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Research paper

A smarter perspective: Learning with and from AI-cases

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ABSTRACT

Artificial intelligence (AI) has only partially (or not at all) been integrated into medical education, leading to growing concerns regarding how to train healthcare practitioners to handle the changes brought about by the introduction of AI. Programming lessons and other technical information into healthcare curricula has been proposed as a solution to support healthcare personnel in using AI or other future technology. However, integrating these core elements of computer science knowledge might not meet the observed need that students will benefit from gaining practical experience with AI in the direct application area. Therefore, this paper proposes a dynamic approach to case-based learning that utilizes the scenarios where AI is currently used in clinical practice as examples. This approach will support students' understanding of technical aspects. Case-based learning with AI as an example provides additional benefits: (1) it allows doctors to compare their thought processes to the AI suggestions and critically reflect on the assumptions and biases of AI and clinical practice; (2) it incentivizes doctors to discuss and address ethical issues inherent to technology and those already existing in current clinical practice; (3) it serves as a foundation for fostering interdisciplinary collaboration via discussion of different views between technologists, multidisciplinary experts, and healthcare professionals. The proposed knowledge shift from AI as a technical focus to AI as an example for case-based learning aims to encourage a different perspective on educational needs. Technical education does not need to compete with other essential clinical skills as it could serve as a basis for supporting them, which leads to better medical education and practice, ultimately benefiting patients.

1. Introduction

The introduction of new technologies in the medical field forces doctors to rapidly change their practice due to new societal and regulatory needs concerning the use of these technologies in the clinic. The development of artificial intelligence (AI) has created many enthusiastic claims because it promises to support the care of patients and improve healthcare. The AI subfield of machine learning (ML), uses mathematical algorithms with statistical techniques to identify data patterns and obtain predictions and is widely viewed as a potentially efficient technique for analyzing complex health data [1]. Other applications such as epidemic modeling and early symptom recognition could subsequently be used for early warning systems and prompting fast mitigation strategies for epidemics [2]. Diagnosis and treatment are also possible applications [3]. Therefore, AI could impact individual health and the health system.

There may be many prospective applications for AI in medicine, albeit there are also concerns and questions regarding its safety, especially when using unintelligible ML models for clinical decisions. ML, particularly those algorithms with multiple decision layers such as neural networks, are challenging to human understanding because underlying explanatory factors might be hidden deep within the model [3,4]. However, accepting the premise that AI's potential clinical benefits will eventually translate into deploying and widely implementing AI in clinical practice raises questions on how to train doctors to perform their jobs with AI. Human experts are expected to retain their agency and have the means to understand - at least contextually - the capabilities and perils of using this technology in the care process. However, even when the AI explainability challenge is resolved, training doctors to work safely with AI remains a stumbling block. Even the most 'explainable' model might require doctors to have sufficient technical literacy to use it safely in practice. The growing spread of AI applications

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adds pressure to reform and adapt educational models to train doctors to handle the challenges and changes introduced by technology.

This article first analyzes the current paradigms in medical education for AI and questions if those practices respond to the identified needs. Second, we propose a dynamic interpretation of case-based learning that utilizes existing clinical AI applications/scenarios as examples for students (hereafter: CBL-AI). This paper provides theoretically informed arguments on why and how to use CBL-AI while also offering benefits to encourage students' reflections, ethical thinking, and an opportunity for interdisciplinary collaboration.

2. Re-interpreting the current medical education paradigm for AI

There is increasing concern regarding how healthcare professionals can acquire knowledge of technology and AI, as the changes generated by any technology have yet to be integrated into teaching and learning across medical education. The inclusion of AI courses in the medical faculty is at present debated. Two reasons may play a role: doctors' education is traditionally focused on clinical work more than technology, and medical curricula might be already overloaded with the teaching of basic science and clinical knowledge. Some academics have suggested formally teaching AI in medical schools, including programming languages, mathematical modeling, and general technical concepts [5,6]. In Europe, pilot research showed that it is feasible to teach computer programming to nurses and doctors in as little as two days [7,8]. Indeed, practical competencies on how to program could benefit medical students by shattering previously-held perceptions, lessening fears, and increasing their willingness to work with technology [7,8].

