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Computers in Emergency Medicine

Artificial Intelligence in Emergency Medicine: Benefits, Risks, and Recommendations

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☐ Abstract—Background: Artificial intelligence (AI) can be described as the use of computers to perform tasks that formerly required human cognition. The American Medical Association prefers the term 'augmented intelligence' over 'artificial intelligence' to emphasize the assistive role of computers in enhancing physician skills as opposed to replacing them. The integration of AI into emergency medicine, and clinical practice at large, has increased in recent years, and that trend is likely to continue. Discussion: AI has demonstrated substantial potential benefit for physicians and patients. These benefits are transforming the therapeutic relationship from the traditional physician–patient dyad into a triadic doctor–patient–machine relationship. New AI technologies, however, require careful vetting, legal standards, patient safeguards, and provider education. Emergency physicians (EPs) should recognize the limits and risks of AI as well as its potential benefits. Conclusions: EPs must learn to partner with, not capitulate to, AI. AI has proven to be superior to, or on a par with, certain physician skills, such as interpreting radiographs and making diagnoses based on visual cues, such as skin cancer. AI can provide cognitive assistance, but EPs must interpret AI results within the clinical context of individual patients. They must also advocate for patient confidentiality, professional liability coverage, and the essential role of specialty-trained EPs. © 2022 Published by Elsevier Inc.

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Introduction

The term 'artificial intelligence' (AI) was coined in 1956 by John McCarthy during a conference at which scientists discussed the concept of creating an "electric brain"—that is, an intelligent machine. AI can perform tasks that formerly required human cognition, such as speech recognition, visual perception, learning, and decision-making (1,2). As computers have become more powerful, functions that were once viewed as instances of AI are now accepted, routine, and rarely thought of in that way, if at all (3). For example, language recognition, which was a uniquely human capacity, is now performed by dictation software, smartphones, and other electronic devices.

The American Medical Association recommends use of the term 'augmented intelligence' rather than 'artificial intelligence' in medicine, to emphasize the assistive role of computers in enhancing human abilities, as opposed to replacing them (4). Although these two terms refer to the same technologies, AI is entangled with decades

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of science fiction and media portrayals that may evoke fear, uncertainty, and distrust. In contrast, augmented intelligence emphasizes the dependent role of technology. Given the similar meanings of the two terms, AI in this paper will be used as an acronym for either artificial or augmented intelligence.

The use of AI technologies in emergency medicine (EM), as in health care generally, is anticipated to increase in the coming years (1). As the integration of these technologies into EM proceeds, it will be important for emergency physicians (EPs) to evaluate their effects and to advocate for applications that enhance patient care in the emergency department (ED). Optimization of patient care with AI technology requires that AI enhance and not undermine EPs' professional responsibilities and humanistic goals. This article will examine legal and ethical issues of AI in EM, with specific attention to protection of patient confidentiality. It will suggest educational and professional responses to AI as physicians work toward optimizing the potential of the emerging doctor–patient–machine relationship.

Discussion

Legal Issues

In recent years, EM practices have increasingly incorporated AI support systems, including some approved by the U.S. Food and Drug Administration. Examples include Critical Care Suite (GE Healthcare, Chicago, IL) and HealthPNX (Nanox, Neve Ilan, Israel), which assess chest radiographs for pneumothoraxes. Another example is BriefCase-ICH (Aidoc Medical, New York, NY) for analysis of noncontrast head computed tomography and notification of providers to assist with triage (5). As AI systems generate specific treatment recommendations, EPs may lack a clear understanding of the reasons for those recommendations or how to use the information in the ED context. That uncertainty may delay, rather than expedite, patient care. Liability issues in these situations are ill defined but potentially significant. Consider this theoretical example: A patient with a wrist injury is evaluated by the EP, who interprets x-ray studies as negative. Additionally, the EP uses a novel deep learning program to better identify fractures, and that program also interprets the x-ray studies as negative (6). The patient later develops weakness in the wrist and a missed scaphoid fracture is diagnosed, despite both EP evaluation and the use of AI. Should the EP still be liable for misdiagnosis, despite having used and relied upon AI to augment diagnostic accuracy?

