Uses of Artificial Intelligence in Healthcare: A Structured Literature Review

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Introduction

Although a precise, universally accepted definition of artificial intelligence (AI) does not exist yet, AI is typically associated with a branch of computer science focused on building algorithm-based machines capable of performing tasks that generally require human decision-making and intelligence (Stone et al., 2016). AI can be categorized based on its capabilities and functionalities. Based on capabilities, AI can be classified as Narrow AI, General AI, or Super AI. Narrow AI, sometimes also called weak AI, focuses on a single or predefined subset of cognitive abilities, and cannot perform outside of these limitations (Kaplan & Haenlein, 2019). Narrow AI enables virtual assistants such as Siri and Alexa to understand human speech and respond when queries are within their breadth of abilities. Narrow AI is also the basis of services such as Google Translate, Facebook's facial recognition abilities, and Tesla's self-driving capabilities. General AI, also known as Strong AI, is the second generation of AI in development that allows machines to apply knowledge and skills within contexts within which they were not designed to function. Such systems can reason, plan, and solve problems independently for tasks that extend beyond their planned uses. Finally, Super AI refers to machine-based systems that are truly self-aware and capable of social skills, scientific creativity, and general wisdom (Kaplan & Haenlein, 2019). Through singularity, these systems can surpass human intelligence and have the ability to perform any task.

Several subfields exist under the umbrella of AI. Machine learning involves giving computers the ability to learn without being programmed and adapt based on previous experiences (Jordan & Mitchell, 2015). Neural networks are a branch of AI that

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attempts to replicate the human brain by using algorithms to discern elemental relationships across copious amounts of data. Robotics focuses on designing and constructing robots that can be deployed for tasks that may be laborious for humans to perform steadily. Finally, natural language processing facilitates the communication between computers and humans by natural language. This subfield enables computers to read and understand data by mimicking human language (Nadkarni et al., 2011).

This paper focuses specifically on the uses of AI in the field of healthcare. Applications of artificial intelligence in healthcare can be categorized as virtual or physical (Hamet & Tremblay, 2017). The virtual branch includes mathematically based algorithms that enable the systems to develop and learn through experience and use. In contrast, the physical branch of AI includes medical devices and sophisticated robots such as the da Vinci Surgical System capable of performing surgery or carebots that serve as companions for elderly individuals with limited mobility or with cognitive decline.

Methods

For this literature review, refereed online journals and other academic resources were searched for publications that described artificial intelligence applications in healthcare settings. This paper used the method of structured review to arrive at a comprehensive and reliable overview of research on artificial intelligence in the healthcare field. The selected articles were found by searching multiple academic databases, including EBSCO, ERIC, and Google Scholar, using one of the following keywords: Artificial Intelligence, Machine Learning, Neural Learning, in conjunction with the keyword, Healthcare or Patient Care. The criteria for articles included in the literature was being published in a peer-reviewed journal between 1950 and 2021, written in English, having online full-text accessibility, and searched keywords appearing in the title. This literature review used document analysis to screen articles and collect initial data. Content analysis was then used to identify research patterns and trends.

Discussion

Timeline of AI in Healthcare

1950s–1960s Although storing digital information had its start in the early 1940s with large computer systems such as Vannevar Bush's Memex, the drive of multimedia in the 1950s would also lead to significant developments in the creation and storage of digital information. During this time, the focus was on creating machines that could make human decisions as accurate as a human could. This interest included multiple areas of science, including medicine. It was during the 1950s that early experimentations of AI were being fabricated. In 1950 Alan Turing created a machine to test whether computers could be designed to think and referred to his creation as the imitation game (Turing, 1950). The goal of the experiment was to test humans to see if they could distinguish between computers and humans based on conversation text, and eventually became known as the Turing Test (Amisha et al., 2019). Since the mere mention of the term AI by John McCarthy in 1956, the world has looked into artificial intelligence and machine learning to not only solve human problems but also predict outcomes before problems occur.

