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Employing A.I. to Improve Healthcare Delivery

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ABSTRACT Artificial Intelligence (AI) has already made inroads into healthcare. The increasing availability of healthcare data has allowed for the deployment of powerful AI techniques to assist drug development as well as clinical practice. These run the gamut from machine learning (ML) techniques that analyse structured data, to natural language processing (NLP) that can extract meaningful information from unstructured data, such as doctors' notes. This brief examines the promises, risks and challenges of adopting AI in healthcare, drawing on evidence from across the globe. It examines how AI can reshape the Indian healthcare ecosystem and what that means for existing stakeholders including hospitals and doctors, as well as technology and insurance companies.

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INTRODUCTION

To understand the long-term impact of AI on healthcare, it is necessary to first understand its influence in the short- to medium-term. The increasing use of AI in the industry will have important ramifications on the healthcare system. In the foreseeable future, AI will become integral to not only acute care delivered through hospitals and clinics but also much of what is considered wellness, such as nutrition, exercise and sleep. It will precipitate a shift from a largely reactive system built to respond to injury and illness, to one geared towards early detection and prevention. These changes, in turn, will lead to shifts in key stakeholders and their roles: insurance companies are likely to play a much larger role in determining care protocols and driving early detection; and pharmaceutical companies will increasingly discover and develop drugs in partnership with technology companies. Companies such as Apple and Google are already investing heavily in healthcare, partnering with hospitals and pharmaceutical companies to develop AI-based tools that reduce cost, increase access and improve quality.

In India, the adoption of AI in healthcare is still in its nascent stage. While various homegrown technology companies have raised funding, e.g. Qure, Niramai and Sigtuple, deployment at scale remains a challenge, due to low levels of digitisation, stakeholder resistance due to low awareness, and a difficult regulatory environment.

THE USE OF AI IN HEALTHCARE

The current model of healthcare delivery is a function of available information. When a patient experiences symptoms, they undergo diagnostic tests, typically under the guidance of a doctor—either a general physician or a specialist. Pathologists use machines to detect blood counts and abnormalities, and radiologists read X-rays and report their findings. The attending doctor then aggregates the information and provides a treatment plan.

A significant challenge that this workflow presents is that the data collected is typically stored in various isolated databases, often in different formats. Before AI can be deployed to improve outcomes, it must integrate this data in a reliable and affordable manner. The creation of a data lake[1] is a typical first step towards consolidating from multiple silos. A data lake helps consolidate raw data into a single source to enable algorithms to make diagnoses or recommendations based on complete datasets. AI-based algorithms can then study data usage, including access frequency, commonly used components, and user roles, which enables them to efficiently solve complex integration problems, e.g. integrating large volumes of data streamed by IoT devices such as wearables. AI tools will improve the quality of care in four significant areas, without introducing any significant changes in the process from the perspective of the patients.

Detection

The use of AI will facilitate the early detection of diseases. Currently, treatment is sought only after experiencing symptoms. However, data from continuous monitoring of health can automatically trigger interventions. There is now a burgeoning ecosystem of monitoring devices, such as smartwatches, phone-based sleep trackers, and wearable blood-pressure monitors. For example, the Apple Watch, which has been licensed by the FDA as a medical device, can passively carry out electrocardiograms (ECGs) at regular intervals and generate alerts upon recording a worrying trend. Moreover, since early detection is key to reducing costs and improving outcomes, insurance companies, too, are now pushing for regular testing and monitoring.

Diagnosis

In the future, diagnoses will increasingly be aided by AI, already evident in imaging-based modalities such as radiology and pathology. Radiology has been leading the charge, with companies focusing on building technology that can perform computer-aided detection (CADe) and computer-aided diagnosis (CADx). Specialised technology companies, such as Zebra in Israel, are using massive imaging databases to train algorithms that can detect abnormalities in X-Ray, MRI and CT Images.

Companies that make imaging hardware, e.g. Siemens, have begun offering supporting AI software such as the AI-Rad Companion, which can be integrated into workflows to reduce the burden of repetitive tasks and increase diagnostic precision. The AI-Rad Companion currently encompasses a suite of offerings including specific modules for chest CTs, brain MRIs and prostate MRIs. Arterys offers FDA-approved software to help reduce reporting time by 30 percent for cardiac and chest X-rays. Algorithms have also achieved dermatologist-level accuracy in the classification of skin cancer.[2] QuantX and Profound AI have built FDA-approved software that helps radiologists in the assessment and characterisation of breast abnormalities in MRI images. Pathology is not far behind. For instance, New York-based PathAI is developing machine-learning technology to help pathologists reduce errors in cancer diagnoses and develop methods for individualised treatment. Their collaborators include Bristol Myers-Squibb as well as the Bill and Melinda Gates Foundation.

