

# INCREASING INVOLVEMENT OF ARTIFICIAL INTELLIGENCE IN HEALTHCARE WITH SPECIAL REFERENCE TO STROKES

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**Abstract :** Artificial intelligence (AI) is to mimic human intellectual functions. It is bringing a noticeable change in healthcare, powered by increasing availability of healthcare data and rapid progress of analytics techniques. In this research paper the present status of AI applications in healthcare is been surveyed and future applications have been discussed. AI can be applied to various types of healthcare data (structured and unstructured). Popular AI techniques include machine learning methods for structured data, such as the classical support vector machine and neural network, and the modern deep learning, as well as natural language processing for unstructured data. Major disease areas that use AI tools include cancer, neurology and cardiology. We then review in more details the AI applications in stroke, in the three major areas of early detection and diagnosis, treatment, as well as outcome prediction and prediction evaluation. We conclude with discussion about pioneer AI systems, such as IBM Watson, and hurdles for real-life deployment of AI.

**Key Words:** *Artificial Intelligence, Health care, Technology, Machine Learning*

## INTRODUCTION TO ARTIFICIAL INTELLIGENCE

AI techniques has created a wave of change across healthcare, to such an extent that doctors are in serious discussion on whether AI will eventually replace human physicians in the future but it is still a topic of debate that human physicians will not be replaced by machines in the near future, but AI can definitely assist physicians to make better clinical decisions or even replace human judgement in certain functional areas of healthcare (e.g. radiology). The increasing availability of healthcare data and rapid development of big data analytic methods has made possible the recent successful applications of AI in healthcare. Through relevant clinical questions, powerful AI techniques can unlock clinically relevant information hidden in the massive amount of data, which in turn can assist clinical decision making.

In this article, following aspects from medical investigators' perspectives have been surveyed:

1. motivations of applying AI in healthcare
2. data types that have be analysed by AI systems
3. mechanisms that enable AI systems to generate clinical meaningful results
4. disease types that the AI communities are currently tackling.

## Motivation

The advantages of AI have been extensively discussed in the medical literature. AI can use sophisticated processes to 'learn' features from a large volume of healthcare data, and then use the obtained insights to assist clinical practice. It can also be equipped with learning and self-correcting abilities to improve its accuracy based on feedback. An AI system can assist physicians by providing up-to-date medical information from journals, textbooks, and clinical practices to inform proper patient care. In addition, an AI system can help to reduce diagnostic and therapeutic errors that are inevitable in the human clinical practice. Moreover, an AI system extracts useful information from a large patient population to assist making real-time inferences for health risk alert and health outcome prediction.

## Healthcare data

Before AI systems can be deployed in healthcare applications, they need to be 'trained' through data that are generated from clinical activities, such as screening, diagnosis, treatment assignment and so on, so that they can learn similar groups of subjects, associations between subject features and outcomes of interest. These clinical data often exist in but not limited to the form of demographics, medical notes, electronic recordings from medical devices, physical examinations and clinical laboratory and images.

Specifically, in the diagnosis stage, a substantial proportion of the AI literature analyses data from diagnosis imaging, genetic testing and electrodiagnosis (figure 1). For example, Jha and Topol urged radiologists to adopt AI technologies when analysing diagnostic images that contain vast data information. Li *et al* studied the uses of abnormal genetic expression in long non-coding RNAs to diagnose gastric cancer. Shin *et al* developed an electrodiagnosis support system for localising neural injury.

