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The Determinants of AI Adoption in Healthcare: Evidence from Voting and Stacking Classifiers

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Abstract

Artificial intelligence (AI) has emerged as a disruptive force in the healthcare industry, driving new breakthroughs that promise to enhance treatment outcomes while simultaneously lowering costs. Artificial intelligence in healthcare has demonstrated promise to help doctors and patients at each step of the healthcare system, from an accurate diagnosis to urgent monitoring of patients and self-management of long-term illness. Despite physician and administrative interest, the use of these technologies in healthcare institutions remains limited. We hypothesized that risks such as black box issue, error rate, and legal risks halt the adoption. Similarly, technical combability in healthcare centers stemming from cloud adoption, the presence of IT skills in healthcare, and digitalized healthcare records significantly explain the AI adoption in healthcare. To test our hypotheses, we applied Ensemble Voting Classifier and Stacking Classifier algorithms. The ensemble voting classifier outperforms the stacking classifier in terms of accuracy. Our findings indicate that majority of healthcare institutions with limited technological compatibility and high perceived risks have no plans to use artificial intelligence at this time. The majority of healthcare institutions with moderate risk perceptions and moderate technical combability are indecisive about integrating artificial intelligence. Healthcare facilities with good technological combability and low (AI) perceived risks are either uncertain or eager to use artificial intelligence approaches. Both classifiers yielded almost identical results, demonstrating the validity of our empirical findings.

Keywords: *Artificial intelligence, Ensemble voting classifier, Healthcare, stacking classifier*

2. Introduction

The worldwide health system is facing a number of issues that are impeding the delivery of improved services. These issues pave the way for the application of contemporary technology in general, and artificial intelligence in particular, to enhance service quality and health outcomes while lowering healthcare costs. Machine Learning may help improve diagnosis and risk forecasting. It can discover important results in clinical and medical imaging studies automatically. It may also avoid and decrease numerous medical error rates [1], [2] .

In contrast to other industries, the healthcare business works with vast amounts of data gathered from a variety of sources. Demography, vital signs, test results, prescriptions, documents and transcripts, medical image processing, payment documents, bio-signal information from smart and clinical devices, drug research, clinical trials, and so on are all examples of health data [3]. In terms of structure and nature, the data is quite varied. Big data in healthcare is quickly expanding and is expected to outpace other industries such as manufacturing, finance, and media during the next five years [4]–[6].

Medical errors are unavoidable and may have severe consequences for the patient, the treating doctor, the nurses, and the facility as a whole. Establishing a safe medical system entail establishing care practices that keep patients safe from harm. Inadequate patient identification procedures, poor admission evaluation, failure to get permission, and failure to educate patients. Errors may also cause negative mental and emotional responses in the caregivers concerned. Medical blunders are common. The majority of these blunders get unreported owing to a lack of willingness to face consequences. Medical mistakes may occur for a number of causes and at various locations within the healthcare system. The reason might be inexperienced carers, caregiver tiredness, insufficient staffing, poor communication and coordination, a lack of set rules and standards in the workplace, and so on [7], [8] .

Diagnostic inaccuracies, delayed diagnosis, misdiagnoses, surgical failures, insufficient follow-up after procedure, inadequate tracking of the patient, unsafe precautions are the most common types of medical errors [9]–[13]. Medical mistakes may range from trivial to catastrophic, with significant consequences for patients and other parties. Minimizing preventable medical mistakes in order to improve patient safety and efficient health services is a difficult undertaking for service providers. Identifying risk elements for medical errors, good coordination and communications, and smooth knowledge transfer are all important steps toward medical error prevention. Intelligent approaches and automated solutions may be of assistance in these endeavors [14], [15].

Patients are highly selective about their healthcare demands in an age of unlimited information. Because of the rivalry among healthcare providers, patient expectations are high. Patients now have more options for where and from whom they get healthcare services. People with digital awareness who are tech-savvy demand active engagement and more connection with healthcare service providers across the whole business process. Many patients demand access to their whole medical history, which is held by healthcare institutions. They are certain that knowledge exchange is a crucial component of providing high-quality services. Similarly, according to a poll, people would switch medical providers if they could obtain an appointment sooner. Patients in clinical trials are no longer considered subjects nowadays. They are trial partners with the pharmaceutical business [16]–[18].

