



Artificial Intelligence in Global Health

Defining a Collective Path Forward



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For contact information, and to download the latest version of Artificial intelligence in Global Health:

Defining a Collective Path Forward, please visit www.usaid.gov/cii

Table of Contents_____

I.	Foreword	4
2.	Introduction	5
3.	Executive Summary	6
4.	Artificial Intelligence Use Cases with High Potential for Impact on Global Health	8
	4.1 Al Use Cases	
5.	Definitions of AI Use Cases and Groupings	10
	5.1 AI-Enabled Population Health	
	5.2 Frontline Health Worker (FHW) Virtual Health Assistant	
	5.3 Patient Virtual Health Assistant	
	5.4 Physician Clinical Decision Support (CDS)	15
6.	Current Challenges to Accelerating and Scaling AI Use Cases for Global Health	17
	6.1 Rate-Limiting Challenges to Scaling AI Use Cases in Global Health	
	6.I.I Data Availability and Quality Challenges	
	6.1.2 Sustainability of Business Model Challenges	
	6.1.3 Data Privacy and Ethics Challenges	
	6.1.4 Regulatory and Policy Challenges	19
	6.1.5 Health System Integration and Capacity Challenges	20
	6.1.6 Challenges Related to Limited Evidence Base for Impact of Al Tools	
	6.2 Lack of Trust in Al	21
7.	Potential Investment Areas Critical to Accelerating the Use of AI in Global Health	22
	7.1 Potential Activities Within Each Investment Area	
	7.1.1 Coordination	
	7.1.2 Innovator Funding	
	7.1.3 Innovator Technical Assistance (TA) Support	23
	7.1.4 ROI and Evidence	24
	7.1.5 Data Capture	24
	7.1.6 Interoperability	
	7.1.7 Capacity Building	25
8.	Conclusion: Going Forward	26
ממ	endix	27

I. Foreword

Over the past several years, we have seen a wave of emerging technologies, from blockchain and Unmanned Aerial Vehicles (UAVs) to artificial intelligence (Al), demonstrate significant potential to alter and disrupt multiple sectors, including healthcare. All too often, though, the global health community is a late adopter of these promising new technologies. We believe that, as technologies like Al are still early-stage and rapidly evolving, the development community has an important opportunity to shape the market to ensure that technologies are appropriately and effectively introduced and scaled.

Recognizing the huge potential of AI in global health, The Rockefeller Foundation and United States Agency for International Development's (USAID) Center for Innovation and Impact (CII) have partnered, in close coordination with the Bill & Melinda Gates Foundation, to identify opportunities for donors, governments, investors, the private sector, and other stakeholders to explore and appropriately accelerate the development and cost-effective use of AI at scale in global health. With AI in Global Health: Defining a Collective Path Forward, we I) explore the current state of the art of AI in healthcare to determine use cases with the highest potential in the global health context, 2) assess the most critical challenges to scaling AI in low and middle income countries to understand which barriers may require more strategic and deliberate intervention, and 3) explore potential investments as part of a coordinated approach to funding this space effectively.

It's important to acknowledge that Al is a means to an end for global health impact and not always the right or best solution for every health challenge. Al is also one component, although an exciting one, of many under the broader digital health umbrella.

We are excited about the potential for Al to bring new solutions to entrenched global health challenges. We encourage your feedback and partnership so that we can continue building, adapting, and sharing our collective path forward. We look forward to hearing from you.







2. Introduction

Project Context and Introduction

rtificial intelligence (AI) has begun to create change in healthcare across developed markets, and has potential to drive game-changing improvements for underserved communities in global health. From enabling community-health workers to better serve patients in remote areas to helping governments in low and middle-income countries (LMICs) prevent deadly disease outbreaks before they occur, there is growing recognition of the tremendous potential of Al tools to break fundamental tradeoffs in health access, quality, and cost. Health systems in LMICs face obstacles including daunting shortages of workers, medical equipment, and other resources that require strategic and innovative approaches to overcome. Al tools have exciting potential not only to optimize existing resources and help overcome these workforce resource shortages, but also to greatly improve healthcare delivery and outcomes in low-income settings in ways never previously imagined.

While this excitement is welcome and has certainly been accompanied by a lot of hype, detailed analysis has been lacking on how best to deploy and effectively scale Al solutions in health systems across LMICs. As the global health and development communities know from prior experience, it is very challenging to take disruptive technology innovations from high-income countries and deploy and scale them so that they address the unique needs of, and have positive impacts on, populations in low-income environments. This paper is intended to fill a key gap by identifying both barriers to Al deployment at scale in LMICs and what actions can best accelerate the appropriate use of AI to improve health in LMIC contexts. In addition, as LMICs are shifting towards digitization, Al solutions like the ones presented in this report are becoming more attractive to addressing global health challenges.

This report reflects the outputs of an analysis carried out by two global health donors, USAID's Center for Innovation and Impact (CII) and The Rockefeller Foundation - which was undertaken in close coordination with the Bill & Melinda Gates Foundation. The Boston Consulting Group also facilitated and supported this analysis. The goal of this effort was to better understand where and how Al could be most impactful, and to develop actionable recommendations for coordinated investments. While there are many publications discussing the potential value of Al in healthcare and social impact, this report provides a holistic look at a wide range of potential Al use cases in global health and assesses which use cases may have the greatest impact and also presents the biggest challenges to scaling in lowresource contexts.

It is important to note that throughout our analysis we consider AI as a means to an end for improving healthcare in LMICs - not as an end in itself. While Al technologies hold great potential for improving healthcare around the globe, we recognize that these technologies are not silver bullets to solve entrenched global health challenges, and acknowledge that scaling Al technologies also has risks and tradeoffs. Therefore, it is critical that all efforts to drive acceleration of Al in global health, including those outlined in this report, are undertaken in alignment with the broader principles and best practices for digital health and global health technologies that have been developed in recent years.² Chief among these principles is the notion that adoption, acceleration, and use of technologies should strengthen local health systems and must be owned and driven by the needs and priorities of LMIC governments and stakeholders in order to help them best serve the needs of their populations. This theme has been central to our work and is integrated throughout this document.

Footnotes

I. For the purposes of this project, our language on 'accelerating the use of AI in global health' refers specifically to scaling the use of AI in low and middle-income countries (LMICs) around the globe in order to improve access to, and quality of, healthcare for low-income and underserved populations.

^{2.} http://www.donorprinciples.org/, https://digitalprinciples.org/

3. Executive Summary

his report shares four key pieces of analysis to help drive thinking across the global health field about deploying and scaling artificial intelligence (AI) in global health:

- I). An overview of AI use cases that could have the greatest impact on improving health quality, cost, and access in LMICs
- 2). Four groupings of AI use cases that show high potential for scale and impact in LMICs:
 - a). Al-Enabled Population Health,
 - b). Frontline Health Worker (FHW) Virtual Health Assistant,
 - c). Patient Virtual Health Assistant, and
 - d). Physician Clinical Decision Support Tools
- 3). A detailed assessment of critical challenges to scaling AI in LMICs: data availability and quality; sustainability of business models; data privacy, ethics, and ownership; regulatory and policy issues; health systems integration; lack of trust; and lack of agreed upon standards for assessing the impact of AI tools
- 4). A discussion of seven priority investment areas we believe are critical in order to accelerate the use of Al in global health: 1) investment in responsible, sustainable innovation 2) scaling support, 3) ROI and evidence, 4) data capture, 5) interoperability, 6) building ecosystems/supporting governments in LMIC contexts, and 7) coordination of stakeholders involved in Al in global health

Definition of Al

Throughout this project, it was important to work from a clear definition of Al and related layers of technology (i.e. machine learning and other technologies that fall under the category of artificial intelligence) so that all stakeholders had a common understanding of the terms used. First, the project adopted the commonly used definition of Al as "the use of computers for automated decision-making to perform tasks that normally require human intelligence." It also defined machine learning as a subset of Al that uses algorithms that give computers the ability to learn without being explicitly programmed. Second, the project also refers to a set of 'Al building blocks' or technologies that are commonly understood as examples of Al. Much of the literature on Al uses slightly different formulations of these building blocks, but overall definitions and the categorization are relatively consistent. The Al building blocks we view as the most relevant to global health are highlighted in Figure I.

Research Methodology

Our work began with a rapid scan of Al use cases in healthcare across both high-income countries (HIC) and low and middle-income countries (LMICs), resulting in a catalogue of over 240 real-world examples. We defined use cases broadly as the way a user leverages technology within a specific context. A wide aperture was considered in order to ensure that no Al use cases or applications would be left out, particularly those that are not commonly considered to be relevant to global health and low-resource contexts. Prioritization criteria were then applied to this broad set of Al healthcare use cases in order to narrow the field to those that appear to have the greatest potential for impact and scale in low-resource contexts. Our analysis showed that the Al use cases that appeared to have greatest potential for application at scale in LMICs most often occurred in combination. Details of the research and further explanation of these terms are included in the following section.

Following this initial research stage, our focus shifted to understanding current challenges to scaling Al use cases. We developed detailed analysis of challenges, some of it specific to particular Al uses cases, and some of it cutting

Figure 1: Al Building Blocks in Global Health

Artificial Intelligence: Use of computers for automated decision-making to perform tasks that normally require human intelligence, specific examples include:

DATA		PROCESSING		ACTION	
	Computer vision Automated methods used to conduct image-based inspection and analysis	Processing of digitized data in ways		<u>0</u>	Image generation Automated creation of images using AI
	and analysis				Speech generation
.n.	Speech recognition Computerized identification and response to sounds produced in human speech	Ŕij	Machine learning Pattern recognition that learns and improves from experience without being programmed	•	Automated generation of human-like speech using Al
9				2-0	Handling and control Automatic handling of objects using
	Natural language processing Processing and analysis of large amounts of data written in natural language (eg. narrative)		Planning & exploring agents Use of AI for strategies or action sequences by agents, robots, or unmanned vehicles		Al methods
ABCDE FGHIJK LMNOP					Navigating and movement Autonomous movement and navigation informed by Al

Source: Al@BCG, Encyclopedia Britannica, Oxford Dictionary

across multiple use cases in LMIC contexts. Lastly, we developed a set of priority areas for investment and focus in order to accelerate the use of Al in global health. Some of these focused on areas where we believe investment in specific technologies or platforms is needed; others outline where actions from diverse stakeholders are required in order to create a more fertile ecosystem for Al solutions around the globe to thrive and reach greater scale.