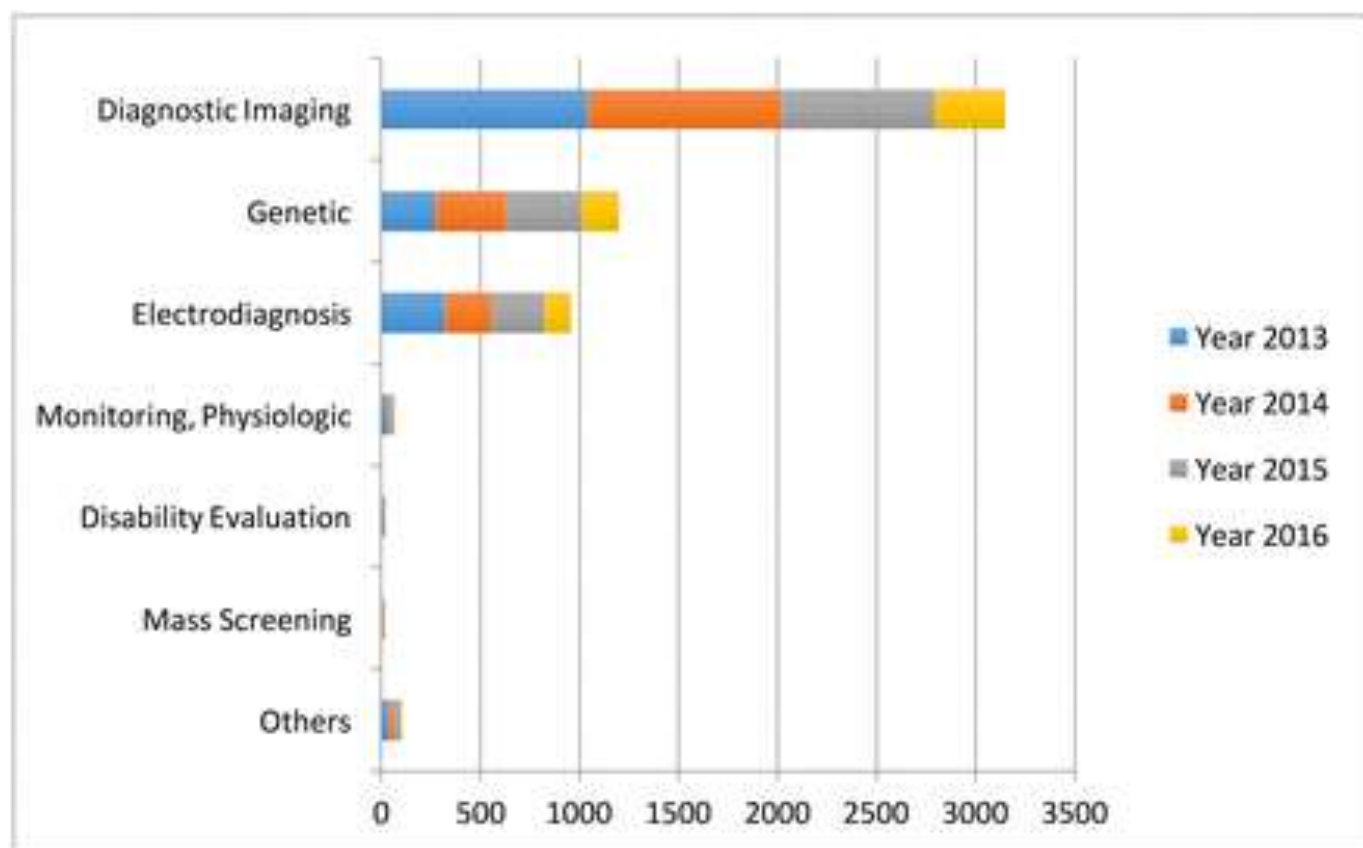


Figure 1

The data types considered in the artificial intelligence artificial (AI) literature. The comparison is obtained through searching the diagnosis techniques in the AI literature on the PubMed database.

In addition, physical examination notes and clinical laboratory results are the other two major data sources (figure 1). We distinguish them with image, genetic and electrophysiological (EP) data because they contain large portions of unstructured narrative texts, such as clinical notes, that are not directly analysable. As a consequence, the corresponding AI applications focus on first converting the unstructured text to machine-understandable electronic medical record (EMR). For example, Karakulah *et al* used AI technologies to extract phenotypic features from case reports to enhance the diagnosis accuracy of the congenital anomalies.

#### AI devices

The above discussion suggests that AI devices mainly fall into two major categories. The first category includes machine learning (ML) techniques that analyse structured data such as imaging, genetic and EP data. In the medical applications, the ML procedures attempt to cluster patients' traits, or infer the probability of the disease outcomes. The second category includes natural language processing (NLP) methods that extract information from unstructured data such as clinical notes/medical journals to supplement and enrich structured medical data. The NLP procedures target at turning texts to machine-readable structured data, which can then be analysed by ML techniques. For better presentation, the flow chart in figure 2 describes the road map from clinical data generation, through NLP data enrichment and ML data analysis, to clinical decision making. We comment that the road map starts and ends with clinical activities. As powerful as AI techniques can be, they have to be motivated by clinical problems and be applied to assist clinical practice in the end.