Understanding and controlling a patient's expectations may increase patient satisfaction and assist a patient's healthcare demands be met. Healthcare businesses must adapt their service models to accommodate patient expectations and involvement while striving for improved healthcare delivery [20]. They must create and execute individualized services while keeping patients' preferences in mind. The healthcare business is shifting to patient-centric health service and focused on patient results and happiness. Understanding patients' wants and expectations is critical to patient centric heath service, which is becoming more important. Artificial Intelligence and data analytics may help generate meaningful ideas from patient data in order to provide personalized services [21]–[23].

The applications of AI in healthcare vary from workflow automation technologies that may increase efficiency and productivity and allocate emphasis for patient care to algorithms that enable patient-centered decision-making and supplement the knowledge of healthcare personnel [24]. Additionally, AI is assisting hospitals in forecasting and managing patient flow, beginning with hospital admission and continuing all the way through discharge, which enables the hospitals to adjust more quickly to rapidly changing situations [25], [26]. And as medical care moves more and more into people's homes, AI-based insights have the potential to enable people to take responsibility for their health and quality of life, thereby reducing the likelihood that they will require hospitalization, all the while maintaining a close connection to medical practitioners through remote health assessment [27], [28].

The fields of medicine and biology stand to benefit enormously from the introduction of artificial intelligence and related fields, such as machine learning. It has enticing possibilities for more rapid and precise medical decision making as well as expanded research and development capacities. However, unresolved questions about legislation and clinical relevance continue to exist; as a result, technology developers and prospective investors continue to struggle with the question of how to overcome the obstacles that now stand in the way of adoption, adherence, and deployment [30], [31].

However, regardless of whether they work in clinical care or in the life sciences, perhaps the facts remains that a wide variety of stakeholders are in a position to be influenced by the growth of AI in medical services and life sciences. The widespread use of artificial intelligence faces a number of challenges, including legal ambiguities, a lack of confidence, and a lack of tested applications. The obstacles that need to be overcome are more than worth it in order to take advantage of the opportunity that the technology offers to alter the quality of care, enhance efficiency, and assist doctors in making better rational decisions [32].

A crucial financial and business risks are often required in order to overcome the assessment and implementation hurdles that must be overcome when dealing with the majority of the newly emerging revolutionary medical technology. However, the realization that AI will one day represent the standard for treating a certain medical condition may encourage some institutions to embrace the technology and reap its benefits ahead of schedule. Other hospitals may decide to hold off on adopting AI modalities until they become the "standard of care," but if they do so, they run the danger of falling behind their competitors in terms of enhancing efficiency and improving patient outcomes.

3. The determents of adopting AI in healthcare

The following are some typical obstacles to the use of AI in healthcare:

The black box

Artificial intelligence (AI) technologies are being developed to mimic human brains. Therefore, in the same way that human brains do, they take in information and produce results. However, we do not know how AI systems reach their conclusions; all that we are aware to is the results that they produce. And without a clear knowledge of the path that led an AI system to its conclusion, it is challenging to make improvements to such systems. The term "black box problem" refers to this obstacle that artificial intelligence systems face [33]–[35]. Interoperability issues provide a significant challenge for artificial intelligence to be adopted.

To this day, a number of professionals in the field of healthcare technology have continued to emphasize the significance of the role interoperability plays in facilitating the exchange of data. Artificial intelligence would not be capable of giving its full advantages to the healthcare industry until it has access to all of the data associated with a patient. Because primary care providers, specialists, and hospitals all use various EHR systems, it is very difficult for any one organization to get access to the whole record of a patient at the same time. Because of this, the artificial intelligence is restricted in the information it can view, which results in an inadequate study of the health record [36], [37].

Adoption history.

Applications of AI have just begun to be used in healthcare. In the field of healthcare, the applications of artificial intelligence that are most often used are typically those that include sophisticated image processing and forecast modeling. Nevertheless, AI still has a great deal more to offer enterprises involved in the healthcare industry. There are a few examples, such as NLP, interactive bots, robotics, and machine learning, that only a small number of hospitals have implemented.

AI professionals

The lack of qualified AI professionals creates further adoption delays. Because there is a limited talent pool and a rising demand for the adoption of AI across all sectors, healthcare providers are finding it extremely difficult to launch AI-based programs due to a lack of resources. This is causing the projects to be delayed. A significant number of them depend on expensive solutions and providers of third-party services. Because there is a scarcity of talent, unfortunately this also implies that hospitals are inclined to narrow internal research and innovation as a result of the IT talent shortfall [38].

