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AI and Big Data Deployment in Health Care: Proposing Robust and Sustainable Governance Solutions for Developing Country Governments

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ABSTRACT

This paper is intended to identify both barriers to AI deployment at scale in developing countries and the types of regulatory and public policy actions that can best accelerate the appropriate use of AI to improve health care in developing countries. While AI technologies hold great potential for improving health care around the globe, they cannot be considered a panacea for solving global health challenges. Scaling up AI technologies has risks and trade-offs. The adoption, acceleration and use of AI should strengthen local health systems and be owned and driven by the needs and priorities of developing country governments and stakeholders to help them best serve their populations.

This paper starts with a landscape assessment of AI and big data analytics deployment in developing countries. It considers three fields of AI deployment in diagnosis and clinical care, health research and drug development, and health systems management and planning. It outlines key challenges that need to be addressed by regulators in governing AI in health care, such as data access, data quality, data privacy and ethics. Lastly, the paper outlines key governance mechanisms for AI innovation in health care in developing countries, such as data collection and management, data sharing and open-source solutions for data de-identification, open-source data banks and data annotation.

Introduction

Merely a generation ago, interest in 'artificial intelligence' (AI) was confined to academic computer science, philosophy, engineering research and science fiction. Today, AI is broadly understood to include not only long-term efforts to simulate the kind of general intelligence humans exhibit but also fast-evolving technologies (such as convolutional neural networks) that affect many facets of modern society, such as health care, national security, social media, agriculture and a variety of other fields.[1]

The sweeping changes caused by AI have significantly increased the gap between government policy and innovative business models that rely on AI deployment. AI is changing norms and business models throughout society, demanding new and effective government policy responses on subjects with little real precedence. While governments struggle to adapt to the rapid pace of change, AI brings new solutions and offers the potential to change how policy is made by providing new tools and methods of policy development.

As a result of the COVID-19 pandemic, policymakers across the globe have started focusing on implementing policies and regulations to ensure that possible long-term effects on inequality, exclusion, discrimination and global unemployment do not become the 'new normal'. In particular, vulnerable groups, such as older persons, people living in poverty, persons with disabilities, youth and indigenous peoples, have been disproportionately affected by the harmful impacts of the pandemic and risk being left behind in the global recovery from it (UNICRI 2021).

In an increasingly digital economy, AI solutions can be essential in addressing these issues. If deployed correctly and with human-centric values at the core, AI can be a vital tool in improving global health, sustainability and well-being, and in bridging the inequality gap. Not all countries around the globe are equally prepared for the impact of AI in health care, however (Han 2012).

Regulation of AI in health care is still in its infancy. Many countries have just issued their national plans, guidelines or codes—which often highlight essential principles for developing ethical AI—without passing much substantive law. Notable examples include the European Parliament's resolution on Civil Law Rules on Robotics (February 2017), the European Union's Ethics Guidelines for Trustworthy AI (April 2019), the European Commission's Proposal for a Regulation on a European Approach for Artificial Intelligence (April 2021) and the Organisation for Economic Co-operation and Development's (OECD) Council Recommendation on Artificial Intelligence (May 2019).

[1] Stanford University Explore Courses. See: https://explorecourses.stanford.edu/search?view=catalog&filter-coursestatus-Active=on&page=0&catalog=&academicYear=&q=LAW+4039.

AI deployment in health care potentially drives game-changing improvements for underserved communities and developing countries. From enabling community health workers to better serve patients in remote rural areas to helping governments in developing countries to prevent deadly disease outbreaks, AI tools have the potential to improve health-care access, quality and cost. Health systems in many developing countries face obstacles, including shortages of health-care workers, medical equipment and other medical resources. AI tools have exciting potential to optimize existing resources and help overcome workforce resource shortages and significantly improve health-care delivery and outcomes in low-income settings in ways never previously imagined.

The quality and availability of health-care services in developing countries lag behind those in developed countries. This leads to disparate health outcomes. According to the World Health Organization (WHO), more than 40 percent of all countries have fewer than 10 medical doctors per 10,000 people, and over 55 percent have fewer than 40 nursing and midwifery personnel per 10,000 people. Only a third to half of the global population could obtain essential health services as of 2017. Not having adequate digital and data infrastructure in developing countries impedes the prospects of AI deployment in health-care settings (Verma et al. 2020a). The deployment of AI in resource-constrained settings has been surrounded by much hype; more research is needed on how to effectively initiate and scale up AI solutions in health systems across developing countries. It is challenging to take disruptive technology innovations from developed countries and replicate them to address the unique needs of the developing world.

Data provide the quantitative basis for the deployment of AI and digital resources. Data are the lifeblood of the digital economy and essential inputs for AI technologies. Many developing countries have been grappling with providing efficient delivery of critical health-care services. To achieve this, health agencies need data about their populations to understand better the needs they must fill. The need for data to ensure efficient management and delivery of health services in low-resource environments has become increasingly important.

Unlike developed countries, which have abundant and readily available data that have driven health-care decisions, governments and organizations in developing countries lack reliable data collection, verification and aggregation systems. Considering that developing countries do not have the necessary systems to generate and maintain robust, accurate and relevant health data, data use to address disease prevention, assess interventions and provide community education has become challenging.

No single country or stakeholder has all the answers to these challenges. International cooperation and multistakeholder discussion are crucial to developing responses to guide the development and use of trustworthy AI for broader public health (OECD 2020).

The principle of 'leave no one behind' is core to the 2030 Agenda for Sustainable Development and its 17 Sustainable Development Goals. United Nations Secretary-General António Guterres has referred to technology's potential to turbocharge COVID-19 recovery and achievement of the goals.

This paper is intended to identify both barriers to AI deployment at scale in developing countries and the types of regulatory and public policy actions that can best accelerate the appropriate use of AI to improve health care in developing countries. While AI technologies hold great potential for improving health care around the globe, they cannot be considered a panacea for solving global health challenges. Scaling up AI technologies has risks and trade-offs. The adoption, acceleration and use of AI should strengthen local health systems and be owned and driven by the needs and priorities of developing country governments and stakeholders to help them best serve their populations (USAID and The Rockefeller Foundation 2022).

This paper starts with a landscape assessment of AI and big data analytics deployment in developing countries. It considers three fields of AI deployment in diagnosis and clinical care, health research and drug development, and health systems management and planning. It outlines key challenges that need to be addressed by regulators in governing AI in health care, such as data access, data quality, data privacy and ethics. Lastly, the paper outlines key governance mechanisms for AI innovation in health care in developing countries, such as data collection and management, data sharing and open-source solutions for data de-identification, open-source data banks and data annotation.

Landscape assessment of AI and big data analytics deployment in developing countries

An estimated 2,314 exabytes of space were needed to store the total volume of global health-care data produced by 2020 (EMC Digital Universe 2014). If these data were stacked on top of each other, they would reach 82,000 miles high or circle the earth 3.2 times (ITU 2019).