Key inputs to this process included over 50 expert interviews with stakeholders from a broad variety of backgrounds, including healthcare-focused investors and incubators; private sector companies (e.g., many leading healthcare AI companies working in emerging markets),

academia, and multilateral organizations (including WHO and the World Bank), foundations, and non-profit organizations. These expert interviews helped us develop a more nuanced understanding of areas where external funders might focus in order to shape the market and accelerate the impact of Al applications in global health. A full list of those interviewed is included in the appendix. The team also conducted research that considered many studies and leading reports on the subject of Al in global health and healthcare. Please see a short bibliography in the appendix of this report for further details. Lastly, the content of this report benefited greatly from the input of a broader set of key thought leaders and stakeholders engaged in Al for global health at a workshop held in Washington, D.C., in November 2018.

Most relevant to global health

Footnotes

I. Artificial Intelligence Definition: "the use of computers for automated decision-making to perform tasks that normally require human intelligence." Oxford Dictionary, 2018 (http://www.oxfordreference.com/view)

^{2.} Machine Learning Definition: "Machine learning as a subset of AI which uses algorithms that give computers the ability to learn without being explicitly programmed." Exact definition from Fermilab is: "Machine learning is a type of artificial intelligence (AI) that enables computers to learn automatically without being explicitly programmed. It focuses on the development of computer programs that can access data and use it to learn for themselves." Fermilab is United States Government's particle physics and accelerator laboratory, http://computing.fnal.gov/machine-learning

4. Artificial Intelligence Use Cases with High Potential for Impact on Global Health

4.1 Al Use Cases

ur research began with a broad scan of instances where AI is being used, tested, or considered in healthcare, resulting in a catalogue of over 240 examples. As we looked across these examples, we determined that they are stratified across four broad functional areas depending on the role they play in the healthcare value chain. These functions include Population Health, Individual Care (including care routing and care services), Health Systems, and Pharma & MedTech. Figure 2.

4.2 Groupings of AI Use Cases and Opportunity Areas

We then distilled this broad catalogue of examples down to a framework of 27 use cases for Al in global health, with use cases aligned to the four functional areas described above. We then conducted a rapid assessment of impact and feasibility to prioritize a subset of these use cases. Within impact, we considered the extent to which each use case might increase healthcare access, quality and efficiency. For feasibility, we considered current activity and maturity of the technology, the extent to which it is already being tested in an LMIC context, and the eventual suitability for LMICs. These relative rankings allowed us to look across the long list of use cases and deprioritize those which were likely to have lower impact and feasibility. For example, use cases around billing improvements were deprioritized as they are less likely to improve patient outcomes and are less well suited to low-income contexts.

Through this prioritization exercise, we found that the remaining use cases fall somewhat naturally into groupings of use cases. These groupings are largely defined by the primary user and include use cases that are often combined

Figure 2: Framework of all Al Use Cases in Healthcare



to create maximum impact. For example, population health use cases around surveillance and prediction unlock even more potential when linked to intervention selection and targeting. These groupings of use cases include (I) Al-enabled population health, (2) Frontline health worker (FHW) virtual health assistants, (3) Patient virtual health assistants, and (4) Physician clinical decision support.

These groupings of use cases are displayed in Figure 3 and also illustrated through color-coding in the framework that shows which use cases are included in each grouping. Throughout the remainder of our work, we used these groupings of use cases as the primary unit of analysis though which to assess challenges and opportunities. For simplicity, Figure 4 also lays out which AI use cases

are included in each grouping which may be helpful as a reference.

We should also note that some stakeholders consulted in this project suggested that Al use cases which strengthen health systems (See Figure 3) could be considered an additional priority grouping of Al applications. We elected to include Al use cases related to health systems in our other four groupings instead of treating them separately from patient and population-facing Al applications. We very much agree that Al use cases' potential for strengthening health systems in LMICs is one of the most important and exciting ways in which Al could transform healthcare around the globe—and this is a theme echoed throughout this report and across the four groupings.

Figure 3: Framework of all Artificial Intelligence Use Cases in Healthcare Categorized into Four Key Groupings



Figure 4: Artificial Intelligence Groupings of Use Cases

Al-enabled FHW virtual Patient virtual Physician clinical population health health assistant health assistant decision support Augmenting FHW expertise Platform ingesting, Assisting patients to direct Providing more specialized analyzing, and providing their own care and wellness, to direct patient care, e.g., expertise to generalist recommendations on e.g., data-driven diagnostics triage and symptom-based physicians, e.g., enabling a population health data with care recommendations diagnostics and care GP to read diagnostic recommendations · Surveillance and • Self-referral images · Self-referral prediction · Personalized outreach Image-based diagnosis Population risk Personalized outreach • Clinical decision support • Behavior change management • Behavior change · Quality assurance and · Data-driven diagnosis Intervention selection • Data-driven diagnosis training · Al-facilitated care Intervention targeting Al-facilitated care Medical records Medical records

5. Definitions of Al Use Cases and Groupings

t is important to note that this was a rapid assessment exercise designed to get a 'fit for purpose' prioritization of use cases for global health. Our analysis included relative assessments of the potential impact and feasibility for scale of these Al use cases in LMICs—including the relative level of maturity of technologies and current level of penetration in LMICs for each Al case. Our relative impact assessment considered the extent to

which each use case might increase healthcare access, quality, and efficiency. Our feasibility study helped us better understand which use cases have already been executed in both high- and low-income contexts, which may already be common in developing world contexts but have yet to be tailored to low-resource settings, and which are still nascent and in need of further development in order to scale.

Our analysis yielded the following insights across our four groupings of AI use cases:

- The Al-enabled precision public health use cases were identified as technologies that are relatively nascent and less widely used (in both high- and low-income contexts) than many other Al technologies—but that are well suited for global health and LMIC contexts in the future.
- The patient and frontline-health worker (FHW) groupings of AI use cases were identified as relatively more advanced technologies that are increasingly common in developed markets, but that need to be tailored and scaled in LMICs.
- Clinical decision support (CDS) Al tools are relatively mature technologies that have greater levels of penetration in high-income markets than other Al technologies in question, but that need greater scaling and adaptation in LMIC contexts. In addition, some of these CDS use cases are relatively less suitable for low-resource settings at present due to broader resource gaps in these markets (i.e. image-diagnostics tools that rely on expensive radiology equipment that is rare in LMICs).



Figures 5-8 illustrate what the world might look like with artificial intelligence at scale in LMICs — through illustrative vignettes of individuals in underserved areas whose lives, and abilities to provide quality healthcare to others, are altered by these AI tools. Some of the AI-enabled platforms presented in these vignettes are available today, others are likely to be available in the years ahead. But they all present a picture of how the AI groupings can fundamentally change healthcare for underserved populations around the globe. Of course, it is important to acknowledge that these use cases can face risks and challenges as outlined in Section 6, and that there are many factors that go into ensuring their successful implementation.

Please note that the individuals and stories profiled in figures 5-8 are <u>not real people</u> but rather illustrative of the potential for AI tools today and in the near future. Some of the technologies portrayed in the stories are real and others, we believe, will be possible and available in the near future.

5.1 Al-Enabled Population Health

Tools for ingesting, analyzing, and providing recommendations on population health data

This grouping involves tools that leverage Al to monitor and assess population health, and select and target public health interventions based on Al-enabled predictive

analytics. It includes Al-driven data processing methods that map the spread and burden of disease while Al predictive analytics are then used to project future disease

Figure 5: A Vignette on an Al-Enabled Population Health Tool (Illustrative only)



Meet Dhesi

Using AI enabled predictive surveillance, intervention selection, and intervention targeting to predict dengue outbreaks and respond most effectively to them

Dhesi applies Al predictive analytics tools in his work for the Ministry of Health in Malaysia

Situation:

- Dhesi's work focuses on controlling infectious diseases
- Until last year, the MoH had no analytic capability to predict when diseases would break out and spread, limiting its ability to protect the population
- The MoH had limited health data from different regions across the country and no means to incorporate non-health data into its work

Action:

- The MoH fully digitized and integrated EMRs from health facilities across the country and then enhanced its analysis further by applying AI to this data
- The MoH started using AI tools which enabled it to:
 - Map various health burdens and disease outbreaks occurring across the country by applying machine learning to identify correlations among multiple variables across complex data sets to identify risk factors and predict the spread of diseases
 - Integrate non-health data (i.e. weather patterns, wind speed, roof angles) to help predict when the next outbreak might occur by using natural language processing to gather intelligence from news reports and social media posts

Impact:

- Applying predictive analytics powered by machine learning to newly gathered/ digitized data enabled Dhesi's team to view, analyze, and react to health data in real time rather than analyzing outdated data after the fact
- Predictive ML algorithms enabled the MoH to predict the exact geo-location and date of the next dengue outbreak three months in advance
- ML-powered algorithms also enabled it to decide which vector control interventions
 would be most effective and to plan where and when to roll out these interventions

spread of existing and possible outbreaks. It also includes risk management tools that use AI to better understand risk across different groups of a given population and stratify these groups according to risk levels. One example of the potential of tools in this opportunity area is Artificial Intelligence in Medical Epidemiology (AIME), an Al-enabled platform that helps a country's Ministry of Health predict future outbreaks of diseases like Zika and dengue in a specific geography months before their possible occurrence, and helps the Ministry select the most appropriate vector control method to prevent the outbreak. While AIME is a very early stage venture and its technologies and tools have not been validated at scale, its work reflects the potential of Al predictive analytics tools in global health. The potential and impact of companies like AIME is laid out in Figure 5.

These Al-enabled population health tools can provide value to populations, governments, and health systems across LMIC contexts. These tools help governments better understand health burdens and potential disease outbreaks across their geographies, and thus enable them to allocate their resources more effectively to prevent and manage outbreaks. These Al-enabled tools can also help diverse stakeholders (beyond a country's MoH) determine which communities are most in need of care and public health interventions and to optimize their resources accordingly. To further illustrate how Al tools can improve healthcare and health outcomes in low-income countries around the globe, figures 5-8 profile people whose stories illustrate the exciting potential of Al tools, in each of our four use case-groupings.