The mid-1950s and 1960s were known for major advancements during the information explosion age due to the innovations in the computer and mechanical industries (Hiagh, 2009). Creating accompanying software to talk to the machines was led by pioneers like Grace Hopper, who is widely accredited for codeveloping the standardized computer language COBOL (Abbate, 2011). The developments of programming languages were considered just as important as the hardware developments; one simply did not advance without the other. It was because of the synchronicity of the advancements that the auto industry could capitalize on AI. In 1961, General Motors built a system named Unimate, which was able to automate die casting steps by following a series of instructions (Kaul Enslin, & Gross, 2020). Soon after, in 1964, Dr. Joseph Weizenbaum used natural language processing (NLP) to create what was considered the first chatterbot named ELIZA, which was designed to simulate conversions between humans in the field of psychology and communication (Kaul et al., 2020). Two years later, in 1966, what was referred to as the "first electronic person" was created by a team at the Stanford Research Institute (now known as SRI International). The robot was nick-named Shakey and was primarily programmed to solve problems on its own by mapping out its surroundings and completing mobile-based tasks. The hope was that Shakey would lead to robots carrying out and improving complicated tasks in factories (Szondy, 2015).

1970s–1980s In 1970, William B. Schwartz published an article titled "Medicine and the Computer: The Promise and Problems of Change" (Swartz, 1970). Schwartz was a medical doctor with great interest in using computers in healthcare. He documented his views on future healthcare system developments and the benefits from such advances in technology. His team developed their own computer program that would consult with a physician by attempting to diagnose a patient based on details provided by the user in what he referred to as "branching of the decision tree" (Schwartz, 1970, p. 1259). Schwartz also issued warnings over some problems that are of concern in our current healthcare system, including high costs, social economics, legal demands, and technical considerations.

As with most technological advancements in history, there were years in which progress lacked technological developments. In the world of artificial intelligence and machine learning, these are known as "Winters." The First AI Winter that occurred in the mid-1970s continued through most of the 1980s. Exceptions to this Winter included William Clancey and Edward Shortliffe, who brought to light the uses of AI applications in multiple healthcare settings. Their 1984 publication (Clancey & Shortliffe, 1984) defined what medical AI meant and considered the potentials of AI applications with the needs of healthcare professionals to improve overall documentation and communication in medicine.

1990s–2000s The Second AI Winter occurred in the late 1980s and early 1990s where the main goals were to improve medical data online accessibility. But by the late 1990s there was regained interest in part due to the American National Library of Medicine awarding contracts to medical institutions to explore new ways to incorporate AI into healthcare, improving overall infrastructures (Kaul et al., 2020). AI took shape in the form of electronic medical records (EMRs), telemedicine, and other areas of information sharing.

2010–present Mintz and Brodie (2019) define several focuses of AI in healthcare: image processing, computer vision, artificial neural network (ANN), machine learning (ML), convolutional neural network (CNN), and deep learning (DL). Deep learning is a subset of machine learning that is constructed to process the information on multiple levels, like the human brain (Mintz & Brodie, 2019). It was first investigated in the 1950s but had limitations mainly due to the absence of computer technology. It took many years, but technology finally advanced enough that DL could be re-investigated and built on. Cardiology, gastroenterology, oncology, radiology, and surgery are a few areas in healthcare exploring the uses of AI, ML, and DL (Kaul et al., 2020).

Jiang et al. (2017) performed a literature review on the topic of AI in healthcare. Their focus was to identify specific specialties in medicine utilizing artificial intelligence to improve clinical practices. They reviewed articles published during the time period 2013–2016 covering medical specialties, healthcare data, and AI categories (ML and NLP). Once the review was completed, the team found diagnostic imaging data to be the main interest in publication content, followed by genetics and electrodiagnosis. The top four diseases that resulted in publications during 2013–2016 included neoplasms, nervous, cardiovascular, and urogenital. A similar search of publications during late 2019–2020 yielded a dramatic shift of focus to the SARS-CoV-2, the novel coronavirus that causes COVID-19 (Bansal et al., 2020).

Healthcare Education and AI

Developments in artificial intelligence have also impacted medical schools and how future medical professionals are trained. The following section reviews common uses of AI in medical schools, and how students and instructors respond to the use of this technology.

Current Applications of AI in Medical Schools

Authors such as Wartman and Combs (2019) have suggested that the system for educating medical professionals requires a revolution because the amount of available medical knowledge exceeds the human mind's organizing capacity and can lead to stress-induced mental illness among learners. Wartman and Combs (2019) suggest remediating this problem by re-engineering the medical school curricula so that it shifts from a "focus on information acquisition to an emphasis on knowledge management and communication" (p. 147). AI applications can aggregate vast amounts of data, generate diagnostic and treatment options, and assign confidence ratings to those recommendations that clinicians can then interpret and communicate to patients. Training in understanding AI systems' recommendations can enable medical students to personalize treatment to the individual characteristics of each patient. Utilizing AI systems also reduces cognitive and information overload that medical students can experience earlier in their careers.