Treatment

AI will provide 'decision support' for protocol-based treatment of routine conditions. It is especially useful in situations that involve substantial data, wherein trends may be hidden by 'noise' that obscures the actual problem. One such example is in sepsis detection and treatment. Sepsis is the leading cause of death in American hospitals, and Johns Hopkins estimates that at least 80 percent of these deaths are preventable if diagnosed in time.[3] AI-based diagnosis, based on vitals and lab data, can help predict the risk of sepsis well before it becomes apparent to clinicians. Since the treatment for sepsis is typically based on clearly defined algorithms, AI-based tools can even be used to decide the most effective course of treatment and drug dosages based on a patient's history and profile. Companies such as Google and Bayesian Health are already working on AI-driven early detection, in partnership with hospitals such as Duke University Hospital and Sentara.[4] Additionally, AI-based tools have successfully helped provide care for chronic diseases such as diabetes[5,6] and Chronic Obstructive Pulmonary Disorder (COPD).[7]

Personalised Medication

Personalised medication, or precision medicine, leverages an individual's unique genetic data, and is an ambitious and emerging field of medicine. Large multidimensional biological datasets are used to optimise diagnosis, prognosis and therapy. Interventions are tailored based on a patient's genetics, environment and biology. Such a method has already proven useful in predicting the risk of cancers[8,9] and cardiovascular diseases.[10,11] Pharmacogenomics, the study of how genes affect drug response, combined with AI-based tools are already being used to successfully predict treatment outcomes.[12,13,14] This helps clinicians not only chose between multiple treatment options but also prevent adverse drug reactions. However, one of the major challenges in deploying precision medicine at scale is the availability of extensive and high-quality datasets, which is crucial to this process.

THE IMPACT OF AI IN HEALTHCARE

Healthcare Delivery

The use of AI in different areas of healthcare will cumulatively drive a shift in both the *focus* and the *format* of healthcare delivery. The focus will shift from reactive interventions and acute care to pre-emptive care and regular monitoring, applying equally to chronically ill, high-risk, and healthy individuals. Consequently, much of what is currently considered "wellness" will eventually become a key component of healthcare delivery.

The format of care delivery will also change, shifting partially from brick-and-mortar facilities such as hospitals to step-down clinics and even patients' homes. Part of this shift will be driven by the growth and proliferation of remote monitoring devices. The development of the devices and the telecommunications bandwidth to transmit large volumes of real-time data are not dependent on AI. However, AI is required to process the large volumes of data, identify warning signals based on thousands of data points, and alert the relevant caregivers in time. A key driver of this change will be the growth of AI-augmented telemedicine, which has the potential to address pressing needs in two ways.

AI can make a valuable contribution in areas where it is difficult to co-locate patients with qualified physicians. Companies such as Buoy, Babylon and Lemonaid have already deployed AI-augmented technology to help triage, diagnose and prioritise patients. They have developed chatbots that can interact with patients to help provide a diagnosis for cases where the symptoms correspond to common problems such as urinary tract infections. More complicated cases are referred to specialists. Not only does this reduce the burden on frontline care staff, such as GPs and ER doctors, it is also useful for populations that do not have physical access to qualified clinicians. Babylon recently entered into a 10-year partnership with the Rwandan government[15] to help it address the country's acute shortage of doctors.

AI-augmented telemedicine also adds value in situations where large volumes of data need to be captured and studied to provide care. Thus, a growing use case for AI-augmented telemedicine is in remote monitoring, wherein data is tracked by sensors such as EEGs, ECGs, blood glucose monitors, heart-rate monitors, pulse oxygen and respiratory monitors. This ecosystem can provide a safety net for patients with chronic conditions such as COPD, diabetes and heart disease. It can also help in reducing the length of a patient's hospital stay by allowing ward-level monitoring to be successfully carried out at home. These tools are especially powerful when integrated with the wider healthcare ecosystem, including tertiary care and specialist referrals, medicine delivery, and emergency response services. Companies such as Ten3t in India, Current in Scotland, and Eko in the US have made significant progress in bringing such solutions to the market.

Pharmaceutical Companies

AI has already begun demonstrating results in the pharmaceutical industry, specifically in drug discovery, drug development and pharmacovigilance (PV). Drug discovery and development are long and expensive processes, with many drugs often taking upwards of 10 years and over US$ 1 billion to make it to the market. AI can address both pain points by reducing the time required and the development cost. It is also being leveraged for PV, i.e. to enhance drug safety.

