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Literature Review

Artificial intelligence in medicine: What is it doing for us today?☆

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ABSTRACT

With its origins in the mid- to late-1900s, today, artificial intelligence (AI) is used in a wide range of medical fields for varying purposes. This review first covers the early work regarding AI in medicine, then aims to elucidate some of the most current applications of machine learning in medicine according to the following four specific categories: (1) its use in assessing the risk of disease onset and in estimating treatment success; (2) its use in managing or alleviating complications; (3) its role in ongoing patient care; and (4) its use in ongoing pathology and treatment efficacy research. Lastly, this paper clarifies some of the potential drawbacks, concerns, and uncertainties surrounding the use of AI in medicine and briefly discusses some of the efforts being made to prepare the health care industry for the implementation of AI.

Early work

According to the history books, the earliest applications of artificial intelligence (AI) in the medical field occurred predominantly in the 1960s and 1970s (the term itself having been coined by John McCarthy in 1955 [1]). On a broader scale, early theorists like Alan Turing [2] first questioned whether or not computers could be made to operate in a manner similar to that of the human brain (i.e., "to think"). Application of early machine learning principles came with the introduction of the Polish "bomba" and British "bombe" machines used to decipher the Germans' Enigma machine codes during World War II [3]. The development of the first AI program (i.e., the Logic Theory Machine) said to be capable of mimicking some aspects of humans' problem-solving abilities is often attributed to Herbert Simon, Allen Newell, and John Shaw in the mid-1950s [4,5], though several researchers in the same decade also explored the possibility of developing chess- and checkers-playing programs [6–8], including Arthur Samuel, who is believed to have introduced the term "machine learning" [8]. Joseph Weizenbaum at the Massachusetts Institute of Technology held a similar role in early artificial intelligence application work with his ELIZA language processing program, which mimicked a human therapist by incorporating key words or phrases input by the user to produce a response [9].

With the eventual revelation that AI could perhaps be used to specifically solve or clarify complex biomedical problems, interest in its potential grew exponentially. In 1961, Warner et al. published a study on the use of an automated diagnostic system for diagnosing congenital heart disease, in which data were drawn from 1035 patients referred for cardiac catheterization and analyzed [10]. MYCIN, a computer program developed by researchers at Stanford University in the 1970s, was used to diagnose and recommend treatment—specifically antibiotics, with the dosage adjusted according to each individual patient's body weight—for serious infections by identifying the bacteria in question causing the infection [11]. An earlier initiative conducted at the same institution, the Dendral project, had aimed to study hypothesis formation and discovery in science, specifically via assisting organic chemists in elucidating the structure of unknown organic molecules [12]. GUIDON, an intelligent computer-aided instruction program that uses AI techniques to represent both subject material and teaching strategies [13] was developed in the late 1970s for teaching infectious disease diagnosis to medical students through the use of case presentations. Other systems like INTERNIST-1 and its successor, Quick Medical Reference, were developed and put into play to assist health care professionals in patient diagnosis: these systems relied on a knowledge database of 570 diseases, which clinicians could reference when presented with a patient, while the latter system could also generate or refine hypotheses in complex cases [14]. Kulikowski and Weiss discussed the CASNET and EXPERT projects in the 1980s; the former was used in the context of glaucoma care, while the latter was established to help build models for reasoning in rheumatology and endocrinology [15]. As far back as 1959, an article in *Science* postulated how computers might fit into the process of patient diagnosis, acknowledging that

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"before computers can be used effectively … we need to know more about how the physician makes a medical diagnosis,"[16] with subsequent research aiming to elucidate this process in the context of computer operation [17].

In later years, research turned towards evaluating computer-aided diagnosis in comparison with the abilities of human physicians. A controlled, prospective, unselected real-time comparison study involving 304 patients with abdominal pain conducted in the early 1970s found that the computing system's overall diagnostic accuracy was higher than that of even the senior member of the clinical team [18]. A follow-up multicenter trial involving eight centers and more than 16,737 patients and 250 physicians, respectively, considered diagnostic accuracy using a baseline diagnosis method (human diagnosis) in comparison with computer-aided diagnosis; importantly, improvements in diagnosis, decision-making, and patient outcomes were noted with use of the latter [19]. Other research efforts attempted to utilize computers to generate new or more efficient methods of diagnosis not previously available through the compilation and use of standardized records, [20–23]; to improve the detection and classification of lesions in areas such as the vascular system, skin, lungs, or breasts via image analysis, [24–28]; and to elucidate biological mechanisms that may have previously been unknown [29,30]. Computer systems also began to find applicability in preventative medicine [31].