Some researchers such as Masters (2019) believe that AI will eventually affect every aspect of human life, including medicine and medical education. Masters (2019) asserts that surgical robotics, for instance, will continue to evolve until intelligent robots with AI software can perform surgery without humans. He cautions that medical schools that have not integrated AI into their curriculum and are not teaching robotic surgery will quickly fall behind this potential standard. Earlier researchers such as Moles et al. (2009) developed a program to teach and assess the development of otolaryngologic residents' basic robotic surgical skills. Moles et al. (2009) suggest AI and robotic surgery training programs be formally established in residency programs because the skill will eventually become an integral part of surgical practice. Alonso-Silverio et al. (2018) conducted a similar study focusing on the laparoscopic surgical skills of ten medical students and six residents. They found that laparoscopic box training systems based on open-source hardware and artificial intelligence improved the learning curve and dexterity of the 16 participants.

Medical schools are increasing their use of artificial intelligence in simulation-based training designed to assess and train the psychomotor skills involved in the surgery. Mirchi et al. (2020) piloted their Virtual Operative Assistant, an educational platform that automatically assesses and provides user feedback, with 28 skilled participants and 22 novice participants who were required to perform a virtual reality-based subpial brain tumor resection task using the NeuroVR simulator. The Virtual Operative Assistant successfully classified novice and skilled participants with an accuracy of 92%, specificity of 82%, and sensitivity of 100%. The researchers concluded that the AI-based system was advantageous over traditional teaching methods because it enabled instructors to identify individual components of psychomotor expertise in tasks too multifaceted for instructors to observe normally. The system mimics real life by using an apprenticeship model with auditory feedback in natural human language in a clinical or operating environment.

Medical Student Attitudes Toward AI

Sit et al. (2020) surveyed medical students (n = 484) at 19 UK medical schools and found most medical school students surveyed (88%) believed that AI would play an essential role in healthcare. However, the students surveyed did not feel adequately prepared to work alongside AI and would find training on the subject beneficial. Some participants (n = 45) experienced AI training in their medical programs, but this group still reported a lack of confidence and understanding required for the critical use of healthcare AI tools.

Discussion of AI in healthcare in the news and lay media often express the concern that AI is replacing radiologists. Park et al. (2020) administered a web-based survey to American medical students (n = 152) to understand their perceptions about radiology and determine if such reports negatively impact medical students' perceptions of radiology as a viable specialty. After analyzing results from the six-question survey, the authors concluded that more than 75% of participants believed AI would significantly impact medicine, with 66% believing the field of diagnostic radiology would be the most heavily influenced. Regarding radiology being a viable career, nearly half (44%) of those surveyed reported that AI made them less enthusiastic about radiology. Gong et al. (2019) conducted a similar study but focused on medical students (n = 322) at all 17 Canadian medical schools. In this study, 67.7% of participants believed AI would reduce the demand for radiologists, and 48.6% responded that AI caused anxiety when considering the radiology specialty. Pinto dos Santos et al. (2019) explored undergraduate medical students' attitudes (n = 263) toward artificial Intelligence (AI) in radiology and medicine at three German universities. Participants in this study had more positive opinions about AI improving radiology and not making the profession obsolete. Results showed 77% agreed that AI would improve radiology, and 83% disagreed that AI technology will eventually replace human radiologists. A total of 77 percent of those surveyed indicated that AI training should be part of the radiology curriculum.

Instructor Attitudes Toward AI in Medical Curriculum

Much of the research on instructor attitudes toward AI in medical education has focused on the assessment of medical students. Gierl et al. (2014) explored the use of AI software to grade essays written by postgraduate medical students and found that scores generated by the AI systems aligned consistently with those of human scorers at a high level. Gierl et al. (2014) concluded that AI-based grading systems could improve medical education by providing consistency in scoring, reducing the time and cost required for assessment, and providing students with immediate feedback on constructed-response tasks. Kintsch (2002) addressed the use of latent semantic analysis (LSA), which is a form of machine learning, to compare student-constructed responses to a target or model essay. Medical school students are frequently assessed using standardized patients. This involves requiring students to compose a full-text written account of the encounter with the patient that is then evaluated using a rubric. Kintsch (2002) suggests that this practice is an effective teaching method, but grading these responses is challenging. LSA, however, could be used to devise automatic grading that could be supplemented with feedback from the instructor.