Price and colleagues have analyzed tort law implications of the use of AI (7). Tort law doctrine maintains that a physician is liable for harm suffered by a patient only if the physician falls below the standard of care in treating the patient and breach of that standard is the proximate cause of the injury. These authors recommend that the safest way to use medical AI under the current liability regimen is as a confirmatory tool to support existing decision-making processes rather than relying solely on AI to make treatment choices. If AI is eventually demonstrated to outperform current standards of care, however, those standards may change. If the use of AI is incorporated into the legal standard of care for a specific clinical situation, an injury caused by not following AI "recommendations" could result in compensable damages (7).

Price and colleagues offer the following recommendations (7):

1) Physicians should learn when to use an AI system; that is, whether and how to implement AI treatment recommendations.
2) Physicians should encourage their professional organizations to evaluate practice-specific AI algorithms.
3) Physicians should advocate for safeguards in the adoption and use of AI systems in their hospitals and health care systems. For example, prior to acquiring an external AI product, that product should be thoroughly vetted, similar to other new medical devices.
4) Physicians should check with liability insurers about coverage for their use of AI and advocate for appropriate liability coverage.

As hospital systems consider implementing AI tools in EM practices, AI developers and health care payers should ensure that use of the tools is consistent with EM practice standards and thus is protected by liability insurance (7). One of the challenges of AI, however, is that it is dynamic and continually developing, often outpacing policies, protections, and legal guidance.

Besides the use of AI in diagnosis and treatment, there is also use of AI in monitoring patients and even caregivers themselves. Health care institutions have long used video monitoring of hallways and common areas. More recently, they have begun to use contactless sensors and machine learning, known as "ambient intelligence" techniques, to monitor patient care for harm reduction in practices such as hand washing and health care providers' time spent with patients or in dictation to increase efficiency (8,9). The liability implications of ambient intelligence monitoring of patients and their caregivers is uncertain. Though some institutions using these techniques may claim liability protection under quality-improvement exceptions, there are potential liability implications for breaching patient confidentiality, invading patients' physical privacy, and failing to obtain patients' informed consent for monitoring (10). However, there are likely few legal remedies for EP claims that their own privacy has been invaded. Administrators may assert a right to observe ED care, but the prospect of EPs and other health care providers being continuously monitored in their treatment of patients is unsettling—it is reminiscent of the Panopticon prison proposed by Jeremy Bentham in the 18th century, in which hidden guards monitored prisoners so that the prisoners could not know who was being watched at any one time (11).

Privacy, Confidentiality, and Big Data

EPs have a fundamental professional duty to maintain patient confidentiality. The Hippocratic Oath affirms that duty, and it has been integral to the practice of medicine for millennia (12). The landmark *Tarasoff* case, and other state court decisions and statutes that preceded and followed it, recognize that clinicians may, or should, override confidentiality in some circumstances to protect third parties who are at significant risk of harm (13). With the advent of electronic data collection and transmission, regulations enacted under the Health Insurance Portability and Accountability Act (HIPAA) created a federal mechanism for enforcement of patient privacy. HIPAA regulations protect the privacy of personal health care information, including 18 specified identifiers and other identifiable personal features such as visages and voice recordings. EPs encounter and address significant ethical and legal challenges in adhering to HIPAA privacy protections (14,15).

