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RESEARCH ARTICLE

Opportunities & Challenges of Artificial Intelligent-Powered Technology in Healthcare

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ABSTRACT:
Artificial Intelligent (AI)-powered technology is expected to significantly alter the way healthcare is delivered. Artificial Intelligence tools, such as machine learning and deep learning, have shown promise in supporting diagnostic assessments, recommending treatments, guiding surgical care, monitoring patients, supporting population health management, and enhancing drug development research. These tools at varying stages of maturity can also reduce provider burden and increase efficiency by recording digital notes, optimizing operational processes, and automating laborious tasks. Challenges surrounding AI tools include high-quality data access, potentially biased data, inadequate transparency, and uncertainty over liability. Fundamental changes in governmental oversight of health care, industry-hospital communication, the patient-provider relationship, and human-AI cooperation will be necessary to take advantage of the opportunities and overcome the challenges. We need to be critical and at the same time receptive as we embrace AI tools to deliver healthcare. It would be important to maintain human oversight and control to avoid unintended consequences of runaway machines making life and death decisions.

Introduction

Artificial Intelligence (AI) enabled technology is poised to make a significant impact in our daily life including our healthcare system. We are exposed almost on a daily basis how this new technology is going to make our lives easier and at the same how AI is going to dominate mankind if we do not pay attention. The evolving nature of AI without robust regulatory oversight makes it subject to speculation of its potential benefits and dangers. However, one can be more optimistic about beneficial applications of AI enabled technologies in healthcare and our abilities to address the challenges. This review on AI in healthcare is divided into three parts: 1. AI basics, 2. application of AI technologies in healthcare and 3. current challenges of applying AI in healthcare.

1. Artificial Intelligence Basics

The goal of AI is to replace humans with machines. More specifically, AI is a branch of science devoted to developing machines (computers) that can behave, i.e., think and act, like humans. These are machines that can be trained, like humans, to read, write, talk, do calculations, draw pictures, generate ideas, and make decisions. The idea of having somebody else or some machines do our daily tasks is nothing new. Doing the tasks started with humans and then animals and is now gradually taken over by machines. Artificial Intelligence can be defined as a machine (or computer systems) that can perform, under some form of human supervision, complex tasks that were once the exclusive domain of humans. These include generating written content, translating text from one language to another, steering a car, recognizing faces, or analyzing data. Note that AI tools have decreased the number of humans involved but have not completely replaced humans yet. It is however clear that we are increasingly dependent on AI technologies to help us perform a myriad of tasks.

There are three types of AI, namely narrow or weak AI, Artificial General Intelligence (AGI) and Artificial Super Intelligence (ASI). Of the three types of AI, we are mostly using the narrow AI or weak AI for performing specific tasks defined by humans. We are working towards AGI or Strong AI that can think, learn, and understand like humans, and dreaming about ASI that can surpass the creativity, problem-solving, and decision-making capabilities of even the most brilliant human mind[1].

Artificial Intelligence tools learn by crunching data and then make decisions based on lessons learned from the crunched data using a sequence of instructions or algorithms[2,3]. This is not much different from how we humans learn to make decisions. Narrow AI encompasses machine learning and deep learning (Figure 1). Machine learning makes informed decisions by focusing on creating algorithms from data received to solve a task, such as Google, household voice assistant and social media feed. Deep learning, a form of machine learning, is based on artificial neural networks and goes further by focusing on making intelligent decisions based on pattern recognition. Deep learning is based on multilayered artificial neural networks, namely convolutional neural network (CNN) and recurrent neural network (RNN). Thus, CNNs enable machines to recognize objects, detect faces and understand images, while RNN can process sequential data for tasks like natural language processing and speech recognition. Generative AI (GAI), like Chat GPT, refers to deep-learning models that can generate high-quality text, images, and other content based on unsupervised or self-supervised machine learning to a data set. Thus, deep learning is applied in various fields including image analysis, recognition of face and speech, machine translation, drug design and natural language processing[2,3]. Many of these applications find direct usefulness in modern healthcare and are further discussed below.