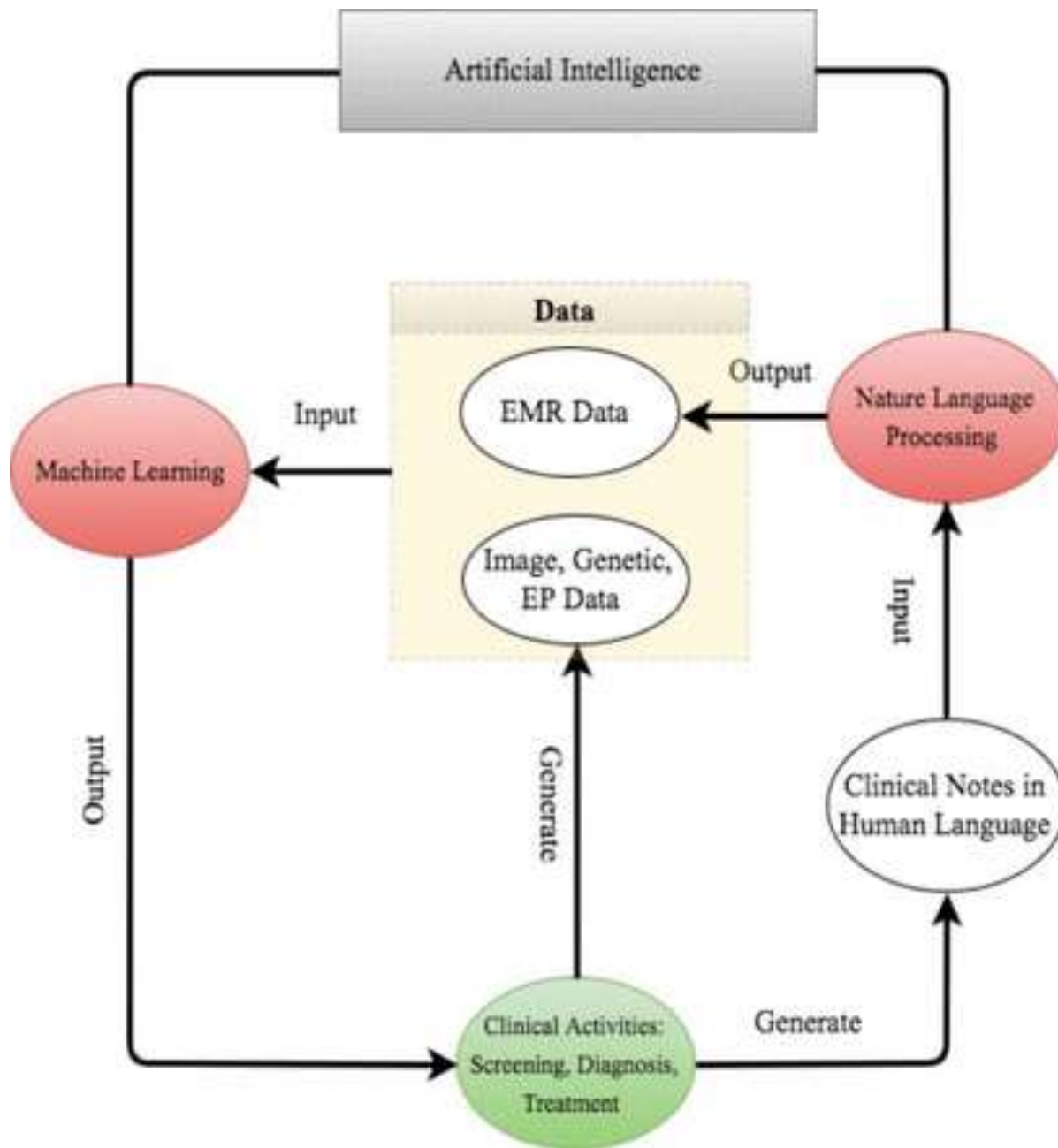


Figure 2

The leading 10 disease types considered in the artificial intelligence (AI) literature. The first vocabularies in the disease names are displayed. The comparison is obtained through searching the disease types in the AI literature on PubMed.