Today, AI is used in a wide range of medical fields for varying purposes. This review aims to discuss some of the most current applications of machine learning in medicine with respect to recent research published and products released, while also clarifying some of the potential drawbacks, concerns, and uncertainties surrounding its use. How the industry is preparing for the incorporation of this technology is also explored.

Current research

For the purposes of this section of the paper, which aims to act as a record of the various trends emerging in AI in medicine today, a PubMed literature search was conducted to identify relevant manuscripts published no earlier than 2015. Keywords included "artificial intelligence" AND "medicine" and "machine learning" AND "medicine." Only original research studies, case reports, or reviews that drew new conclusions from the studies they surveyed with available abstracts and which had been published on the subject of AI in medicine were included. Papers published in languages other than English without an available English translation were excluded. Once trends were identified, a broader Internet search using the same keywords was conducted to identify any other relevant studies that may have been overlooked, though the findings from this search were limited.

From this literature survey, it became apparent that AI is being employed in the medical space in at least four distinct ways: (1) in the assessment of risk of disease onset and in estimating treatment success prior to initiation; (2) in an attempt to manage or alleviate complications; (3) to assist with patient care during the active treatment or procedure phase; and (4) in research aimed at elucidating the pathology or mechanism of and/or the ideal treatment for a disease. The following presents specific study examples of these four categories and discusses their significance.

In evaluating the risk of disease onset and potential treatment outcomes

The cardiovascular space represents one area of medicine in which AI has been largely influential. In a study published in *Medicine,* Li et al. developed an artificial neuron network (ANN)—a computational model constructed similarly in form to that of a biological neural network that "learns" based on information that it is given—to predict the risk of congenital heart disease (CHD) in pregnant women, and found that the model was helpful in identifying those patients at high risk of developing CHD early on in pregnancy [32]. An ANN was also used in a multicenter comparison study evaluating whether the use of an ANN-based diagnostic system and conventional quantitation were comparable in diagnosing coronary artery disease [33]. Additionally, in a cohort of more than 370,000 patients free from cardiovascular disease, the use of machine learning was found to be beneficial in that it improved the accuracy of cardiovascular disease risk prediction through identifying patients who could benefit from preventative treatment, while also ruling out those in whom treatment would be unnecessary [34]. Jeganathan et al. evaluated the use of AI in mitral valve analysis, which is typically completed manually to diagnose patients with mitral valve disease. Their findings indicated that good reproducibility with minimal user intervention could be achieved via automated diagnosis [35]. Dawes et al. found that a machine learning model that uses three-dimensional cardiac motion was able to predict outcomes independently of conventional risk factors in patients with newly diagnosed pulmonary hypertension [36].

Machine learning has also been proven to be advantageous in assessing and identifying patients at risk for other diseases. One study by Kind et al. found that its use was beneficial in flagging individuals at high risk for colorectal cancer based on electronic medical records, including those with no visible clinical signs or symptoms [37]. Another employed machine learning to construct pretest models for predicting whether a patient would test positive for a particular respiratory virus [38]. Researchers at the Massachusetts Institute of Technology have developed a neural network model to identify depression from human speech patterns, regardless of what the speaker tells their physician [39]. Along this line, several papers also detail work being done to translate brainwaves into decipherable speech, which could eventually benefit those patients who are unable to talk [40]. Additionally, the use of AI in the diagnosis of melanoma [41], dementia [42], diabetic retinopathy [43], tuberculosis [44], and glaucoma [45] has also been investigated, as has its employment in predicting the outcome of radiation therapy [46], the occurrence of acute respiratory disease events and mortality in smokers [47], the success of substance abuse disorder treatment [48], the onset of diabetes [49,50], HIV transmission patterns [51], and the findings of breast cancer [52] and depression [53] in breast cancer patients, respectively. Assistance from AI to define certain subgroups within a patient population, such as individuals in the intensive care unit with similar clinical needs [54], or those patients with certain temporal bone abnormalities [55], has also been relied upon. Furthermore, while not representing an investigation on disease, per say, Stonko et al. were able to use an ANN to successfully predict trauma volume, the number of emergent operative cases, and average daily acuity at a level 1 trauma center by integrating temporal and weather data [56]. Ryynänen et al. considered the use of an AI method based on causal Bayesian networks to compare different treatment alternatives and identify patients who would benefit from treatment [57]. Though they evaluated the approach's application in continuous positive airway pressure treatment of sleep apnea, they acknowledge that it may be applicable in other conditions as well [57]. Other researchers at IBM Research (Yorktown Heights, NY, USA) and Google (Mountain View, CA, USA) are focusing on the prediction of emergency room visit [58] and hospital outcome [59] trends using machine learning as well.