5.2. Frontline Health Worker (FHW) Virtual Health Assistant

Tools augmenting FHW expertise to direct patient care, such as triage and symptom-based diagnostics and care recommendations

This grouping of use cases involves placing Al in the hands of frontline health workers (FHWs), enabling them to better serve—and bring top-notch medical technology and advice to—their patients. FHWs in LMICs use Al-enabled tools to triage and diagnose

patients (often outside of health facilities), to assist with clinical decision support, and to monitor compliance of their patients. Rapid and accurate triage and diagnosis functions are enabled when Al is applied to real-time patient data collected by FHWs. FHWs are then able to

Figure 6: A vignette on a Frontline Health Worker (FHW) Virtual Health Assistant Al tool (Illustrative only)





Anita lives in a rural village in Western Kenya, six hours from Nairobi and two hours on dirt roads from the closest hospital



Last year, Anita became a community health worker; now she goes door to door in her community helping local patients with health advice and selling basic health products to address their needs



Anita has a smartphone with various apps that she uses in her work; she enters simple information on her patients' health condition, including symptoms they are currently experiencing



Her Al-enabled apps then provide health recommendations, diagnoses, treatment advice, and self-care recommendations that allow her to provide the best possible care to her patients



Meet Eric

Using triage, data diagnostics, and clinical decision support to provide top notch medical care and give a mother peace of mind

One of Anita's patients, Eric, is a sick child whose mother doesn't know what is wrong

Patient Situation:

- Two year old, Eric, has a high fever and an unusual rash
- His mother is unsure if she should travel to a hospital or what else to do

Action

- Anita enters Eric's symptoms and a photo of his rash into her app
- The app uses advanced algorithms leveraging machine learning to determine that Eric very likely does not have dengue but might have malaria; the app also uses computer vision to identify the rash as very likely a spider bite
- Following CHW health protocols provided by the app, Anita then follows up with a malaria rapid diagnostic test, using her phone camera and a disposable blood test
- Another Al-enabled app ensures the results of the blood test are read and interpreted correctly; in this case, the app verifies that Eric does not have malaria and does not need to be referred for care
- Drawing from health protocols on her app, Anita gives Eric's mom suggestions on how to best care for her son, with specific instructions on when to visit a health facility if his condition changes

Impact:

- Without her Al tools, Anita would not have been able to provide timely and accurate medical advice for Eric she might have misdiagnosed the rash and even recommended the wrong medications
- Without AI, Eric's mother would likely have had to travel to a health facility hours away
- With AI, Anita was also able to save an unneeded visit to an already overburdened health system enabling providers to see patients who may have been in greater need of care

provide targeted health recommendations for patients on whether, where, and how to seek care.

Overall, the AI uses cases in this opportunity area provide value by strengthening FHWs' abilities to serve their patients by providing health information and advice (and eventually even possibly diagnoses), without them having to visit a facility. This, in turn, reduces the patient burden on already overburdened facilities, and enables FHWs to focus on their most at-risk patients, helping them to optimize their time and effort.

This grouping of tools illustrates how Al technologies can overcome prior constraints of access, cost and quality. Patients without easy access to health facilities and with little ability to pay may be able to better access quality health advice and avoid unnecessary trips to health facilities.

5.3. Patient Virtual Health Assistant

Tools helping patients direct their own care and wellness, including data-driven diagnostics and recommendations

The use cases in this opportunity area put Al in patients' hands for self-referral, behavioral change, data-driven self-diagnosis, personalized outreach, medical record collection, and Al-facilitated self-care functions. Through the collection of real-time data at the patient level, these Al-enabled tools can help identify the type and severity of a patient's condition and provide health recommendations directly to the patient. Recommendations may include how and where to seek care if it is needed, or guidelines for self-care and behavioral changes to address health issues outside of

the health system. It is important to note that these Al tools are not intended to replace humans in the provision of diagnosis and care. Rather, these tools can provide helpful recommendations on if, how, and where someone should seek formal care from a health professional—and what they can do in the meantime to best manage the situation. This can be critical for patients who may have to wait days to see a doctor or reach quality care.

These AI use cases provide tremendous value to patients by enabling them to access medical information,

Figure 7: A Vignette on a Patient Virtual Health Assistant Al tool (Illustrative only)



Meet Kehinde

Using self-referral and data diagnosis to help a young woman stay healthy

Kehinde uses an AI enabled tool to get sexual and reproductive health information and advice

Patient Situation:

- Kehinde is 21 and is at vocational school in Kumasi, Ghana
- She is sexually active and has questions about sexual and reproductive health, but doesn't know where to go to get answers (she can't ask her conservative family!)
- Recently, she has experienced some pelvic pain and other gynecological symptoms.
 She would like to see a doctor but fears it will be expensive and doesn't know where to go

Action:

- Kehinde heard about a chatbot that can answer all of her questions on sexual and reproductive health she downloaded it and now asks it all of her questions. The chatbot uses speech recognition and speech generation to process and answer her questions, and machine learning to analyze her questions and provide answers
- The app also provides additional materials for her to read based on what she seems most concerned about
- She puts her symptoms into the app and it tells her if she should seek care. At present it says she does not need to seek care, but it advises her what to do if symptoms worsen, what annual appointments she should have, and where to go for them. It also provides an option for her to text with a nurse if she has further concerns
- Best of all, the app also tells her that there are free women's health clinics near where she lives where can get contraceptives and women's hygiene products and have a confidential consultation with a female health worker

Impact:

- Without AI, Kehinde didn't have access to resources to answer her questions on her sexual and reproductive health
- She might have wondered if and when she should see a doctor, but now she knows where and when to seek care

behavioral and lifestyle recommendations, care routing advice, and even potential diagnoses without having to go to a health facility, which can be time-consuming and expensive in LMIC health systems. They can also provide value and efficiency gains to the broader health system by ensuring that only patients who truly need to go to health facilities do so, freeing up health providers' time for acute patients, and by remotely collecting ongoing patient data which can be linked to a patient's broader medical record.

An example of a patient-facing AI tool reshaping healthcare in LMIC contexts is Babyl, a subsidiary of Babylon, operating in certain LMIC geographies such as Rwanda. Developed in the UK, Babylon provides an integrated AI platform for patients, including an AI triage symptom checker, health assessment, and virtual

consultations with a physician when referral is needed. In Rwanda, Babyl aims to build toward the Al-powered services available in the UK, but has started with virtual consultations, prescriptions, and lab tests through mobile phones, including special phone options to reach underserved populations. The Babyl experience in Rwanda also provides broader value to the global health field by studying how Al-enabled technologies can be ported from developed country markets to LMIC markets. See figures 5-8, and vignettes in Figure II of the appendix, for compelling stories of other patients across low-income markets who have experienced significant impact in their lives from these patient-facing Al tools.

5.4. Physician Clinical Decision Support (CDS)

A tool providing specialized expertise to physicians, for example, by enabling a GP to read diagnostic images

This grouping includes AI use cases which support and improve the decisions of clinical physicians. Examples of AI tools in this grouping are: image-based diagnosis support for radiologists and pathologists, decision support tools for clinicians, and quality assurance and training to

provide insights for clinicians on past performance and indicate where errors may have been made.

Just as with the patient virtual health assistant use case, it is important to note that Al tools in this use case are

Figure 8: A Vignette on a Clinician Decision Support Al tool (Illustrative only)



Meet Jacinta

Using image-based diagnosis to improve timeliness and quality of cancer diagnosis to get more patients into treatment

With a new Al pathology tool, Jacinta can provide faster diagnoses and better care for her patients

Situation:

- Jacinta is a radiologist at a public hospital in Quito, Ecuador
- Hundreds of women come to her breast cancer clinic every day, they are lined up when she arrives in the morning and when she leaves (far after dark) at night
- Jacinta is passionate about her work she wants to help as many women as possible fight breast cancer, but there are simply not enough radiologists and she cannot work fast enough

Action:

- Jacinta's hospital gets an AI enabled radiology tool for her to use in her work
- Jacinta uses it to diagnose tissue samples from women who came in the prior day reporting lumps in their breasts. This Al tool quickly analyzes the radiological images of potential lumps and, using machine learning and pattern recognition, identifies areas of potential cancerous growth and provides its diagnosis of potential cancer within each sample. (It also provides Jacinta with the percent certainty of its assessment)

Jacinta

(continued)

- Jacinta still examines each radiology image in detail with her own eyes and follows all clinical protocols - but she can go much more quickly in her work with this new tool. She also feels very comforted to have the technology double-checking and confirming her own diagnosis
- Within days of using this new tool, Jacinta knows that she can review three to five times more samples per day and make more accurate diagnoses with this new tool. She is confident that she will be able to provide diagnoses to women much more quickly, and help diagnose and treat hundreds more women each year as a result

Impact:

- Without Al, Jacinta had no means to diagnose more patients in a day (and thus help put them on a track to treatment); and she had no resource to double check her work or thinking
- Normally, the nurses tell women that it will take one to two weeks for them to receive a diagnosis (which is difficult if they have traveled far from home to visit the clinic). Now Jacinta strives to provide a diagnosis within one to two days, helping them get treatment as soon as possible

not intended to replace the physician. Overall, the Al use cases in this CDS grouping provide value by augmenting physicians' roles and their capacity to serve their patients, helping them provide faster and more accurate diagnoses to patients, and widening a significant bottleneck in provision of care in LMIC contexts, enabling them to focus on their patients most in need of care. Given the often extreme scarcity of health providers in LMIC contexts, and how overburdened providers in these contexts are, this function of helping doctors optimize their time and focus on those most at risk can save patients' lives and provide catalytic impact across health systems.

As one clinician put it, Al-tools like this "give super powers" to health providers and can greatly improve the quality of care they provide to their patients. Figure 8, and appendix Figure II, provide additional examples of how these types of Al solutions could provide value to clinicians and patients in LMIC contexts in the years ahead.

6. Current Challenges to Accelerating and Scaling Al Use Cases for Global Health

We originally hypothesized that each grouping of Al cases would likely face unique challenges to implementation on a large scale, but ultimately we found that there are eight common key challenges faced by all Al technologies in LMIC contexts (See Figure 9). The exact nature of these challenges varies somewhat across groupings of Al use cases but the overall challenges are common to all (e.g. the type of data required for Al population health tools differs from those for patient-facing Al tools, but data availability and quality are challenges for both). We discuss these challenges in greater detail in the section below.