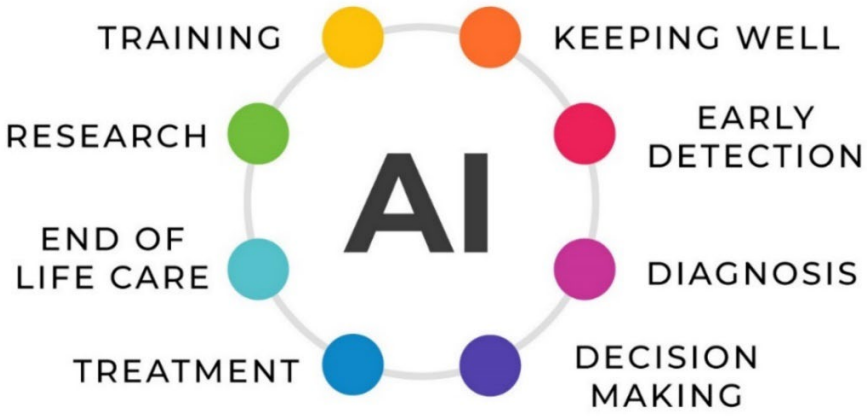
AI is creating a seismic shift in the way people interact with technology. If deployed ethically, it stands to help address critical global challenges and deliver considerable benefits to developing and least developed countries. AI's cognitive, learning and reasoning capabilities might improve industrial productivity and result in new added value across industries by maintaining an optimal environment for production and predicting and managing obstacles. In addition, greater use of AI-based precision diagnostic and real-time risk-detection functions will significantly contribute to solving social problems such as caring for the elderly in the context of an ageing population, preventing crime and strengthening public safety. As AI exploits data to drive innovation, a critical contemporary source of growth and well-being, its transformative effects are bound to expand further

in a wide array of domains. The main question, however, remains: How will developing countries deal with these seismic changes, and how prepared are they for them?

The vision of big data and AI in health care is comprehensive, evidence-based, personalized, stratified precision medicine, which combines the best available scientific knowledge with the professional experience of health professionals to benefit the individual patient (UNESCO 2017). Hence, the application of AI to health care and pharmaceuticals can aid in detecting health conditions early, delivering services, optimizing clinical decision-making, and discovering new treatments and medications (OECD 2019). It can facilitate personalized health care and precision medicine while powering self-monitoring tools, applications and trackers. Many benefits can be attributed to big data and AI in health care as they can offer higher quality and lower costs.

AI can be deployed in health training, keeping well, early detection of diseases, diagnosis, decision-making, treatment, end-of-life care and health research (Figure 1).

Figure 1. Potential uses of AI in health care



DEPLOYMENT OF AI IN DIAGNOSIS AND CLINICAL CARE

Diagnosis

AI can support medical diagnosis in radiology, medical imaging and other medical areas. While more widely used than other AI applications, such applications are still relatively new. AI is not yet routinely used in clinical decision-making. Currently, AI is being evaluated for use in radiological diagnosis in oncology (thoracic imaging, abdominal and pelvic imaging, colonoscopy, mammography, brain imaging and dose optimization for radiological treatment), in non-radiological applications (dermatology, pathology), in diagnosing diabetic retinopathy, in ophthalmology, and in RNA and DNA sequencing to guide immunotherapy. In the context of developing countries, AI may be used to improve the detection of tuberculosis in a support system for interpreting staining images or for scanning X-rays for signs of tuberculosis, COVID-19 or other conditions (WHO 2021).

Clinical care

Clinicians might use AI to integrate patient records during consultations, identify patients at risk and from vulnerable groups, aid in difficult treatment decisions and catch clinical errors. In developing countries, AI can manage antiretroviral therapy by predicting resistance to HIV drugs and disease progression to help physicians optimize treatment. Yet clinical experience and patient knowledge are essential. AI will not substitute for clinical due diligence for the foreseeable future. If it did, clinicians might engage in 'automation bias' and not consider whether an AI technology meets their needs or those of the patient.

DEPLOYMENT OF AI IN HEALTH RESEARCH AND DRUG DEVELOPMENT

Uses of AI in drug development

AI is already being used to simplify and accelerate drug development. This could change drug discovery from a labour-intensive to a capital- and data-intensive process using robotics and models of genetic targets, drugs, organs, diseases and their progression, pharmacokinetics, safety and efficacy. AI could be used in drug discovery and throughout drug development to shorten the process and make it less expensive and more effective.

In Nigeria, Ubenwa is using signal processing and machine learning to improve the diagnosis of birth asphyxia in low-resource settings. Bellemo et al. deployed AI to diagnose diabetic retinopathy in Zambia which showed significant and promising results when compared with human assessments. It showed clinically acceptable performance in detecting referable diabetic retinopathy. The Delft Institute's CAD4TB software has been employed in pilot studies examining the use of a computer-aided diagnosis of pulmonary tuberculosis from chest radiographs in Tanzania and Zambia. The performance of CAD4TB compared well with that of human experts.

Source: Owoyemi et al. 2020.

For instance, AI was used to identify potential treatments for Ebola virus disease. As in all drug development, however, identifying a lead compound may not result in a safe, effective therapy. In December 2020, DeepMind announced that its AlphaFold system had solved what is known as the 'protein folding problem'. The system can reliably predict the three-dimensional shape of a protein. Although this achievement is only one part of a long process in understanding diseases and developing new medicines and vaccines, it should help speed the development of new drugs and improve the repurposing of existing medicines against new viruses and new diseases. While this advance could significantly accelerate drug discovery, there are ethical concerns about intellectual property ownership and control of an AI technology that could be critical to drug development. This problem is even more accentuated in developing country settings where the use of AI may be contingent upon restrictive contractual licensing terms that further limit its diffusion and use.

The question of ownership of AI for drug development is relevant in current times. How appropriate is it for a few major private sector players to control intellectual property rights for technologies with potential as a widespread public good? Often these technologies have been funded by public grants or other public funding mechanisms.

The COVID-19 pandemic has exemplified the vulnerability of our societies to infectious agents. The danger to our health and political stability was underappreciated until this pandemic. Some estimates consider that it typically takes about 10 years (Mohs and Greig 2017) for a new medicine to complete the journey from initial discovery to the marketplace, at a cost on the order of $2.6 billion (Gardner 2020). On the other hand, the societal value of a drug could be much higher, as we see with the COVID-19 vaccines (Ahuja et al. 2021). In addition, drug discovery has shifted from simple chemical entities that treat common conditions affecting large populations to more complex biological molecules that treat particular conditions, often associated with specific mutations or genetic profiles, among smaller populations, making it more difficult for developers to recover their investments. Therefore, current and future public health needs—for example, those concerning infectious diseases and pandemics—are often unmet by the drug discovery ecosystem due to increasing costs and market failures (such as with antibiotics, neglected diseases or addressing pandemics too late).

The use of AI to speed up and reduce those costs is a huge opportunity but would be much more likely to succeed under an open-science and data-sharing governance framework. The specific research and innovation challenges involved with unmet public health needs at the global level would be better served (at a lower cost per country and with a more significant positive global impact) through the coordination of funding and incentives among nations as well as international and philanthropic organizations. One such international

endeavour is the Global Partnership on Artificial Intelligence, a multistakeholder initiative with 19 member nations, guided by the principles that informed the OECD's recommendations on AI.[2]

It seems imperative to explore new technologies like AI and associated data governance with the potential to drastically speed up and reduce drug development costs especially where the industry lacks incentives (McKenna 2020). As we have seen with COVID-19, the danger of emerging infectious pathogens can quickly reach a global scale and is best addressed with a coordinated international effort. While humanity as a whole is at risk (and we can even talk of an existential threat), poorer countries often suffer the most from infectious agents.

