending on personal preference, an individual may choose to use a single platform or a combination of two or more. Each platform offers a catalog of courses, question banks, events, and plans tailored to suit an individual's budget and time, according to their level of training or practice. Making it more engaging is the use of e-mails to send reminders and updates, a feature utilized by all the platforms.

Since its establishment in 2012, Amboss has been adopted by over one million healthcare professionals in more than 180 countries and by over 50 medical schools globally, as stated on their website. Prominent institutions such as New York University School of Medicine and Yale University have incorporated Amboss into their educational frameworks. More than half a million learners and educators from more than 175 countries are using Lecturio. Similarly, Osmosis has millions of users worldwide.

Social media has become a common tool among students and medical practitioners and serves as a vehicle for the delivery of information and health education. With significant potential to augment formal education, social media allows users to share various content, including texts, images, videos, and files of different formats. By making use of high-speed internet and mobile devices, these platforms present a growing medium to capture and share high-quality audiovisual media. Platforms in common use include Facebook, Twitter, Instagram, WhatsApp, and podcast-hosting applications. Accelerated by the COVID-19 pandemic, many physicians have effectively utilized social media as a platform to discover and disseminate health-related information, facilitate communication with colleagues and trainees, promote their clinical practices, advocate for health initiatives, influence health policy decisions, share advancements within their fields, and publicize their research initiatives [12]. While harnessing its effectiveness, the negative impacts of social media still exist, as will be discussed further.

YouTube is a large and highly accessed video-sharing platform that provides a wealth of medical education content, in both formal and informal education standards. Many channels owned by individuals, physicians, and organizations present high-quality videos to augment learning and inform the public [12]. It is amazing to learn that these platforms maintain an algorithm based on one's most accessed content and provide similar updates and suggestions to attract regular engagement and individualize the benefits.

4. Overall benefits of digital integration

Digital transformation in medical education is a journey of diverse benefits that favor adoption and increase use, despite challenges, limitations, and some negative effects accompanying such developments.

4.1 Flexibility

Different from the traditional system of face-to-face learning, the use of e-learning, digital devices, and online platforms makes learning flexible, allowing students and educators to access resources anytime from anywhere [1, 13]. This addresses barriers such as time and location and creates a remote opportunity to teach, learn, and assess learners. It facilitates time management while providing access to unlimited resources at one's convenience [14].

4.2 Convenience

The convenience of online learning is one of its greatest strengths, empowering students to study from home at their own pace and on their own schedule. This flexible approach encompasses both synchronous learning, where students participate in live lectures together, and asynchronous learning, which allows individuals to access materials whenever it suits them. Moreover, this model effectively supports diverse learning styles, enabling slower learners to take charge of their education through self-paced knowledge acquisition [14]. They can review lectures, complete assignments, and confidently catch up with their peers, ensuring everyone has the opportunity to succeed.

4.3 Accessibility

This has to do with relatively similar functions to flexibility and includes simplicity in finding what matters at any point in time, allowing students to learn at their own pace [14]. As with computers and mobile devices, the ability to search in seconds, navigate through the content, and go directly to the index or an individual page with a few clicks is invaluable. Simply put, scrolling through screen pages is easier than turning the pages of a book or moving through the catalog of a physical library.

4.4 Adaptability and personalization

Adaptive features of e-learning tools and mobile devices, such as storage and retrieval of files [2], enhance their usability. Specialized functions of devices to suit individuals' needs include the ability to snap captivating details, take screenshots, copy, highlight, underline the desired texts, and save files to favorites for quick access. Arranging folders according to course or subject similarity and receiving focused suggestions from an algorithm in online resource searches provide a wider opportunity to explore diverse literature. Moreover, keeping track of the history and chronology of recent files, as well as sorting them, facilitates ease of access.

Visual enhancement of readability, such as customizing the view to adaptive brightness, resizing pages, and occasionally choosing display colors, makes the user more attracted to their device while learning.

4.5 Cost effectiveness

The access to knowledge in an established digital system has been proven cost-effective, with reduced costs compared to traditional systems, although the cost to initiate the system appears substantially higher [13–15]. Transport to the learning environment, finding and purchasing knowledge resources, and the burden of carrying and storing them are all costly efforts associated with the traditional approach, which are no longer a concern with digital systems.

4.6 Global collaboration

The advent of e-learning and the use of online platforms accelerated international collaboration through webinars and conferences, facilitating real-time interaction among professionals and the dissemination of innovative practices [1, 16]. This also fosters students' unity across different nationalities, sharing fun, knowledge, and experience.

5. Challenges and the negative impacts

As the global landscape continues to evolve, the incorporation of digital technologies into medical education and routine interactions has established itself as a lasting reality. However, it is imperative to recognize the limitations pertaining to usage, accessibility, and credibility in specific domains, alongside the potential adverse effects that may emerge. Acknowledging these challenges underscores the

critical need for a thorough understanding and prudent management of their implications.

5.1 Digital divide

The geographical location of students has significantly influenced the variability of internet connectivity, playing a crucial role in the effectiveness of online education. Students from lower socioeconomic backgrounds and rural areas have encountered considerable challenges due to inadequate access to technology, the necessity of device sharing, and unreliable network connections [17].

