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Artificial Intelligence–augmented public health interventions in India

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Abstract

The adoption and scaling of technology in public health settings in the Global South have traditionally been challenging. The introduction of artificial intelligence (AI) technology has exacerbated the challenges, but AI also brings with it exciting new frontiers. India is a large, diverse country that encapsulates well the challenges and opportunities for AI in the Global South. Here, we describe the landscape for AI as a force for driving public health outcomes in India and the critical role in this played by technology platforms. We give examples of our own work in Tuberculosis and infant health to illustrate how AI can be fruitfully integrated into large-scale platforms in order to meaningfully address gaps in public health. Finally, we point out the importance of learning lessons from early deployments on these platforms, despite the varying levels of AI maturity and readiness across modalities.

Key words: artificial intelligence; public health; Global South; India; health interventions; technology platforms; Tuberculosis; maternal and child health.

Key Points

- Deploying artificial intelligence (AI) in public health contexts in countries like India is difficult but impactful.
- Several challenges can be addressed by integrating AI into large tech platforms and ensuring human-in-command for safety.
- Two examples of integrating AI systems into existing tech platforms in India are discussed.

Introduction

The global public health landscape faces numerous challenges, exacerbated by the COVID-19 pandemic. The UN Sustainable Development Goals are particularly off-track in the Global South,[1] driven by rising inequality and suboptimal decision-making amid scarce resources. This creates a self-reinforcing, vicious cycle. Climate change intensifies the threat of infectious diseases such as chikungunya and dengue, while COVID-19 has diverted resources from critical diseases such as TB, creating a fragmented environment for effective public health interventions.

India, despite facing similar challenges due to its diverse population and inequality, presents a unique opportunity through technological innovations. While a "technology-first" approach has been critiqued,[2] low-cost digitization and mobile phone adoption can revolutionize public health delivery.[3] Technology enables telemedicine, information dissemination, data collection, remote training, real-time surveillance, and overall efficiency. Interoperable electronic medical records (EMRs) are emerging as the standard for storing patient data in Global South public health, forming a digital infrastructure for technology-enabled applications.

Artificial intelligence (AI) is in its early stages of public health adoption, and its potential remains largely untapped, even with the advent of large language models (LLMs). Its value depends crucially on technology platforms that systematically collect data.

This article discusses the application of AI in public health, based on experiences in India, a large and diverse country that we believe is representative of many themes that are broadly reflected in the Global South. We highlight opportunities and challenges for AI-based systems, examine the role of health technology platforms, provide case studies integrating AI systems on large platforms, and discuss the future of AI in public health deployments.

AI in public health: opportunities and challenges

We do not aim to present an exhaustive overview of AI applications in global health[4] but rather to emphasize how AI can enhance end-to-end processes, from gathering grassroots information to guiding interventions and policy, to impacting outcomes through health programs. We also discuss in detail the challenges encountered in this process.

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High-level AI opportunities

- *Information gathering and surveys*: Developments in speech processing[5] and LLMs[6] can revolutionize health information collection and digitization. Multilingual AI bots can converse with patients or health workers, capture medical data, and store it in structured EMRs that enable downstream applications such as telemedicine, clinical decision support, and data aggregation for public health policy. Large language models can provide wellness information, augment health worker skills, and improve health-seeking behavior.[7] Furthermore, AI aids health survey design by predicting responses and reducing survey burdens.[8]
- *Prediction and diagnosis at individual and population levels*: AI models can aid in disease screening, diagnostics, prediction of disease spread, and prediction of patient behavior,[9] utilizing multi-modal inputs (voice, video, images, text, tabular data, etc.). While AI is widely applicable in clinical contexts, there are concerns about technology takeover.[10] Artificial intelligence should augment doctors, not replace them, and the clinical decision must remain with the doctor. Human oversight is crucial and responsible because AI errors are often inexplicable and unpredictable.[11]
- *Guiding interventions*: Artificial intelligence outputs do not directly translate to prescriptions for health interventions. Unlike rule-based systems, AI often outputs a continuous score that requires thresholding, providing an opportunity to optimize various tradeoffs (sensitivity/specificity, precision/recall) depending on the application context. This allows for flexibility of use under different conditions and locations.
- *Improving intervention effectiveness*: Disseminating knowledge effectively through social and behavior change (SBC) programs is crucial. Recent advances in LLMs, augmented with visual capabilities, can open up powerful pathways to driving SBC through automated chatbots, calling and nudging mechanisms, automatic creation of visual materials, and multilingual operations.
- *Policy-making*: Artificial intelligence can aggregate and make sense of disparate data streams, craft public health communications, build early warning systems for future outbreaks that can inform policy, and so on. This is an emerging application area.[12]