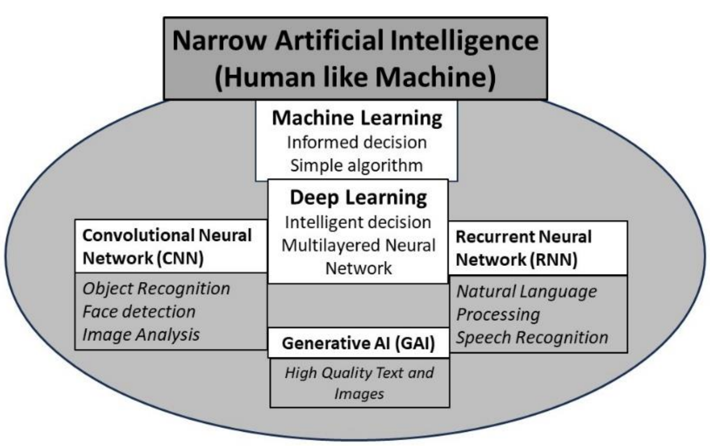

Figure 1. Basic components of narrow artificial intelligence.

2. Applications of Artificial Intelligence technologies in healthcare

The goal of healthcare is to prevent, diagnose, treat, and manage diseases by especially trained healthcare providers. It is becoming more apparent that some of those services traditionally provided by humans can be performed by machines developed by humans. This is where AI technology comes into play. When it comes to medicine, AI is able to review large amounts of data from patient records, diagnostic images, DNA sequences, etc. and use that information to detect, classify, and make predictions much faster than a human (Figure 2). For example, based on data provided about an infectious disease occurrence in various countries, and the algorithm for pandemic, the system can predict whether it is a pandemic or not. Similarly, based on patient health record and diagnostic images, the system can suggest diagnosis and treatment plan. Thus, AI is defined as a machine (or computer systems) that can help perform complex healthcare associated tasks that were once the exclusive domain of humans[4]. It should be noted that many of the AI tools discussed below are in preliminary stages of implementation and others are still in developmental stage[5].

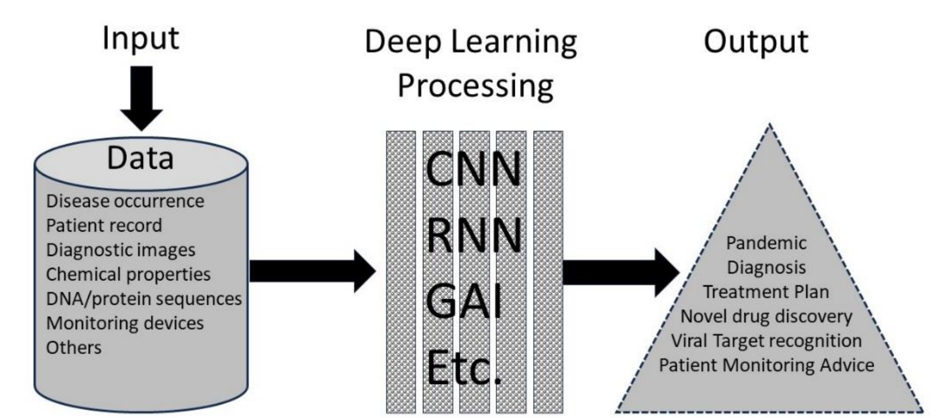

Figure 2. An overview of deep learning processing of health-related data into healthcare relevant output. CNN=Convolutional Neural Network; RNN=Recurrent Neural Network; GAI= Generative Artificial Intelligence.

