

AI-driven Predictions to Improve Health System Efficiency in sub-Saharan Africa



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Table of Contents

Executive Summary	4
Introduction	7
1. Efficiency: Definition and Concepts	9
1.1 Sources of Health System Inefficiency	9
2. AI-powered Predictive Analytics	11
3. Using AI-powered Predictions to Improve Efficiency	14
3.1 Precision: Increasing Accuracy of Future Outcomes	15
3.2 Prioritization: Improving Data Usability for Targeted Resource Allocation	16
3.3 Prevention: Enabling Proactive Health Systems	17
4. Case Studies	18
4.1 Case Study: Leveraging ML models to predict vaccine utilization	18
4.2 Case Study: Harnessing AI technologies to produce hyper-localized population data	19
4.3 Case Study: AI-based solutions to improve frontline health worker performance	20
4.4 Case Study: Using Natural Language Processing to reduce maternal mortality	21
5. Considerations for Optimizing AI-powered Predictions in Decision-Making	23
5.1 Governance	24
5.2 Capacity	26
5.3 Investments	27
6. Conclusion	29
References	31

Executive Summary

With the spread of COVID-19 threatening to derail decades of advances in health, countries will need to develop strategies that promote resilient health systems*. This is especially important as governments continue to work towards universal health coverage by 2030. There are multiple health system challenges, however, that make it hard for countries to effectively expand quality health services to everyone that needs them. Inefficiencies in health systems compound the difficult task of appropriately allocating health resources based on supply and demand. Healthcare spending is particularly vulnerable to inefficiencies because of underlying issues like uncertainty around the demand for health services, as well as uncoordinated financing from external donors and other stakeholders.

The cost of healthcare inefficiencies can be significant. In the United States, a panel of experts found an annual excess cost from systemic waste at USD 765 billion, which amounts to approximately 30 percent of total health expenditures.¹ Strategies to address inefficiencies vary from country to country, and depend heavily on context. For instance, the goal for many high-income countries like the United States may be to improve patient outcomes, while reducing costs or “do more with less”. On the contrary, the objective for low- and middle-income countries (LMICs) may not be to necessarily reduce healthcare spending (e.g. increase fiscal space for health), but to maximize available resources or “do more with the same”.

New insights generated from Artificial Intelligence (AI) have the potential to support decision-makers to make data-driven decisions, and offer an opportunity to improve efficiency.

By providing additional information on “what is likely to happen?”, AI-driven predictive analytics can be used to forecast human behavior – resulting in a better understanding of who, what, when, and where health services will be needed. Enhanced computing capacities, coupled with the increasing volume of healthcare data, have made AI-powered predictive analytics more attractive over traditional predictive methods. According to Accenture, AI-based health applications may result in annual savings of USD 150 billion for the United States healthcare economy by 2026.² This excitement for applying AI in health is also gaining momentum in LMICs.³⁻⁵

* According to USAID, the term health system is defined as consisting of all people, institutions, resources, and activities whose primary purpose is to promote, restore, and maintain health. This includes the spectrum of health services ranging from primary care (i.e., family planning, vaccinations) to tertiary care (i.e., emergency care, inpatient care).

It is important to note, however, that AI is not a silver bullet or panacea for all healthcare challenges. Decision-makers will need to parse out the hype from the enthusiasm, and approach the issue of AI with cautious optimism. Integration of AI-based solutions needs to be problem-specific and based on country context. As with the introduction of any technology, AI has the potential to do more harm than good – such as exacerbating existing societal biases and stereotypes*. Governments will need to be clear-eyed about the relevance of AI for different health problems to fully understand the benefits, as well as the limitations of AI-powered solutions. This is especially important for countries in sub-Saharan Africa, as the region's digital divide has implications on its ability to collect, access, and meaningfully use good quality, trusted data.

If deployed thoughtfully, however, sub-Saharan Africa has the potential to benefit greatly from AI technologies by gaining new interpretations of their data.

Armed with this information, decision-makers can improve their ability to forecast, plan, and manage their resources for health. These insights offer an opportunity to improve health system efficiency by shaping the way health services are delivered and accessed, health conditions are identified and treated, and resources for health are allocated and used. Notably, new information generated from AI-powered predictions can support data-driven decision-making by: 1) more **precisely** predicting the individual and system-level demand, use, and provision of health services, 2) improving the **prioritization** and the allocation of resources based on demand and efficacy, and 3) generating timely insights that enable decision-makers to **prepare** for system-level issues and public health events (expected and unexpected).