Challenges in AI use

While opportunities for AI abound, it must be used judiciously because of its several shortcomings. The utility of AI critically depends on data quantity, quality, and type. Training and deploying AI models is expensive and therefore requires sufficient relative upside to offset costs. Deterministic models, like rule-based models, should be preferred when they perform similarly to AI, as they are easier to build and maintain, and are much more interpretable.

Data challenges

- Gathering patient data for training AI raises privacy issues. Personal and identifiable information should not be used in training and ideally not even made available to the AI developer or annotator.
- Data annotation for health care is time-consuming and expensive, often requiring expert annotators or costly lab tests. Obtaining labeled data can be difficult when the ground truth is a delayed consequence, e.g., in early prediction of disease propensity.
- Data quality and completeness vary, especially in Global South public health scenarios, requiring statistical or other AI-based methods to weed out bad data and/or impute missing data. High-quality data are generally preferable to big data, although occasionally data scale can compensate for quality.
- Training data may not faithfully represent the deployment scenario, causing bias or drift. In some cases, this is a genuine error, whereas in others it could happen because it is not possible to mimic the deployment context in training data in the first place. For example, in our work on detecting TB through cough sounds, it was very difficult to get training data from asymptomatic TB-positive individuals, although the AI is supposed to provide greatest value for that cohort. Approaches to bias mitigation involve starting with cohort-based evaluations (bias audits) followed by techniques such as data augmentation and fairness-aware training. We find, however, that these approaches typically do not perform as well in practice as working with representative training data in the first place.

Challenges of deployment, adoption, and scale

- In India, AI often must integrate into lightweight apps for basic smartphones to function offline in rural areas. Models require compression, potentially sacrificing accuracy. Apps need intuitive, prescriptive interfaces, human override options, and confidence scores on AI inferences. For example, our anthropometry solution, discussed below, includes an offline mode for remote areas with limited network access, using AI models adapted for such conditions.
- Driving adoption requires systemic approaches (ecosystem education, solution demonstration, applied abstractions) and specific approaches (nuanced problem definition, integrated expertise). Early adoptions create reusable frameworks that reduce uncertainty when adapted to new domains. As an example, we created an AI bot that extracts disease outbreak patterns from the web for public health monitoring. This was subsequently repurposed to deliver sector-specific information for agriculture, demonstrating reuse. Scaling requires interoperability, workflow adjustments, and incremental implementation approaches.
- Artificial intelligence solutions, in their design, must account for adoption environment constraints upfront such as network availability, device limitations, response latency, and user-centric simplicity. Human-in-loop designs build trust, while realistic expectations management supports scaled adoption through long-term commitment. When deploying our AI-driven clinical diagnosis system, we underestimated the effort required for health officers to enter data. This made adoption difficult. To fix this, we are designing a voice-based interface that makes data collection easier and faster. This change aims to improve usability and shows how important it is to design solutions that fit real-world adoption needs.