5.2 Quality and credibility

Among the challenges online education faces is a lack of credibility. Medical education requires fidelity of content and accreditation, which cannot be ascertained in some online courses or resources from these platforms [14]. There is a possibility that misinformation, incorrect information, and overzealous advertising can disrupt students' attention and reduce the quality of information.

5.3 Lack of physical interaction and low clinical skills

The interactive nature of digital technologies, especially in online platforms and e-learning, emphasizes the theoretical aspect more than clinical and practical skills. Patient simulation and 3D visuals might provide some useful information, but face-to-face interaction, with the opportunity to receive real-time feedback and monitoring, is the best way to gain hands-on clinical acumen and training, as well as to demonstrate empathy in patient care [14].

5.4 Plagiarism and malpractice

Integrity of assessments through the online education system is questionable, as students might have access to the course materials [18]. The presence of multiple resources accessible may increase dependency on other people's work in the field of research and liability to plagiarism. Susceptibility to information overload may push some students off track and make it difficult to find the focus needed to use the necessary information.

5.5 Cost of implementation

Digital integration costs are high to initiate, although the access can be cost-effective [2, 15]. Similarly, the cost of maintenance and the technical skills are important demands for institutions to effectively establish a reliable system of education [16].

5.6 Lack of motivation

Physical interactivity strengthens student engagement, and this provides adequate motivation in the traditional approach. However, a lack of motivation and support from educators and peers remains an important challenge in online education [14].

5.7 Digital health issues

Internet use and the advent of mobile devices have brought about changes in human behavior, with the potential for addiction, increased screen time, and social isolation. This leads to emotional burnout and mental health imbalances.

The increased amount of time spent by young people using digital technologies was found to have a relationship with mental health outcomes, including depression, anxiety, suicide-related behaviors, and well-being-related outcomes such as loneliness, low self-esteem, and stress [19].

The digital landscape presents a multifaceted set of challenges for young people today. One of the most pressing concerns is the prevalence of cyberbullying, which not only affects emotional well-being but can also have lasting psychological effects. Moreover, exposure to violent content and pornography can skew young individuals' perceptions of reality and relationships, impacting their development. Another significant issue is the pressure to conform to unrealistic standards of beauty and lifestyle. This pressure often leads to harmful behaviors, including disordered eating and other health issues. The threat of sextortion further compounds these challenges, creating an environment of fear and vulnerability for many. Additionally, targeted marketing of harmful products and the allure of online gambling open further avenues for potential harm. It is essential to address these issues to protect the well-being of young individuals in the digital space [19].

6. Recommendations

The increased adoption of digital technologies in medical education, with its promising positive outcomes and potential to develop newer opportunities, comes with growing concerns about the challenges, limitations, and negative impacts. Hence, the following recommendations were made.

The educational institutions need to develop a sound infrastructure necessary for utilizing digital technologies and to recruit technical staff who are competent in handling and maintaining these developments. Effective network connectivity and the sound functioning of the devices should be ensured.

Students should be encouraged to develop digital literacy skills through extracurricular activities. Alternatively, basic digital knowledge should be integrated into the medical curriculum.

Public health practitioners need to enlighten health workers, students, and the general public on the digital harms associated with health and well-being. This can be augmented by mental health specialists, with massive advocacy and support, as well as clinical consultations when necessary.

Clinical skills and practical experience are best gained through physical interaction. Although the use of virtual reality, 3D printing, and case simulation can help prepare students, their use is more beneficial as an augmentation to human interaction, not as a replacement. Authorities can prepare medical professionals with basic knowledge of teaching and research by using newer technologies through updated courses, workshops, seminars, or presentations at academic conferences.

Further research is needed to study individual online platforms and their impact on medical education and training.

7. Conclusions

Digital accessories and online platforms offer a variety of applications designed to enhance learning and facilitate practice. However, it's important to acknowledge the limitations and disadvantages that accompany these technologies. We must embrace technologies to successfully harness the beauty of knowledge and to effectively train the current and coming generations of health professionals. While maintaining the fact that the quality of service and showing empathy in care are priorities, students need to be aware that human interaction is the cornerstone. But we cannot fold our hands and fail to adopt newer developments that are becoming part of us. Knowledge of how these functions work, the promising benefits, and the potential negative impacts associated with their use is essential. By developing a thoughtful and informed approach to integrating these newer technologies into the learning process, students can harness their benefits while mitigating any adverse effects.

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*Edited by Michael S. Firstenberg,
Stanislaw P. Stawicki and Julie M. Aultman*

This Edited Volume, *Medical Education in the Age of Digital Transformation*, is a collection of reviewed and relevant research chapters that offer a comprehensive overview of recent developments in medical education. The book comprises single chapters authored by various researchers and edited by an expert in the field. All chapters are complete in themselves but united under a common research study topic. This publication aims to provide a thorough overview of the latest research by international authors in education and to open new avenues for further development.

*Katherine Meltzoff,
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