More challenging to patient confidentiality than individual physician or other health care professional breaches has been the illegal access to millions of patient records by individuals “hacking” into central repositories of electronic health records (16). AI’s reliance on large amounts of information, so-called “big data,” adds further complexity to the challenge of safeguarding patient confidentiality and privacy (17). EPs have been traditionally concerned with an individual patient’s confidentiality and privacy. But the challenge of protecting the privacy of large collections of data from many thousands of patients goes beyond the EP’s ability to control. Health systems are now contracting with information technology giants such as Google (Mountain View, CA) to help them analyze data (18). Systems use this information not only for patient benefit and quality improvement, but also for business and marketing purposes. To lessen the potential for disastrous breaches of confidentiality and invasions of privacy, some commentators propose decoupling personal identifiers from the information subjected to AI analysis (19). Others have proposed ethics review committees to oversee specific requests for de-identified information.

EPs should be aware of these challenges of AI for patient confidentiality and privacy and should advocate collectively, as practice groups and specialty organizations, for safeguards that protect the confidentiality of patients whose health care data are being monitored and used for justifiable purposes. EP groups and professional organizations can, for example, support regulations and legislation that protect confidentiality and privacy and encourage their state, regional, and national organizations to do the same.

Potential and Pitfalls of AI in EM

AI can improve clinical practice in a variety of different ways. Levin et al. showed that a machine learning algorithm can triage ED patients more accurately than a commonly used triage tool (20). Patel et al. have shown that AI might predict the need for hospital admission in pediatric asthma patients based solely on triage information (21). A study by Wu et al. concluded that an AI system can read a chest radiograph at the same level of competency as a third-year radiology resident (22). An AI system in another study was not superior to an experienced radiologist in interpreting mammograms, but use of the system by radiologists did improve their diagnostic specificity (23). AI has also been shown to identify opiate use disorders earlier than traditional methods and has been used to identify risk factors for prolonged opioid use after neck surgery (24–26). In other studies, AI mechanisms successfully diagnosed COVID-19 based on clinical presentation and imaging (27,28). These AI clinical tools do not replace physician expert clinical judgment, but they can save time and effort and improve workflow.

Future AI algorithms could be used to “data-mine” the electronic medical record to enable early diagnosis of complicated medical conditions, such as neutropenic fever, that require aggressive management and also help to choose appropriate antibiotic therapy (29). Other algorithms could be used to recognize early signs of shock requiring immediate stabilization (30). Some have suggested that AI algorithms could mine data from the electronic medical record and even from social media to guide decision-making for incapacitated ED patients who cannot express their treatment wishes (31).

Implementation of AI has the potential to improve diagnostics, therapeutics, population health, administration, and regulation (32). The studies cited above provide examples in which AI tools can help clinicians synthesize complicated information rapidly and effectively as they care for patients in the ED (33). Ethical implementation of AI in EM can support clinicians in their practice, but AI, at least in its current health care applications, should not be viewed as a replacement for a clinician’s expertise (34). Implementation of AI in clinical practice also requires clinicians to verify that the guidance provided by an AI tool is trustworthy and accurate (35,36).

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In many respects, EPs have been using AI for years. The automatic measurements printed on electrocardiograms (ECGs) provide data that would otherwise take precious time to calculate. This technology has been available for several decades and is virtually ubiquitous in practice. As a long-accepted AI tool, it has become routine and likely is not even considered AI by most practitioners. ECG machines also commonly offer preliminary interpretation in addition to raw data. Learners have long been taught to question these machine readings, but automatic interpretations do have some utility. An ECG performed in triage that is automatically interpreted as "normal" may not need urgent interpretation by an EP, as findings on the ECG seldom change triage management (37). Implementation of a protocol using this information could reduce the number of distractions to which an EP is subjected and could improve flow within the ED.

Over-reliance on this technology is also problematic, however, as nothing can completely replace individual patient care provided by the EP. In one study of machine interpretation of atrial fibrillation ECGs, 9.3% of the interpretations had errors. Of those ECGs with erroneous reads, 7.8% were not corrected by the clinician interpreting the ECG at the time, leading to unnecessary testing (38). Although this study did not delve into why a physician did not "overread" the ECG—whether the physician also misread the ECG or was reluctant to override the machine—it demonstrates the potential pitfall of hesitancy to override an AI application. In general, people tend to consider computer-generated results as accurate and reliable.