However, in a comprehensive review of medical curricula in Germany (2021), the most frequently mentioned need by the institutions is to gain practical experience with AI, such as getting to know AI's field of application and its implications for the work environment and society [9]. Although, the majority of institutions offer only extracurricular or elective education on the fundamentals of AI. Therefore, it is possible to question if these educational methods, providing knowledge on AI fundamentals, will be enough to fulfill the practical needs observed by the institutions.

Medical education should apply caution to the consideration of adding technical knowledge to the medical curriculum. Adding knowledge about programming or focusing on technical concepts could misplace and over-focus the attention on theoretical principles. The rigid separation created between AI knowledge and clinical knowledge could fail to accomplish the teaching of competencies necessary to complete everyday medical work with AI. An important building block of competence-oriented focus might require focusing on practical problem-solving skills, i.e., learning *computational thinking*. *Computational thinking* is a cognitive skill that goes before and beyond writing the programming code. It is an analytical and methodological approach that enables students to solve challenges by processing information and dividing a problem into solvable pieces, similar to how a computer would do. Therefore, it includes literacy to understand which issues can and should be solved with AI and how to formulate and decompose those problems for a machine's understanding. For example, by creating instructions for computers, assessing the technology's limitations, evaluating the solutions' performance, and anticipating how interactions between humans and machines will work [10].

Computational thinking requires understanding the underlying assumptions that are the foundation of AI, including understanding how an AI might solve a problem. In response, educational systems worldwide have integrated computational thinking classes at the school level[1] (e.g., Estonia, Israel, Finland, the United States, and the United Kingdom), aiming to support students' analytical and critical thinking concerning technology [10] (Table 1).

Computational thinking is a fundamental skill beyond any specific programming language that generally benefits doctors and people, especially with AI's increased usage in everyday circumstances requiring everyone to evaluate the capabilities, benefits, and potential problems of using technology. For example, menstrual tracking apps can utilize AI to predict menses and fertility windows. However, this prediction comes with the caveats that it depends on: accurate information being provided, regularity of the menstrual cycles, and contextual knowledge of life events. Suppose a woman uses an app for family planning contraception (avoiding intercourse in the fertile window). In that case, it

Table 1
Example of implementation of computational thinking in the UK's national school curriculum for computing education [11].

Key general steps for computational thinking: • Decomposition • Pattern Recognition • Pattern Abstraction • Algorithm Design
Example of the UK's national curriculum: • Understand what algorithms, how are they implemented that programs execute by following precise and unambiguous instructions • Create and debug simple programs • **Use logical reasoning to predict the behavior of simple programs** • Use technology purposefully to create, organize, store, manipulate and retrieve digital content • **Recognize common uses of information technology beyond school** • Use technology safely, respectfully, responsibly and securely • Design, write and debug programs that accomplish specific goals • **Solve problems by decomposing them into smaller parts** • Use sequence, selection, and repetition in programs • **Use logical reasoning to explain how some simple algorithms work and to detect and correct errors** • Understand computer networks, including the internet • Use search technologies effectively, appreciate how results are selected and **be discerning in evaluating digital content** • **Design, use and evaluate computational abstractions that model the state and behavior of real-world problems and physical systems** • Understand several key algorithms that reflect computational thinking [for example, ones for sorting and searching] • Understand simple Boolean logic • Understand how numbers can be represented in binary • **Understand the hardware and software components that make up computer systems** • Understand how instructions and data are stored and executed within a computer system • Develop their capability, creativity and knowledge in computer science, digital media and information technology • Understand how changes in technology affect safety, including new ways to protect their online privacy and identity, and how to report a range of concerns