**Disease focus**

Despite the increasingly rich AI literature in healthcare, the research mainly concentrates around a few disease types: cancer, nervous system disease and cardiovascular disease (figure 3). We discuss several examples below.

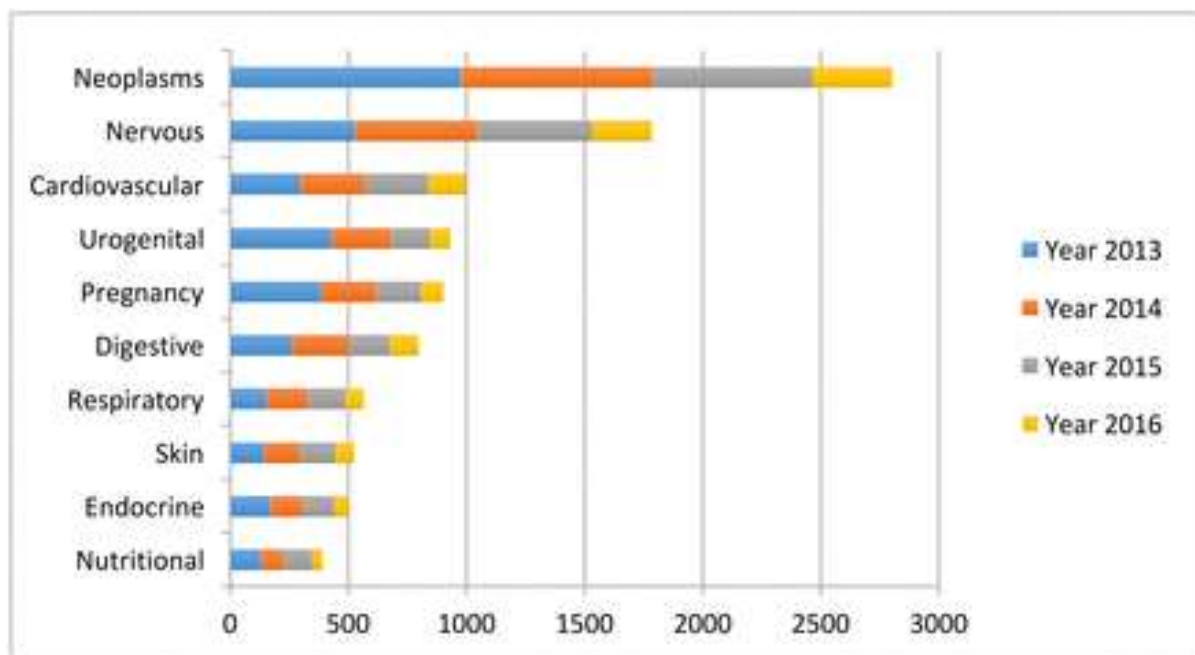


Figure 3

The road map from clinical data generation to natural language processing data enrichment, machine learning data analysis, clinical decision making. EMR, electronic medical record; EP, electrophysiological.

1. Cancer: Somashekhar *et al* demonstrated that the IBM Watson for oncology would be a reliable AI system for assisting the diagnosis of cancer through a double-blinded validation study. Esteva *et al* analysed clinical images to identify skin cancer subtypes.
2. Neurology: Bouton *et al* developed an AI system to restore the control of movement in patients with quadriplegia. Farina *et al* tested the power of an offline man/machine interface that uses the discharge timings of spinal motor neurons to control upper-limb prostheses.
3. Cardiology: Dilsizian and Siegel discussed the potential application of the AI system to diagnose the heart disease through cardiac image. Arterys recently received clearance from the US Food and Drug Administration (FDA) to market its Arterys Cardio DL application, which uses AI to provide automated, editable ventricle segmentations based on conventional cardiac MRI images.

The concentration around these three diseases is not completely unexpected. All three diseases are leading causes of death; therefore, early diagnoses are crucial to prevent the deterioration of patients' health status. Furthermore, early diagnoses can be potentially achieved through improving the analysis procedures on imaging, genetic, EP or EMR, which is the strength of the AI system.

### AI APPLICATIONS IN STROKE

Stroke is a common and frequently occurring disease that affects more than 500 million people worldwide. It is the leading cause of death in India. Stroke had cost about US\$689 billion in medical expenses across the world, causing heavy burden to countries and families. Therefore, research on prevention and treatment for stroke has great significance. In recent years, AI techniques have been used in more and more stroke-related studies. Some of the relevant AI techniques in the three main areas of stroke care: early disease prediction and diagnosis, treatment, as well as outcome prediction and prognosis evaluation.