Drug discovery, despite improvements in medical technology, has become slower and more expensive over time. Pharmaceutical companies are under pressure and increasingly turning to partnerships with technology companies that can help them use AI to accelerate the drug-discovery process. Companies such as Recursion Pharma are trying to tackle this by building drug-delivery platforms that reveal new therapeutic candidates. In 2016, Pfizer and IBM Watson announced a partnership to accelerate drug discovery in immuno-oncology. In 2017, Sanofi partnered with Exscientia to employ their AI-driven platform to help identify and design drugs that can tackle metabolic diseases.[16] Exscientia has also partnered with GSK for a similar drug-discovery project. These partnerships have already begun to yield results: the GSK-Exscientia collaboration found its first candidate molecule in April 2019.[17]

Roughly half the time and cost of getting drugs to market is spent on the clinical trial phase. These have high failure rates, due to costs associated with identifying and enrolling appropriate subjects (86 percent of trials do not meet enrolment timelines),[18] monitoring them over the period of the trial, managing non-adherence, and reducing the drop-out rate. Companies such as Mendel.AI, Antidote and Deep 6 AI have developed platforms that can be used to efficiently match patients with clinical trials. Mayo Clinic recently released the results of a study that found that using IBM Watson helped increase trial enrolment by 80 percent.[19] At the same time, companies such as Brite Health have targeted a different pain point by developing solutions to help manage patient engagement over the course of a trial, which reduces the non-adherence and drop-out rates. Researchers have also successfully used AI to design better clinical trials by iteratively adjusting drug dosages to optimise treatment.[20]

Major tech companies have been particularly active in this space. The world's second-largest pharmaceutical company, Roche, is trialling Amazon's Comprehend

Medical tool to help match patients to available clinical trials.[21] Novartis and Microsoft have announced a five-year partnership, where the former will draw on the latter's AI expertise to design a tool for calculating personal drug dosage to treat macular degeneration, optimising the manufacturing of CAR-T cells, and shortening the time required to develop new drugs by using neural networks to generate, screen and select promising molecules.[22] Google, too, has collaborated with London-based DeepMind to build AlphaFold, a model that can help predict protein structure, allowing scientists to target and design new cures more efficiently.

AI-based tools are increasingly being deployed to improve drug safety by monitoring manufacturing processes in real time, determining efficacy, and collecting and processing data on adverse events (AEs). The mounting regulatory focus on safety and the consequent increase in compliance burden are important drivers for the growing use of AI, particularly when it comes to AE case processing. Moreover, studies indicate that case processing consumes at least two-thirds of drug companies' overall PV budget.[23] Pilots have already demonstrated the feasibility of applying AI to automate safety case processing and thereby favourably impact the strongest cost driver of the overall PV budget.[24] Similarly, AI tools can be used in healthcare for post-marketing surveillance to study the effects of drugs on specific populations, especially in light of concerns that clinical trials may not ensure adequate representation. For instance, Chazard et al. successfully used data from over 100,000 health records to generate rules for the detection of AEs.[25] Thus, AI-based tools have a two-fold utility in this area: retrospective AE detection as well as prospective AE prevention when embedded within clinical decision support systems.

Stakeholders

AI-driven changes will inevitably lead to a shift in power away from doctors and hospitals, as insurers and technology companies become increasingly relevant players in the ecosystem. Companies that harvest and process patient data, e.g. Apple and Fitbit, and those that carry out genetic testing, will possess a valuable resource, which will be deployed towards prevention, early detection, and better diagnosis. Insurance companies are likely to utilise this data to adjust premiums and drive prevention and early detection. The speed of this shift will depend on the rate of increase in insurance penetration. For example, it will accelerate if the world moves towards an accountable care model, where insurers are paid a fixed amount to maintain the health of a defined population, based on objective outcome indicators.

It is too early to predict how healthcare will evolve in a country such as India, where insurance penetration is low and the majority of healthcare expenditure is private. The government's most recent National Health Policy (2017) explicitly lists "progressively achieving Universal Health Coverage" as a goal. To this end, the document outlines a goal of increasing health expenditure to 2.5 percent of the budget and over eight percent of states' budgets.[26] The stated visions of schemes such as Ayushman Bharat[27] and the National Health Stack proposed by NITI Aayog are further indications that the government is keen to move in this direction.

However, ground-level implementation remains patchy.[28]

Major technology companies will become increasingly important stakeholders in the healthcare ecosystem. Already, the Google-Deep Mind partnership has successfully developed algorithms to help detect breast cancer (the algorithm produced six percent fewer incorrect diagnoses and nine percent fewer false negatives relative to regular clinical practice)[29] and diabetic retinopathy (using a dataset from India and the US, their algorithm performed marginally better than a panel of ophthalmologists).[30] Google is also partnering with other tech companies, such as Viz.ai,[31] which built a tool to analyse CT scans and notify healthcare professionals about potential strokes.