As indicated in Figure 9, we expect that two current challenges will be resolved as technology evolves and technology penetration rates across LMICs continue to

increase. Gaps in Al building blocks (defined previously in this paper) and gaps in the required infrastructure for Al (such as smartphone penetration and 4G access) are likely to be addressed in the coming years through advances in technology and efforts of other global health and development projects. The focus of this report remains on the other six key challenge areas.

Many of these challenges are not unique to AI, but are hurdles to scaling digital health technologies across LMICs generally. The global health community has done admirable work in past years to try to solve these challenges. This report takes these efforts into account and hopes to build on, and generate additional momentum around, this important work.

Figure 9: Challenges Facing Al Use Cases in Global Health

Challenges likely to be **Cross-cutting challenges** Challenges likely to be rate-limiting for specific likely to require attention resolved as technology continues to evolve use case groupings at systemic level Data availability Integration into Gaps in Al and quality health system building blocks Business model Required evidence Gaps in required sustainability of positive impact infrastructure Privacy, ethics, and ownership Regulations and policy

6.1 Rate-Limiting Challenges to Scaling AI Use Cases in Global Health



6.1.1 Data Availability and Quality Challenges

A significant challenge to accelerating the use of Alenabled tools in LMICs relates to the quality and quantity of available data, due to the general lack of digitization in these markets. A strong digital health infrastructure is needed to provide the data required for Al tools—a challenge in many low-resource contexts. Low EMR adoption rates (estimated at less than 40% in LMICs) hamper the ability to aggregate historic and real-time patient data. Even in those countries that digitize their health data, few collect and analyze it in real time—necessary for all of these Al-enabled tools to function correctly.

In addition, to be accurate in new geographies, Al tools need millions of historical health data-points to train their algorithms to provide accurate outputs appropriate to the geography and population—and this type of broader health data are generally absent in LMICs. This lack of training data not only inhibits the accuracy of these tools in LMICs context - but it also creates a bias within these tools. Since Al algorithms naturally reflect the bias of training data, Al tools will show a bias reflecting the highincome countries where they are developed. Efforts will be required to adjust for these biases in the application of these AI tools in contexts distinct from where their training data is generated. All of this means that even if Al tools are deployed in new markets with functioning digital infrastructures, the efficacy of these tools is still inhibited by lack of historical health data and less health data overall relative to developed markets.

Finally, some AI tools require data from non-health sources to function. Access to non-health data may pose similar challenges as weather pattern and population demographic data are also often lacking in LMICs.

The nature of this challenge was made evident in the remarks of one interviewee in our project, the provider of an Al-enabled population platform in Southeast Asia. This company promotes an Al tool in which governments of several countries expressed strong interest—but were unable to use because most of the health data in these countries exists only on paper. Without stronger digital health infrastructure and the data it produces, these Al tools cannot be applied across LMIC countries.

Another example of data-related challenges to scaling Al in LMICs is a case where a patient-facing Al tool was built in the US and then exported to markets in East

Africa. A problem arose for the company providing the tool because it could not use US-based health data to develop accurate predictions or diagnoses for patients in LMICs.

For physician CDS tools, the data challenges stem more from the general lack of digital health data and integration of data across diverse sources. Because most health facility data across LMICs remain in analog form, CDS tools do not have a sufficient base of digitized data. Further, many CDS AI-enabled tools require ingestion of data from diverse sources in order to ensure comparability of data and to produce large training data sets needed for accuracy of their algorithms. This type of data integration and interoperability across data sets is a significant barrier across LMIC markets at present as EMR and other systems differ by country and region and even within hospitals.



6.1.2 Sustainability of Business Models Challenges

Sustainability of business models is another challenge likely to limit the scaling up of Al use cases across low-resource contexts. Even for governments, health systems, and private or non-profit customers across LMICs who understand the value proposition of these Al platforms, few have the resources to purchase Al tools at a price that would enable financial sustainability for the companies offering them. As a spokesperson for one private insurance company based in East Africa stated, "I absolutely see the value of Al risk management tools and I realize that this would save us money, but I do not have the budget to buy something now which will save me money 12 months down the line." The sentiment applies to many LMIC governments that understand the value of these Al tools, but do not have the resources to buy them, or the human resources or internal IT capabilities to implement them.

This cost challenge applies to patient-facing AI tools as well. Patients in developed countries are often unwilling to pay directly for digital health solutions, so it stands to reason that many patients in LMIC markets, with their limited ability to pay, would be even more resistant to paying for these solutions. In addition, sales to governments in these markets are complicated, even for those who might be able to find third-party funding. Procurement and contracting periods are long and often difficult to understand.

With cost concerns in mind, companies providing Al solutions are exploring alternative payment models and revenue streams, though some of these alternate revenue opportunities increase ethical and data privacy

concerns (for example, a company selling patient data to third-party pharmaceutical or medical device companies). Similarly, advertising on, and product/ service sales of, both CDS and patient-facing apps are the most natural monetization paths for these types of virtual health assistants, but Al tools that are underwritten by advertising or product/service routing may have misaligned incentives and face strong pressure to generate content in favor of their sponsors and not necessarily to the benefit of patients.

In addition, for both FHW and physician CDS tools, workflow integration presents a significant challenge to developing sustainable business models. Given that physician and FHW workflows, clinical protocols, and EMRs vary greatly across and within LMICs, providers of these types of Al tools must develop multiple versions and/or embed capacity to adapt tools to allow integrations with different workflows, EMRs, and IT systems. This fragmentation creates a significant business model challenge for scaling up provider-facing Al tools because it requires a high degree of customization, thus increasing the cost of implementation and slowing up scale.



6.1.3 Data Privacy and Ethics Challenges

Data privacy and ethical use of data raise significant concerns among many LMIC governments and other stakeholders—not only for those working on Al specifically, but also for those involved in digital health and other sectors more broadly. Data privacy issues are particularly important for digital health and Al solutions since health data is generally government owned, raising concerns about private companies gaining access to the data and potentially profiting by leveraging it for their own uses. In fact, many LMICs already have regulations prohibiting private companies from taking health and other types of data outside their borders. In addition, many local stakeholders are concerned about Al tools requiring access to large amounts of health data because they fear that this would increase the risk for monopolistic behavior if a single private player assumes such a large role within a country's health system.

Furthermore, since many tech companies offer Al tools as free products directly to their users (patients, FHWs, or physicians), the users often become the 'product' for the company to monetize—a challenge around data privacy not exclusive to Al but faced by other digital health players as well. This dynamic means that companies that own these tools could sell their customers' sensitive health data. This is a resolvable issue, but highlights concerns around data privacy surrounding both digital health and Al health solutions and will need to be addressed thoughtfully with local players and national governments.

These Al use cases also raise ethical concerns about whether private companies with access to patient and population health data should be obligated to disclose the data to individual patients, local populations, health workers, and other local constituencies. For the Alenabled population health tools, a possible dilemma could arise if a private company analyzes data which indicates a potential outbreak of a highly contagious infectious disease in a given region. Is it obligated to inform health workers or communities within that region immediately? For an Al patient-facing platform, a dilemma might be whether AI tools should disclose a diagnosis to patients without appropriate counseling or other confidentiality measures that would otherwise be provided by health providers or FHWs.

Lastly, patient virtual health assistant and physician clinical decision support Al-enabled tools face particularly thorny ethical and fairness issues given that 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. In other words, the digital divide is likely to impact these tools on varying levels. For patient-facing tools, benefits will initially go to those with smartphones and 4G connectivity—most likely higher-income segments of the population. For CDS platforms, well-resourced facilities are likely to be earliest adopters.



6.1.4 Regulatory and Policy Challenges

Scaling up of Al-enabled tools is further complicated by differing and uncertain regulatory and policy environments, not only between countries, but also across regions and states within countries. For example, many LMIC governments lack the resources and technological capabilities to create consistent policies on population health, such as disease burden analysis and monitoring and treatment protocols for use, across their various regions or states. This creates a barrier for Al tools for population health to scale at a national level.

In addition, as this is an emerging field, many LMIC countries also lack consistent regulations for the use of Al tools by various actors and Al providers, particularly for those used outside of health facilities. This challenge is not only about regulations differing across countries or regions, but also that there is a lack of clear regulation on Al tools in a given jurisdiction. This lack of consistent regulation is true across all four groupings of Al use cases and means that the license to operate for many Al providers in a market 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 Al technologies. While we are not calling for stricter regulations on many Al tools, it is important to note that clear guidance from multilateral bodies and governments (and consensus among LMIC governments when possible) on when and where regulation on Al tools is needed, would be enormously helpful for technology companies operating across LMIC markets.

In addition, the patient and FHW virtual assistant Al tools face unique barriers, as many LMICs have restrictive regulations on what services or health advice can be provided to patients outside of health facilities or without the presence of a physician. For example, existing laws in India, China, Brazil, and other markets require physicians to make diagnoses and highly trained health workers to carry out certain medical tests, negating the value of these Al tools. Some patient-facing Al tool companies have not confronted regulatory issues because they are categorized as providing "educational health information" and therefore are not regulated for providing care guidance. But as health regulations in LMICs become more robust, this is likely to change—with a risk that regulations will become more complex and inconsistent across countries.



6.1.5 Health System Integration and Capacity Challenges

Global health practitioners and in-country stakeholders agree that AI tools should be consistent with current local health workflows and systems, ranging from IT systems to clinical protocols, in order to truly provide value, efficiency, and optimization of existing resources. Similarly, AI tools should not require additional data inputs or actions beyond current standards in a given health system in order to avoid creating inefficiencies and additional burdens on health workers or providers. While these may seem like straightforward notions key to AI tools' value propositions in LMICs, tremendous variance in IT systems and workflows among LMICs (and often among facilities or regions within a country) makes this a difficult challenge to overcome in reality.

As mentioned previously, workflows, clinical protocols, and EMRs vary greatly across and within LMICs-so providers of all types of Al tools must develop multiple versions of these tools to enable them to integrate and work with different workflows, EMRs, and IT systems. The need to integrate with local health systems means many Al tool providers have to offer highly customized

Al tools for local or regional contexts and health systems, slowing the scale-up of these tools.

A related issue is that weaker health systems in LMICs, with limited means of collecting or storing digital health data, could inhibit the use of AI tools where they may be needed most. Further, while AI tools can enable better identification of health burdens and diagnoses at both population and individual levels, the potential impact of these tools will be negated if local health systems lack capacity and resources to implement population-level interventions or effectively treat at-risk patients.