#### Early detection and diagnosis

Stroke, for 85% of the time, is caused by thrombus in the vessel called cerebral infarction. However, for lack of judgement of early stroke symptom, only a few patients could receive timely treatment. Villar *et al* developed a movement-detecting device for early stroke prediction. Two ML algorithms — genetic fuzzy finite state machine and PCA — were implemented into the device for the model building solution. The detection process included a human activity recognition stage and a stroke-onset detection stage. Once the movement of the patient is significantly different from the normal pattern, an alert of stroke would be activated and evaluated for treatment as soon as possible. Similarly, Maninini *et al* proposed a wearable device for collecting data about normal/pathological gaits for stroke prediction. The data would be extracted and modelled by hidden Markov models and SVM, and the algorithm could correctly classify 90.5% of the subjects to the right group.

For diagnosis of stroke, neuroimaging techniques, including MRI and CT, are important for disease evaluation. Some studies have tried to apply ML methods to neuroimaging data to assist with stroke diagnosis. Rehme *et al* used SVM in resting-state functional

MRI data, by which endophenotypes of motor disability after stroke were identified and classified. SVM can correctly classify patients with stroke with 87.6% accuracy. Griffis *et al* tried naïve Bayes classification to identify stroke lesion in T1-weighted MRI. The result is comparable with human expert manual lesion delineation. Kamnitsas *et al* tried three-dimensional CNN (3D CNN) for lesion segmentation in multi model brain MRI. They also used fully connected conditional random field model for final postprocessing of the CNN's soft segmentation maps. Rondina *et al* analysed stroke anatomical MRI images using Gaussian process regression and found that the patterns of voxels performed better than lesion load per region as the predicting features.

ML methods have also been applied to analyse CT scans from patients with stroke. Free-floating intraluminal thrombus may be formed as lesion after stroke, which is difficult to be distinguished with carotid plaque on the CT imaging. Thornhill *et al* used three ML algorithms to classify these two types by quantitative shape analysis, including linear discriminant analysis, artificial neural network and SVM. The accuracy for each method varies between 65.2% and 76.4%.

### Treatment

ML has also been applied for predicting and analysing the performance of stroke treatment. As a critical step of emergency measure, the outcome of intravenous thrombolysis (tPA) has strong relationship with the prognosis and survival rate. Bentley *et al* used SVM to predict whether patients with tPA treatment would develop symptomatic intracranial haemorrhage by CT scan.<sup>55</sup> They used whole-brain images as the input into the SVM, which performed better than conventional radiology-based methods. To improve the clinical decision-making process of tPA treatment, Love *et al* proposed a stroke treatment model by analysing practice guidelines, meta-analyses and clinical trials using Bayesian belief network. The model consisted of 56 different variables and three decisions for analysing the procedure of diagnosis, treatment, and outcome prediction. Ye *et al* used interaction trees and subgroup analysis to explore appropriate tPA dosage based on patient characteristics, considering both the risk of bleeding and the treatment efficacy.

### Outcome prediction and prognosis evaluation

Many factors can affect stroke prognosis and disease mortality. Compared with conventional methods, ML methods have advantages in improving prediction performance. To better support clinical decision-making process, Zhang *et al* proposed a model for predicting 3-month treatment outcome by analysing physiological parameters during 48 hours after stroke using logistic regression. Asadi *et al* compiled a database of clinical information of 107 patients with acute anterior or posterior circulation stroke who underwent intra-arterial therapy. The authors analysed the data via artificial neural network and SVM and obtained prediction accuracy above 70%. They also used ML techniques to identify factors influencing outcome in brain arteriovenous malformation treated with endovascular embolisation. While standard regression analysis model could only achieve a 43% accuracy rate, their methods worked much better with 97.5% accuracy.

Birkner *et al* used an optimal algorithm to predict 30-day mortality and obtained more accurate prediction than existing methods. Similarly, King *et al* used SVM to predict stroke mortality at discharge. In addition, they proposed the use of the synthetic minority oversampling technique to reduce the stroke outcome prediction bias caused by between-class imbalance among multiple data sets.