Two recent developments could help change the nature of the AI game in drug development:

- The proliferation of biological and robotics technologies to measure and collect relevant data on a growing scale
- The development of machine-learning algorithms that take advantage of that data to help better capture the appropriate causal mechanisms and more efficiently search in the space of new therapeutic agents

In 2020, Halicin, a new class of antibiotics, was identified through AI-based in-silico screening of chemical structures of molecules and the impact of their activity on bacteria (Stokes et al. 2020). A second recent example is the discovery of novel antibiotics using generative AI (Das et al. 2021). Another notable recent success, more on the side of understanding targets than searching for new therapies, is the breakthrough achieved by DeepMind with AlphaFold2,[3] hailed as “transformational” and “solving a 50-year-old biology challenge” in predicting the most likely three-dimensional configuration of a protein, given its sequence. This is the first step in the ambitious goal of predicting if a given protein (characterized by its sequence) will bind to a given drug molecule (Callaway 2020).

Although we are seeing the early evidence of the potential of AI in drug discovery, many basic research and applied research questions require significant efforts to bring this potential to fruition. Many of these questions will require highly multidisciplinary efforts and a scale of funding that poses societal challenges. Below are some leading examples of how AI can accelerate the drug discovery process.

Estimating the properties of a candidate drug from data: A supervised learning system can be trained with the appropriate data to associate candidate molecules (represented by their molecular structure) with properties of interest, such as drug-likeness (is the molecule small enough and with suitable properties to get

[2] For more on the Global Partnership on Artificial Intelligence, see: https://gpai.ai/.
[3] For a description of AlphaFold, see: https://en.wikipedia.org/wiki/AlphaFold.

into the right places in the body), toxicity, low production price, ease in storage, length of shelf life, ease in transportation and manufacturing, and of course, affinity to one or more protein targets of interest.

Improving relevant biological, chemical and physical models so they can be simulated: With limited amounts of costly experimental data, or simply to obtain better generalization, one can take advantage of appropriate causal knowledge, either in the design of the machine-learning predictors introduced above or to generate cheaper approximate data on expected associations between drugs and proteins, which can be crucial when very little experimental data are available. These models can benefit from other kinds of data to tune some of their parameters, or machine learning can approximate and accelerate their computation. Recent advances in causal machine learning could help combine existing biological knowledge with these observations and experiments, leading to progress in target identification (potentially multiple targets at once). Such models could also help to predict side-effects or prevent resistance or dependence (Yong 2018).

Active learning iterating between expensive experiments and machine learning: This is necessary to go from the approximate knowledge in computational models to decisions based on real experiments. Knowing that the machine-learning predictors will generate candidates not just once but multiple times means that a form of exploration can be beneficial in selecting these candidates (compared to only picking the best guess). The algorithms can be set up and optimized to take advantage of this interactive context. The learning system can ask questions and propose experiments to acquire relevant knowledge, capture causal structures and efficiently explore the vast space of molecules or drug combinations.

Learning to search in the space of molecules: Combining all the above advances, the question of learning a search policy for controlling the sequence of data acquisitions can be framed in the context of reinforcement learning, and raises additional questions around figuring out the suitable abstract action space (how to move in the space of candidate molecules, e.g., moving or adding atoms, or larger blocks?), and discovering the appropriate abstract area for representing molecules and planning such a search. Extending such studies to broadly cover a range of emerging viruses should enable us to dramatically improve readiness for future pandemics and possibly create a stockpile of vaccines targeting specific predicted proteins.

High-throughput screening technologies: The speed at which experimental data can be acquired is going to be key to success and mainly relies on research outside machine learning. Examples include biological and chemical technologies enabling the simultaneous screening of hundreds of thousands or more candidates at once, such as with DNA Encoded Libraries (Goodnow, Jr. 2016), robotic chemistry platforms (Schwaller et al. 2020), synthetic biology screening and similar ideas.

Incorporating patient-specific information and real-time monitoring: The choice of treatment can be personalized by conditioning machine-learning models on patient data, such as gene expression, ethnicity, vital signs (possibly from new devices, such as wearable sensors) and patient history (immunity history). This is important because the appropriate treatment may depend on the stage of the disease and the patient's particulars. This requires a very different kind of data from health records or medical measurements from patients. Patient-specific combinations of drugs could also be considered, using machine learning to predict which variety is more appropriate given patient data. Anti-virus drugs that aim to inhibit virus replication are most effective when the virus actively replicates during the incubation and early symptomatic periods. In contrast, inhibitors of inflammation are best used later to properly control inflammation. This requires continuous and real-time monitoring to detect the disease stage and anomalies at the earliest possible point in time, as was found for COVID-19. One pioneering example of such attempts is the Warrior Watch Study at Mount Sinai.[4]

Improving and scaling up trial designs: Machine learning could also take advantage of data from new trial designs aimed at reducing the cost and duration of clinical trials while making them more representative by targeting volunteers from the larger population of infected patients, using digital technology to report the effects of treatments, potentially with randomized cross-trials and models trained on the background population as a control (synthetic arm). Such trials could at least eliminate the need for unnecessary but costly classical clinical trials. Machine learning could also be used as part of adaptive clinical trials to extract more useful information faster (Pallmann et al. 2018).

Vezeeta, an Egyptian-based start-up with a leading digital health-care platform in the Middle East and North Africa, connects patients and health-care providers through state-of-the-art technology, allowing patients to search, compare and book the best doctors in private clinics and hospitals. In addition to this, patients can also book lab tests, scans and services, and operations.

Another notable mention is Altibbi, a digital health platform that offers telemedicine consultation services, allowing patients to connect directly with a database of doctors via audio calls and chats.

A Dubai-based start-up—Dimension14—uses an AI engine for scheduling patients and doctors by mapping out personalized journeys for both parties.

Sources: Vezeeta at: https://www.vezeeta.com/en; Altibbi at: https://magnitt.com/startups/2921/altibbicom; Dimension14 at: https://www.dimension14.com/.

Application of AI in health research

An important area of AI health research is based on data generated from electronic health records. Such data may be challenging to use if the underlying information technology system and database do not discourage the proliferation of heterogeneous or low-quality data. AI can be applied to electronic health records for biomedical research, quality improvement and optimization of clinical care. From electronic health records, AI

[4] See Mount Sinai's Warrior Watch Study at: https://reports.mountsinai.org/article/mount-sinai-warrior-watch-study-covid-19-heart-rate.

that is accurately designed and trained with appropriate data can help to identify clinical best practices before the customary pathway of scientific publication, guideline development and clinical support tools. AI can also assist in analysing clinical practice patterns derived from electronic health records to develop new clinical practice models. A second application of AI for health research is in the field of genomics (Davenport 2018).

DEPLOYMENT OF AI IN PUBLIC HEALTH SYSTEMS MANAGEMENT AND PLANNING

Data collection and analytics

Developing countries frequently deploy data collection and AI analysis to gather vital information. For instance, in Côte d'Ivoire, Data for Development (D4D) makes large health-care and telecommunications data sets available to the public (Bram 2015). In The Gambia, a probabilistic decision-making system was used to assist rural health workers in identifying life-threatening conditions in outpatient clinics. Medical AI performed tolerably well in detecting 88 percent of cases. Nurses used computerized aid to treat (CATT) in drug prescriptions in South Africa based on a cost-and-effectiveness algorithm. More recently, South Africa tested a multinomial logistic classifier-based system in human resource planning to predict how long health workers might stay in public service (Owoyemi et al. 2020).

Maternal and newborn deaths have plagued Africa in part because the right lifesaving interventions may not reach the right person at the right time. The vast majority of these deaths could be prevented with relatively simple and inexpensive tools. AI could play a crucial and transformative role, particularly in more impoverished and remote areas, in providing critical intelligence to help community health workers prioritize and triage care and resources to those most at risk (Rao 2019).