Promising AI Applications in Medicine

The following section explores several applications of AI in healthcare that are used by patients and healthcare professionals. This section represents a small selection of the AI tools that are currently available or in development.

Chatbots

AI-powered chatbots simulate human conversation with a patient to help assess their symptoms and determine the next steps for care. These automated systems are important in healthcare because they provide information to help patients cure some common illnesses without the intervention of a healthcare professional. Approximately 60% of doctor visits are due to simple health concerns, and 80% of these can be cured with home remedies, simple lifestyle changes, or over-the-counter medication (Bhirud et al., 2019). If additional medical help is needed, the chatbots can provide guidance.

One example of a widely used text-based chatbot is the Centers for Disease Control and Prevention's (CDC) coronavirus self-checker. This AI-based program is designed for use by patients rather than medical professionals. After the user agrees to the terms of service and inputs demographic information relating to age, gender, race, and location, the chatbot proceeds to list potentially life-threatening symptoms. The user must respond using the on-screen "yes" or "no" buttons. Based on the response, the chatbot will either encourage the user to seek immediate medical attention or will continue asking more specific questions to gather more information. The chatbot can provide general recommendations for avoiding getting sick as well as help users determine if they should see a doctor. The AI-based software provides immediate information to the user from the comfort of their home.

Medical Imaging

Since the onset of the COVID-19 pandemic in 2019, researchers have been looking for ways to help track, diagnose and prevent the spread of the virus. Bansal et al. (2020) reviewed the potential ways in which AI and ML could be utilized to develop predictive models in the battle against COVID-19. Key highlights from their article outline how DL, NLP, sentiment analysis, and machine vision can help with predicting COVID-19 outbreaks. Diagnostic imaging can also harness the power of AI and ML for predicting COVID-19 by using algorithms to detect the virus on lung x-rays. Minaee et al. (2020) developed a deep learning algorithm that used a dataset containing 5000 chest x-rays to teach the program how to identify COVID-19 on the images. The results of the experiment were considered promising by showing a sensitivity rate of 98% and specificity of 90%. The researchers were so impressed with the outcomes that they made the dataset of 5000 chest images publicly available for other researchers.

Several other areas in medicine are currently exploring the potential uses of artificial intelligence to detect and predict the disease. For example, AI is being used to detect different types of cancers. Medical imaging such as computed tomography (CT) colonography can identify the location and size of polyps, but it lacks the ability to help radiologists always differentiate between precancerous and noncancerous tissue. Grosu et al. (2021) demonstrated the ability of ML to distinguish between benign and premalignant colorectal polyps by identifying their differences on CT images with an area under the curve (AUC) of 0.91. In Costa Rica, scientists used AI to create an automated process of reviewing cervical images for the detection of cancerous tissue. Although image quality was a limitation in the study, Hu et al. (2019) proved the algorithm showed promise by having higher accuracy when compared to the traditional cervigram interpretations or conventional cytology (Fig. 1). Dermatology studies for leveraging AI for the identification of cancerous lesions on the skin are also being investigated. Soenksen et al. (2021) used deep convolutional neural networks (DCNN) in their study to distinguish between suspicious pigmented lesions and nonsuspicious lesions on photographs of patient's backs. The results were considered promising by the researchers in that the algorithm could be used by physicians for providing rapid assessment of patient skin lesions.

Innovative uses of AI are also being used in the field of cardiology. Taylor et al. (2013) are leveraging DL and computational fluid dynamics (CFD) to create