To alleviate or reduce complications

In addition to its uses prior to or at the time of disease onset, AI may also be useful in mitigating progression or further adverse events of a disease. In a study by Dente et al., machine learning algorithms were used to identify predictive profiles of bacteremia and pneumonia in patients with combat wounds treated at the Walter Reed National Military Medical Center between 2007 and 2012 [60]. The researchers suggested that the implications of this study should also be considered in civilian trauma patients as well. Machine learning was also employed in the European Union-funded MOSAIC project to develop predictive models of type 2 diabetes mellitus complications such as retinopathy, neuropathy, and nephropathy using electronic medical records data [61]. Additionally, Wise et al. evaluated preoperative factors independently associated with prolonged postoperative ventilation in patients undergoing coronary artery bypass grafting, and aimed to optimize the identification of patients at risk before surgery using an ANN [62]. AI has also been used to estimate neurosurgical outcomes in focal epilepsy patients [63] and in predicting ischemic stroke and thromboembolism in patients with atrial fibrillation [64]. It may be beneficial in mitigating renal transplant rejection [65]. Furthermore, on the administration side, Hu et al. employed machine learning to better identify common complications in electronic health records data, as part of an effort to collect data for secondary purposes including research [66].

In ongoing patient care

With respect to its use during active treatment, AI predominantly appears to be beneficial in augmenting physicians' work. A study evaluating the use of computer-aided detection (CAD) of brain metastasis on radiologists' diagnostic performance in interpreting three-dimensional brain magnetic resonance imaging (MRI) scans found that CAD assistance helps radiologists to improve their diagnostic performance [67]. Researchers also employed AI to assess whether patients would tolerate major surgery or chemotherapy by analyzing their body morphometric age via muscle quantification [68], as well as in bone age assessment in the evaluation of patients with endocrine and metabolic disorders, respectively [69]. Other investigations indicate that AI may also have implications in intraoperative pathological diagnosis [70], the clinical management of patients undergoing echocardiographic evaluation [71], in collagen proportional area extraction during liver biopsy [72], in reducing the number of false-positive results when detecting nodules in chest radiographs [73], and in evaluating neurological deficit in stroke victims [74]. AI may also have some use in predicting long-term individualized disease progression [75], in evaluating childhood malnutrition [76], and in the analysis of breath samples to determine a patient's health status [77].

In clinical research and drug development

AI is also further expected help expedite clinical diagnosis and research. Researchers in Japan employed AI in the sequencing of cancer genomes to better identify patients with hematological malignancies and determine applicable drug information [78]. Additionally, a separate study by Heinson et al. on the use of machine learning indicated its applicability in distinguishing bacterial protective antigens (BPAs) from non-BPAs in reverse vaccinology, which could eventually assist in the development of new vaccines [79], while one by Romeo-Guitary et al. employed a systems biology approach and AI to identify a neuroprotective agent for the treatment of peripheral nerve root avulsion [80]. Researchers more recently published a proof-of-concept study on a computer system that can teach itself to design new drug molecules from scratch with certain desirable physical properties [81].

AI may also help to reveal new avenues for the diagnosis or monitoring of diseases that may ultimately simplify the task: in one study, Beck et al. used a machine-learning algorithm in the prediction of breast cancer prognosis and identified stromal morphologic structure as a previously unrecognized prognostic determinant for breast cancer [82], while researchers in a separate study used retinal fundus images to predict cardiovascular risk factors they report were not previously thought to be present or quantifiable in retinal images, including age, gender, smoking status, and major adverse cardiac events [83]. Other applications of AI in the medical research setting include as part of a recent study aiming to generate accurate classification models using machine learning techniques that could be used to identify insulin-degrading enzyme modulators, which the researchers hope will lead to an effective treatment for Alzheimer's disease [84]. A study considering the use of machine learning in the development of membranolytic anticancer peptides reported that, of 12 sequenced, 10 were active against cancer cells [85]. Some researchers have also suggested that AI may be a solution to answering fundamental questions in the drug development pipeline, including who to recruit and what outcomes to measure in clinical drug trials [86], as well as the potential drug responses that could present [87,88]. Lastly, AI may change the manner in which animal testing as part of drug development and clinical trials is performed: in a study published in the journal *Toxicological Sciences*, the training of an AI interface to predict what the toxicity effects of thousands of unknown chemicals might be using data on the outcomes of previous animal tests showed an accuracy comparable to that obtained using live animal tests [89].