- AI must be deployed with a "Market of One" Paradigm. AI's strength lies in personalized delivery with contextual relevance, linguistic/cultural congruence, and meaningful individual interaction, enabling adoption 1 person at a time. Geographical disparities further challenge adoption, as urban areas benefit first, widening health benefit gaps. Deploying AI in rural areas requires addressing infrastructure and cultural acceptance barriers. The sustained success of AI depends upon our ability to think, design, implement, and deploy using the constraints imposed by this paradigm.
- Data availability and quality variation also lead to adoption challenges. India's diverse and fragmented healthcare system lacks standardized records, with data collection methods differing across states and facilities. Limited availability of longitudinal patient data adds complexity. A multilingual, voice-based approach can help by extracting codified data from speech, improving AI model performance. In India and other Global South countries, large-scale deployment presents both challenges and opportunities. A well-planned strategy can build the world's largest domain-specific dataset, enhancing AI's ability to generalize. Establishing this virtuous cycle early is key to successful AI adoption.
- Public health relies on experienced human support systems that have built trust and community knowledge over years. Successful AI adoption must integrate these systems, fostering a 2-way dialog where technologists adapt to real-world constraints while educating stakeholders on future possibilities. Resistance may arise due to unfamiliarity and job security concerns, making it essential for AI to augment, not replace, human capacity, ensuring long-term acceptance and impact.
- Artificial intelligence adaptation to Indian health care is crucial, as models from other countries often fail to account for local disease patterns, systems, and socioeconomic factors. Training AI on country-specific, diverse data improves relevance and performance. Some problems may require new AI design approaches, making multiple localized models more effective than a single generic one.

Long-term sustainability challenges

AI technology, with its critical dependence on input data streams, has a long maintenance tail. AI models need to be periodically evaluated on fresh data and re-trained as necessary. There are cost implications to this that, in the long term, must be borne by governments. Hybrid financial models could work, where the AI is developed for clinical settings and financed by private hospitals but provided for free or at subsidized rates for public health use, with long-term maintenance contracts being part of the agreement. This is as yet largely unexplored territory because adoption of AI in the public health space is still somewhat nascent.

Regulatory challenges

AI in health care must be regulated to a certain extent in order to ensure safe and responsible use. As of writing, India is in the process of developing a regulatory framework through the India AI Mission (https://indiaai.gov.in/article/report-on-ai-governance-guidelines-development). The framework is likely to build upon a number of best practices from other countries as well as to address specific challenges such as the digital divide and the need for indigenous AI innovation. Among the greatest areas of concern are the need to enable effective compliance to existing laws, and to maintain cybersecurity and intellectual property rights. For the AI developer, the challenge is to build in the face of an evolving regulatory environment. Liability for AI-assisted errors requires clear guidelines as policies develop.

Responsible AI challenges

We have discussed above the relevance of bias mitigation strategies. Trust remains a key barrier to AI adoption in health care, with skepticism among participants caused by limited awareness of the way AI works. Building trust requires transparent communication and demonstrated impact. For AI to scale meaningfully, it must move beyond research labs and align with real-world challenges. Effective deployment blends experimentation, engineering, user feedback, contextual relevance, and continuous iteration. This holistic approach can ensure AI adoption, impact, and scale. In addition, explainability of AI in health care is often termed essential. This is certainly true of imaging, where an AI decision cannot be considered trustworthy unless it is clear what part of the image scan is responsible for the diagnosis. However, explainability may not be critical for applications such as risk prediction, because risk is often the cumulative effect of a number of disparate factors. Also, explainability is an area of active research, and different explainability methods often yield different results. At this stage of evolution of the technology, it is therefore prudent to adopt a human-in-command approach, in which AI decisions can be over-ridden by expert humans. This is natural in public health scenarios, where AI is much more likely to aid screening and risk prediction rather than diagnosis, thus necessitating further assessment.

The enabling role of technology platforms

Technology platforms that are already deployed at scale, when integrated with AI, mitigate many of the data, adoption, and scaling challenges discussed above. These platforms collect data, serve multiple stakeholders, enable annotation and model integration, and facilitate adoption and scaling of the AI.

Examples include e-Sanjeevani,[13] the Integrated Health Information Platform,[14] Poshan Tracker[15] and Nikshay (https://nikshay.in) in India, and TIBU[16] in Kenya.