Cloud adoption

Utilization of AI is slowed down by a lack of cloud adoption [39]. Many of the AI solutions now accessible to businesses are expected to be cloud-hosted and cloud-delivered. It is common knowledge that several cloud service providers, like Amazon, IBM, Google, and Microsoft, make available a variety of AI solutions to their customers. Nevertheless, there are still some healthcare companies who are unwilling to migrate their data to the cloud. Because of this, some companies have decided to stop using AI applications that are hosted in the cloud in the healthcare industry and instead turn to on-premises solutions. These on-premises solutions may have fewer capabilities and may be more complicated due to the requirements placed on the IT environment [40], [41].

Digital platform

Because not all medical data is stored in a digital format that can be read by AI, it is possible that AI will not get access to all important patient data. Simply explained, digital health records are the electronic equivalent of patient medical records that were formerly kept on paper. There has been considerable hesitation among medical professionals to use this technology since many of them believe that it is burdensome. Because of this, it is difficult for companies to guarantee that all patient records is readily accessible for processing in a manner that is discrete and that AI is able to access all of it [42], [43].

Knowledge and comprehension of AI

AI can mean a variety of things to a variety of people. Some people think of it as the application that runs the robot that roams the hospital hallways supplying a variety of equipment to nurses, while others think of it as the platform that can conduct in-depth analysis on large data sets in order to spot anomalies in patient records. There is no denying the fact that AI has a multitude of applications within the realm of healthcare. Due to a lack of comprehension regarding what AI is capable of and what it is not, there is a lack of buy-in from certain stakeholders within hospitals, which will impede the implementation of artificial intelligence [44]–[47].

Awareness among both the professionals and the patients

Utilizing AI technologies may result in a wide variety of positive outcomes; yet, working with them can be challenging. Skill gaps may emerge in businesses when there is a lack of knowledge of the promise of artificial intelligence (AI) and how to exploit it. And healthcare companies need to educate their workforce about artificial intelligence systems and the capabilities they have in order to fill the gaps in their skill sets [48]. Training seminars on how to utilize artificial intelligence systems may be organized by hospitals and individual specialists for a variety of hospital departments [49]–[51].

The effective use and adoption of AI in healthcare cannot occur unless the patients who will be treated by it are prepared to accept therapy based on AI. Therefore, patients also need to be aware of AI's potential in order for them to have faith in healthcare services that is based on AI. For example, robotic surgery has a number of advantages, including shorter hospital stays, decreased levels of pain and discomfort, reduced levels of scarring, and decreased levels of blood loss [52], [53]. Patients can be hesitant to have surgery performed by AI robots owing to a lack of education and confidence in the technology. Patients should be made more aware of the advantages that may be gained by undergoing robotic surgery by healthcare institutions. They are also able to teach patients on the processes involved in AI robotic surgery before performing the treatment on them. Patients and employees that are educated about Ai systems will have a higher likelihood of having increased faith in AI systems [54]–[56].

Healthcare businesses need the appropriate infrastructure and management in order to successfully overcome the problems connected with the adoption and application of AI. With this in place, massive volumes of data can be saved and converted into information that is available for analytics, allowing AI and ML projects to discover insights and provide significant outcomes.

4. Methods

Based on the discussion in the previous section, this research divides adoption determinants into two categories: a) technological combability, and b) perceived risks. We implemented two machine learning classifier algorithms to examine the pattern in AI adoption in healthcare. The dataset came from 150 Healthcare IT professionals from different hospitals across the country.

Ensemble Voting Classifier

The Ensemble Voting Classifier is a meta-classifier for mixing machine learning classifiers that are similar or conceptually distinct for classification by majority or plurality vote. (To keep things simple, we'll refer to both plurality and majority voting as majority voting.)

The Ensemble Voting Classifier allows for both "hard" and "soft" voting. In hard voting, we anticipate the ultimate classifier as the class label predicted by the classification methods the most often. We forecast the class labels in soft voting by averaging the class probability.