As a subset of digital technologies, AI-based solutions require a robust digital ecosystem to fully deliver on its potential. Several foundational elements need to be in place before countries can successfully and optimally leverage AI-driven analytics in decision-making. The three strategic priorities presented in this paper have been adapted from the U.S. Agency for International Development's *A Vision for Action in Digital Health*** . First, data **governance** is a critical component of ensuring the availability, access, and effective use of good quality data. Second, countries need to cultivate local **capacity** to collect, analyze, and

*Dealing With Bias in Artificial Intelligence - The New York Times (nytimes.com)

**A Vision for Action in Digital Health (usaid.gov)

routinely make data-driven decisions. Third, digital *investments* should create an enabling environment for AI technologies, while at the same time, stay consistent with national digital health strategies, prioritize global goods*, and support the broader digital ecosystem transformation.

Governance

- Apply a governance perspective that promotes data protection rights;
- Promote a culture of responsible data sharing across stakeholders, sectors, and geographies; and
- Establish a data quality improvement strategy.

Capacity

- Institutionalize data-driven decision-making at all levels of the health system;
- Foster research and innovation hubs; and
- Develop a roadmap that aligns AI technologies and the local workforce.

Investments

- Prioritize digital investments that are aligned with national digital health strategies, promote the use of global goods, and have the potential to benefit multiple sectors/geographies;
- Proactively shape private sector investments; and
- Increase investments to routinely evaluate AI projects.

COVID-19 has accelerated the digital agenda by disrupting all aspects of society, and has forced governments, organizations, and other stakeholders to increase investments in the digital ecosystem.

As digital transformation agendas continue to be drafted and implemented, countries in sub-Saharan Africa have a unique opportunity to consider the role of AI in a post-pandemic era, and leverage it where appropriate.

The opportunity cost of not capitalizing on the power of AI may be too great for governments to ignore. As countries work to recover from the socioeconomic impacts of the pandemic, the strategic and responsible use of AI-based solutions can pave the way for proactive, resilient, and responsive health systems.

*Global goods are digital solutions that are open-source, adaptable, and reusable.

Introduction

Competing priorities, as well as other factors like flattening budgets, make it difficult for governments to strategically allocate their resources across sectors and to achieve their health objectives. Moreover, the 2010 World Health Report highlighted that between 20-40 percent of all resources spent on health are wasted.⁶ Inefficiencies like misdiagnoses, inability to accurately predict demand of health services, and proactively prepare for potential shocks, all add to the challenging task of appropriately allocating resources across the health system. Yet, these issues are difficult to address without fully understanding the underlying issues. Meeting these challenges will require actionable information to enable decision-makers to make data-driven decisions about allocation of scarce resources.

The growing volume of digitized data, coupled with advanced computing technologies, is making it easier to take a data-driven approach to health system planning.

AI is one analytic tool increasingly applicable in digital health systems. There is growing interest and recognition of the potential for AI-driven interventions to address global health issues.⁷ Much has been written about the challenges and foundational considerations for deploying AI-powered approaches in LMICs, as well as the different domains for assessing digital health readiness.⁷⁻⁹ Key stakeholders ranging from donors to the private sector all have a stake in ensuring that sub-Saharan Africa is not left behind in an increasingly digital world. Moreover, the rapid adoption of mobile phones and other digital health technologies have contributed to the readiness for AI.¹⁰ Countries will need to assess their digital maturities and make strategic choices about whether and when to invest in AI-based solutions.

The purpose of this paper is to provide an exploratory analysis of the potential for AI-driven predictions to address factors associated with health system inefficiencies.

Section 1 defines efficiency as it applies to health systems, and defines the various sources of inefficiency. Section 2 describes some of the key differences between AI-powered predictions and traditional predictive analytics. Section 3 highlights the benefits of using AI-driven predictions, and how insights generated from AI can be used to support data-driven decision-making. Section 4 presents case studies to illustrate how AI use cases have been used to support the resource allocation process. Section 5 recommends three priorities for countries to consider as they develop strategies to deploy AI technologies – governance, capacity, and investments.