Specifically, e-Sanjeevani is a good model platform for AI integration. It is one of the world's largest telemedicine platforms, serving nearly 300 000 patients per day through a network of over 200 000 health professionals. It enables both provider-to-provider consultations and direct provider-to-patient consultations. AI can be integrated at multiple points due to the large data volume and velocity. AI applications include structured data collection and reporting, clinical decision support, patient information capture, computer vision models for image scans, and identification of disease outbreak hotspots. Physician inputs serve as expert-labeled data to improve AI models.

The e-Sanjeevani example highlights the utility of large platforms for supporting AI. In their absence, the onus on AI increases: systems need to be designed and developed from scratch to supply data, AI performance can fluctuate, adoption becomes more challenging, and human–AI interfaces need to be built from scratch.

We now discuss 2 case studies from our own work. First, we describe the ongoing integration of AI into India's Nikshay platform for TB. Second, we discuss AI-based newborn anthropometry and its potential for multi-platform integration.

Case study: integration of AI into Nikshay

Nikshay is a web-enabled application to monitor data on patients with TB in India. It is also accessible through a mobile app. It is the world's largest database and software platform of its kind and is designed to be modular and operational at various levels, enabling monitoring and research for TB eradication. Nikshay ingests patient data daily, which multiple stakeholders use to prioritize treatments and expand testing.

The Nikshay database consists of patient linelist information partitioned into "registers'." Each register represents a semantically linked set of longitudinal patient information. There is a notification register, which contains basic details about patients collected at notification time; a comorbidity register, listing patient comorbidities such as HIV and diabetes when they are available; a patient data register, which has demographic details; an adherence register, which has information about the adherence technology used to monitor the patient; and so on.

Prediction of adverse treatment outcomes

Effective TB treatment relies strongly on patient adherence to their medication regimen. AI models[17] can predict loss to follow-up (LFU, treatment interruption for 30 or more consecutive days) among patients with TB, at treatment initiation time. In India, about 3% of all patients with TB who start treatment and about 9% of patients with drug-resistant TB (DR-TB) eventually become LFU.[18] Early indicators such as alcoholism, smoking, migrant status, and lack of economic and social support correlate with the LFU outcome.[19,20] AI models built upon longitudinal Nikshay data (~600 000 patients in the training set) that is available at treatment initiation time prioritize patients with TB who may need counseling the most in order to adhere to the medication regimen. The models are hosted on the cloud and interfaced through an app used by TB health workers, with integration into Nikshay for nationwide rollout (Figure 1). They output a score that is thresholded, and the threshold can be dynamically tuned depending on health worker resource availability at the local TB unit. The models significantly outperform decision rule-based methods[21]: AI can potentially impact nearly twice as many lives as the best decision rule at the same level of patient targeting.[17] The scale and velocity of Nikshay data allow incorporating aspects that bear on applicability and adoption: fairness, robustness,[22] and good future generalization performance. We carried out extensive bias auditing by evaluating on protected cohorts such as gender, age, and location, and we incorporated fairness-aware techniques to mitigate differences in accuracies.[17]

The Nikshay platform more broadly serves as an enabling structure for AI development, deployment, adoption, and scaling. In other examples, AI-predicted case counts combined with Nikshay data can identify hotspots for active case finding missions. Voice capture and conversational chatbots, integrated into Nikshay, can augment health worker capacity. Cough sounds collected through the Nikshay app are being used for AI-based TB screening in pilot deployments.

Case study: newborn anthropometry and infant health

The weight of a newborn baby is an important measure of its overall health.[23,24] Estimating infant weight in rural Global South settings is challenging. While most babies are accurately weighed in hospitals and clinics at birth, they have no interaction with the healthcare system between birth and their first immunization at 1.5 months and are therefore not weighed accurately in that period. Frontline health workers (FHWs) who carry out home visits use spring balances, which lead to human and instrument errors. Logistical factors such as distance to a clinic, weather and rough terrain, and poverty further affect health service access.