[1] There is a variety of resources to teach computational thinking, from pattern recognitions or decomposition activities to debugging. The International Society for Technology in Education or the Digital Technology Hub offer several resources to teach computational thinking. (Available at: https://learn.iste.org/d2l/lor/search/search_results.d2l?ou=6606&lrepos=1006 and https://www.digitaltechnologieshub.edu.au/search#/site-search?pageNumber=1&keyword=GoogleCT)

becomes vital to understand these are estimates that cannot be 100 % accurate, as they also need to be taken within that person's context and with precaution. When one understands machines' competence, applicability, constraints, and the context behind their behavior, it becomes easier to assess the capacity of any technology realistically. Therefore, *computational thinking* becomes a vital skill for developing critical awareness regarding the technology we use daily. Additionally, it helps people have pragmatic expectations of the machines' performance and technical capacities, avoid being entrapped by 'hype' or 'wishful thinking' and see unfounded risks and doomsday scenarios.

Yet, doctors have the specific need to learn how to use AI directly in the clinical context. The applicability of *computational thinking* in the clinical context, sometimes called "intuition of AI", includes understanding the theoretical and technical basics of AI, its practical application, and the ethical, legal, and social issues AI prompts in healthcare [9]. Translating these skills to the medical context requires doctors to critically dissect AI solutions and avoid a passive and disjointed understanding of technical concepts that still permits them to continue focusing on patient care (Table 2).

According to a literature review published in 2021, there is a consensus in the academic literature that doctors have insufficient AI understanding and that a shift from "knowledge acquisition" to "knowledge management and communication" might be required to overcome the need for understanding AI [12]. This transition entails doctors focus not on AI knowledge but on developing the skills to handle AI from technical terms and clinical implications. In technical terms, input data directly affect the output, which is reflected in the colloquialism "garbage in, garbage out," which refers to the fact that the quality of the data/input can misguide the output [13]. The clinical implication is that an algorithm should be trained with relevant clinical input and provide reasonable outputs to the health scenario. Therefore, adjustments to current teaching models in medicine are necessary to create a link between technical and clinical knowledge. The transformation of teaching models includes introducing dynamic teaching strategies that support and guide the learners on the skills they need to work with AI but also to be doctors with good medical skills who positively impact the development of healthcare and reflect, evaluate, and critically think about clinical practice.

Table 2
Examples of learning opportunities by utilizing CBL-AI. Glaucoma Example from Raghavendra et al. (2018) [16]. Example of racial bias in algorithm from Obermeyer et al. (2019) [17].

Example of AI scenarios/ applications existing in practice ('cases')	AI system for glaucoma's diagnosis with image recognition	AI system to predict patients' health needs and allocate resources accordingly
Details	Deep convoluted neural network for the diagnosis of glaucoma from fundus images trained with 1426 images	Risk prediction algorithm design to predict healthcare needs based on historical patients' data. Goal: Target policy interventions and allocate more resources to those with the greatest health needs. Results: In reality, the algorithm prediction of risk is a prediction of health cost. This results in a bias of underestimating the needs of Black patients due to systemically being offered less care and secondarily being less costly
Highlighted concepts of clinical practice	Definition of glaucoma, epidemiology, the eye's anatomy, risk factors for glaucoma, diagnostic criteria	Comorbidities and risks, health disparities, and social determinants of health
Highlighted technical concepts of AI	Pattern recognition in images, features of deep convoluted neural networks, limitation of image recognition, specificity, sensitivity	Risk score prediction models, analysis of biasing mechanisms, the importance of feature selection, and problem formulation

3. Changing the perspective: case-based learning using AI as examples

Learning theory holds that students learn new knowledge and skills most effectively when presented in the application context and when the material is immediately useful [14]. Therefore, raising the question of how to teach students about AI directly in the clinical context and allow them to integrate technical and clinical knowledge. The utilization of case-based learning (CBL) might be the answer. CBL is an established pedagogical method that utilizes examples (called 'cases') to effectively correlate medical knowledge and clinical practice [15]. CBL can move students from acquiring knowledge to seeking meaning through analysis skills to specific situations. In that sense, CBL applied to AI education entails studying scenarios where AI is currently used in clinical practices as examples (CBL-AI). This application exposes doctors to the various components of AI and builds a framework to explore relevant topics that affect clinical practice and AI. Therefore, AI does not need to be viewed as a competing educational need but could be viewed instead as an educational resource.