When an automatic interpretation of an ECG is incorrect, physicians are more likely to interpret that ECG incorrectly than when the correct diagnosis is presented (39). Not surprisingly, cardiologists perform better at correcting an incorrect automatic interpretation, but the difference is far more pronounced when the cardiologist has clinical information about the patient (40). When an automatic interpretation comes with a certainty index, correct interpretation is more likely, stressing the importance of transparency in AI and the interface between human and machine (41).

The phenomenon of erroneous acceptance of an incorrect automatic interpretation is known as automation bias, which occurs when an overreliance on streamlined clinical processes leads to complacency and reduced vigilance in information seeking and processing (42). When an individual is presented with an answer from an existing system, that individual runs the risk of anchoring too heavily to that answer and not considering alternatives. Humans are thus susceptible to errors in cognition, but they are also able to identify and correct errors made by others, including AI systems. Optimal interpretation of these data requires human–computer collaboration (43).

Big Data and Machine Learning in EM

Machine learning is an AI application in which computer algorithms use past experience, documented in electronic health records, to improve performance or make more accurate predictions (44). Machine learning processes vast amounts of data to create or refine diagnostic or therapeutic algorithms. The advancement of AI in non-medical fields, however, has also revealed some potential harms. For example, machine learning design of flight algorithms has led to accidents; computer-assisted prison-sentencing guidelines have perpetuated racial biases; and private data repositories have been bought, sold, and illegally accessed (45). AI tools may inform clinical practice, but EPs must understand potential pitfalls of these tools and apply the tool within the specific context of ED clinical care.

The great advantage of machine learning systems is their ability to review medical record data from many thousands of patient encounters to identify significant associations and patterns that can guide diagnosis and treatment decisions. Because machine learning algorithms are based on data about a specific patient population, they can provide useful recommendations for that population. These recommendations may not, however, be applicable to a different patient population (46). A widely cited non-medical example of this limitation of AI is the report that Google facial recognition software, trained primarily on photos of white individuals and still in the early phases of development, initially placed photos of black individuals into a folder labeled "gorillas" (47). If, moreover, the patient data used in machine learning applications include information about specific patient groups that reflects pervasive implicit or explicit bias against that group, the resulting machine learning algorithms may offer flawed recommendations that perpetuate that bias (48). A study reported in *Science* in 2019 offers a striking example of racial bias in an AI health care algorithm (49). In this study, Obermeyer and colleagues examined an AI algorithm used by U.S. health systems and health insurers to manage care for some 200 million Americans (49). They report that this algorithm systematically underestimated the health care needs of black patients and excluded them from eligibility for expanded care management services. The algorithm used patients' annual health care spending as a proxy for their health status, despite the fact that black patients' average spending on health care is considerably less than that of white patients with the same medical conditions.

Multiple commentators have recognized the potential for bias in machine learning systems in health care and have proposed strategies for preventing that bias. If the problem is limited or missing data, AI developers can seek additional data, and they can use sensitivity checks to identify when the available data are not sufficient for reliable recommendations (48). McCradden et al. argue that novel machine learning models must be subjected to clinical trials to compare their performance to existing standards of care for different patient populations (50). Other commentators propose the development of AI tools to help clinicians provide more humanistic care by creating a clearer picture of their patients as individuals or by alerting them to a heightened risk of bias in specific situations (48,51). Israni and Verghese, for example, propose the development of AI tools to help clinicians identify and understand the environmental and social circumstances of their patients and to use that information to respond to patients' needs more effectively (51). Finally, Emanuel and Wachter observe that despite current enthusiasm about the uses of AI applications in health care, these applications, like other innovations, confront a major obstacle in changing the habitual health care practices of both clinicians and patients (52).