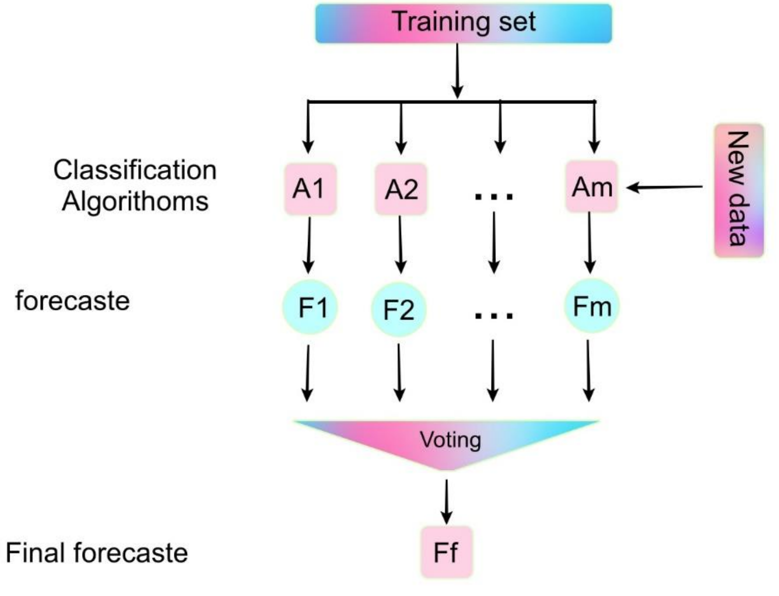

Figure. Ensemble Voting and Stacking classifiers

Hard voting

Hard voting is the most basic kind of majority voting. We forecast the class label $\hat{y}$ here using the majority vote of each classifier A:

$$\hat{y} = mode\{A_1(\mathbf{x}), A_2(\mathbf{x}), ..., A_m(\mathbf{x})\}$$

Assuming that we combine three classifiers that categorize a training sample in the following manner:

- classifier algorithm 1 -> class 0
- classifier algorithm 2 -> class 0
- classifier algorithm 3 -> class 1

$$\hat{y} = mode\{0, 0, 1\} = 0$$

We would designate the sample as "class 0" by majority vote. A weighted majority vote may be computed in addition to the simple majority vote mentioned in the preceding section by associating a weight w_j with the classifier A_j :

$$\hat{y} = \arg\max_i \sum_{j=1}^{m} w_j \chi_L (A_j(\mathbf{x}) = i),$$

where χ_L is the characteristic function $[A_j(\mathbf{x}) = i \in L]$, and L is the set of unique class labels.

Continuing with the previous section's example

- classifier 1 algorithm -> class 0
- classifier 2 algorithm -> class 0
- classifier 3 algorithm -> class 1

assigning the weights {0.2, 0.2, 0.6} would yield a prediction $\hat{y} = 1$:

$$\arg\max_i [0.2 \times i_0 + 0.2 \times i_0 + 0.6 \times i_1] = 1$$

Soft Voting

In soft voting, we forecast the class labels based on the classifier's projected probabilities p ; however, this strategy is only suggested if the classifiers are well-calibrated.

$$\hat{y} = \arg\max_i \sum_{j=1}^{m} w_j p_{ij},$$

Where, w_j is the weight that can be assigned to the j th classifier algorithm.

Assuming a binary classification problem with class labels $i \in \{0,1\}$, our ensemble may predict the following:

- $A_1(\mathbf{x}) \rightarrow [0.9, 0.1]$
- $A_2(\mathbf{x}) \rightarrow [0.8, 0.2]$
- $A_3(\mathbf{x}) \rightarrow [0.4, 0.6]$

We obtain the average probability using uniform weights:

$$p(i_0 | \mathbf{x}) = \frac{0.9 + 0.8 + 0.4}{3} = 0.7$$
$$p(i_1 | \mathbf{x}) = \frac{0.1 + 0.2 + 0.6}{3} = 0.3$$

$$\hat{y} = \arg\max_i [p(i_0 | \mathbf{x}), p(i_1 | \mathbf{x})] = 0$$

However, using the weights {0.1, 0.1, 0.8} would result in the prediction $\hat{y} = 1$:

$$p(i_0 | \mathbf{x}) = 0.1 \times 0.9 + 0.1 \times 0.8 + 0.8 \times 0.4 = 0.49$$
$$p(i_1 | \mathbf{x}) = 0.1 \times 0.1 + 0.2 \times 0.1 + 0.8 \times 0.6 = 0.51$$