Brain images have been analysed to predict the outcome of stroke treatment. Chen *et al* analysed CT scan data via ML for evaluating the cerebral oedema following hemispheric infarction. They built random forest to automatically identify cerebrospinal fluid and analyse the shifts on CT scan, which is more efficient and accurate than conventional methods. Siegel *et al* extracted functional connectivity from MRI and functional MRI data, and used ridge regression and multitask learning for cognitive deficiency prediction after stroke. Hope *et al* studied the relationship between lesions extracted from MRI images and the treatment outcome via Gaussian process regression model. They used the model to predict the severity of cognitive impairments after stroke and the course of recovery over time

## CONCLUSION AND DISCUSSION

We reviewed the motivation of using AI in healthcare, presented the various healthcare data that AI has analysed and surveyed the major disease types that AI has been deployed. We then discussed in detail the two major categories of AI devices: ML and NLP. For ML, we focused on the two most popular classical techniques: SVM and neural network, as well as the modern deep learning technique. We then surveyed the three major categories of AI applications in stroke care.

A successful AI system must possess the ML component for handling structured data (images, EP data, genetic data) and the NLP component for mining unstructured texts. The sophisticated algorithms then need to be trained through healthcare data before the system can assist physicians with disease diagnosis and treatment suggestions.

The IBM Watson system is a pioneer in this field. The system includes both ML and NLP modules, and has made promising progress in oncology. For example, in a cancer research, 99% of the treatment recommendations from Watson are coherent with the physician decisions. Furthermore, Watson collaborated with Quest Diagnostics to offer the AI Genetic Diagnostic Analysis. In addition, the system started to make impact on actual clinical practices. For example, through analysing genetic data, Watson successfully identified the rare secondary leukaemia caused by myelodysplastic syndromes in Japan.

The cloud-based CC-Cruiser in can be one prototype to connect an AI system with the front-end data input and the back-end clinical actions. More specifically, when patients come, with their permission, their demographic information and clinical data (images, EP results, genetic results, blood pressure, medical notes and so on) are collected into the AI system. The AI system then uses the patients' data to come up with clinical suggestions. These suggestions are sent to physicians to assist with their clinical decision

making. Feedback about the suggestions (correct or wrong) will also be collected and fed back into the AI system so that it can keep improving accuracy.

Stroke is a chronic disease with acute events. Stroke management is a rather complicated process with a series of clinical decision points. Traditionally clinical research solely focused on a single or very limited clinical questions, while ignoring the continuous nature of stroke management. Taking the advantage of large amount of data with rich information, AI is expected to help with studying much more complicated yet much closer to real-life clinical questions, which then leads to better decision making in stroke management. Recently, researchers have started endeavours along this direction and obtained promising initial results.

Although the AI technologies are attracting substantial attentions in medical research, the real-life implementation is still facing obstacles. The first hurdle comes from the regulations. Current regulations lack of standards to assess the safety and efficacy of AI systems. To overcome the difficulty, the US FDA made the first attempt to provide guidance for assessing AI systems. The first guidance classifies AI systems to be the 'general wellness products', which are loosely regulated as long as the devices intend for only general wellness and present low risk to users. The second guidance justifies the use of real-world evidence to assess the performance of AI systems. Lastly, the guidance clarifies the rules for the adaptive design in clinical trials, which would be widely used in assessing the operating characteristics of AI systems. Not long after the disclosure of these guidance, Arterys' medical imaging platform became the first FDA-approved deep learning clinical platform that can help cardiologists to diagnose cardiac diseases.

The second hurdle is data exchange. In order to work well, AI systems need to be trained (continuously) by data from clinical studies. However, once an AI system gets deployed after initial training with historical data, continuation of the data supply becomes a crucial issue for further development and improvement of the system. Current healthcare environment does not provide incentives for sharing data on the system. Nevertheless, a healthcare revolution is under way to stimulate data sharing in the USA. The reform starts with changing the health service payment scheme. Many payers, mostly insurance companies, have shifted from rewarding the physicians by shifting the treatment volume to the treatment outcome. Furthermore, the payers also reimburse for a medication or a treatment procedure by its efficiency. Under this new environment, all the parties in the healthcare system, the physicians, the pharmaceutical companies, and the patients, have greater incentives to compile and exchange information. Similar approaches are being explored in China.

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