Even in a single-payer, government-run system, health systems may be overly complex and involve many actors who contribute to, pay for or benefit from health-care services. The management and administration of care may be laborious. AI can assist personnel in complex logistical tasks, such as optimizing the medical supply chain, assuming mundane, repetitive tasks or supporting complex decision-making. Some possible functions of AI for health systems management include identifying and eliminating fraud or waste, scheduling patients, predicting which patients are unlikely to attend a scheduled appointment and assisting in identifying staffing requirements (WHO 2021).

AI could also be useful in complex decision-making and planning. For example, researchers in South Africa applied machine-learning models to administrative data to predict the length of stay of health workers in underserved communities. In a study in Brazil, researchers used several government data sets and AI to optimize the allocation of health-system resources by geographical location according to current health challenges. Allocation of scarce health resources using AI has raised concerns, however, that resources may not be fairly allocated, due, for example, to bias in the data.

Health promotion

AI can be deployed for health promotion or to identify target populations or locations with high-risk behaviours and populations that might benefit from health communications and messaging (microtargeting). AI programmes can use different forms of data to identify such populations, with varying accuracy, to improve message targeting.

Microtargeting can raise concerns, however, such as its use for commercial and political advertising, and the opaqueness of processes that facilitate it. Furthermore, users who receive such messages may have no explanation or indication of why they have been targeted. Microtargeting also undermines a population's equal access to information. It can affect public debate and facilitate exclusion or discrimination if the public or private sector misuses it (WHO 2021).

Disease prevention

AI has been used to address the underlying causes of poor health outcomes, such as environmental or occupational health risks. AI tools can identify bacterial contamination in water treatment plants, simplify detection and lower costs. Sensors can improve environmental health by analysing air pollution patterns or using machine learning to make inferences between the physical environment and healthy behaviour. One concern with such use of AI, however, is whether it is provided equitably or if such technologies are used only on behalf of wealthier populations and regions with relevant infrastructure for their use.

Public health surveillance, emergency preparedness and outbreak response

AI has been used in public health surveillance for collecting evidence. Technology is changing the data collected for public health surveillance by adding digital 'traces' that are not generated specifically for public health purposes (such as blogs, videos, official reports and Internet searches). Videos (e.g., YouTube) are another 'rich' source of information for health insights. After rigorous evaluation, new developments in AI could improve the identification of disease outbreaks and support surveillance.

Several concerns about the use of AI for public health surveillance, promotion and outbreak response must, however, be considered before using AI for such purposes, including the tension between the public health benefits of surveillance and ethical and legal concerns about individual (or community) privacy and autonomy.

Characterization of digital traces as 'health data' raises questions about the types of privacy protection or other safeguards that should be attached to such data sets if they are not publicly available. For example, the use of digital traces in health data could violate the data protection principle of 'purpose limitation'. Individuals who generate such data should know how they will be used at the collection point (WHO 2021).

Such use also raises questions of accuracy. Models are helpful only when they apply appropriate data. Machine-learning algorithms could be more valuable when augmented by digital traces of human activity yet these could also negatively impact an algorithm's performance. Google Flu Trends, for example, was based on search engine queries about complications, remedies, symptoms and antiviral medications for influenza, and was used to estimate and predict influenza activity. While Google Flu Trends first provided relatively accurate predictions before those of the US Centers for Disease Control and Prevention, it overestimated the flu prevalence between 2011 and 2013. The system was not retrained as human search behaviour evolved.

Although many public health institutions are not yet making full use of these data sources, surveillance itself is changing, especially real-time surveillance. For example, researchers could detect a surge in cases of severe pulmonary disease associated with electronic cigarettes by mining disparate online sources of information and using HealthMap, an online data-mining tool. Similarly, Microsoft researchers have found early evidence of adverse drug reactions from weblogs with an AI system. In 2013, the company's researchers detected the side-effects of several prescription drugs before they were found by the US Food and Drug Administration's warning system. In 2020, the US Food and Drug Administration sponsored a 'challenge', soliciting public submissions to automatically develop computation algorithms to detect adverse events from publicly available data. Despite its potential benefits, real-time data collection, like collecting and using digital traces, could violate data protection rules if surveillance is not the purpose of its initial collection, which is especially likely when data collection is automated (WHO 2021).

Magic Box, built by the Office of Innovation at the United Nations Children's Fund, is a big data programme developed in response to the 2014 Ebola crisis in West Africa. It uses real-time data to inform decision-making in emergency situations such as epidemics.

Magic Box's AI uses real-time aggregated data from public sources and private sector partners to generate actionable insights and a better understanding of complex and changing situations. It builds on machine learning, network analysis and complex systems research to provide decision-makers and relevant front-line health workers with disease spread predictions, key counter measures and population level insights.

It considers precipitation and weather data, high-resolution population estimates, air travel data, aggregated and anonymized mobility data from mobile phone records, geotagged social media traces, temperature data and case data from WHO reports to build better models and understanding of epidemics and other humanitarian and development contexts affecting children.

Magic Box has benefited from partnerships with Amadeus, Google, IBM, Vodafone and Telefonica, further increasing its capabilities and allowing its application to other mosquito-borne diseases like Zika, dengue, and yellow fever, new Ebola outbreaks and the COVID-19 crisis.

Source: Broadband Commission for Sustainable Development 2020.

Before the COVID-19 pandemic, WHO started developing EPI-BRAIN, a global platform that will allow data and public health experts to analyse large data sets for emergency preparedness and response. AI assisted in both detection and prediction during the COVID-19 pandemic, although some consider that the development of new

techniques and programming will 'pay dividends' only during a subsequent pandemic. HealthMap first issued a short bulletin about a new type of pneumonia in Wuhan, China, at the end of December 2019. Since then, AI has been used to 'now-cast' (assess the current state of) the COVID-19 pandemic. In some countries, real-time data on the movement and location of people have been used to build AI models to forecast regional transmission dynamics and guide border checks and surveillance. To determine how such applications should be used, an assessment should be conducted of whether they are accurate, effective and valuable.

AI can assist public health authorities in tracking, monitoring and managing pandemic outbreaks. AI and big data can also facilitate social distancing. AI has been used to map the movements of individuals to approximate the effectiveness of government-mandated orders to remain in confinement. In some countries, it has also been applied to identify individuals who should self-quarantine and be tested. The deployment of AI in this context has raised legal and ethical concerns about privacy and the risk of discrimination, however, and possibly unnecessary restrictions on movement or access to services, which can heavily impact the exercise of a range of human rights. As with all AI technologies, actual effectiveness depends on whether the data sets are representative of the populations in which the technologies are used, and they remain questionable without systematic testing and evaluation. The WHO issued interim guidance on the ethical use of proximity-tracking applications in 2020. Another development has been the robots that have begun to replace clinicians in hospitals, with applications such as helping to disinfect rooms, providing telehealth services, and processing and analysing COVID-19 test samples.

One example of the use of AI during the pandemic was the Canadian health surveillance start-up called BlueDot. It was among the first in the world to accurately identify the spread of COVID-19 and its risks (Panjabi 2020). The start-up's AI software discovered a cluster of unusual pneumonia cases in Wuhan, China in late December 2019, and predicted where the virus might spread. It used geographic information system (GIS) data and flight ticket sales to create a dispersion graph based on the airports connected to a city and where passengers were likely to fly. It also used anonymized location data from 400 million mobile devices to track flows from the outbreak epicentre to other parts of the world. BlueDot applied this methodology to identify many of the cities that were among the first

Leveraging AI-powered sensors to support triage in sophisticated ways

Florida's Tampa General Hospital deployed an AI system in collaboration with Care.ai at its entrances to intercept individuals with potential COVID-19 symptoms. The technology conducts a facial thermal scan and picks up other symptoms, including sweat and discoloration, through cameras positioned at entrances to ward off visitors with fever.