AI is unlikely to replace healthcare professionals such as doctors, nurses, diagnosticians and technicians and will only serve as a "computer-aided" decision support system. However, doctors will no longer be the only source of truth. They will still be key decision-makers in both disease diagnosis and treatment (planning as well as execution), but these tasks will increasingly become a team effort, with AI-based machines facilitating better diagnosis and treatment decisions.

Employment in the Healthcare Sector

According to a 2019 report published in the *Future Healthcare Journal*, "To our knowledge thus far there have been no jobs eliminated by AI in health care." Thus, any panic regarding AI creating mass redundancies in healthcare is premature. However, not only could this change in the future but AI could also impact the workforce in other ways.

Moreover, AI will also change task profiles across the healthcare workforce. It will allow clinicians to spend less time gathering and monitoring data and is likely to replace a minority of routine tasks across the workforce. A 2019 study[32] by the American Hospital Association found that AI could take over roughly one-third of the tasks currently carried out by clinicians. The responsibilities of nurses and paramedical staff could shift away from work that can be automated and towards computer-based work, such as data entry and reviewing automatically captured data.

The increased use of AI will also create redundancies in a small set of middle and lower-end jobs, such as patient monitoring (typically done manually by nurses at regular intervals) and radiologists who report basic scans. Jobs that are routine, repetitive, predictable, and where the stakes are relatively low can easily be automated. However, in the long run, studies predict that AI will create at least as many jobs as are destroyed,[33] e.g. roles in data science, software and device engineering, and data governance. Further, given the global shortage of qualified care professionals,[34] it is unlikely that healthcare will witness significant job losses in the foreseeable future.

KEY RISKS

Increasingly, healthcare is shifting towards evidence-based and probabilistic automated models for decision-making, which comes with its own set of risks.

Biased Models

AI models are developed based on datasets and "learn" using the data provided to them.

However, datasets can have inherent biases, such as the underrepresentation of a certain race or gender. The use of biased datasets in treating or diagnosing marginalised group can inadvertently compromise outcomes and safety. A 2016 report[35] that aggregated the results from 2,511 studies found that 81 percent of participants in genome-mapping studies were of European descent. Researchers who download these datasets to study diseases or develop AI-based models may unwittingly reproduce the same biases in their work. According to a 2014 study,[36] the lack of diverse research subjects is one of the reasons that black Americans are significantly more likely to die than white Americans after a cancer diagnosis.

Data Security

The collection, storage and transmission of data on a large scale drastically increases the chances of inadvertent leaks or breaches of privacy. This, in turn, can lead to secondary harms where sensitive health information is misused, e.g. to discriminate against individuals when determining their eligibility for employment or housing. Such concerns have resulted in the adoption of standardised security protocols for health information, including the Health Information Portability and Accountability Act, 1996 and the Fast Healthcare Interoperability Resources (FHIR) standard for the electronic exchange of healthcare information. Moreover, the availability of personal data poses significant risks in areas with poor telecommunications or power infrastructure. Therefore, relying on this data for clinical decisions can delay care if the data becomes temporarily or permanently unavailable. This is especially relevant for rural populations or for populations in developing and lower-income countries, where internet access is not yet reliable.

Inequity in Access

There is a 'black box' problem associated with AI-based tools, especially with models developed using neural networks. Unlike in traditional studies, it is difficult to understand the connection between inputs and outputs in such models. While this is not a major problem when the goal is mere prediction, in diagnosis or treatment, the inability to establish links can pose a risk. If not effectively managed, these risks can not only compromise patient safety and healthcare outcomes but also exacerbate existing inequalities in access to care. For example, model bias is likely to compromise care for segments of the population that already have relatively poor access to care. Women are more likely to wait in emergency rooms and are less likely to be given effective painkillers;[37] they are also more likely to have physiological ailments written off as psychological ailments.[38] Models trained on current treatment protocols run the risk of "hard-coding" these inequalities and making them harder to recognise, address or reverse.

AI-based algorithms typically require significant supporting infrastructure, such as hardware, software and telecommunications infrastructure. Thus, the deployment of AI in healthcare is likely to remain restricted to privileged spaces, such as affluent cities, exacerbating existing inequalities in access to healthcare. Moreover, inequalities may extend beyond socio-economic parameters. For instance, although the US has enacted legislation that prohibits employers and health insurance companies from discriminating on the basis of genetic data (the Genetic Information Nondiscrimination Act), this does not apply to other kinds of insurance, such as life insurance.