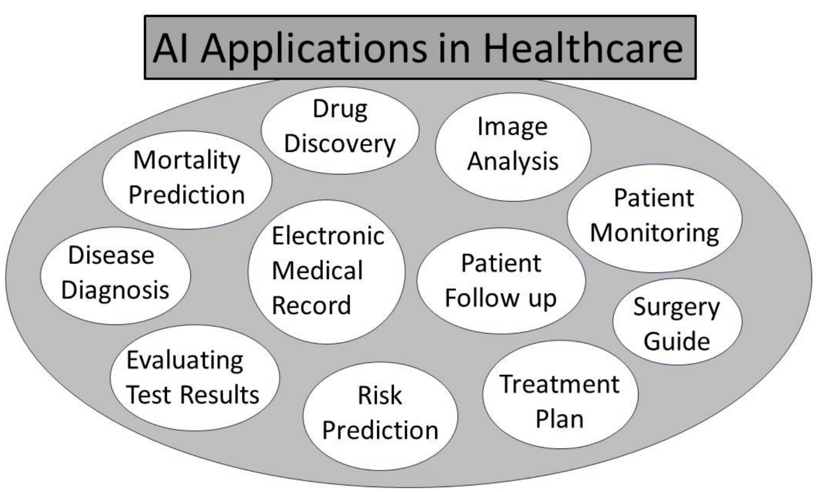

Figure 3. Potential applications of Artificial Intelligence in various healthcare fields.

A typical healthcare service these days involves making an appointment, getting a reminder, visiting a healthcare provider, conducting tests, evaluating rest results, making a diagnosis followed by a treatment plan and follow up or monitoring plan. Artificial Intelligence technology has the potential to facilitate many of these healthcare services (Figure 3) and thereby improve accuracy, efficiency, and efficacy. Some of these applications are discussed in more details below.

Making an appointment and receiving confirmation can often be done now without direct contact with a person. In these cases, a patient interacts with a machine that is taught to make an appointment and send confirmation. Multiple reminders are then sent by automated voice mail and/or messages to avoid no shows and thereby improve efficiency. However, availability of and familiarity with personal computers, iPads and/or smart phones are needed to take full advantage of this AI supported technology. This can be a major challenge for many older patients unfamiliar with the technology.

A few tasks need to be performed when the patient has an appointment with the healthcare provider. A patient's medical history needs to be recorded and reviewed. The process of recording by time-consuming manually entering or dictating/transcribing method can be replaced by much faster voice recognition and natural language processing (NLP) technologies for recording digital notes into Electronic Health Record (EHR). Ideally, providers would benefit most if these technologies can be used to transform a live provider-patient conversation into digital notes. Attempts are being made to realize this goal of creating automatic clinical documentation and companies are offering "The digital scribe" [6,7]. However, clinical validity and usability require further testing and validation. When successfully implemented, the digital scribe or equivalent technology would be able to help improve quality of patient-provider interaction by allowing more direct contact between patients and providers.

Once the current complaints are heard and recorded, a diagnosis needs to be made before a treatment plan is considered. The initial diagnosis, more often than not, is tentative and the attending physician may have to consider possible diagnosis by applying a differential diagnosis approach. Differential diagnosis involves considering the diseases that can produce the symptoms presented and the results of any diagnostic test, if performed. A physician will consider the list of differential diagnosis and then decide. However, diagnostic error in outpatient setting is not uncommon and may result from atypical patient presentations, incomplete differential diagnosis, and lack of time among other reasons[8-10].

It is suggested that AI generated differential diagnosis list may help the physicians reduce diagnostic errors[11-12]. For example, algorithms can be set up to go through the stored data and come up with a list of differential diagnosis based on symptoms. The physician can check the list and decide on a diagnosis or order further tests to confirm a diagnosis. An advanced AI tool may already suggest such tests. One advantage of an AI tool for differential diagnosis is that rare diseases unfamiliar to the physician will have a better chance to be identified as a possible cause. However, AI-driven differential-diagnosis lists generated based on symptoms alone failed to show high diagnostic accuracy[13-14]. This may be because the program did not consider the medical history of patients. Interestingly, when AI-generated differential-diagnosis lists was combined with physician-driven clinical documentation, the diagnostic accuracy increased in one study[15]. However, a recent study found that physicians' diagnostic accuracy using AI-driven automated medical history did not differ between the groups with and without AI-driven differential-diagnosis lists[16]. Thus, further improvements in AI accuracy as well as AI-generated differential-diagnosis lists are needed before AI tools can help reduce diagnostic errors.