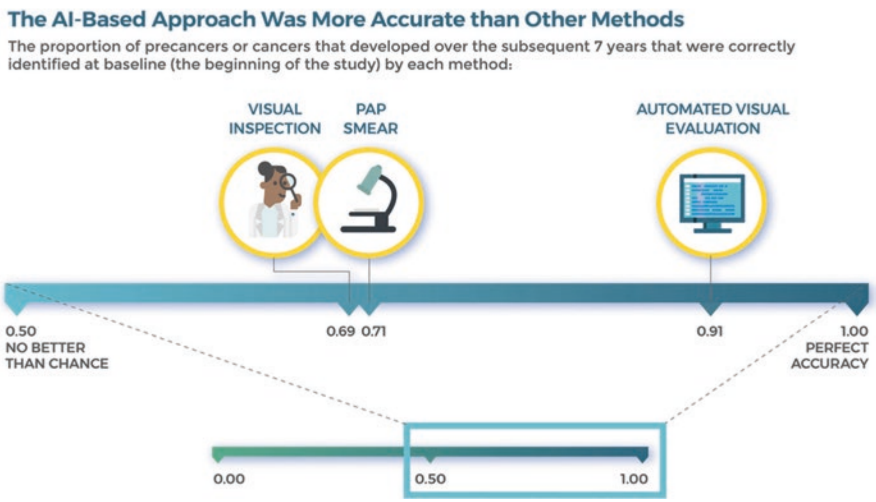

Fig. 1 Infographic demonstrating the accuracy of AI used to detect cervical cancer
Note: From "An Observational Study of Deep Learning and Automated Evaluation of Cervical Images for Cancer Screening" by Hu et al., (2019). *Journal of the National Cancer Institute*, *111*(9), 923–932. https://doi.org/10.1093/jnci/djy225. Copyright 2019 by the National Cancer Institute (NCI). In the public domain

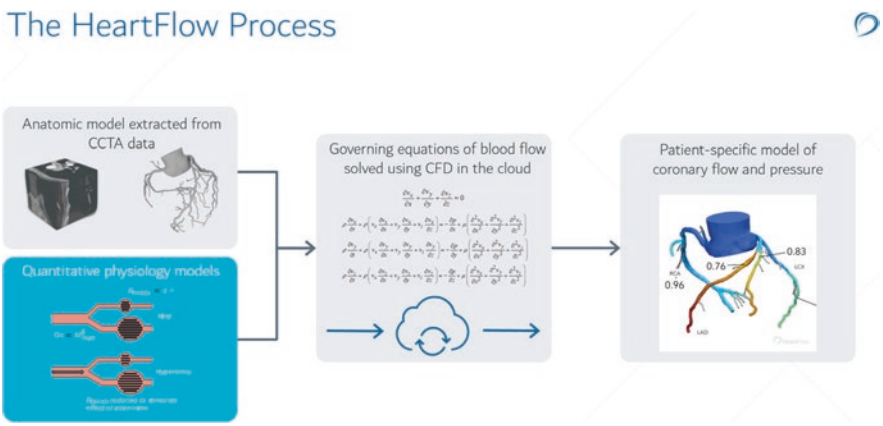

Fig. 2 Sample image of an FFRct analysis demonstrating blood flow simulation of the coronary arteries of a patient
Note: Adapted image from "Computational fluid dynamics applied to cardiac computed tomography for noninvasive quantification of fractional flow reserve: scientific basis" by C. A. Taylor, T. A. Fonte, and J. K. Min, 2013, *Journal of the American College of Cardiology*, *61*(22), 2233–2241. Copyright 2021 by HeartFlow., Inc. Reprinted with permission

simulated models of the blood flow of the coronary arteries derived from coronary CT images. Physicians are then able to review 3D models and measurements of the coronary blood flow specific to each patient. The 3D representations also give doctors a communication tool to discuss coronary artery disease diagnosis with their patients. An overview of this simulation process can be seen in Fig. 2.

Han et al. (2021), Schock et al. (2020), and York et al. (2020) are all pioneering ways to use AI to aid in the area of skeletal radiology. Han et al. (2021) explored using neural symbolic learning (NSL) and deep neural learning (DNL) to help create autogenerated reports on spinal structures identified on magnetic resonance images (MRI). The team developed a two-step framework for autocreating reports with a system demonstrating 95.8% pixel accuracy. Schock et al. (2020) developed a convolutional neural network (CNN) to aid radiologists by automatically segmenting and measuring anatomy on long-leg radiographs (n = 225). The experimental AI system showed to be faster than radiologists at measuring anatomy by 33 seconds. Lastly, York et al. (2020) wanted to gain insight into how patients felt about the use of AI in diagnostic imaging of bones and joints. The team sent questionnaires to patients (n = 300) with a 72.2% completion rate (n = 216). Overall findings from the study suggest that patients prefer a human doctor to read and assess their medical images instead of AI-based systems.

Ethics with AI in Medicine

Ethical Concerns

In 1970, medical doctor Willaim B. Schwartz published an article that provided valuable insights into the upcoming changes that would happen to the healthcare system due to advances in technology. Dr. Schwartz not only described the innovative uses that new technologies could deliver to the medical world, but he also understood the ethical considerations that would likely arise. The first item he listed as a potential threat was the ability to keep medical records confidential with the soon-to-be implementation of computer systems in hospitals and other medical institutions (Schwartz, 1970). The next issues that Schwartz questioned were the legal and liability of such things as data breaches and incorrect record keeping. Today, over 50 years later, some of those very worries are still a large concern for ethical, legal, privacy, and security reasons. As we bring AI and ML into the world of medicine, these concerns also need to be addressed with firm leadership.