KEY ADOPTION CHALLENGES

The potential for AI to reduce costs and improve quality in healthcare has already been established. However, large-scale adoption is a significant challenge and likely to remain so for the foreseeable future. This is mainly due to the constraints of legacy systems, workflows and cultural norms, which are difficult to replace. This is exacerbated by the lack of compatible supporting infrastructure, in terms of not only technology but also regulatory infrastructure.

Lack of Data

The single biggest constraint on the development of AI-based tools is the availability of high-quality datasets with enough data to train robust models. For example, an imaging model will require numerous images, with the annotations on each required to be clean, bias-free, exhaustive, error-free, and presented in a way that the model is capable of processing. Moreover, the "feature space" being larger than the observations (a common case in healthcare due to limited data) results in overfitting, wherein the model does not generalise well in production. Workflows are typically not set up to produce vast quantities of properly annotated scans, and many organisations are reluctant to share such scans for fear of patient privacy being compromised. Once datasets are assembled and models developed, integrating these models into existing systems and workflows is another difficult process. For instance, the AI-based diagnoses and recommendations might not be available as part of the existing software ecosystem, e.g. radiology storage and reporting software such as the RIS and PACS or the electronic medical records that are in use. The recommendation will then need to be manually reviewed, which, in practice, is likely to constrain uptake in fast-paced and high-stress environments. Replacing existing systems is an expensive and risky undertaking. The promise of AI providing an incremental improvement in care quality often does not justify the costs or the risks that would be incurred.

Resistance from the Medical Community

Another important constraint in the adoption of AI-enabled decision-support is resistance from the medical community. Doctors who are unfamiliar with the technology and do not fully understand how it works are often reluctant to use it. This is only compounded by concerns of AI replacing humans and the absence of any clear medico-legal guidelines regarding liability in case of adverse outcomes. India is currently lagging in the establishment of a regulatory framework for the testing, licensing and usage of AI-enabled tools and devices. Countries such as Singapore and the US have notified regulations that allow for certain products to be classified as Software-as-a-Medical-Device (SaMD). However, while the draft medical devices rules issued by the (Union) Government of India in 2016 included SaMDs, the final guidelines issued in 2017 do not. The absence of a clear regulatory framework hinders deployment as well as investment in R&D.

CONCLUSION AND RECOMMENDATIONS

Healthcare is a conservative discipline, since mistakes can cost lives. For AI to reach its full potential, this conservatism must be balanced with pragmatism. To this end, the public sector will have to create a favourable regulatory ecosystem that addresses the concerns of all relevant stakeholders in a holistic manner. A favourable regulatory ecosystem is one that considers the incentives and constraints on all stakeholders—from tech companies and their investors to hospitals, doctors and patients. Moreover, such a system must be sensitive to the nature of AI-enabled tools and how they differ from traditional drugs and software. Other important issues to consider include intellectual property rights over AI-enabled tools; medico-legal responsibility for AI-aided diagnosis and treatment; regulation around the storage and transmission of patient data, including data localisation requirements, security standards and transmission protocols; licensing software as a device; regulations around the quality and robustness of datasets used to develop models; regulations for models developed using neural networks, where the relationships between inputs and outputs are effectively a 'black box'; and import and export regulations.

Since policy is responsible for not only enabling but also supporting the nascent ecosystem, it is necessary to evaluate a broad range of policies, including education policies, grant budgets and even intellectual property frameworks. For instance, the curriculum in medical schools must include appropriate modules on AI to familiarise future generations of clinicians with the advantages as well as the risks of using AI in clinical settings. For start-ups, taxation policy must be reviewed and grants be earmarked based on clearly defined success metrics. The public healthcare system will have to invest strategically in the collection and storage of relevant data, i.e. financial expenditure as well as the training of public health workers. Public bodies must be encouraged to partner with technology companies and government institutions, such as the Medical Council of India and the Indian Council of Medical Research. Finally, the Public Health Foundation of India must invest in developing a deep understanding of AI, to provide relevant and informed policy guidance over the coming years.

The private sector, too, must make a concerted effort to invest in AI. Recent developments in the field indicate that partnerships between technology, education, healthcare and pharma are the only viable path to the development of AI tools. Large hospital networks, such as Apollo and Fortis, must find new ways to collaborate with technology companies and lobby the government for the necessary regulatory changes. These initiatives will take years to deliver financial returns and must, therefore, be conducted with a view to long-term, sustainable benefits. ORF

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ENDNOTES

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