A tentative diagnosis is confirmed with laboratory tests, tissue biopsy results and/or radiographic procedures, such X-ray, magnetic resonance imaging (MRI), computed tomography (CT) scan, etc. These diagnostic tests play an important role in disease diagnosis. A majority of these diagnostic tests include image analysis. Images from scan and tissue biopsies are typically evaluated by radiologists and pathologists, respectively, and the process involves analysis of images for telltale signs of a disease, such as the presence of an abnormal cell in a biopsy or an unusual shadow in a scan. Artificial Intelligence and more specifically deep learning algorithms, has proven to be a valuable aid in the interpretation of medical images[17-19].

Typically, an AI system is trained using supervised learning on images labeled "normal" and "abnormal" and then the system is asked to identify an unlabeled image (Figure 4). The result is compared against human experts to determine the learning efficiency and applicability of the system. Teaching an AI system image analysis is like teaching a small child. For example, a child needs to be told several times the difference between a cat and a dog, before the child is proficient in differentiating a dog from a cat. Similarly, an AI system has to be exposed to good quality data representing "normal" and "abnormal" images, before the AI system can distinguish an abnormal image from a normal image. AI systems trained using this type of supervised learning are increasingly being used successfully in medical specialties heavily dependent on interpretation of images, such as radiology, pathology, gastroenterology and ophthalmology.

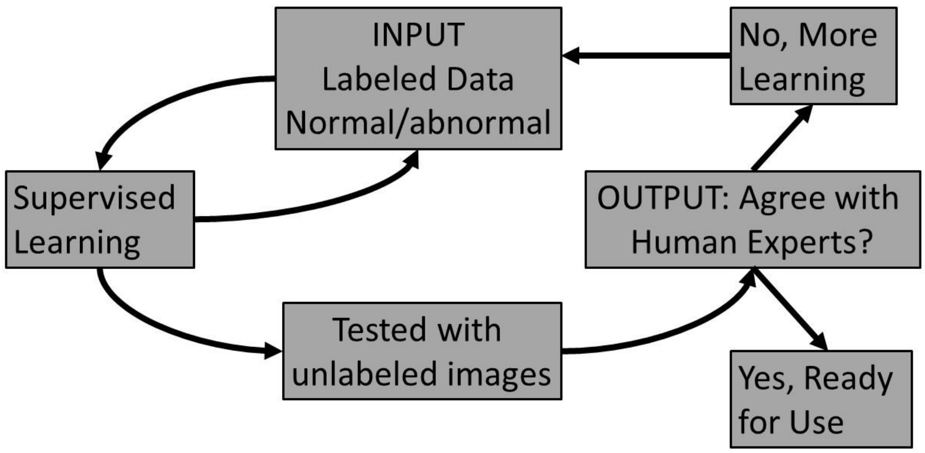

Figure 4. Basic steps involved in supervised training for image analysis.

Radiographic assessment of diseases most commonly relies upon visual evaluations, the interpretations of which may be augmented by advanced computational analyses[19]. Indeed, the ability of AI tools to help provide accurate interpretations of radiographs has been improving. These include interpretation of mammographs, screening test for lung cancers and assessment of cardiac functions[20-24]. Researchers have developed and validated a deep learning–based method to detect Alzheimer's disease based on routinely collected clinical brain images. The tool may help clinicians identify patients who would benefit from treatment[25]. Similarly, AI system can help pathologists make a diagnosis faster and more accurately[26-27]. For example, the sensitivity for the detection of micro metastases rose from 83.3% (by a pathologist alone) to 91.2% (by a pathologist combined with a computer algorithm)[28]. However, challenges remain in the accurate detection, characterization, and monitoring of cancers despite improved technologies[29].