6.1.6 Challenges Related to Limited Evidence Base for Impact of Al Tools

There is no current definition of acceptable performance standards, accuracy rates, and patient health outcomes against which to measure Al. Further, perspectives vary widely on what standards Al tools should adhere to in order to be used across LMICs, and for patients and doctors to have trust in them. At a more granular level, there is also debate over variability in accuracy standards across different types of Al tools—for example, epidemic predictive modeling may require a lower degree of accuracy than clinical decision support tools or FHW diagnostic tools.

Some in the medical community assert that Al tools, particularly those that provide outputs directly to patients, must always have accuracy rates equal to or greater than those provided by highly trained doctors. Others argue that, given some of these tools are providing recommendations to patients who would not otherwise have access to qualified doctors (and may have little access to formal healthcare of any kind), lower accuracy rates are acceptable. This debate is further complicated by the facts that acceptable algorithm accuracy rates are likely to vary depending on clinical area, and that physician performance in diagnosis and treatment is itself highly variable. Many global health practitioners urge that the Hippocratic oath-do no harm-must be the guiding principle for all efforts to scale Al tools. Yet, how to operationalize this standard is unclear, since there is not enough of an evidence-base from the use of these tools in LMICs to know which tools might have potential to create harm (if misused) and how to avoid it.

A closely related issue is the limited evidence base for the impact of these Al tools, particularly for concrete changes in patient health outcomes in LMICs. There have been very few studies on the impact of Al tools in lowresource contexts, particularly at a PHC level and with underserved populations. While there is excitement within the global health community about the potential of these tools, there needs to be far greater evidence in low-resource contexts in order to enable stakeholders to determine which Al platforms should be scaled up and how to avoid creating any unintended harm.

6.2 Lack of Trust in Al

We found that lack of trust was a consistent theme underlying many discussions around AI in LMIC contexts. Many of these same trust issues are also true for other digital health tools and not specific to AI tools. There are a variety of trust issues around how providers, FHWs, health facilities, and national governments think about collecting and using digital data, as well as questions on what companies will do with this data. While the international community often talks about the value potential of digital health data, in reality this data is often more politicized and contentious for local actors. Many LMIC governments and other health system actors at local and national levels may be hesitant to provide

data if it can be used against them in performance evaluations. They may even have perverse incentives to provide false data to make their performance appear better than it is. Similarly, providers and FHWs may be hesitant to provide data if they fear it can be misused or used against them by surfacing areas where they have made clinical errors.

In addition, there are trust issues around how closely various actors follow the guidelines for use of Al tools. Even with the best of intentions, FHWs or physicians may skip a few steps on their Al tools in order to save time. This exemplifies how tools will not always be used as intended or envisioned, and that their impacts on, and interplay with, local health systems will likely be more complicated and multifaceted than planned.

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I. For clarity, we consider AI regulations here as rules which define what players may and may not do using health tech for AI within a certain geography or country. We define AI policies as clinical protocols or guidelines on how AI tech should be used within a certain geography or context. There are intersections and interplays between the two, but they are distinct.

7. Potential Investment Areas Critical to Accelerating the Use of Al in Global Health

o unlock the tremendous potential of AI to improve healthcare access and outcomes around the globe, investment from the global community will be critical. Through our detailed analysis of AI use cases and scaling challenges, we identified seven potential areas of investment that we suggest global health donors and other stakeholders explore further (see Figure IO below). These areas span individual innovator support and ecosystem support to capture

the spectrum of opportunities for exploring and appropriately accelerating AI in global health.

7.1 Potential Activities Within Each Investment Area

Defining these potential investment areas provides an initial path for common understanding and coordination among global health stakeholders. Further efforts will

Figure 10: Priority Investment Areas Critical to Accelerating the Use of AI in Global Health



Specific investments for each use case grouping considered in greater detail to inform investment roadmap

be needed to flesh these out and determine the best sequence for investments, particularly as they relate to specific Al use cases and groupings of those use cases.

7.1.1 Coordination

In general, we believe that all of these activities laid out in Figure 10, and detailed in the following pages, can be executed more optimally and efficiently, and with a greater chance of success, if efforts are better coordinated across global health stakeholders. Ideally, coordination efforts should encompass some Al global health investment areas and focus on helping global health funders and other stakeholders better collaborate across funding and broader activities in order to reduce unnecessary duplication and/or funding gaps.

Coordination would allow stakeholders to work together toward common ends when they find that they have parallel and overlapping priorities and activities (such as various funders supporting an incubator to scale Al health providers in a given LMIC market). It also means stakeholders can divide the work needed in order to leverage different players' comparative advantages in different areas. For example, WHO could lead on data aggregation and sharing of lessons learned on scaling Al use cases among diverse stakeholders; the World Bank could lead on policy support for LMIC governments; global standards bodies on developing a standardized data ontology; and so on. There are existing platforms around coordinating digital health efforts which could serve as an example for Al coordination.

7.1.2 Innovator Funding

Funding for testing and evaluating Al innovators and solutions is critical to accelerate the use of Al in global health. In order to best support Al innovators as they prove concepts and achieve scale across low-resource contexts, our analysis found that innovator funding could benefit from a focus on the following areas:

- Prioritize use cases and align on selection criteria:
 Coordinate with funders and other stakeholders to identify selection criteria and prioritize specific use cases according to their individual focus and concerns
- Align on evaluation metrics and criteria: Identify
 metrics and criteria to be used to evaluate Al
 projects and pilots to improve the consistency and
 quality of evaluations across funders and provide
 consistent data to inform investment case/ROI
 analyses

- Provide funding to prove Al solution concepts:
 Provide funding to early-stage Al concepts to pilot or otherwise show proof of concept, for example for funding field tests of Al-enabled ultrasound device in LMICs, and encourage future procurement if validated
- Facilitate blended financing for Al in global health: Encourage the extension of private sector investment in Al through collaboration with other pools of private capital, such as venture funding, to de-risk investments and otherwise encourage investment
- Support proven solutions to transition to scale: Provide funding and support for specific, proven Alenabled global health solutions to enable transition to scale. For example, work with providers of these solutions to help them develop sustainable business models and build operational, strategic, and technical capabilities. This should include providing funding for proven Al-enabled global health solutions to expand into new geographies

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7.1.3 Innovator Technical Assistance (TA) Support

In addition to funding, technical assistance and advisory support will also benefit Al innovators, through both targeted support to specific innovators and broader cross-cutting mechanisms that can serve multiple innovators. This is likely to be a sequential three-step process, rather than a set of independent opportunities that could be executed separately. This support could also include helping innovators navigate the challenges outlined in Section 6, such as ethical and legal obstacles.

- Identify innovator needs for technical assistance and advisory services: In conjunction with other funders, collect data on the critical needs of innovators aiming to apply AI to global health, leveraging deliverables from this project on challenges facing AI in global health as a starting point.
- Identify/create a mechanism for innovator TA and advisory services: Coordinate with other funders and specialist groups (such as lawyers, policymakers, AI experts) to identify or create a flexible, scalable mechanism for providing technical assistance and advisory support to innovators looking to apply AI to global health.
- Invest in enabling TA and advisory services for innovators at scale: Expand advisory services

mechanisms to provide TA and advisory services to many innovators across geographies on all topics relevant to their critical needs (as determined in the first step in this category).

7.1.4 ROI and Evidence

To support both existing AI innovators and the field more broadly, it will be important to gather evidence on both the economic and health impact of AI solutions in global health. Given the lack of activity in this space, we suggest a coordinated effort upfront to align on a standard approach to gathering and assessing evidence. Over time, this could be applied to specific AI solutions, and can be incorporated in an investment case that articulates the economic and health arguments in favor of AI.

- Agree on high-level framework for evaluation of health and financial impact of AI: Align with other global health funders on high-level framework for evaluation of health and financial impact of AI use cases.
- Draft detailed evaluation standards: Continue coordinating with other global health funders to detail and expand evaluation standards.
- Gather evidence and build the investment case for Al use cases: Gather evidence on health (quality, access, and cost) and financial (ROI) impacts of existing Al efforts for high priority Al use cases and/ or groupings to build an investment case (noting and plugging gaps through supplementary evidence generation where needed).
- If evidence is promising, build investment case:

 Use investment cases to facilitate discussion with potential Al buyers to help increase their political will and willingness to pay for Al solutions at scale.

7.1.5 Data Capture

Due to the many current efforts by global health funders to capture digital health data, we recommend that stakeholders strengthen coordination of their efforts in order to maximize overall potential impact. Additional investments in this category include:

• Identify or create an open data platform for sharing datasets relevant to Al in global health: Coordinate with other funders and technical groups to identify or create a flexible, scalable, open platform for publication of datasets relevant to Al in global health; and then publicize its availability among potentially interested AI innovators and data contributors.

- Add datasets to the platform, ensuring data is representative of a variety of contexts: Create open datasets for Al in global health and aggregate data, ensuring representation of relevant subpopulations by gender, ethnicity, class, geography, etc. Such datasets could draw from academic studies, best practice diagnostic protocols, population health data (for example by leveraging WHO data and protocols), medical images, and colloquial and formal medical terminology corpora in various languages.
- Encourage funded innovators to collect and share data where possible: Coordinate with other global health funders to add terms to grants/investments requiring funded innovators to collect data that meets the standards of the chosen open platform and, as much as possible, to share data on that platform.
- Encourage scaling of sustainable data collection systems: Collaborate with other funders, governments, and health systems to support developing and deploying at-scale data collection systems. These may include electronic medical record (EMR) systems, use of smart phones for data capture by frontline health workers, and digitization hubs to convert historical analog data.

7.1.6 Interoperability

One of the main challenges facing the global health community and its burgeoning landscape of digital solutions is interoperability. Coordinated action is needed to ensure the AI ecosystem enables, or even requires, interoperability, since no individual actor can force the ecosystem to be interoperable. Several activities will build the foundation of interoperability of solutions—from setting up a common language and standards, to setting a common architecture on which developers can build applications (thus also giving them a head start in the solution development process), and even sharing key building blocks of code that can be used to more efficiently create interoperable solutions. As an example, app developers could create integration points for Al data systems (one system transmitting data to another system), and international standards bodies and governments could create standards for such data-sharing to facilitate alignment with global and local health protocols and systems. Investments in this area are also linked to those in the data capture and capacity-building categories.