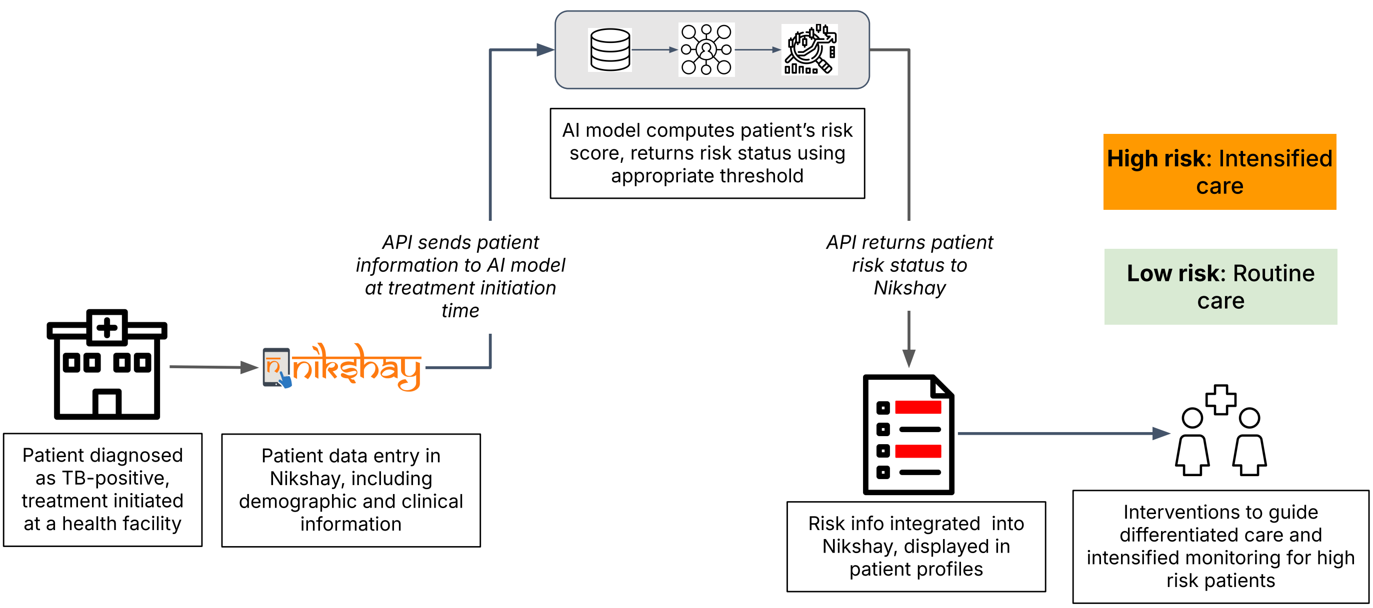

Figure 1. Proposed patient journey incorporating the loss to follow-up (LFU) prediction AI model in Nikshay. Note that the model computes a risk score that needs to be thresholded to create a binary output. This threshold is a function of health worker resource available for intensive counseling, as explained in the main text. Adapted from Kulkarni et al.[17]