Apart from disease diagnosis, AI systems can also be trained to predict risk, suggest treatment plan based on CT scan and medical history of the patient and provide mechanistic insight[30-32]. The development of a new AI algorithm to improve brain stimulation devices to treat movement disorders and epilepsy has been reported. It is suggested that this new type of algorithm may help us better treat patients with epilepsy, movement disorders like Parkinson's disease, and psychiatric illnesses like obsessive-compulsive disorder and depression[33]. A recent study validated a deep learning model capable of predicting postoperative mortality risk[34]. Furthermore, AI applied to histo-morphological properties of cells during microscopy may enable the inference of certain genetic properties, such as mutations in key genes and deoxyribonucleic acid methylation profiles[35-37]. Artificial intelligence systems using deep learning have shown promise in improving detection of colorectal cancer by assisting endoscopists in detecting polyps and assessing if colonic lesions are malignant[38-39]. These systems have the potential of making colonoscopy a more reliable diagnostic tool[40-42].

Once a diagnosis is confirmed, a treatment plan needs to be established. The plan may involve treatment with a drug, surgery and/or follow up observations with tests to evaluate the progress of the disease. Before a drug treatment can be recommended, the prescribing physician must consider the best drug to treat the disease and for a given medical history of the patient, potential side effects of the drug, the duration of the treatment (short term or long term), etc. Similarly, the best surgical approach has to be worked out as well as the best follow up plan. An AI system trained with appropriate data can help a physician with all these tasks with its ability to scan a hugh amount of data rapidly and efficiently. For example, AI systems can be trained to predict risk and suggest treatment plans based on CT scan and medical history of the patient[31].

There has been some progress in applying AI tools in surgery [43-44]. Artificial intelligence tools have been tested to analyze surgical video to identify adverse events[43,45] and the successful performance of the first laparoscopic surgery (suturing two ends of intestine) by a robot without human help has been reported[46]. This later report raises the possibility of fully automated surgery in the future. However, wide-spread application of AI enabled technology in surgery would require further validation and comparison with larger sample sizes. Nevertheless, the advances so far has been impressive and are likely to continue with further cooperation between surgeons and AI specialists[44].

Patient monitoring is another area where AI-enabled tools are likely to have quite an impact[5,47]. Artificial intelligence tools can use the data from EHR, smart watches, and other sensors, to inform health care providers about a patient's status in health care facilities as well as at home. For example, providers can use AI enabled remote patient monitoring (RPM) devices for patient monitoring in the ICU, ECG-based arrhythmia detection and Hemodynamics and Vital Sign monitoring[47]. Health care facilities can also use AI-enabled monitoring tools in hospitals to prevent patient falls, which can result in serious injury and extended hospital stay. The monitoring tool uses computer vision, Bluetooth, and sensors to analyze movements in the patient's room to predict a fall and to alert the care team[5]. Similarly, RPM can also collect data from patients at home. A study reviewing the currently available AI enabled RPMs suggested that the market needs more innovative RPM solutions with more transparency on the technical aspect of AI algorithms [47].

Artificial intelligence technology has been widely accepted, after an initial hesitancy, by pharmaceutical industries and especially in the field of drug discovery[49-51]. It is a time-consuming costly process to bring a prescription drug to the market with an average cost of USD 2.6 billion[52] and an average time of 10-15 years[53]. The steps involved in drug discovery is comprised of drug target recognition, drug repurposing, drug screening, target authentication, preclinical molecule determination, preclinical evaluation and then clinical testing[49,51]. Advances in AI methodologies, such as message-passing models, spatial-symmetry-preserving networks, hybrid de novo design, and other innovative machine learning paradigms, are expected to decrease the time and hence the cost associated with any of these steps[49,50,54].