$$\hat{y} = \arg\max_i [p(i_0 | \mathbf{x}), p(i_1 | \mathbf{x})] = 1$$

Stacking Classifier

Stacking classifiers combine numerous estimators to decrease their errors and then provide them as inputs in the final estimator, which may perform as well as or better than the best estimation method in the base layer. It uses a meta-learning technique to find the optimum way to integrate forecasts from several underlying machine learning methods. The advantage of stacking classifier algorithm is that it may combine the powers of many high-performing algorithms on a classification job to create predictions that outperform any particular algorithm in the ensemble. Different classifier methods are trained using the whole training set, and is fitted using the outputs (meta-features) of the ensemble's distinct classification models. The meta-classifier may be trained using either anticipated class labels or ensemble likelihood.

We assign 3 labels to the dependent variable as follows:

No intention to adopt AI= ***0***
Undecided = ***1***
Intend to adopt A= ***2***

5. Results

The decision boundaries for the ensemble voting classifier are presented in Figure 5.1. it shows that there are 3 well classified regions based on the intention to adopt artificial intelligence in healthcare. The healthcare IT professionals who currently has no intention to adopt artificial intelligence resides on the grey region located on the right of the figure 5.1. The healthcare IT professionals who are still undecided about implementing artificial intelligence are mostly in the dark pink middle region. Those who intend to adopt artificial intelligence are on the green region. The y-axis in the figure represents the perceived risk associated with the adoption of artificial intelligence, and the x-axis represent the technical combability of the hospitals. It can be seen that the majority of healthcare centers with low technical compatibility and high perceived risks has currently no intention to adopt artificial intelligence. The healthcare centers with moderate risk perceptions and moderated technical combability are mostly undecided whether to integrate artificial intelligence.

The healthcare centers with high technical combability and low (AI) perceived risk are either undecided or or are willing to adopt artificial intelligence techniques. The stacking classifier produced almost similar results, indicating the robustness of our empirical results. However, as shown in table 5.1, and 5.2, the Ensemble voting classifier has a better accuracy (0.82) than than stacking classifier with accuracy of 0.71.

Figure 5.1. Ensemble Voting Classifier

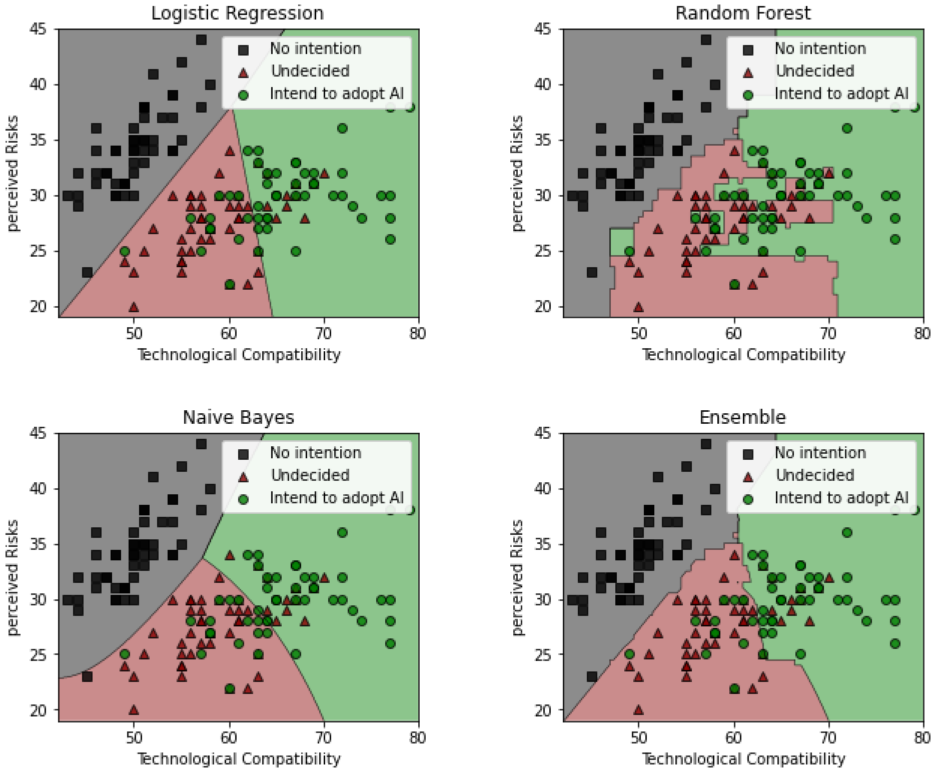

Table 5. 1. Ensemble Voting Classifier accuracy
5-fold cross validation
Accuracy: 0.82 (+/- 0.06) [Logistic Regression]
Accuracy: 0.74 (+/- 0.04) [Random Forest]
Accuracy: 0.79 (+/- 0.05) [Naive Bayes]