Furthermore, using CBL-AI can be a basis for students to move to case-based reasoning (CBR) and apply what they learned with CBL-AI to new experiences. While CBL is a methodology for medical education in which a 'case' is utilized as a focus example for learning purposes, CBR is a cognitive process that applies reasoning from old experiences to solve new problems or situations [18]. By identifying commonalities between problems, students can adapt to new demands and reason by experience - a beneficial skill for clinical practice. For example, students can understand that using relevant clinical features for an algorithm brings better results and apply this knowledge in the discussion for another algorithm while analyzing other CBL-AI or advising AI developers in feature engineering (Fig. 1).

Furthermore, CBL-AI could offer the opportunity to integrate technical concepts with other aspects of the curriculum. The competencies required to work effectively with AI often overlap with those needed to fulfill other core aspects of doctors' roles [6]. AI and its implementation in clinical practice here function as a facilitator of learning. Discussions on the importance of AI explanations could encourage learning on technical challenges and the essential foundation of doctor-patient communication. For example, examining the quality and type of explanations provided by AI can demonstrate the importance doctors' explanations have for patients to support their active and autonomous participation in clinical decision-making. Viewed in this way, CBL-AI as a dynamic methodology becomes a learning playground to learn other essential medical skills.

4. A smarter perspective: implementing AI education and supporting medical skills

The academic literature emphasizes how AI might be a supplement or tool for doctors rather than a complete substitution [21]. The same can be valid for medical education, as AI does not need to replace other modules. AI could provide a valuable and relevant opportunity to be a tool for doctors to learn from and for their current clinical practice - a new paradigm of medical education *with* AI instead of medical education *for* AI. In the following section, we present how utilizing CBL-AI can support the development of three vital skills of doctors: reflection and critical thinking, ethical thinking, and interdisciplinary collaboration. However, this is not meant to be an exhaustive list; instead, it is intended as a snapshot of three skills that would benefit most (easily) from learning with AI.