The usual discovery time of 4-5 years for a candidate drug can be decreased to less than a year, as it has been demonstrated recently for the discovery of an A2 receptor antagonist using 'Centaur Chemist' AI design platforms[55]. This system can computationally sort through and compare various properties of millions of potential small molecules, looking for 10 or 20 to synthesize, test and optimize in lab experiments before selecting the eventual drug candidate for clinical trials[55]. Although various challenges, including availability of high-quality data and ethical issues discussed later, remain to be overcome, it is expected that AI technology will play an important role in drug discovery by decreasing human workloads and speeding up drug development at a more reasonable cost (Artificial Intelligence in Health Care: Benefits and Challenges of Machine Learning in Drug Development [Reissued with revisions on Jan. 31, 2020.] | U.S. GAO).

3. Challenges of applying Artificial intelligence tools in healthcare.

Despite the opportunities described above, wide-spread applications of AI technology in healthcare face a number of challenges. Major challenges include access to high-quality data, potentially biased data, inadequate transparency, and uncertain liability (Figure 5).

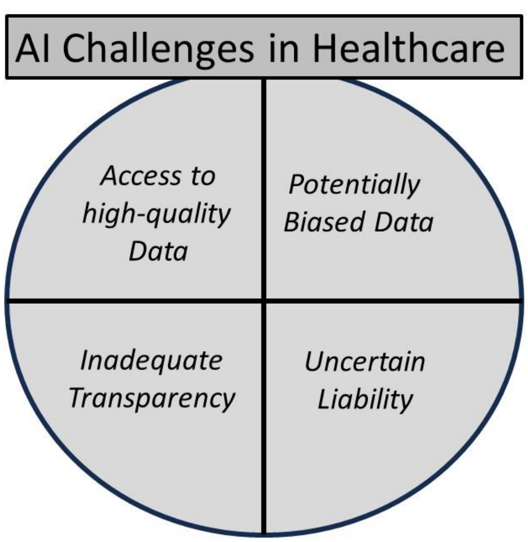

Figure 5. Major challenges of artificial intelligence application in healthcare.

Large quantities of high-quality data are needed to train, tune, evaluate, and validate AI models. For example, machine learning models often require millions of pieces of information for training[56,57]. However, there are several hurdles to accessing high quality data. Data stored in various databases, such as insurance databases, medical imaging archive systems, electronic medical record, etc., may not be formatted the same way, making it difficult to easily retrieve the data and incorporate in the AI technology of choice. The need to get patient authorization to meet the requirements of Health Insurance Portability and Accountability Act (HIPAA) of 1996 may pose a challenge for data providers. Other obstacles may be the fear of losing competitive advantage, incomplete healthcare data, not large enough databases and the long delay in accessing some federal health data. Difficulties accessing sufficient high-quality data may hamper innovation in this space. In addition, current intellectual property law does not provide adequate incentive for big data driven medicine[58,59]. Thus, there is a need to find ways to make high-quality data in sufficient quantities available to AI system developers without violating patient confidentiality and infringing on proprietary rights.

Artificial intelligence technology makes decisions based on data used to train and if the training data is biased the decision will also be biased. Artificial intelligence bias is also called machine learning bias or algorithm bias. It refers to the occurrence of biased results due to human biases that skew the original training data or AI algorithm. This will lead to distorted outputs and potentially harmful outcomes (What is AI Bias? | IBM). It follows the adage that "garbage in garbage out" or "bias in bias out". For example[60-63], if a machine is trained with disease prevalence data in a specific population or ethnic group, and then asked to predict the disease prevalence in another population or ethnic group, the prediction may not be valid since the training data may not be relevant for another group. Similarly, data collected from a military healthcare center may not be applicable to female patients or from an urban healthcare center may not be applicable to patients in rural setting. Thus, AI technology trained on biased data will have reduced effectiveness and accuracy for ethnic group/population/gender not included in the data. However, just because the data came from one group does not necessarily invalidate its applicability in another group. This is because there are many similarities in the prevalence, diagnosis and treatment of diseases among different populations and between genders. Thus, until data related to relevant population are available, a warning can be added in the output statement that clearly states the source of training data. This should allow the healthcare provider and the patient to evaluate the potential applicability of the AI-enabled decision in a specific case. Addressing bias can be a big challenge, and it will require algorithm fairness, transparency and collaboration between data scientists, healthcare providers, consumers, and regulators[64].