Accuracy: 0.82 (+/- 0.06) [Ensemble Voting Classifier]

Figure 5.2. Stacking classifier

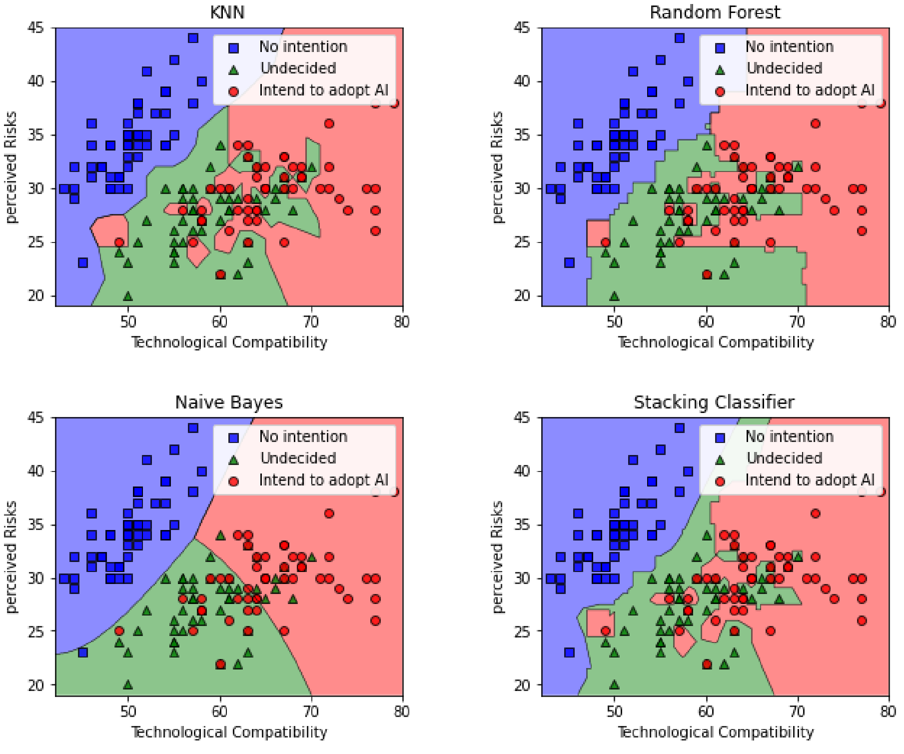

Table 5.2. Stacking Classifier Accuracy
3-fold cross validation
Accuracy: 0.69 (+/- 0.02) [KNN]
Accuracy: 0.72 (+/- 0.03) [Random Forest]
Accuracy: 0.79 (+/- 0.04) [Naive Bayes]
Accuracy: 0.71 (+/- 0.05) [Stacking Classifier]

6. Conclusion

Significant AI-based developments in the healthcare sector are to be anticipated. With regards to patient care, it is anticipated that artificial intelligence (AI) will assist with anything from early detection to quick diagnostics. For clinicians, artificial intelligence (AI) is expected to play a growing role in optimizing scheduling and securing patient information.

Nonetheless, there remains a basic misunderstanding of how AI could be employed in many health domains. Most healthcare practitioners have not been trained in the responsible and efficient use of AI, despite the fact that they must accept new capabilities and broaden their practice area. With the essentials in place, the involved healthcare community must foster the next level of competence, moving beyond "AI literacy" and including individuals who are most suited to be leaders in the development, use, and regulation of AI in the clinical setting. Artificial intelligence - based Care will depend on partnerships of different AI-minded individuals who are prepared and motivated with the toolsets required to develop and adjust in the coming AI-enabled environment.

There are clearly barriers to AI's broader adoption, ranging from legal uncertainty to a lack of confidence to a scarcity of established use cases. However, the potential presented by technology to alter the quality of healthcare, enhance efficiency, and assist doctors in making better informed choices are worth the work required to overcome them.

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