Concerns

Despite these applications, however, there are still a number of concerns surrounding the adoption of AI into medicine. First and foremost, ethical concerns have been voiced, in particular with respect to the use of artificial intelligence in the care of elderly patients [90]. It is largely understood that the AI movement in medicine is represented by two separate branches: the virtual and the physical [91]. The virtual branch is best characterized by the use of mathematical algorithms that induce learning through experience, while the physical branch encompasses most predominantly the use of robots. Though these robots are being used in the surgical setting to improve procedural outcomes [92–94], there is also a growing interest in their use in the care of elderly individuals. Here is where many of the ethical concerns surrounding the use of AI stem from. Sharkey et al. highlighted a number of such in their article, including (1) the potential for a reduction in the amount of human contact; (2) increased feelings of objectification and the loss of control as well as deception and infantilization in the elderly; and (3) a loss of privacy, personal liberty, and the existence of conflict regarding the circumstances in which elderly people should be allowed to control robots [95]. However, despite these thoughts, it has been suggested that, overall, the use of robot technology in elder care is beneficial [96], though more research on the subject is ultimately needed [97]. With respect to the former branch, there may be racial bias that could arise as a result of the data provided to the AI system: Char et al.[98] cite the example of the fact that data from the Framingham Heart Study used in nonwhite populations led to both the overestimation and underestimation of cardiovascular disease risk [99]. More broadly, Char et al. further stress that bias could possibly introduced into health data in three ways: via human bias; as bias that is introduced either by accident or on purpose (e.g., by the manufacturer) into the AI system's design; and as bias in the ways in which health care systems use the data (e.g., as a result of physicians' tendencies to possibly avoid patients with certain diagnoses, AI systems may designate these diagnoses as being always fatal and may adversely adjust treatment protocols in response) [98].

There is also lingering concern that AI might one day replace medical technicians or physicians, especially those in medical disciplines in which diagnosis is based on pattern recognition. Indeed, one recently published article asked radiologists, “are you working with AI or being replaced by AI?”[100] In an editorial published in the *Archives of Pathology & Laboratory Medicine*, Granter et al. hypothesize that, based on the recent success of Google’s (Menlo Park, CA, USA) AI computer program, AlphaGo, in beating the world’s best player of Go, a complex board game with ancient roots, that it is likely that AI may eventually replace the human microscopist [101]. A follow-up editorial by Sharma et al. refutes Granter et al.’s argument, but acknowledges that, in time, it is likely that human clinicians’ “cognitive lead” over AI will narrow [102]. Char et al. note that AI could represent a boon as clinical medicine moves progressively toward a shift-based model and the number of clinicians who see a patient from presentation to the end of treatment decreases, but may also gather unintended levels of power as the only consistent observer of the patient’s progression [98]. Other reports, however, while they have called to mention the potential threat of AI, have suggested that it will likely augment, rather than hurt, physicians’ work [103–105].

Even if AI does not replace physicians, reliance on its capabilities may lead to the deskilling of medical professionals, or to inadequate or incorrect computer-aided diagnosis. In a study by Anh et al., of 2298 electrocardiograms (ECGs) characterized as atrial fibrillation by a computer algorithm, 442 ECGs from 382 patients were deemed to represent incorrect diagnoses by two electrophysiologists who reviewed the scans [106]. Southern et al. detailed the presentation of a 62-year-old female who was mistakenly diagnosed via computer interpretation of her ECG with acute ischemia, and used the case report as the basis for a study evaluating the effects of incorrect computer diagnosis on medical resident decision-making [107]. Hakacova et al. found that automated systems were not on average significantly better than nonexpert physicians in diagnosing cardiac rhythm disorders based on ECG scans, and that automated systems can be incorrect in cases in which physicians are incorrect as well, leaving open the potential for misdiagnosing a patient [108]. Komorowski et al. also noted concern regarding the possibility of AI use resulting in the dissemination of too much patient data, leading diagnosis to become more complex than necessary [109].