Another such example is the Israeli company Diagnostic Robotics, an AI-based triage platform that allows public health officials to continuously monitor the virus's patterns. The platform has been adapted to tackle the current pandemic, offering an analytics tool that produces risk assessment and predictive models, thus allowing a quicker and better targeted medical response.

Sources: Venture Beat n.d., Council 2020, Singer 2020.

to experience the spread of the coronavirus, such as Tokyo, Bangkok, Hong Kong (Special Administrative Region of China), Seoul and Taipei (Khan 2020).

The Government of the Republic of Korea released an app that allowed users to self-report symptoms, alerting them if they leave a 'quarantine zone' to curb the impact of 'super-spreaders' who might otherwise infect large populations (Shendruk 2020).

Priority challenges that need to be addressed by regulators in governing AI in health care

The COVID-19 pandemic has intensified the deployment of AI in health care. This rapid uptake has created governance challenges, such as those related to access to quality and accurate data, data protection, sharing and privacy (health data are sensitive information), identity (public health crises could enable the swift passage of regulations for identification without public debate or transparency) and bias (the use of AI and big data analytics in health carries inherent biases, such as those linked to gender, race and socioeconomic status).

Many developing country governments do not have the technological capabilities and resources to create suitable policies and regulations to deploy AI technologies in health care. There is a lack of consistent regulation, which is often highly dependent on the discretion of local officials and can change quickly. This variability creates an uncertain regulatory environment that generally impedes the scale-up of AI technologies. Clear guidance from multilateral bodies and governments on when and where regulation on AI tools is needed would be helpful for AI companies operating across developing country health-care markets.

Many developing countries have regulations limiting which health services or advice can be given to patients outside health facilities or without the presence of a physician. For instance, laws in Brazil, China, India and other markets require physicians, not algorithms, to make diagnoses, and highly trained health workers to carry out specific medical tests. Yet some AI companies have not confronted regulatory issues because they are categorized as providing 'educational health information' and are not regulated in terms of providing care guidance. But as health regulations in developing countries become more robust, this situation is likely to change, with a risk that regulations will become more complex and inconsistent across countries.

AI deployment in health care has raised legitimate concerns and anxieties. Its use in standard health care delivery and administration is still minimal, more so in developing countries. There are difficulties in scaling up projects and questions about the quality of health data fed into AI systems. Moreover, many AI systems are black boxes; their decision-making process remains a mystery even for their designers. AI

systems also carry different types of bias and thus can be used to accentuate existing inequalities and unwarranted variations in care. AI's technological capabilities could result in potential breaches of human rights driven by risks that did not exist before (e.g., remote biometric surveillance or facial recognition technology). What is more, due to the nature of AI technologies, it may be difficult to assign liability to a particular human action or omission since human control might be several times removed.

AI and big data in health care create a novel set of ethical challenges that must be identified and mitigated, since AI technology has tremendous capability to threaten patient preference, safety and privacy. For instance, machine-learning algorithms might not provide equally accurate predictions of outcomes across race, gender or socioeconomic status. Another example involves facial recognition technologies that assist with identification, monitoring and diagnosis. As these are increasingly utilized in health-care settings, informed consent will need to be obtained to collect and store patients' images and for the specific purposes for which systems might analyse those images. Patients might not be aware that their images could be used to generate additional clinically relevant information (Martinez-Martin 2019).

The following key challenges to regulating AI in the health-care sector in developing countries cover data access, data quality, and data privacy and ethics.

DATA ACCESS

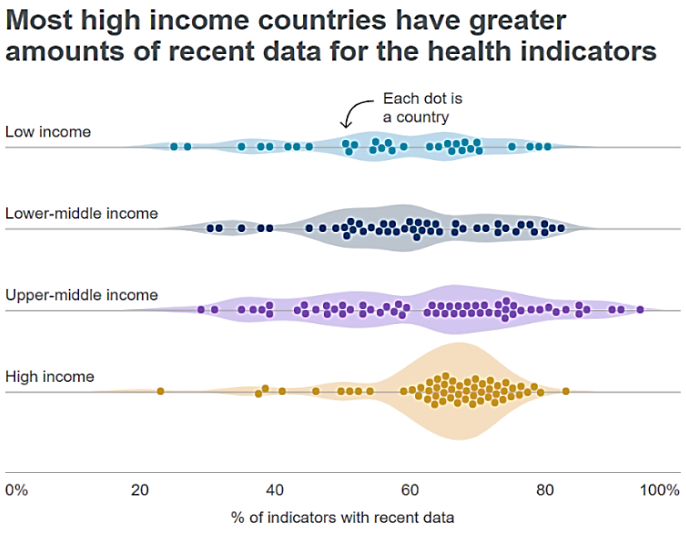
Data fuel digital health care. They are the basis of research and the discovery of new treatments, fuelling the personalization of medicines, and demonstrating the value of treatments to power AI and machine-learning algorithms. Data enable health-care providers and policymakers to make informed decisions about allocating resources.

Health data constitute 30 percent of globally stored data.[5] For health data to make decision-making better, data sets need to be more diverse and robust. Data access and quality barriers still prevent innovators from using data more efficiently and effectively in health care, however. The COVID-19 crisis has exposed these data gaps even further (Gwee 2021).

Often, health data in developing countries are incomplete or of low quality. As a result, policymakers may be misled in their attempts to allocate resources effectively. Health data sets are siloed and locked within institutions. Many countries are grappling with linking different data sources and using data for secondary research (Figure 2).

[5] See Data Saves Lives at: https://datasaveslives.eu/.

Figure 2.



Source: WHO, see: https://www.who.int/data/gho/data-availability-a-visual-summary.

According to the OECD, many countries still cannot extract and harness the information they need to deliver better public health outcomes. Interoperable and good-quality health record data would inform better care delivery and support more significant national health research goals (Oderkirk 2017).

Apart from data access, data interoperability is another challenge. Often, health data sets are not interoperable or portable among institutions. This leads to less diverse data sets that might not represent the patient population at the national level. Moreover, interoperability and standardization affect the building of regional and global health data sets and impede AI and machine-learning solutions across borders. COVID-19 has demonstrated the need for data interoperability and standardization.

Many health-care data are unstructured, which impedes uniformly compiling and analysing data sets. The proliferation of wearables and digital health devices provides the ability to capture and leverage real-world data as a supplement to clinical data.

DATA QUALITY

One of the key impediments to the effective deployment of AI in health care is access to FAIR (findable, accessible, interoperable and reusable) data. In developing countries, this problem is exacerbated when data

are not digitized or easily accessible due to private sector capture. It has been suggested that "data quality issues are critical when building AI for clinical settings. It is, therefore, incumbent on the regulators of AI models to also ensure that the data used adheres to the FAIR principles and is collected ethically before certifying the model as fit for the market. This could be further supplemented by organizational quality assessment in pre-market checkpoints. These conditions can signal to the industry that data integrity and ethical collection are paramount to being eligible for the market, and lead to positive structural changes in how enterprises function" (Verma et al. 2020b, p. 6).

Data representativeness is another problematic issue related to data quality. AI's output is shaped by the data fed into it. Computer-based recommendations are often taken at face value, assuming that whatever result an AI algorithm portrays is objective and impartial. Humans choose the data that goes into an algorithm, and these choices can embed human biases, which in turn might negatively impact underrepresented groups. These biases might occur at any phase of AI development and deployment.