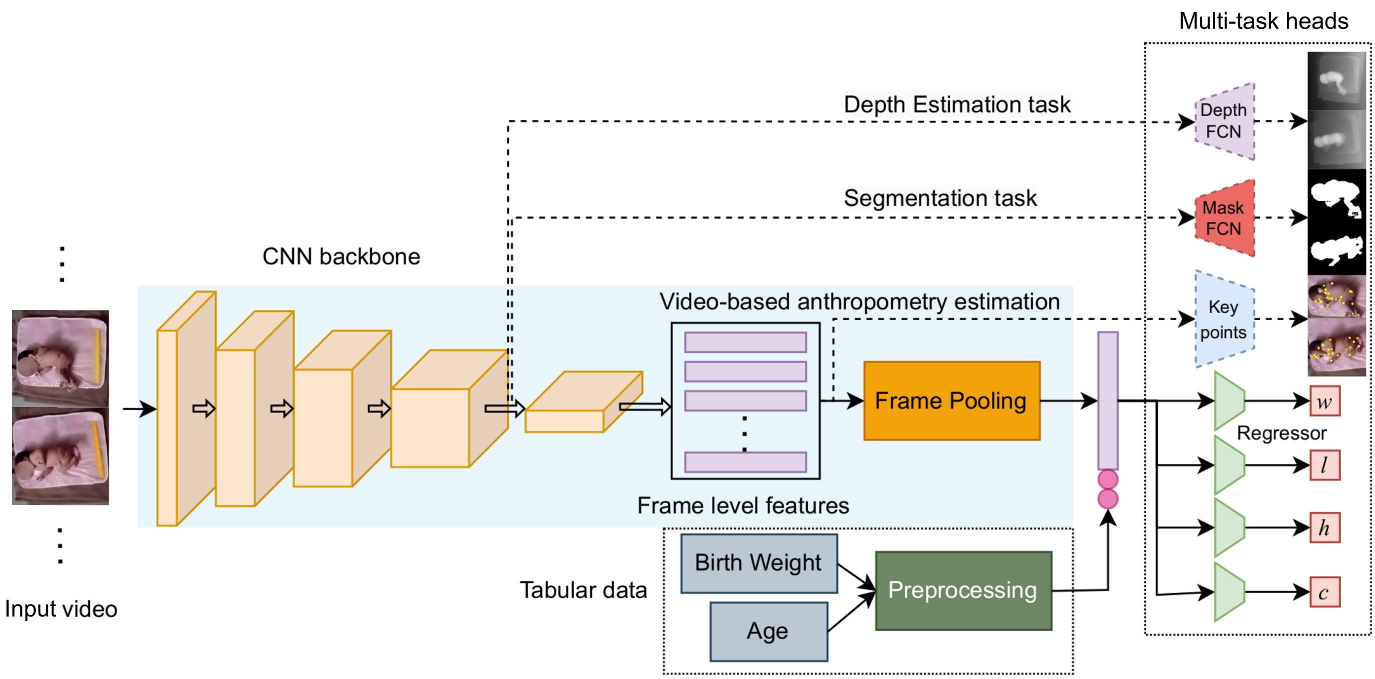

Figure 2. Overview of the anthropometry model architecture. Input video frames are sub-sampled and processed using a convolutional neural network (CNN) and fused using a pooling module. Tabular data are normalized and concatenated to this video representation. We use independent regressors to predict anthropometry measures: weight, length, head circumference, and chest circumference. Additionally, we introduce 3 frame-level proxy tasks only used during training: depth estimation, newborn pixel segmentation, and keypoint estimation. Adapted from Khandelwal et al.[25]

We developed a computer vision AI solution hosted on a smartphone to address these challenges.[25] Usage of the AI entails taking a short video of the baby in its home setting, and the AI works with varied backgrounds and poor lighting conditions. A fixed-length reference object (a simple wooden ruler) is placed next to the baby and in the frame of the video so that the AI can estimate distance. The AI outputs the baby's weight and other anthropometric parameters, such as height, head, and chest circumference. The solution is contactless, geo-tagged, easy-to-use, and accurate. It is edge-hosted and does not need internet connectivity.

The model architecture (Figure 2) involves processing the video frame by frame and regressing on the baby's weight. It also predicts other important anthropometric parameters, as well as a segmentation mask and the distance between the camera and the baby (depth). Birth weight and age in days are additional inputs.

The AI has a mean weight error of ∼114 g on babies up to 6 weeks in age. It significantly improves on conventional practice, ensures home visits, back-end digitization of anthropometric data, and is contactless, tamper-proof, and geo-tagged.