AI tools may provide useful information and recommendations, but EPs must also attend to the specific needs of individual patients. For example, a patient may have anxiety over costs of care and may decline some or all of the tests suggested by AI-based decision-support software. Out of respect for patient autonomy, physicians should inform their patients about AI algorithm suggestions for their care. In addition to the electronic data available for AI analysis, EPs also recognize that hospital resources, the legal environment, patient preferences and fears, provider experience, and situational factors can influence patient care decisions. An AI algorithm, for example, may indicate that a patient can be safely discharged, but it may not recognize that she does not have an appropriate social support system or is at risk for domestic violence or human trafficking. Attention to these multiple factors in patient care by skilled and experienced clinicians is essential, and so clinicians should retain the responsibility to interpret and apply AI algorithms with care.

Machine learning may also affect the perceived need for physicians in various health care settings. Reduction of physician staffing costs is a primary motivation for health systems to embrace data analytics and AI. Some facilities may perceive AI as a decision-support system for advanced practice providers (i.e., nurse practitioners and physician assistants) that makes them an acceptable replacement for a fully trained, board-certified EP. Government-run systems in New Zealand and the United Kingdom have concluded that AI will help nonphysician providers bridge gaps in training, promote workforce democratization, and control health care costs (53–56). If AI systems can contribute to better control of health care costs, that is clearly a valuable outcome, provided that it does not compromise the quality of care. Excellent quality of care may frequently depend on the advanced education, clinical experience, and interpersonal skills of EPs.

Integrating AI Topics and Techniques into Medical Education

Recent commentators have called for a "reboot" in medical education to align physicians and machines more effectively in education and practice (57). Medical knowledge is continuously expanding, and it far exceeds the capacity of individual human minds. Wartman and Combs argue that "[t]he current learning environment, with its excessive information-retention demands, has proven to be toxic and in need of complete overhaul" (58). He discusses how AI has the promise to serve as the information repository to alleviate unrealistic information retention demands on students. He proposes a shift in focus from information acquisition to knowledge management and increased education on how to interpret and communicate to patients the diagnostic and therapeutic recommendations generated by AI.

Because EPs assess and treat patients across the entire spectrum of acute and chronic medical conditions, AI technologies that can supplement their knowledge base may ease cognitive stress and enhance therapeutic relationships. As the number and quality of AI technologies for making diagnoses and treatment recommendations increase, EPs should seek and obtain education about when and how to integrate AI into their practice. They must also exercise caution, not relying on technologies that are unproven or using AI for inappropriate tasks. Wartman and Combs suggest that simulation education can help physicians integrate AI technology into clinical care and develop skills for its use (57).

Other commentators suggest that concepts of machine learning be incorporated into medical school curricula and that electives offer in-depth study of computer science (59). As AI technologies expand, the EM core curriculum will need to reflect the concepts that all trainees must master in this area. EM training programs and professional societies should encourage interested EPs to develop expertise in topics such as big data and machine learning. EPs with computer science expertise can provide guidance in the integration of AI into clinical practice and train others to have the appropriate literacy for this integration. EPs with interest and relevant skills should be involved in research and development of AI in EM for advancement of the field.

A novel area of research is AI's potential to improve education with the use of virtual reality (VR). VR involves computer-generated simulation of real or imaginary settings. VR hardware, such as a headset and controller, allows for real-time interaction with the environment, providing an immersive experience. VR has been tested in laparoscopic and orthopedic surgery and has been reported to improve technical surgical skills (60). In a recent study comparing traditional vs. VR cardiopulmonary resuscitation training for medical students, students in the VR group reported significantly greater learning gains based on subjective questions (60).

An exciting area of research is in the realm of "Embodied AI." Embodied AI recognizes that biological cognitive systems depend on their physical composition and their interaction with the surrounding environment (61). We tend to develop empathy more easily with members of a group with whom we identify. In contrast, implicit biases and cultural stereotypes, mediated by automatic processes, tend to mitigate empathetic responses, even in individuals with egalitarian values and beliefs. Although much attention has been paid to implicit bias in recent years, there is little in the way of effective interventions. Embodied VR is an immersive experience that uses multisensory and motor stimuli with a first-person perspective to make the subject feel as if they have become the avatar presented. Studies have reported that embodied VR can be used to increase prosocial behavior and empathy with outgroup members and decrease implicit bias (62,63).