The most common source of bias in data is when they do not sufficiently represent the target population. This can have adverse implications for specific groups. For example, women and people of colour are typically underrepresented in clinical trials. If algorithms that analyse skin images were trained on images of white patients and then applied more broadly, they could potentially miss melanomas in people of colour. As another example, the use of an algorithm designed to prioritize care for COVID-19 patients could put populations lacking access to COVID-19 testing at a disadvantage. Algorithms may fail to factor in their needs and characteristics if they are underrepresented in training data (Siwicki 2021).

DATA PRIVACY AND ETHICS

Any regulatory framework should provide for both health and privacy rather than forcing a choice between them. AI technology will serve the welfare and well-being of developing countries only if certain safeguards, such as human-in-the-loop and privacy by design, are introduced.

Several existing frameworks might serve as a base for the checks and balances necessary for such a regulatory framework. The European Social Charter clearly states the "right to health" in Article 11 of the Oviedo Convention, and Convention 108+ ensures the protection of personal data and privacy. A dedicated legal instrument with a global reach in governing AI is needed, however. It should consider AI's specific characteristics, and establish benchmarks for privacy, confidentiality, data safety, informed consent and liability (Böke 2021).

Data privacy and the ethical use of data raise significant concerns among many developing country governments and other stakeholders—not only for those working on AI, specifically, but also for those involved in digital health and other sectors more broadly. For instance, data privacy issues are significant for digital health and AI solutions since health data are generally government owned, raising concerns about private companies gaining access to the data and potentially profiting by leveraging them for their own uses. Many developing countries already have regulations prohibiting private companies from taking health and other data types outside their borders. In addition, many local stakeholders are concerned about AI tools requiring access to large amounts of health data because they fear this would increase risks for monopolistic behaviour if a single private player assumes such a significant role in a country's health system (USAID and The Rockefeller Foundation 2022).

Tech companies and health systems have trained AI to perform remarkable achievements using health data. Start-ups like K Health source from databases containing hundreds to millions of [electronic health records] to build patient profiles and personalize automated chatbots' responses. IBM, Pfizer, Salesforce and Google have also attempted to use health records to predict the onset of conditions like Alzheimer's, diabetes, diabetic retinopathy, breast cancer and schizophrenia. And at least one start-up offers a product that remotely monitors patients suffering from heart failure by collecting recordings via a mobile device and analysing them with an AI algorithm.

The data sets used to train these systems come from a range of sources, but in many cases, patients have not been made fully aware that their information is included among them. This situation is even more complicated in developing countries where there is a lack of regulation and awareness among key stakeholders (regulators included) about the importance of preserving the privacy of health data sets that are harvested by AI and big data analytics.

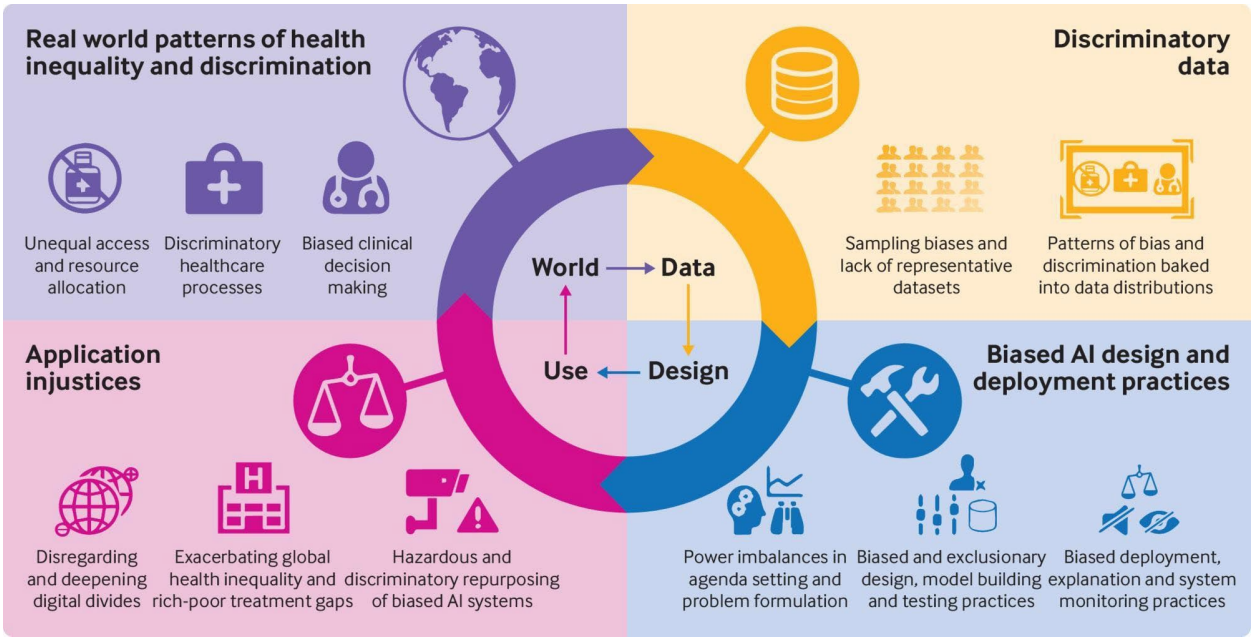
Source: Venture Beat 2021.

The concept of algorithmic bias, which implies that AI is as good as the data on which it is trained, is an important factor in how AI and big data are used for development. Algorithmic bias has a more pronounced effect when AI applications are introduced to developing country settings. Most AI applications are being created outside the developing world, and most data sets available are from people from developed countries. This might affect the sensitivity of AI systems. AI systems could also embed algorithms that contain specific beliefs and biases of their creators. This can lead to discriminatory outcomes if systems are applied to low-resource settings without considering developmental inputs and data (Owoyemi et al. 2020).

Given these constraints, developing country regulators should ensure that AI-powered tools can be applied equally to different groups of people. Information from specific population groups tends to be missing from the data used to train these tools, meaning that they might work less well for those communities. For instance, a team of scientists in the United Kingdom found that almost all eye disease data sets come from patients in China, Europe and North America, meaning that algorithms diagnosing eye diseases are less certain to work well for racial groups from underrepresented countries (Knight 2020). Another example is that skin cancer-detecting algorithms tend to be less precise when used on Black patients because AI models are trained chiefly

on images of light-skinned patients (Lashbrook 2018). Figure 3 gives an overview of global patters of health inequality and discrimination and related biased AI design and deployment practices.

Figure 3. Biased AI design and deployment practices



Source: World Economic Forum 2021.

Even if diverse data sets are generated, however, this might not translate into AI tools rolled out reliably in low-income countries, where disease profiles differ from those in developed nations. To illustrate this, in sub-Saharan Africa, women are diagnosed with breast cancer younger, on average, than their peers in developed countries, and their disease is more advanced at diagnosis. Diagnostic AI tools trained on mammograms from Europe are trained to identify disease early in older women. These AI training sets could have devastating results if/when deployed in sub-Saharan Africa (Nordling 2019).

One way to solve this problem is to give AI developers access to low-income countries' data. This might raise concerns related to data protection for vulnerable populations, however. For instance, information such as HIV status could discriminate against specific populations. Often, private companies offer to pay for such data. It might be tempting for cash-strapped national health systems or individual researchers to part with patient data, perhaps without thinking hard about the rights of those whose data they are sharing. Data companies could also lure people into giving up their privacy in return for medical care or financial rewards. Such practices could create a privacy divide between the rich and the poor (Nordling 2019).