Platform integration can happen at various levels, for use by FHWs. In India, the main categories of FHWs who carry out home visits to pregnant and new mothers are Accredited Social Health Activist (ASHA) workers, Auxiliary Nurse Midwives (ANMs), and Anganwadi Workers (AWWs). The model is being deployed for use by ASHAs through the Public Health Management Platform in Daman and Diu, India. It is also being piloted via integration into a sandbox for the ANMOL platform in Ratlam, India. Data entered into ANMOL is synced with the Reproductive and Child Health (RCH) portal, which tracks pregnant women and early childhood services.

Full scaling up will be enabled through integration into ANMOL/RCH and platforms like the Poshan Tracker,[15] which identifies stunting and tracks nutrition service delivery.

Implications for the Global South

While this article focuses on the Indian context, similar considerations apply elsewhere in the Global South. Many developing countries have health platforms that operate at scale. These include the TIBU platform for TB surveillance in Kenya,[16] the Atipan project in Philippines,[26] a telemedicine platform in Peru,[27] and the BornFyne prenatal management platform in Cameroon.[28] A general perspective on the design of public health technology platforms that takes into account developing country constraints is provided.[29]

Although digital health platforms exist, AI integration is still rare (an exception being AI initiatives to address COVID-19[30]). Instead, there is a profusion of point AI solutions, many of which are reported in the literature as proofs of concept or piloted in pockets across the Global South.[31] This results in the fragmented use of a technology that works best when it is integrated, unified, and operating at scale. Our observations in the Indian context suggest that integration of AI solutions into a single, scaled digital platform is beneficial in multiple ways: (i) data issues and the availability of fresh data can be addressed at scale, (ii) regulatory constraints can be baked into the platform, and (iii) AI performance can be improved in a streamlined manner, incorporating regular feedback from the ground. We therefore see the digital platform integration of AI as a largely open opportunity across the Global South.

We would like to further point out that in smaller countries the need for platform integration of AI is even more acute than in a large country like India, because a platform has the potential to extract all of the available scale and diversity, thus enabling the building and rollout of robust AI solutions. We do not envision a situation where such a construct may not work.

Discussion

We have presented here a view on AI deployments in public health programs in the developing world, namely the importance of platform integration and associated challenges.

Clearly, as platforms scale, AI will increasingly become integral to public health interventions in countries like India, and deepen their impact. The main challenge will be the ability of AI practitioners to directly address the greatest pain points of public health: prevention, cost, and reach. Other important issues are data quality and standardization, AI robustness, the ease of integration, adoption and use, and the value it provides over existing systems. Some AI technologies, eg, image processing, will become a standard component of the medical arsenal in public health settings because they have reached a certain level of ease of use, maturity and cost. Others, such as LLMs in concert with speech recognition, hold great promise for data gathering, standardization, information extraction, and dissemination, but do not as yet perform robustly in clinical settings. Risk prediction models and models that work on modalities other than image, speech, and text (for example, audio and video), as well as reinforcement learning models, may still be considered in their infancy with respect to their potential for scaled adoption.

The need for ethical guidelines around the use of data, data privacy, and the use of AI outputs is very important, especially in the health sphere, so as to prevent misuse. In the public health space, however, efforts to improve interpretability and reduce bias should be balanced with utility on the ground. It may be advantageous to deploy an AI solution whose performance is not as yet uniform across cohorts, but in each case performing better than existing solutions, rather than not deploying it at all. A pragmatic view to deploying AI early, with sufficient guardrails, both technological and human, will potentially save lives. Similar considerations apply to AI readiness. Where platforms exist, they are not necessarily AI-ready. Even so, it is important to deploy early whenever possible, and in this manner create back-pressure on getting systems AI-ready. We note that we are still in the early days of unlocking AI's potential for public health in India, and as in all early days, the road is rough; with time and sufficient adoption, it will become smooth and well worn.

Supplementary material

Supplementary material is available at *Health Affairs Scholar* online.

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Contributions statement

Both authors conceptualized the paper and wrote it.

Conflicts of interest

Please see ICMJE form(s) for author conflicts of interest. These have been provided as supplementary materials.

The authors have no competing interests.

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