- Support common AI standards and terminology, in sync with broader health data standardization: As the basis of interoperability, different systems need to use common standards and terminology in their coding and documentation to ensure uniformity. Funders can collaborate with standards bodies, such as HL7 International, to fund and manage a mechanism for bringing AI experts together to create common data standards and terminology, ensuring they sync with ongoing efforts to standardize health data more generally (ICD-I0, FHIR, etc.).
- Create integration points for AI data systems, leveraging agreed upon standards and code: Support a consortium of developers, health systems administrators, and governments to build the "pipes" and protocols for health data systems integrations, by creating common APIs, data exchanges, etc., focusing on the most used systems (e.g., DHIS2).
- Identify or create an open platform for sharing code relevant to Al in global health: Many tech platforms currently exist where developers share code to help other developers and to help ensure interoperability of digital solutions. For example, Github is a robust platform where millions of developers go to collaborate and share code. We suggest that funders can coordinate and with technical groups to either identify an existing online code-sharing platform, or create one, with the specific aim of sharing code relevant to Al in global health.
- Create a broad, open code base for Al in global health: Once there is an open platform for sharing code, funders can also accelerate the development of code building blocks by funding a mechanism for engaging expert Al developers so that they can amass a useful code base for Al in global health. Such a code base can add to the common architecture to bring developers even closer to a complete solution, improving efficiency and interoperability of development efforts for Al in global health.

7.1.7 Capacity Building

To enable the success of AI, support must go beyond innovators to include capacity-building for LMIC governments and other players in the ecosystem. Building capacity at a local level also mitigates the risk of bias when AI is developed in a HIC and then deployed in LMICs. As potential customers and partners, these stakeholders must understand, adopt, purchase, and regulate AI solutions in these markets. Specific activities needed are:

- Identify best practices and foundational principles for Al policy, regulation, and ecosystem capacity:
 We suggest that funders and technical groups identify best practices and foundational principles for Al policy, regulation and ecosystem capacity.
- Identify or create a mechanism to support adoption of best practice Al regulation and policy: Coordinate with other funders, international organizations, and advisory groups to identify or develop a mechanism (such as World Bank's policy support facility) to support adoption of best practice Al policy and regulation as shaped by previous investment.
- Build government and ecosystem capacity for ongoing Al use at scale: We suggest that stakeholders across the ecosystem (government, civil society, etc) support developing capabilities for ongoing Al use at scale, potentially including: funding Al research, providing Al education and training, and improving startup financing infrastructure. This should also include strategic purchasing support for LMIC governments to enable them to purchase and adopt Al technologies in a way that is strategically consistent with their procurement processes, long-term priorities, and resource constraints.

We believe that investments across these seven categories can help accelerate the potential of Al in global health. While investing in any one category can drive progress in overcoming challenges, a systematic and prioritized approach across categories will have the most impact. Given competing priorities and the scale of work needed in Al in global health, we hope that funders and other interested stakeholders continue to come together to prioritize and coordinate efforts on the work ahead.

Appendix

I. Use Case Detailed Definitions

Table 1: Detailed List of Use Cases in Global Health

Category	Use Case	Definition
	Surveillance and protection	Processes data from multiple sources to more accurately map current spread and burden of disease and uses predictive analytics to map likely future spread, thereby enabling: Better understanding of burden of disease and epidemiology Prediction of future disease spread, including outbreaks
	Population risk management	Leverages AI and inference generation technologies to better understand risk across different groupings of population and stratify groups according to risk levels to enable more accurate projection of medical needs and costs of care for populations
Population Health	Intervention selection	Analyzes specific characteristics of populations and geographic areas flagged as high risk and recommends specific population health interventions likely to be most effective and efficient in that context
	Intervention targeting	Combines data on disease spread and risk from surveillance/prediction with additional data on population and geography to pinpoint areas where intervention will have highest impact and define: • Who to target • Where to target • When to apply
	Self-referral	Patient enters real-time data, and Al-enabled system identifies type and severity of condition and provides recommendations directly to patient on: • Whether to seek care • What type of care is needed • Where to seek care
Care Routing	Triage	Health workers enter real-time patient data and receive targeted recommendations on if and how to provide care to patients
	Personalized outreach	Passively captures and analyzes real-time patient data to identify patterns and track variation in order to trigger personalized, direct patient outreach (i.e., messages from HCP and chatbots, care recommendations)

Table 1: Detailed List of Use Cases in Global Health

(continued)

Category	Use Case	Definition	
	Behavioral change	Suite of tools to provide customized guidance on various elements of health and wellness: • Diet: Creates customized nutritional and dietary guidance and provides real-time coaching and advice • Exercise: Analyzes patient data to provide real-time, customized feedback and coaching on exercise • Wellness: Provides targeted recommendations for mental health and general wellness	
	Data-driven diagnosis	Analyzes symptoms and other data to diagnose disease (beyond simple triage and carerouting); often engages user directly through multiple rounds of data collection (e.g., through a chatbot asking questions)	
	lmage-driven diagnosis	Suite of tools including: Radiology: Identifies abnormalities on radiological images to directly infer diagnoses or prioritize image areas for clinician review Pathology: Identifies abnormalities (e.g., tumors) based on digitized pathology images to directly infer diagnoses or prioritize image areas for clinician review	
Care Services	Clinical decision support	Provides best practice treatment guidance to caregivers in real time based on patient diagnosis, symptoms, and other data	
Services	Monitoring	Includes in-patient and out-patient monitoring: In patient - Alerts clinicians of potentially problematic values or trends in patient vital signs and other real-time health data based on evidence-based guidelines; Out-patient: alerts patient, family, or clinician to problematic values or trends in patient vital signs or disease markers with recommendations on specific actions to take	
	Al-facilitated care	Guides patient through best practices for self-care given symptoms and context	
	Al physical interventions	Controls robotic surgical devices to perform surgery and controls robot that facilitates a patient's physical therapy routine	
	Compliance monitoring	 Suite of tools including: Medication compliance: Uses data on if and how patient takes medication to alert patient, families, or clinicians to medication needs or to suggest personalized interventions Dietary compliance: Analyzes dietary data and triggers alerts on compliance or recommends dietary alterations to stay within recommendations 	
Health	Medical records	Assists in medical records creation and analysis (e.g., writing medical notes based on EMR data and limiting clinician time spent on documentation)	
Systems	Capacity planning & personnel management	Analyzes data on facility/community-level care alongside data on health workers to predict and plan for resource needs	

Category	Use Case	Definition
	Claims processing	Incorporates AI into advanced analytics to review medical records plus patient-generated data to automatically execute claims processing
Health	Fraud prevention	Analyzes claims data and uses pattern recognition algorithms to identify fraud and waste in claims
Systems	Quality assurance and training	Analyzes previous clinical decisions, indicating where errors may have been made given the patient context; uses insight on past performance as key input into quality and efficiency improvement efforts
	Coding and billing	Supports provider finance functions by analyzing medical notes to ensure proper coding; also optimizes billing strategies
	Clinical trial support and recruitment	Combines power of machine learning with analysis of unstructured data (e.g. handwritten doctors' notes) to improve all facets of clinical trial: optimize trial design (including endpoints, arms, powering, inclusion/exclusion criteria, etc); more efficiently recruit and enroll subjects in trials; better monitor safety during and after trials; automate clinical trial management functions
	Drug discovery	Leverages genomics and proteomics, to analyze and predict the likely impact of a drug on its target(s) and the risk of toxicity, thereby enabling faster, more accurate drug discovery
Pharma &	Drug safety and pharmacovigilance	Analyzes data to better automate processes related to response to drug safety events; functions include gathering relevant data about the case, automating case classification processes, and managing targeted case follow-up
MedTech	Supply chain and planning optimization	Automates and improves resource planning in pharma and medtech supply chain management and resource planning
	Process optimization	Automates and improves medtech and pharmaceutical companies' production and manufacturing processes
	Real world evidence and HEOR	Leverages AI to mine and analyze real-time data from EMRs, patient-reported data, and other sources to assess real world efficacy of drugs and medical devices and correlate to outcomes. This function may complement or even substitute for clinical trials, and could ultimately lead to better targeting of specific drugs to individual patients

Figure 11: Vignettes on Potential Opportunity of Al Tools

AI ENABLED POPULATION HEALTH TOOLS



Meet Dhesi

Using AI enabled predictive surveillance, intervention selection, and intervention targeting to predict dengue outbreaks and respond most effectively to them

Dhesi applies Al predictive analytics tools in his work for the Ministry of Health in Malaysia

Situation:

- Dhesi's work focuses on controlling infectious diseases
- Until last year, the MoH had no analytic capability to predict when diseases would break out and spread, limiting its ability to protect the population
- The MoH had limited health data from different regions across the country and no means to incorporate non-health data into its work

Action:

- The MoH fully digitized and integrated EMRs from health facilities across the country and then enhanced its analysis further by applying AI to this data
- The MoH started using Al tools which enabled it to:
 - Map various health burdens and disease outbreaks occurring across the country by applying machine learning to identify correlations among multiple variables across complex data sets to identify risk factors and predict the spread of diseases
 - Integrate non-health data (i.e. weather patterns, wind speed, roof angles) to help predict when the next outbreak might occur by using natural language processing to gather intelligence from news reports and social media posts

Impact:

- Applying predictive analytics powered by machine learning to newly gathered/ digitized data enabled Dhesi's team to view, analyze, and react to health data in real time rather than analyzing outdated data after the fact
- Predictive ML algorithms enabled the MoH to predict the exact geo-location and date of the next dengue outbreak three months in advance
- ML-powered algorithms also enabled it to decide which vector control interventions would be most effective and to plan where and when to roll out these interventions



Meet Anu

Using predictive surveillance and population risk management to better understand diabetic patients' needs Anu uses AI tools to better meet the needs of patients in her hospital network in Bangalore, India

Situation:

- Anu, a nurse and hospital administrator, knows diabetes has become a huge health burden for Bangalore and the populations served by the hospital network for which she works
- The hospital network collects digital health data on its patients, but historically Anu never had a means to analyze that data in her work or use it to understand the specific needs of her growing number of diabetic patients

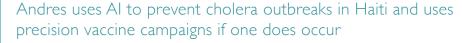
Action:

- Anu helped the hospital network launch a new Al platform which automatically turns patient consultations into inputs for the digital EMR system by using ambient listening and speech recognition tools to convert speech into EMR inputs
- She also helped implement an Al tool which risk-stratifies all patients seen in the hospital network to identify both at-risk individuals and communities/facilities with greater need, by applying predictive analytics powered by machine learning