Since many tech companies offer AI tools as free products directly to their users (patients or physicians), the users often become the 'product' that the tech companies monetize. The companies that own these tools can

sell their customers' sensitive health data. This issue highlights concerns around data privacy surrounding digital health and AI health solutions and will need to be addressed by local players and national governments.

AI deployment in health care also prompts ethical concerns about whether private companies with access to patient and population health data should be required to disclose the data to individual patients, local populations, health workers and other local constituencies. For AI-enabled population health tools, a dilemma could arise when a private company analyses data indicating a potential outbreak of a highly contagious infectious disease in a given region. In this case, should that company inform health workers or communities within that region immediately? For an AI patient-facing platform, a dilemma might be whether AI tools should disclose a diagnosis to patients without appropriate counselling or other confidentiality measures that health providers would otherwise provide.

Limited access to health care for certain people is one way that AI tools could widen the health gap globally. Patient virtual health assistants and physician clinical decision-supporting AI-enabled tools face ethical and fairness issues; the distribution of benefits from these tools will likely be uneven across low-resource contexts and may not reach the most underserved populations in the near term. The digital divide across poverty and racial lines is likely to impact these tools on varying levels. For patient-facing tools, benefits will originally go to those with smartphones and 4G connectivity—most likely higher-income segments of the population (USAID (United States Agency for International Development) and The Rockefeller Foundation 2022).

Key governance mechanisms for AI innovation in health care in developing countries: recommendations

AI in health must support humans and seek to improve health outcomes, not simply replace humans in full automation. Expressed as a formula, this means: Humans + AI = Better outcomes.

—Broadband Commission for Sustainable Development 2020, p. 19

Data and algorithms are an integral part of the ability of machines to learn. The outcome of AI depends on the quality of data and algorithms. Data should not be biased, data ownership should be clearly defined and algorithms should be transparent enough to identify stakeholders' liabilities. The responsibilities of all stakeholders need to be delineated to prevent damage and repair or compensate for harm in the worst-case scenarios. A proper regulatory framework would ensure these properties for data, algorithms and the whole AI process (Böke 2021).

The governance framework for AI in health care should be based on multistakeholder accountability, independent oversight, and adequate evaluation of socioeconomic and human rights impacts. Governance

structures that allow for screening and certification of AI applications for health-care services at the national level are critical to ensure their safety and rights compatibility. These processes should be handled by independent authorities that are not politically or commercially driven.

There is also a need to resist the commercial capture of public health through AI. For this reason, we should encourage national public health-care authorities to adopt a strategic approach, coordinating digital transformation policies, research and investment, and the management and use of personal data. Seeking a healthy balance between individual, private and public interests will protect public health in developing countries.

Any regulatory framework for AI in health care should ensure multifaceted quality certifications for the composition of teams, the nature of the data and the operation of algorithms. For the efficiency and safety of AI-driven health applications, developing country governments need to ensure that there is always a human in the loop, in other words, that AI never fully replaces humans and that adequately trained professionals validate health-care decisions. AI is only as good as the data, human capital and expertise of the interdisciplinary team involved in the development of the AI solution. An adequate regulatory framework should define the respective liabilities of all stakeholders. It should put in place the necessary conditions and guarantees to protect human rights while working towards the collective interest. This could be done through the public certification of AI systems to ensure that data and algorithm quality are guaranteed to prevent deepening existing inequalities. Public certification of AI applications would build public trust and allow users to give informed consent. Instead of only receiving information about an AI application, end users would be empowered to understand the implications of their decisions before they 'click and consent' (Böke 2021).

Is informed consent possible in the age of AI?

Often, the standard consent form that patients sign at the point of care is not sufficient to justify the use of their data for commercial purposes, even in anonymized form. These documents, which ask patients to consent to the reuse of their data to support medical research, are often vague about what form that medical research might take. Often, anonymized medical data are sold to commercial entities that use the data sets to train their AI and machine-learning tools. Patients are mostly not aware of this. AI and machine learning make re-identification of data a reality. Hence, societies need to come up with adequate health data-sharing regimes that preserve privacy and foster innovation at the same time.

Regulators and policymakers need to address concerns over the privacy and protection of sensitive health data. Adequate data protection systems for preserving data privacy need to be in place.

Legal and regulatory frameworks for AI in health care should be iterative and adaptable, and go hand-in-hand with the pace of AI development. Regulatory frameworks should be built on a foundation of mutual support and global solidarity.

Enabling an ecosystem for AI in health care requires developing countries to have at least a minimum set of principles and standards for data governance. While there can be a range of comprehensive regulatory frameworks for data governance in health care, the leanest way to ensure a well-functioning AI ecosystem is by focusing on two elements of data infrastructure: data collection and management (for ensuring quality, interoperable and machine-readable data) and data sharing (in a way that preserves privacy).

DATA COLLECTION AND MANAGEMENT

Developing country regulators should incentivize health data recording that adheres to a minimum set of national/international standards. A common set of standards will ensure semantic and technical interoperability between all players. FAIR data management practices should be prescribed for storing data in a findable, accessible, interoperable and reusable manner while also emphasizing machine actionability. This involves standardizing data structures (consistency in how data such as those related to health event summaries, prescriptions, care plans, etc. are stored) and common medical terminologies (to describe diseases, symptoms and diagnoses, such as the WHO-ICD10, SNOMED CT, DICOM, etc.) (Lashbrook 2018).

DATA SHARING

Suitable governance mechanisms in sharing health data build on two considerations: Health data are considered data of public interest, and any health data-sharing mechanisms should always incorporate privacy-by-design considerations. This requires a policy consensus on key questions of how to ensure the consent of the patient and define the ownership of data, especially to share it with AI developers for processing. This is where policies and standards around de-identification and anonymization can balance privacy and use health data for health innovation. There are experimental and novel models for data-sharing, such as data trusts, sandboxes and collaboratives, especially in developed countries. These experimental models might not be readily transferable to developing countries, however. Hence, the first and quickest step should be to define a standard model agreement for data-sharing between all stakeholders that prescribes privacy and security measures to be undertaken by both the data fiduciary and the party requesting data access (Lashbrook 2018).

Developed country governments have devised innovative approaches to regulating AI in sharing health data, such as regulatory sandboxes, public policy labs and fast-track programmes. The main questions remain largely unresolved, however: Are these mechanisms readily transferable to developing and the least developed countries? How do governments stimulate AI innovation in the health-care sector without overregulating and while preserving privacy simultaneously?

One way to ensure that AI tools do not widen existing health inequalities is to incorporate equity into their design. For instance, the National Health Service in the United Kingdom was criticized for not giving enough attention to the potential for AI to widen health gaps in its updated Code of Conduct for Data-driven Health and Care Technologies, released in February 2021. Likewise, the US Food and Drug Administration, which regulates and approves new medical technologies, has been urged by the American Medical Association to highlight bias as a considerable risk of machine-learning in its approval process for medical software. It has been argued that AI tools that continually improve their performance by learning from new data should come under increased scrutiny (Nordling 2019).

Some research funders are tackling the issue head-on by launching research to study how the introduction of AI tools affects access to care and its quality. Wellcome, a London-based biomedical charity, kickstarted a £75 million ($90 million) five-year programme to look at ways to make sure that innovations in the use of health data will benefit everyone, not just in the United Kingdom, but also in other parts of the world, such as East and Southern Africa and India, where Wellcome has a strong presence.