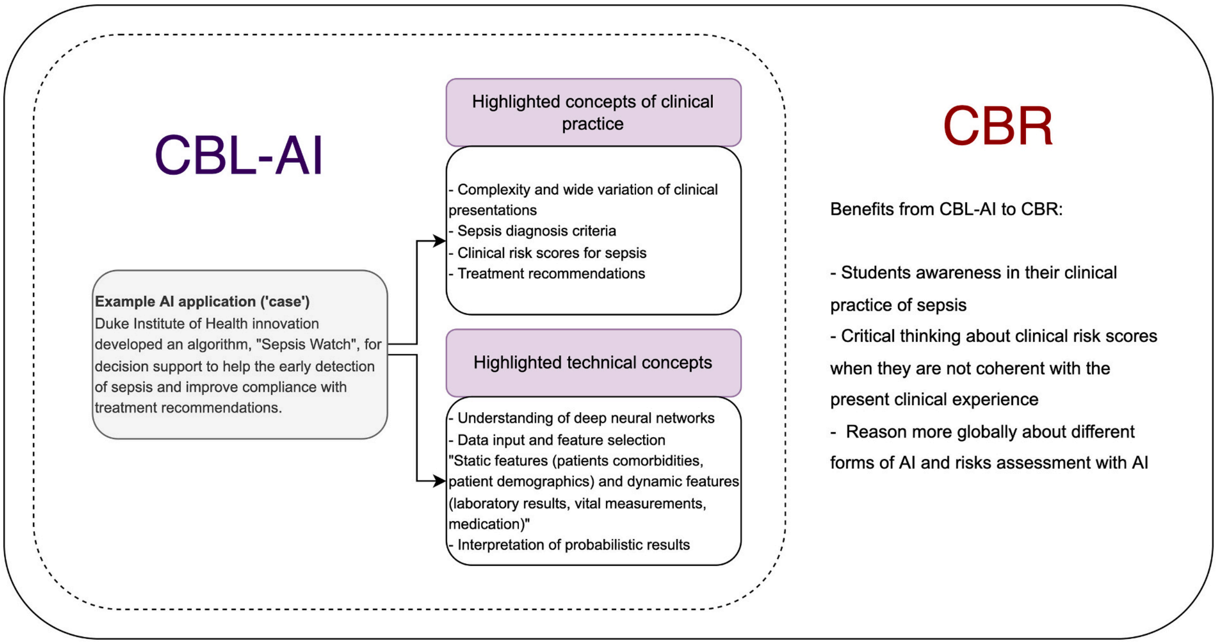

Fig. 1. CBL-AI to CBR using a sepsis algorithm as an example. Sepsis is a complex clinical condition and is one of the leading causes of morbidity and mortality worldwide. The Duke Institute of Health innovation developed an algorithm, 'Sepsis Watch', for decision support to help the early detection of sepsis and improve compliance with treatment recommendations [19]. In this case, the creators identified clinically relevant features that are indicators of sepsis but confirmed that other commonly used clinical risk scores used in practice perform worse in comparison [19,20]. Medical students could connect the clinical knowledge of sepsis from the discussion to technical knowledge of ML and apply their understanding to further clinical and ML situations.

4.1. The mirror: reflection and critical thinking

Reflection in medical education tries not to focus on solving the clinical problem at hand but instead looks critically at the underlying conceptual framework that constructs the initial understanding of the problem [22]. It is a source of knowledge that allows doctors to gain insights into their assumptions, beliefs, attitudes, and behaviors. It can also help them "examine and critique the underlying assumptions of modern medical practice" [23]. Therefore, it carries out a fundamental function of assisting doctors in seeing the shortcomings of their practice and the practice of others - including AI-, maintaining ethical conduct, and questioning standard practices in the healthcare system.

Overarching concerns about AI behavior have prompted guidelines to avoid errors and biases [24]. However, in technical terms, a well-performing AI could mirror the imperfect real world with biases, errors, and knowledge gaps [25]. An AI algorithm that learns from electronic health records (EHR) could be less likely to suggest testing for cardiac ischemia in an older woman due to considering their symptoms atypical for myocardial infarction [25]. The operationalization of error-free recommendations during the development and implementation of AI are helpful; however, reflecting upon and analyzing the existence of those problems could carry learning opportunities. Even with proof-of-concept AI, the opportunity to learn from its findings or limitations is widely available. Using CBL-AI to reflect upon AI behavior could "present an opportunity for us to decode the present and reshape existing practice" by discovering past incorrect clinical assumptions, finding new medical correlations, and helping acknowledge the limitations of AI or current medical knowledge [26]. For example, there is a hypothesis that external factors such as emotional stress cause higher knee pain severity in Black patients. ML's ability to identify previously overlooked x-rays findings correlated to more severe knee pain could debunk possibly wrong assumptions [27]. CBL-AI can focus the discussion on the etiology of knee pain, the clinical management, and how AI and doctors are susceptible to biases. Utilizing this knowledge and broadening to CBR allows students to consider knowledge gaps in other medical applications and encourage doctors to question and reflect if their clinical assumptions are supported (or not) by objective, reliable and replicable evidence.