Embodied AI has promise, but additional research is necessary to assess its value in medical education. In an isomorphic (i.e., similar) empathetic response, the observer feels distress in response to the observed person's distress. An unhealthy empathetic response can lead to withdrawal or personal distress (62). Embodied AI also has a multitude of potential therapeutic applications and has shown promise in the field of mental health (64).

The rapidly increasing role of AI may indicate a transition from the information age to the AI age in medicine (58). EPs must be prepared to adapt to changes in the clinical environment, including the growing role of AI. EPs should be encouraged, for example, to relieve some of their cognitive strain by delegating appropriate computational tasks to AI, allowing for a greater focus on the individual patient and synthesis of data across the clinical encounter.

The Doctor–Patient–Machine Relationship

In 2012, Vinod Khosla, a legendary Silicon Valley investor, predicted that "By 2025, 80 percent of the functions doctors do will be done much better and much more cheaply by machines and machine learned algorithms" (65). This claim may not prove accurate, but some current technologies do perform on par with, or better than, physicians in certain health care tasks, such as interpreting radiologic images, planning and assessing response in radiotherapy, and making diagnoses based on visual pattern recognition, such as in skin cancer and onychomycosis (66–69). AI has a long history of evoking fear that machines will replace humans, but Khosla did not assert that machines would replace doctors, as some have interpreted his statement. Technologies such as the smartphone, for example, change our lives and workflow, but cannot replace interaction with other people. As computers outperform humans at some tasks, the goal should not be to compete with computers in contests we cannot win, but rather to adapt and focus greater efforts on areas where humans outperform machines.

Areas of focus for contemporary medical education and practice, in addition to how to use AI effectively, include communication, teamwork, leadership, and compassionate and patient-centered care (57). Individual patient preferences vary based on elements such as moral values, culture, and socioeconomic factors, all of which may be dynamic and cannot be easily captured by an algorithm. Physicians rely on recognition of emotions and nonverbal communication to interpret patient needs and respond empathetically, which machines cannot do (70). Selective reliance on AI has the potential for cognitive unburdening to allow for greater empathy and patient-centered care.

Recommendations

Based on this analysis of the role of AI in EM, we offer the following recommendations:

- AI is best understood as augmented intelligence that assists and enhances the skills and clinical judgement of specialty-trained EPs.
- EPs should exercise caution and use their own clinical skills to interpret the information and recommendations produced by AI systems.
- Professional societies and health care systems should develop policies to promote best practices in the use of AI in clinical care.
- AI tools and applications should be evaluated with the same scientific rigor as other interventions prior to widespread implementation.
- Physicians should advocate for liability coverage that aligns with professional standards of care for the use of AI in EM.
- EPs should support regulations and legislation that protect patient confidentiality and privacy.
- EPs and their professional societies should continue to advocate for the central role of physicians in the provision of medical care. A nonphysician ED caregiver with an AI application may not provide care that is equivalent to—or as safe as—care provided by a specialty-trained, board-certified emergency physician.
- Cognitive unburdening in one dimension of clinical care provides an opportunity to excel in others, in-

cluding spending more time listening to and communicating with patients, promoting multidimensional advancements in patient care.

Conclusions

EM is inherently unpredictable and presents challenges that require creative solutions based on expert knowledge and clinical skills. The integration of AI in EM offers opportunities to supplement its knowledge base, improve computational abilities, and streamline work flow, among other benefits. AI assistance in some areas allows for increased focus on areas where EPs excel, including innovation in clinical care, synthesis of data from multiple sources, leadership, communication, and compassion. This integration, however, must proceed with the same skepticism that is the bedrock of scientific inquiry and with appropriate guidance and protection for patients and providers that is afforded by other clinical guidelines.

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