To investigate these issues in today's healthcare world, Hochheiser and Valdez (2020) reviewed articles published between 2017 and 2019 with a focus on biomedical informatics and ethics in research. The authors discovered three themes among the articles selected: current systems, system designs, and research conduct. They also highlighted the important role newer technologies such as social media could have on patient recruitment for research purposes, but responsible use is needed to maintain study integrity.

Patient Privacy

To protect patients' medical records, the Health Insurance Portability and Accountability Act (HIPAA) of 1996 was introduced (U.S. Department of Health and Human Services, 2013). HIPAA provides a set of standards for medical institutions to follow in order to protect patient information. Prior to this act, the healthcare industry did not have a national set of requirements to adhere to. Most of the privacy protections addressed under HIPAA cover multiple forms of patient data. The use of AI in healthcare presents newer concerns that will need to be addressed properly even as new technology continues to emerge. Biosensors are one of such newer technologies in which the protection of patient data is causing alarm. Wearable biosensors are sensing devices attached to the human body that recognizes, measures, and/or records a biological element of that person (Kim et al., 2019). Examples of wearable biosensors documented by Kim et al. (2019) include contact lenses, watches, finger clips, and patches designed for blood glucose monitoring. Many of these sensors are approved by the Food and Drug Administration (FDA) and are contributing to patient care. However, the area of patient data and who has access is of great concern. Kim et al. (2019) highlighted the importance of designing information collection infrastructures with strict security and privacy while maintaining proper data management.

It is also important to understand that different countries comply with unique rules and regulations regarding protecting patient health information. Most nations have their own government entities that are responsible for data safety and compliance. Schönberger (2019) reviewed 300 articles covering legal and ethical issues on the topic of AI in healthcare in Europe and the United Kingdom. He concluded that current laws could be applied to AI technology in healthcare or could be adjusted to accommodate issues with modern technologies. This is a similar viewpoint shared by Vayena et al. (2018) as in their article, it was noted that the European General Data Protection Regulation (GDPR) imposes restrictions regarding the creation, storage, and communication of patient data.

Cyber Security

The important role of cyber security becomes very apparent when discussing the safeguarding of patient health information (PHI). Health information technology (IT) has the complex task of preventing data breaches and ensuring patient information is safe and used properly. In 2018, a team from Western Michigan University investigated cyber security threats in healthcare. Ronquillo et al. (2018) reviewed data breaches during the years of 2013–2017 and found there to have been 128 medical record breaches and 363 hacking occurrences reported in the United States. The team noted that because of the increased use of EMRs (electronic medical records), medical institutions had become targets for hackers to obtain private patient information illegally. The authors concluded that informatics and cyber security infrastructure in healthcare will have to evolve in order to maintain secure environments.

Limitations in AI

The greatest weakness of artificial intelligence and machine learning is the process in which the learning result is underspecified because data points outnumber the parameters and are known as underspecification (D'Amour et al., 2020). Another term for this complicated issue is called overfitting and occurs when the ML algorithm is too focused. Reliability and credibility can then become problematic in machine learning because results may be incorrect due to the algorithm overlooking certain data or focusing only on certain data points. The team at Google decided to research this weakness in several areas, including computer vision, radiology images, NLP, clinical risk predictions, and medical genomics (D'Amour et al., 2020). The result of their deep dive into each category helped them conclude that creating training models with more trusted biases may help prevent inaccurate solutions produced by some ML algorithms.

Conclusion

In conclusion, the past few decades have shown fascinating new developments using AI in healthcare to improve patients' health. Advances in AI show the potential for creating innovative solutions in the field of medicine. Both innovative and powerful, AI can be a turning point in solving medical problems and predicting outcomes. However, ethical, privacy, and security measures must be taken under thoughtful consideration when integrating AI into the healthcare setting. With proper and responsible use, AI can change the field of medicine by giving medical professionals an opportunity to learn and develop new pathways.

Although the intention of this literature review was to introduce and offer a historical overview of applications of AI in healthcare for those outside of the field, our study has some limitations that could be addressed by more in-depth future studies. First, the study was limited to articles written in English and with full-text accessibility, which may have excluded promising research. Second, our literature review took a broad approach to reviewing literature on AI in healthcare. Future studies could explore AI-based tools in specific areas of healthcare to produce results and strategies that can be implemented by healthcare professionals.

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