It is widely assumed that AI technology will be widely used in healthcare in the coming days. However, whether AI-enabled technology can be trusted is a question often raised. This is in part because the inner workings of the technology is not always transparent even to the programmers in some cases. In other words, the users or the beneficiaries of the technology often do not know how AI arrives at decision65. Is it a "Black box"? Thus, for AI to be universally accepted, it must gain the trust of healthcare professionals and patients. This is exemplified in a recent Pew research center survey revealing that 60% U.S. adults would feel uncomfortable (39% would feel comfortable) if their own health care provider relied on artificial intelligence to do things like diagnose disease and recommend treatments. A major factor is that a majority of the public is unconvinced that the use of AI in health and medicine would improve health outcomes[66]. Thus, considerable progress in improving AI transparency must yet be made in order to gain the trust of and acceptance by patients as well as healthcare professionals.

A transparent system is also needed because a transparent system, when fails, allows for inspection of the system to determine the reason for the failure and to suggest improvement. In the case of health care, where people's lives are at stake, transparency in the decision-making process is paramount. That is to have a prior knowledge of how the algorithmic input is turned into the specific output (still a black box) and what were factors that could have contributed to the failure[67]. So, what is needed is Explainable AI or XAI[68]. To address this and other issues related to AI, the European Commission issued the first legislative proposal to regulate AI at the EU level in 2021[69]. Transparency will be one of the core requirements and as stated in article 13(1), "high-risk AI systems, that pose significant risks to the health and safety or the fundamental rights of persons, shall be designed and developed in such a way to ensure that their operation is sufficiently transparent to enable users to interpret the system's output"[69]. 'High-risk' AI systems are defined as those that create adverse impact on people's safety or their fundamental rights. It is expected that more transparent AI will be developed to gain the trust and acceptance of AI users in healthcare and beyond.

Who is liable if a problem arises from the use of AI-enabled technology in patient care? The answer is unclear as far as current regulatory standards are concerned. The issue of liability is complicated by the fact that the cause of an error may not be easy to determine for lack of transparency. In addition, it may be difficult to identify the responsible person or party when considering many parties, such as developers (data scientists, engineers) of AI technology and healthcare providers, involved in developing and using these tools. Also, lack of case law dealing with AI in clinical medicine adds to the uncertainty of how a case will be adjudicated. Currently, it is the human behind the development and application of the AI technology that is liable rather than AI itself[70]. Thus, it is important to develop regulations to address the liability issue for the use of AI in healthcare. In the meantime, contractual agreements may be used to reduce liability. Such a contract may include a statement that AI systems are designed to operate under direct human supervision[70]. Some progress in addressing the liability issues is made. A 2019 report from the Expert Group on Liability and New Technologies (set up by European Commission) made recommendations on how liability regimes should be designed to address the challenges associated with AI liabilities[71]. The recommendations include situations where a person using the technology, or a manufacturer is liable. It is expected that such recommendations will form the basis of liability regulations in the future.

Conclusion

In summary, AI-enabled technologies are here to make a significant difference in the way healthcare will be delivered in the future. With improving deep learning algorithms, transparency, liability laws and easy accessibility of high quality and unbiased data in sufficient quantities, the applicability of AI in the prevention, diagnosis and treatment of diseases along with acceptance of AI by healthcare providers and patients will increase. It would be important to maintain human oversight and control to avoid unintended consequences of runaway machines making life and death decision. Before long, healthcare providers with AI-assisted evaluation of our medical records would be able to predict our mortality more precisely[72].

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