Lastly, there are also concerns regarding the compilation of data associated with electronic medical records. Even as far back as 1960, patient data were being collected via electronic systems, and there were both advantages and disadvantages to such noted [110]; one paper from 1964 acknowledged “it appears that the most difficult and controversial subject is the handling of medical records,” due in part to the fact that no protocols were yet in place regarding what should be collected and how it should be maintained, despite the fact that collection of some sort was already ongoing [111]. With the increase in the complexity of computer systems, concern over patient data collection and storage as well as the efficacy of associated security measures has only grown [112,113]. As technology continues to advance and devices become more connected, patient privacy will become an increasingly larger, more worrying, and more complicated issue [131,114]. Also adding complexity is the idea that patient medical records represent a potential significant source of data to use in breakthrough research [115]; indeed, Char et al. suggest that data gathered about specific patients’ health, diagnostics, and outcomes will likely become part of large datasets and may be incorporated in future published literature or clinical trials without the patient’s consent or knowledge [98]. In such a situation, many have asked—who really owns the data? [116] In light of this, practitioners should perhaps strive to keep their patients as informed as possible regarding how their medical records might be used and to obtain informed consent where they believe it might necessary.

Market offerings

At this time, there are a small but growing number of AI health care products on the market. Most current offerings appearing to be for use in patient diagnosis, and many seem specifically to supplement the abilities of existing imaging modalities. One example is the IDx-DR software program (IDx, LLC, Coralville, IA, USA) recently approved by the United States Food and Drug Administration (FDA), which uses an AI algorithm to analyze images of the eye taken with a retinal camera to spot symptoms of diabetic-related vision loss [117,118]. 20/20NOW similarly announced the release of its Eyelogic AI technology to assist in the diagnosis of retinal diseases [119]. Separately, the Viz.ai system (Viz.ai, Inc. Palo Alto, CA, USA), which connects to a hospital computed tomography scanner to alert the stroke specialist that a suspected large vessel occlusion stroke has occurred by relying on machine learning, was granted de novo classification by the FDA [120], while Imagen Technologies (New York, NY, USA) also obtained FDA approval to market its OsteoDetect computer-aided detection and diagnostic software, which employs an AI algorithm to analyze two-dimensional X-ray images for signs of distal radius fracture in adult patients [121]. Bay Labs (San Francisco, CA, USA) also recently received 510(k) clearance from the FDA for its EchoMD AutoEF software for the fully automated clip selection and calculation of left ventricular ejection fraction [122], with previous research having already demonstrated its good accuracy as compared with human cardiologists [123]. Butterfly Networks has received FDA clearance for the application of its Butterfly iQ® for iPhone AI-powered ultrasound imaging system in 13 clinical applications [124]. Subtle Medical has received both 510(k) clearance from the FDA and the European CE mark for its SubtlePET AI platform, which enhances the quality of images taken during positron emission tomography scans performed at a quicker pace [125], enabling an overall faster completion of patient imaging procedures. Similarly, HeartVista’s AI-driven, one-click autonomous MRI acquisition software can purportedly drastically cut the length of cardiac MRI scan procedures while simultaneously monitoring image quality [126]. Arterys, another manufacturer of an AI solution to supplement cardiac MRI, has added a number of enhancements to its original Cardio AI^{MR} platform [127]. Aidoc and MaxQ AI have additionally received FDA clearance for their respective AI technology offerings designed to assist with patient triage by flagging intracranial hemorrhage cases in head computed tomography scans [128,129]. Bayer and Merck have also jointly received a breakthrough device designation from the FDA for their chronic thromboembolic pulmonary hypertension AI pattern recognition software for use in conjunction with computed tomography pulmonary angiography [130]. QView Medical offers QVCAD, an FDA-approved AI system for concurrent reading of automated breast ultrasound scans [131].