CBL-AI encourages reflection where doctors can compare their thought processes to AI's solutions and potentially decipher and assess the influences, uncertainties, biases, and illusions that guide a clinical decision. AI's output (or errors) studied through CBL-AI could help decode the social constructs that influence decision-making during clinical practice, such as subjective ideas on gender and racial characteristics. Errors and biases require reflection if these also exist in clinical practice, for example, an AI solution trained to help diagnose schizophrenia could have biases toward the over-diagnosis of schizophrenia in African-Americans. In contrast, a ML algorithm that accurately predicts mortality risk after myocardial infarction could be used by doctors to reflect on their biases, support offering early treatment to women, and reduce the higher mortality rates among them [29].

The AI community favors values such as performance, generalization, efficiency, and novelty, meaning that doctors will be required to reflect and question whether AI is meeting clinical needs and to consider any negative impacts [30]. Doctors would also be required to reflect and question claims made around technologies to detect if AI capabilities are as good as they seem. Utilizing CBL-AI could prompt reflection to determine whether AI is necessary to critically solve a particular clinical problem. Therefore, doctors will be better positioned to decide when and how to integrate AI into their practice. AI solutions could be useless if not combined with, for example, universal access to healthcare. The development of AI could divert economic resources from problems that might be more effectively addressed through public health strategies.

4.2. The center stage: ethical thinking

It is widely acknowledged that ethics education is fundamental to training healthcare professionals, as they will inevitably encounter situations requiring them to judge their decisions clinically and ethically [31,32]. In Europe, researchers found (in 2007) that there is a wide disparity in the teaching of ethics and that only a limited number of hours is devoted to learning ethical concepts [32]. In Switzerland, medical ethics is part of the curriculum of all training courses, but there is heterogeneity in scope, learning content, and teaching methods between the faculties [33]. Due to the difficulties in integrating ethics into the medical curriculum, students might feel unprepared to deal with ethical concepts and discussions. For example, German medical students tend to feel unprepared to deal with complex ethical issues regarding consent [31,34]. In the United States, a 2012 survey showed that doctors are not always open or honest with patients; for example, not all doctors completely agreed with disclosing all significant medical errors (34 %) or fully informing patients of benefits and risks (11 %) [35].

Viewed this way, AI can create ethical challenges or exacerbate the existing ones. Undeniably, AI might be subject to errors, biases, breaches in data security, or misuse that could pose risks to patients [36]. Even in well-functioning AI, the complexity involved in explaining its results might lead to paternalistic behavior and risk the autonomy of doctors and patients alike [37]. Therefore, AI demands doctors to perform and safeguard ethical principles in a context that can be more challenging. For example, informed consent requires doctors to consider patients' wishes and communicate openly and honestly about the clinical journey. Involving AI challenges doctors to do all that while also communicating the consequences of using complex technology.

Using CBL-AI could bring the discussion of ethical behavior to center stage as the introduction of AI might be - in part - a representation of the ethical challenges that already exist in medical practice. For example, consider an AI developed for breast cancer screening: an algorithm will have thresholds for when the probability of breast cancer requires recall and when the patient does not have to return for further testing [38]. CBL-AI can encourage students to question if those thresholds exist in clinical practice and if screening tests improve outcomes and benefit patients. Therefore, focusing on beneficence (when are screening tests beneficial for patients?) and respecting patients' autonomy (are patients' values about acceptable risks integrated into the clinical decision-making?) [38,39].

The central ethical questions AI raises could and should also be examined in current medical practice. When applying CBL-AI, students understand that AI might be old problems in new clothes; with or without AI, satisfying consent or fostering trust with shared decision-making should always be present. In a broader sense, it highlights to students the importance of ethical principles and their practical considerations. Furthermore, CBL-AI facilitates students to identify when these ethical issues are present in their clinical practice. For example, AI raises the difficulty bar on what informed consent means, although the parameters, settings, and consequences of informed consent remain. Thus, the same degree of teaching importance put into assessing the ethical implications of AI should also be used to evaluate the ethical aspects of clinical practice. CBL-AI could be an ally in reaching the goal of teaching ethical thinking.