• The tool helps Anu and her team to better understand the distinct needs of TI/T2 diabetics, and to reorganize their diabetes clinics to better manage the needs of these two patient segments by using predictive analytics to test different scenarios of resource allocation to optimize for efficiency and effectiveness

Impact:

- The AI speech recognition tool provides huge efficiency gains for the hospital: it saves each nurse more than two hours a day of inputting information, enabling them to see five to ten more patients a day (which translates to hundreds more patients across the system)
- The Al population risk management tool has also transformed Anu's ability to do her job: she has a much better view of population-level health needs and can better design programs (such as targeted outreach) to help patients best manage their conditions



Situation:

- Andres works for a large multilateral organization in Port-Au-Prince, Haiti, where he focuses on preventing and controlling cholera
- Andres and his organization have long known that cholera outbreaks are the result of diverse environmental, WASH, and population migration factors
- His organization has not had a way to analyze these non-health factors to better predict and control cholera outbreaks

Action:

- Now he and his organization use an Al tool which combines weather, environmental, and migration data (among other inputs) to give them a map of health burdens and at-risk areas; the tool uses natural language processing to gather data from diverse media and news sources, and uses ML algorithms to predict areas most likely to be at risk
- With a map of high-risk areas, often IDP camps, Andres and his team then work quickly to prevent an outbreak by addressing contaminated waste sources
- Andres also uses this AI tool to carry out precision cholera vaccine campaigns, targeted to at-risk populations and timed around the predicted outbreak, by applying machine learning algorithms to determine where and when campaigns should be carried out

Impact:

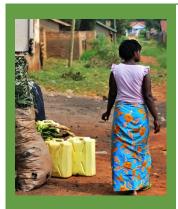
- The AI-enabled cholera prediction program is game-changing for Andres and his team's work they moved from a reactive model driven by personal knowledge and 'gut instinct' to a data-driven approach to predict and respond to disease
- Thanks to these Al tools, the global community can be much better prepared to quickly contain (or even prevent!) the next cholera outbreak in Haiti by vaccinating those who are most at risk



Meet Andres

Using predictive surveillance and intervention design to ensure that Haiti will never again be devastated by cholera outbreaks

FRONTLINE HEALTH WORKER (FHW) VIRTUAL HEALTH ASSISTANT



Meet Anita



Anita lives in a rural village in Western Kenya, six hours from Nairobi and two hours on dirt roads from the closest hospital



Last year, Anita became a community health worker; now she goes door to door in her community helping local patients with health advice and selling basic health products to address their needs



Anita has a smartphone with various apps that she uses in her work; she enters simple information on her patients' health condition, including symptoms they are currently experiencing



Her Al-enabled apps then provide health recommendations, diagnoses, treatment advice, and self-care recommendations that allow her to provide the best possible care to her patients



Meet Eric

Using triage, data diagnostics, and clinical decision support to provide top notch medical care and give a mother peace of mind

One of Anita's patients, Eric, is a sick child whose mother doesn't know what is wrong

Patient Situation:

- Two year old, Eric, has a high fever and an unusual rash
- His mother is unsure if she should travel to a hospital or what else to do

Action:

- Anita enters Eric's symptoms and a photo of his rash into her app
- The app uses advanced algorithms leveraging machine learning to determine that Eric very likely does not have dengue but might have malaria; the app also uses computer vision to identify the rash as very likely a spider bite
- Following CHW health protocols provided by the app, Anita then follows up with a malaria rapid diagnostic test, using her phone camera and a disposable blood
- Another Al-enabled app ensures the results of the blood test are read and interpreted correctly; in this case, the app verifies that Eric does not have malaria and does not need to be referred for care
- Drawing from health protocols on her app, Anita gives Eric's mom suggestions on how to best care for her son, with specific instructions on when to visit a health facility if his condition changes

Impact:

- Without her Al tools, Anita would not have been able to provide timely and accurate medical advice for Eric she might have misdiagnosed the rash and even recommended the wrong medications
- Without Al, Eric's mother would likely have had to travel to a health facility hours away
- With AI, Anita was also able to save an unneeded visit to an already overburdened health system – enabling providers to see patients who may have been in greater need of care



Meet Samuel

Using triage, data diagnostics, and clinical decision support to provide top notch medical care

Another patient, Samuel, has a bad cough

Patient Situation:

- Samuel, 30, suffers from a bad cough
- He woke up coughing blood, which prevented him from going to work

Action:

- Anita asks him about his symptoms and enters them into her phone. Samuel doesn't speak English but the app 'speaks' Swahili through speech recognition and natural language processing, converting their conversation, and her manual inputs, into usable data
- Her Al-enabled app tells her that Samuel might have TB, based on a machine learning algorithm that identifies correlations between both global and localized data sets
- Anita then records the sound of his cough in her app, which compares the sound with a database of other coughing sounds. The app determines that Samuel very likely has TB. It recommends that Anita call a nurse at a nearby health facility to discuss this situation further and that Samuel seek care in order to have a trained health provider ensure that this is the correct diagnosis
- Anita's app pulls in live data on capacity and wait times at nearby health facilities and helps route him to the nearest clinic where he can quickly receive the care he needs for TB (Anita's app also links with digital medical records of that facility, so they will have all of this information on Samuel by the time he arrives)
- Anita is also able to tell Samuel what to expect in terms of treatment, including an Al-app he can download himself to ensure compliance with the medication protocol
- Anita recognizes that Samuel's family is also at risk of TB infection, so she recommends place they can go to get tested for latent TB, and what symptoms to watch out for

Impact:

- Without AI, Samuel might not have received a timely and accurate diagnosis; his condition might have worsened and he might have transmitted TB to others
- With these AI tools, Samuel now knows exactly where to go for care, which helps him better use his time and money and reduce time out of work

PATIENT VIRTUAL HEALTH ASSISTANT



Meet Mary

Using compliance monitoring and medical records to enable a grandmother to care for her family

Mary has hypertension and few tools to track and assess her health status

Patient Situation:

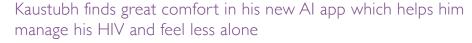
- Mary, 70, is blind and has hypertension
- She says she feels fine, but sometimes forgets to take her medication

Action:

- During this week's visit with Mary, Anita puts Mary's recent symptoms into her app and it determines that her symptoms likely correlate with not taking her medications
- The app also alerts Anita that she should test Mary for diabetes based on Mary's symptom history and her vital sign measurements taken that day. Anita's hand-held device has tracked Mary's current blood sugar levels and other symptoms and uses machine learning algorithms to determine that Mary is likely pre-diabetic
- Anita follows new CHW protocols including a diabetes test through an AI enabled tool on her phone, and provides contact information to a nurse who is available to speak by phone
- Anita's app also makes personalized recommendations to help Mary change her behavior through diet and exercise, pushing notifications to Mary's granddaughter so that she can work with Mary when Anita is not there
- Anita also helps Mary's granddaughter set up another app which uses computer vision to verify that Mary is taking her medication each day; this app can alert Anita, and Mary's granddaughter, if nonadherence persists

Impact:

- Given the general nature of Mary's symptoms, Anita may not have necessarily connected her prior history and complaints with her current readings to diagnose that Mary is pre-diabetic
- Without Al, Mary might have had to go to a nearby town for direct observational therapy to ensure medication adherence
- Because she was tested early, Mary might now be able to prevent diabetes

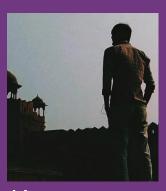




- 23-year-old Kaustubh lives with his family outside of Calcutta, India
- Kaustubh has HIV and sometimes suffers from depression related to his HIV status
- Kaustubh has heard that there are apps that can help him manage his condition and feel more supported

Action:

- Kaustubh downloads one of these apps and logs how he is feeling, what he has eaten that day, his recent symptoms, and whether he has taken his medications. He also enters some data points from his last doctor's appointment including his CD4 count. Once he creates a profile, the app also pulls his broader medical history from his EMR online
- The app uses natural language processing to convert his inputs in Bengali into usable data then it uses ML on this data (and data from his broader medical history) to flag if Kaustubh is at risk, in nonadherence, or needs to seek care. If his symptoms indicate



Meet Kaustubh

Using Al-enabled personalized outreach and behavioral change tools to help him manage HIV

- that he is having a depressive episode, it recommends free mental health counseling resources nearby and flags for his provider that he is in need of care
- The app also introduces Kaustubh to a new personalized health coach in the form of a chatbot that speaks Bengali. The chatbot checks in with him periodically to see how he is doing, reminds him to take his medications, reminds him of when he needs viral load testing, and provides information on HIV support groups (in his own neighborhood) which he could join
- The chatbot uses speech generation to speak to Kaustubh and speech recognition when Kaustubh speaks to the app. It also uses ML to generate specific behavioral and mental health advice based on Kaustubh's specific inputs (like mental health symptoms, food preferences)

Impact:

- Without AI, Kaustubh would not have had remote monitoring and personalized outreach to help him manage his HIV and to provide wellness coaching and support in the process
- He might have had more frequent infections and acute health events (as he did before using the app) which meant more days spent waiting at overburdened health facilities

Kehinde uses an AI enabled tool to get sexual and reproductive health information and advice

Patient Situation:

- Kehinde is 21 and is at vocational school in Kumasi, Ghana
- She is sexually active and has questions about sexual and reproductive health, but doesn't know where to go to get answers (she can't ask her conservative family!)
- Recently, she has experienced some pelvic pain and other gynecological symptoms. She
 would like to see a doctor but fears it will be expensive and doesn't know where
 to go

Action:

- Kehinde heard about a chatbot that can answer all of her questions on sexual and reproductive health she downloaded it and now asks it all of her questions. The chatbot uses speech recognition and speech generation to process and answer her questions, and machine learning to analyze her questions and provide answers
- The app also provides additional materials for her to read based on what she seems most concerned about
- She puts her symptoms into the app and it tells her if she should seek care. At present it says she does not need to seek care, but it advises her what to do if symptoms worsen, what annual appointments she should have, and where to go for them. It also provides an option for her to text with a nurse if she has further concerns
- Best of all, the app also tells her that there are free women's health clinics near where she lives where can get contraceptives and women's hygiene products and have a confidential consultation with a female health worker

Impact:

- Without Al, Kehinde didn't have access to resources to answer her questions on her sexual and reproductive health
- She might have wondered if and when she should see a doctor, but now she knows where and when to seek care



<u>Me</u>et Kehinde

Using self-referral and data diagnosis to help a young woman stay healthy

PHYSICIAN CLINICAL DECISION SUPPORT



Meet Jacinta

Using image-based diagnosis to improve timeliness and quality of cancer diagnosis to get more patients into treatment

With a new Al pathology tool, Jacinta can provide faster diagnoses and better care for her patients

Situation:

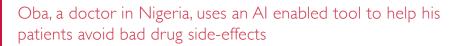
- Jacinta is a radiologist at a public hospital in Quito, Ecuador
- Hundreds of women come to her breast cancer clinic every day, they are lined up when she arrives in the morning and when she leaves (far after dark) at night
- Jacinta is passionate about her work she wants to help as many women as possible fight breast cancer, but there are simply not enough radiologists and she cannot work fast enough

Action:

- Jacinta's hospital gets an AI enabled radiology tool for her to use in her work
- Jacinta uses it to diagnose tissue samples from women who came in the prior day reporting lumps in their breasts. This Al tool quickly analyzes the tissue samples and, using machine learning and pattern recognition, identifies areas of potential cancerous growth and provides its diagnosis of potential cancer within each sample. (It also provides Jacinta with the percent certainty of its assessment)
- Jacinta still examines each sample in detail with her own eyes and follows all clinical protocols - but she can go much more quickly in her work with this new tool. She also feels very comforted to have the technology double-checking and confirming her own diagnosis
- Within days of using this new tool, Jacinta knows that she can review three to five times more samples per day and make more accurate diagnoses with this new tool. She is confident that she will be able to provide diagnoses to women much more quickly, and help diagnose and treat hundreds more women each year as a result

Impact:

- Without Al, Jacinta had no means to diagnose more patients in a day (and thus help put them on a track to treatment); and she had no resource to double check her work or thinking
- Normally, the nurses tell women that it will take one to two weeks for them to receive a diagnosis (which is difficult if they have traveled far from home to visit the clinic). Now Jacinta strives to provide a diagnosis within one to two days, helping them get treatment as soon as possible





- Oba, 40, is a doctor at a health clinic in a village outside of Kano, Nigeria
- There is a pharmacy in the clinic where Oba works and he provides his patients with prescriptions, and recommendations for over-counter medications, when needed
- He is very careful to follow all protocols and guidelines in making prescriptions, but he struggles to track of all the potential side effects from drug combinations which his patient are using (many of his patients take three or four different medications a day)
- He is frustrated that he doesn't have a better way to flag problematic drug combinations

Meet Oba

Using clinical decision support around drug combinations to ensure that his patients avoid adverse drug reactions

Action:

- Recently, a friend told him about a computer program that could alert him to potential risks of drug combinations he downloaded it on his office computer the next day
- Now, when he is about to provide a prescription for a patient, Oba enters the medication information into their profile on his computer and the new program



- provides him with an assessment of drug combination risks
- The program uses ML algorithms, built from a large training data library on how different chemical compounds interact with one another and can impact the human body
- Oba is particularly grateful that the program processes information on a large range of generic and branded medications since it is hard for him to keep track of all of them

Impact:

- Without Al, Oba did not have a systematic way to keep track of the risks of drug combinations
- With Al, Oba is far better able to protect the health of his patients
- Last week, a new mother came to see Oba and asked for medication to increase her milk supply Oba was ready to write her a prescription, but his Al program alerted him that this drug could be lethal for a child when combined with another medication the mother was taking. Oba, and this mother, are so grateful he was able to flag this issue and prevent something awful from happening



Meet Abdullah

Using clinical decision support and image-based diagnostics to ensure he provides the best possible care for his patients

Abdullah has a new Al tool which helps him make the best possible decisions for his patients

Situation:

- Abdullah, 68, is a physician in a regional health center in Mozambique
- He has been practicing for 35 years and wishes he could have a second round of medical school to learn about medical breakthroughs and recent changes in clinical guidance
- He believes his medical knowledge is out of date, but he doesn't have resources to fix this
- Often he wishes he had more colleagues around to offer second opinions on his diagnoses, or to discuss treatment pathways, but he is the only doctor within a two-hour drive

Action:

- This year, the national MoH provided him with a new Al tool for his office computer which helps him in making clinical decisions it listens when he has a patient consultation (using speech recognition, NLP) and then uses ML to formulate a possible diagnosis based on data received
- Abdullah also puts his own notes, questions, and possible diagnoses into the Al program and it provides him with guidance on the most likely of these diagnoses along with additional questions to ask or tests to carry out
- When Abdullah recommends a possible diagnosis for a patient or suggests a patient care pathway the program double checks if it agrees with his analysis of the data. It flags if it has concerns and lays out recommended next steps for Abdullah to take to double check that this is the best path forward
- Also, his computer program links with several image-based diagnostic apps which he
 and his team use to make more timely and accurate diagnoses

Impact:

- With Al, Abdullah has a means to double check his thinking, ask for clinical guidance, and double check his diagnoses, which he finds very comforting and affirming
- With Al image diagnostic tools, Abdullah and his team are able to diagnose, and then provide treatment to, patients which he wasn't able to previously (for example, in the past he had to refer patients with hearing problems to an ENT in a nearby city, now he can diagnose and treat them himself)

II. Acknowledgements and List of Interviewees

We would like to acknowledge and thank the many people who contributed to this work, including the individuals named below who generously provided their time to be interviewed for this endeavor.

Table 2: Detailed List of Interviewees

Category	Organization	Name		
		Austin Ward		
		Caitlin Mazzilli		
	5	Suhel Bidani		
	Bill & Melinda Gates Foundation	Charlotte Hubbert		
		Tim Wood		
		Arunan Skandarajah		
_	The Rockefeller Foundation Fellow	Wendy Taylor		
Sponsor Organizations	The Rockefeller Foundation	Manisha Bhinge		
9	The Nockeleller Foundation	Nikita Japra		
		David Milestone		
		Adele Waugaman		
	US Agency for International Development	Merrick Schaefer		
		Aubra Anthony		
		Temi Ifafore-Calfee		
		David Stanton		
	Rock Health	Bill Evans		
	World Health Organization	Ali Okhowat		
	Living Goods	Chuck Slaughter		
		P. Anandan		
		Raghu Dharmaraju		
	Wadhwani Institute for Artificial Intelligence	Rahul Panicker		
Group		Kirti Kandade		
Recommendations	Team Fund	Tim Ring		
	Stanford Medical School	Mark Cullen		
	Staniord Medical School	Matt Lundgren		
	BotMD	Dorothea (Dot) Koh		
	Ada Health	Hila Azadzoy / WWSabrina Golde		
) A (-	Mickey Chopra		
	World Bank	Marelize Gorgens		

Category	Organization	Name		
	Villgro	Paul Belknap		
Investors & Incubators	B Capital	Gavin Teo		
Gudusore	Andreessen Horowitz	Jeffrey Low		
	Buoy	Andrew Le		
	Babylon Health	Olly Finding		
	Epic	Seth Hain		
	Human Diagnosis Project	Shantanu Nundy / Jay Komarneni		
	TNH Health	Michael Kapps		
	Amazon	Nina Lin		
	Amazon	Maggie Carter		
	Verily	Casimir Starsiak / Kasumi Widner		
Private Sector &	Superconductive Health	Abe Gong		
Academia	Harvard Medical School	Andrew Ellman		
	Wellframe	Trishan Panch		
	Facebook AI Research	Larry Zitnick		
	Microsoft Healthcare	Miah Wilson		
	MIT (BioAccess and Sana Initiatives)	Leo Anthony Celi / Stacy Springs		
	BluePrint Health	Mathew Farkash		
	Simpa Networks	Michael MacHarg		
	University of New South Wales, Sydney	Dr. Teng Liaw		
	Ona/Open SRP	Matt Berg		

III. Example Companies Across Groupings of Al Use Cases and Categories

In addition, Figures 12 through 15 provide further detail on these Al use cases and groupings by laying out example companies in each use case category and painting a picture of the potential impacts on individual lives from these types of Al applications.

Figure 12: Example Providers Within the Al-enabled Population Health Grouping



Figure 13: Example Providers Within the Frontline Health Worker (FHW) Virtual Health Assistant Groupings of Al Use Cases

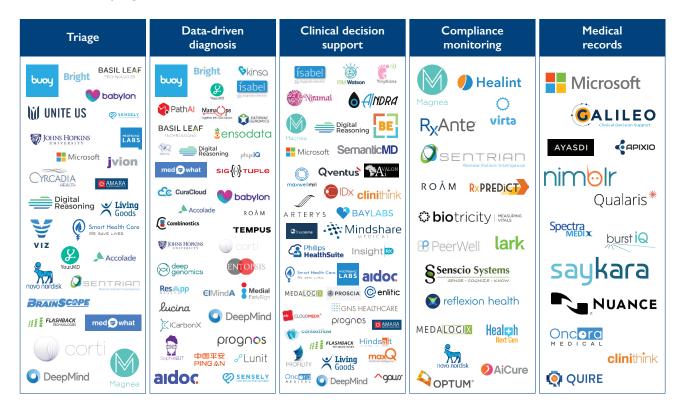
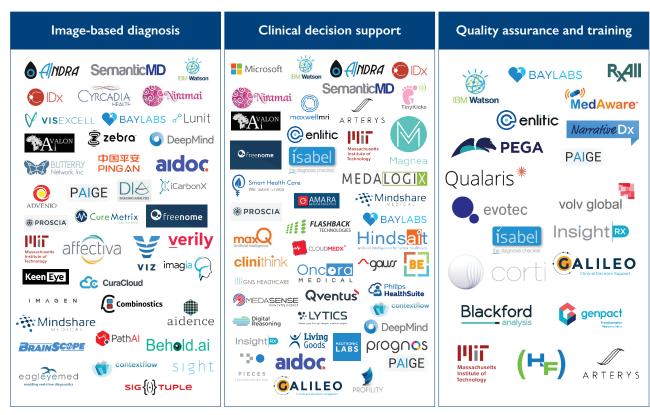


Figure 14: Example Providers in the Patient Virtual Health Assistant Groupings of Al Use Cases



Figure 15: Example Providers Within the Physician Clinical Decision Support Groupings of Al Use Cases



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