Regarding other AI products that do not necessarily supplement the abilities of existing imaging systems, AliveCor has been busy in the realm of AI with the approval of their Kardia Pro AI-enabled monitoring platform for the early detection of atrial fibrillation [132] as well as the organization of a partnership with the Mayo Clinic for the development of tools for medical and non-medical personnel to easily screen for long QT syndrome through the combination of the company’s AI technology and the clinic’s patented algorithms [133]. A separate collaboration that yielded the KardiaK Platform, which screens for elevated levels of blood potassium without requiring any blood from the patient, has also received the FDA’s “Breakthrough Device” designation [134]. Another offering in the cardiology space that grew out of a collaboration between iRhythm Technologies and Stanford Medicine yielded a AI-powered algorithm capable of diagnosing a variety of arrhythmias through single-lead electrocardiograms at a level similar to a human cardiologist; the algorithm recently received 510(k) clearance from the FDA [135].

Conversely, some AI applications support ongoing patient care after a diagnosis has been made. Beta Bionics, Inc. (Boston, MA, USA), a medical technology company working to incorporate AI into the world's first autonomous bionic pancreas, was previously granted investigational device exemption approval, allowing the company to move forward with the recruitment of both adults and children for home-use studies to test its iLet™ Bionic Pancreas System [136]. AliveCor has previously touted the release of medical research highlighting the potential use of the company's AI technology as a potential alternative to surgically implanted heart monitors, although this indication has not yet been FDA-approved [137]. VRHealth offers Luna, a virtual reality AI therapist trained with evidence-based psychological protocols that aims to reduce the physical and psychological effects of hot flashes in users [138]. Notal Vision is also moving forward with efforts to introduce an AI-enabled optical coherence tomography system for monitoring wet age-related macular degeneration at home in the elderly [139].

In some cases, manufacturers are focusing on how AI could support physicians directly. Amazon has launched its Comprehend Medical service, a HIPAA-eligible service that uses machine learning to identify patient diagnoses, symptoms, medical test findings, treatments, and other relevant medical data for easier review from "unstructured" medical text such as doctor's notes [140]. AiDoc and SaferMD have also announced a partnership aimed at improving the Medicare reimbursement of AI radiology procedures [141].

Reflection

Overall, while AI has come a long way since its infancy in terms of its incorporation into medicine, it still has a long way to go—and, it may never, in fact, reach a point at which it will be totally independent of a human physician. Considering whether AI is on par with physician assessment, a letter by van Smeden et al. [142] in response to a study evaluating the use of deep learning algorithms for the detection of lymph node metastases in women with breast cancer [143] cautioned that certain criteria must be standardized and employed to ensure fair comparison—something that, at this time, a human must develop and "feed" to the AI system.

Still, AI's possible uses in diagnosis, treatment, and clinical research remain numerous, and the industry on some levels is beginning to prepare for the inevitable through the establishment of working groups, guidelines, frameworks, and the like [144–147]. Only several months ago, for example, the American Medical Association passed its first policy guidelines on "augmented intelligence," detailing five tasks that the organization will strive to perform [148]. In the image of the first workshops held in conjunction with the birth of modern AI [149], in more recent years, webinars, lecture series, and even entire conferences dedicated to the topic of AI in medicine have begun to spring up en masse [150–153]. Schools, too, on the subject of AI in health care are being established [154].

Furthermore, similar to how technology as a whole has become more readily adopted by younger individuals, AI's possible implications have begun to be considered more strongly in the education of the next generation of physicians [155]. One study by Uemura et al. suggested based on the findings of a study that employed an AI-based measure to analyze the hand movements of expert and novice surgeons that such could be used to provide feedback on surgeons' current skill levels and/or to inform them of areas in which they need to improve in [156]. Indeed, other research suggests that the majority of medical students agree that AI will improve certain medical disciplines (i.e., radiology) and that there is a need to include AI in medical training [157].

Considering all of the above, more studies must be completed in a preparatory manner so as to further elucidate the potential of AI. Physicians must educate themselves on the advantages of this new technology as well as the pitfalls. Formal guidelines and regulations must be established with regard to not only determining the situations in which AI should or can be used or not but also with respect to the handling of patient data and company oversight; this is especially of importance in the wake of revelations from exposed internal company documents that IBM Corp.'s (Armonk, NY, USA) Watson supercomputer gave physicians inaccurate cancer treatment advice, with company medical specialists and customers reporting "multiple examples of unsafe and incorrect treatment recommendations" [158,159]. Thorough testing of AI systems in development [160] should also be completed against human clinicians so as to quantify and define the technology's abilities and limitations. The social, legal, and ethical implications of using AI in medicine must also be considered thoroughly [98,161]. The completion of these steps and others will ensure a smoother and more effective integration of AI into medicine.

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Ethical approval

Not required

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