4.3. The bridge: interdisciplinary collaboration

Engineers, doctors, data scientists, ethicists, and lawyers, among other professions, could and should be involved in developing medical AI. Although only 14 % of healthcare start-ups consider doctors' involvement essential in the design phase [40], doctors have a lot to offer because they can understand the context of the clinical journey and help focus on the patients' choices [41]. Therefore, an essential competence needed by doctors is the capacity to collaborate within and across professional boundaries and outside clinical practice. However, collaboration is complex, and challenges already exist to cooperate in the care of patients due to fragmented care between primary and secondary care doctors. Barriers to collaboration include lack of respect, undefined roles and responsibility, lack of mutual knowledge and understanding, and incomplete communication [42]. Collaboration carries additional challenges across professional boundaries because each group (e.g., doctors and engineers) develops its scientific methods, communication structures, and competencies in silos [43].

Interprofessional education is a pedagogical approach suggested to supporting doctors' collaboration skills. Students from different professional programs learn together during specific periods to enhance collaboration, teamwork and ultimately improve patient care [44]. Traditionally, interprofessional education has been applied to healthcare professions. However, if applied to AI, the opportunity to use CBL-AI for this type of education could be a step toward common understanding between AI development teams and doctors. Hence, CBL-AI would be a fitting tool to educate, facilitate and ultimately create interdisciplinary collaboration while still providing a basis for learning vital aspects of patient-centered care and AI technical constructs.

Moreover, CBL-AI would be a practical example for doctors to develop and improve their collaboration skills and build explicit partnerships among doctors, engineers, patients, and technology [45]. A shift from doctors as gatekeepers of medical knowledge or engineers as gatekeepers of AI knowledge to a multi-partnership journey where patients are the center and most important entity. A functioning team might be more valuable than a single 'know-it-all' individual who is unlikely to integrate the vast amounts of knowledge from engineering, data, information science, and medicine. Finally, the skills needed to work effectively with AI teams (e.g., communication, coordination, cooperation, assertiveness, autonomy, and mutual trust and respect) frequently overlap with those needed to fulfill other core aspects of clinical practice, and acquiring them will positively impact patients' care. The university in Heidelberg, Germany, offers an interdisciplinary course on medical AI in which computer science and medicine students solve scientific questions together [9].

5. Conclusions

The purpose of this paper is to encourage readers to consider a different perspective and see AI as an educational resource instead of merely an educational need. The emphasis on interlinking clinical and technical knowledge using CBL-AI could prove a valuable resource for teaching students essential clinical and technical skills. Doctors can explore topics relevant to clinical practice through AI; for example, turning concerns over the intelligibility of AI into reflection about the importance of explaining the clinical decision to patients and supporting shared-decision making. Moreover, CBL-AI can positively impact three fundamental skills: critical reflection, ethical thinking, and interdisciplinary collaboration. These skills take on particular value in AI because doctors will be better equipped to handle AI in its context and potentially contribute to developing accurate, ethical and valuable AI systems. Therefore, considering educational needs from a smarter perspective leads to implementing AI for CBL to improve medical education and practice and ultimately benefit patients.

Although using CBL-AI as a methodology is applicable across the whole education continuum, it requires further examination of some implementation questions on how and when to use CBL-AI. This might require empirical discussions with stakeholders such as students, doctors, medical educators, and AI experts. With the never-ending development of technology, it seems fundamental that we make concerted efforts to recognize and cultivate doctors' skills that allow them to perform their best clinical functions, with or without AI. Making sure that patients benefit from the surge of AI will remain a key challenge in the coming years. New approaches in medical education that improve doctors' skills and better integrate patients' perspectives will be critical.

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Declaration of competing interest

The Authors declare that there is no conflict of interest.

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