Medical studies initiated by partner institutions, like the Mount Sinai Asthma Health and Stanford Medicine MyHeart Counts projects, can access 23andMe research services using the ResearchKit app, through which customers can choose to share data. Customers of 23andMe's services can also elect to participate in other surveys to aid medical research, and provide data to 23andMe's industry, academic and non-profit partners. The data collaborative allows research partners to use 23andMe data to investigate over 1,000 diseases, conditions and traits to identify new associations among genetic markers.[6]

In developing countries, building trust in AI solutions in health care is about ensuring that AI tools meet demand on the ground and build trust and buy-in from the communities they are intended to help. Rolling out health-care AI tools in developing countries requires an in-depth understanding of existing bottlenecks in health-care systems. For example, the AI that can identify people with tuberculosis from chest X-rays,

[6] See the 23andMe Patient-Centric Research Portal at: https://datacollaboratives.org/cases/23andme-patient-centric-research-portal.html.

primed for use in India, could save time, money and lives in South Africa, especially in rural areas without specialists to examine such images. To obtain images in the first place, communities will need X-ray machines and people to operate them. A failure to provide those resources will mean that AI tools will simply serve those already living near better-resourced clinics.[7]

Data trusts

Data trusts are data-sharing frameworks that ensure that all parties involved have defined rights and responsibilities towards the data, and that individuals' personal and other sensitive data are protected. Data trusts allow two or more parties in any sector to partner in data-sharing agreements and shape the agreements according to their needs. They enable multiple organizations to work together to solve common problems.

Data trusts are still experimental forms of data-sharing piloted mostly in the developed world. Possible forms that can be considered by developing country governments include national and local public health data trusts and public data research trusts. National and local health data trusts can be charged with maximizing the public benefit from health data while respecting privacy and consent, for example, while linking patient records, diagnoses, genomic, and socioeconomic and behavioural data. A public data research trust can act as the authorized guardian of a range of types of administrative and social data (from national and local governments, etc.), offering these to authorized projects by authorized providers with built-in auditing of data uses. Access could be allowed via application programming interfaces (APIs). Some commercial data could

Data trust examples

In the United Kingdom, the National Health Service's Digital Independent Group Advising on the Release of Data has been deliberating over prospective uses of data on behalf of the organizations that hold it.

'Bottom-up' data trusts, such as LunaDNA, support groups of individuals to contribute data to an entity that stewards them on their collective behalf. Some personal data stores and information management systems already operate under this kind of delegated authority, where they enable people to contribute data about and defer some rights to decide who can access and use the data. This happens for non-personal data as well.

The UK Biobank, set up in 2006 to steward genetic data and samples from around 500,000 people, is a charitable company with a board of directors that acts as charity trustees under charity law and company directors under company law.

Data trusts have been included in the Canadian Government's Digital Charter as a mechanism to support particular sectors, activities and technologies. The European Commission considered trusts as a personal data intermediary with significant potential in the European data strategy published in February 2020.

Sources: Open Data Institute at: https://theodi.org/article/data-trusts-in-2020/; LunaDNA at: https://www.lunadna.com/; UK Biobank at: https://www.ukbiobank.ac.uk/wp-content/uploads/2011/05/EGF20082.pdf.

[7] Ibid.

be added to these data pools. Individuals could be given the option to opt in and decide if their data would be part of the public data research trust (Mulgan and Straub 2019).

Data sandboxes

The term 'data sandbox' describes any isolated environment through which data are accessed and analysed, and analytic results are only exported, if at all, when they are non-sensitive. These sandboxes can be realized through technical means (e.g., isolated virtual machines that cannot be connected to an external network) and/or through a physical on-site presence within the facilities of the data holder (where the data are located). Data sandboxes would typically require that the analytical code be executed at the same physical location where the data are stored.

Compared to the other data access mechanisms presented above, data sandboxes offer the strongest level of control. They are therefore promising for providing access to very sensitive/personal and proprietary data. One such example is the Centers for Medicare and Medicaid Virtual Research Data Center in the United States. This virtual research environment provides timely access to Medicare and Medicaid programme data, such as beneficiary-level protected health information. Access is provided over a virtual private network and a virtual desktop to satisfy all privacy and security requirements.[8]

Data philanthropy

The promise of big data for development will not be fulfilled if institutions—primarily private corporations—refuse to share data. UN Global Pulse, for instance, has put forth the concept of 'data philanthropy', where "corporations [would] take the initiative to anonymize their data sets and provide this data to social innovators to mine the data for insights, patterns and trends in real time or near real-time" (Kirkpatrick 2011, p. 2).

OPEN SOURCE SOLUTIONS FOR DATA DE-IDENTIFICATION, OPEN SOURCE DATA BANKS AND DATA ANNOTATION

Establishing open source programmes by collectives or governments in developing countries that collaborate with initiatives such as the United States Privacy Engineering Program under the National Institute of Standards and Technology might help set a cohesive direction for AI in health care in different countries (Lashbrook 2018).

The prohibitive cost of collecting representative health data frequently serves as an entry barrier to entities building AI health interventions. To make the development of solutions economically feasible and avoid bias in health-care models, developing countries need to build a robust repository of data sets representing their

[8] See the CMS Virtual Research Data Center FAQs at: https://www.hhs.gov/guidance/document/cms-virtual-research-data-center-vrdc-faqs.

populations. Research institutions and non-profit organizations such as Child Health and Development Studies or OpenfMRI have created several health data repositories. A concerted institutional push for establishing such databanks under a single platform in developing countries will be the first step towards kick-starting a local health-care AI hub (Lashbrook 2018).

Recommendations for policymakers

Do not leave data invisible groups behind. Access to information and our collective values are the bedrock of democracies and the rule of law. Facts inform public debate and evidence-based policymaking. Information from our offline world, erroneous data sets and skewed coding unintentionally creep into AI algorithms, however, leading to bias and discrimination. Viewing the impacts of AI models cannot therefore be a binary discussion focused only on gains, losses, costs and benefits, as these models govern significant decisions impacting individuals that can ripple through societies at large (The Rockefeller Foundation 2020). Regulators and policymakers are at a critical juncture in regulating AI. Designing or evaluating new technologies, such as AI, assumes the existence of a so-called 'standard human' yet this assumption is inherently flawed and clearly biased. It is based on a partial and exclusive vision of society and its constituents, overlooking the impact of AI on underserved, underrepresented and marginalized groups—in other words, data invisible groups. As a result, instead of fostering inclusivity and equality, AI may be used to harden lines of difference as the data it is fed tend to overlook the impacts of technology on marginalized groups. Groups invisible in data disproportionately bear the brunt of the increased use of technology in our societies and most often experience discrimination in three main areas—punishment and policing, essential services and support, and movement and border control.

Remember that data and algorithms are integral to the ability of machines to learn. The outcome of AI depends on the quality of data and algorithms. Data should not be biased; data ownership should be clearly defined; and algorithms should be transparent enough to identify stakeholders' liabilities. The responsibilities of all stakeholders need to be delineated to prevent damage and repair or compensate for harm in the worst-case scenarios. A proper regulatory framework would ensure these properties for data, algorithms and the entire AI process.

Building trust in AI solutions in health care is about ensuring that tools meet demand on the ground and build trust and buy-in from the communities they are intended to help. Rolling out health-care AI tools in developing countries requires an in-depth understanding of existing bottlenecks in health-care systems. An AI that can detect tuberculosis from chest X-rays, intended for use in India, could save lives in South Africa's rural areas. Access to X-ray machines and operators is crucial for its effectiveness, however. Without them, only those near well-equipped clinics will benefit.

No single country or stakeholder has all the answers to these challenges. International cooperation and multistakeholder discussion are crucial in guiding the development and use of trustworthy AI for broader public health.

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