1. Efficiency: Definition and Concepts

To be efficient is to be “capable of producing desired results with little or no waste*.” There are two commonly used definitions of efficiency from economics that are adapted when assessing health systems – allocative efficiency and technical efficiency. Allocative efficiency is achieved when resources like vaccines and health workers are distributed optimally based on demand, while technical efficiency is producing the maximum output (e.g. high childhood vaccination rates) using the minimum amount of inputs or resources.¹¹

The strategies for increasing efficiency to achieve health goals varies from one country to the next, and depends heavily on context. For instance, with the rise in healthcare spending in high income countries, the goal of an efficient health system is one that can improve patient outcomes, while reducing costs. In other words, high income countries aim for technical efficiency by using resources that minimize costs, but also deliver quality healthcare or “do more with less.”

However, most health systems in LMICs may not necessarily want to reduce healthcare spending (e.g. increase fiscal space for health), but instead strive for allocative efficiency by making better use of available resources.¹¹

In this paper, improved health system efficiency for countries in sub-Saharan Africa is focused on allocative efficiency.

1.1 Sources of Health System Inefficiency

There are several factors that make healthcare spending particularly vulnerable to inefficiency. Uncertainty related to the use and demand for health services, information and power asymmetry between patient and provider, challenges with linking inputs to outputs, and fragmented financing – all contribute to the challenge of allocating and using resources for health efficiently.¹² The table below summarizes and defines the factors associated with health system inefficiency.

* <https://www.merriam-webster.com/dictionary/efficient>

Table 1: Factors Contributing to Health System Inefficiency

	Definition
Uncertainty	Not knowing who, when, where, and for what people will need health services makes it difficult for Ministry of Health officials and other decision-makers to appropriately forecast, budget, and manage their resources.
Information Asymmetry	The imbalance of healthcare knowledge and information exchange between patient and provider can contribute to an increase in inappropriate use of resources – leading to inefficient provision of health services.
Disconnect Between Input/Output	Health outcomes (outputs) are difficult to measure and observe, which in turn make it challenging to assess whether the right mix of inputs are being used. This makes it difficult to determine whether health systems are “doing the right things”, “doing the right things in the right place”, or “doing things right”.
Fragmented Financing	Uncoordinated financing from multiple sources makes it difficult to understand the full resource envelope for a given health program – leading to duplication and waste of resources.

Source: *Measuring Health System Efficiency in Low- and Middle-Income Countries: A Resource Guide*. 2019, Joint Learning Network for Universal Health Coverage, International Division Support Initiative (iDSI), The World Bank Group

All of these issues impact the resource allocation process at both the system and individual level – contributing to inefficiencies throughout the health system. For instance, uncertainty around future demand for childhood vaccines makes it challenging for immunization programs to plan accordingly, resulting in sub-optimal allocation decisions and inefficient use of resources. Additionally, it is difficult for healthcare providers to determine the right mix of resources (e.g. labs, medications) needed for a given patient when that patient fails to disclose relevant health information to the provider (information asymmetry).

Predictive analytics is a tool that can be used to support health system planning by strengthening the resource allocation process.

The following section presents an overview of predictive analytics – the difference between traditional methods and AI-driven approaches – and how insights derived from AI-powered predictions can strengthen the decision-making process.

2. AI-powered Predictive Analytics

Predictive analytics leverages a variety of statistical methods and techniques to analyze existing data sets. It attempts to answer the question “What is likely to happen?” by identifying trends and patterns using historical data to predict future outcomes*. AI-powered predictive solutions have been gaining traction globally, as countries and institutions seek to achieve more with available resources and minimizing costs. Machine learning (ML) is a subset of AI approaches that refers to using computer algorithms to develop predictive models. It is a set of methods for getting computers to recognize patterns in existing datasets (input) and make predictions about new datasets (output) based on the rules “learned” from these patterns. As algorithms continue to receive new input data, they develop “intelligence” over time by optimizing their operations to improve performance. These algorithms can analyze a wide variety of data types such as numeric, text, audio, and image files**. While there are other types of AI that do not rely on ML, for the purposes of this paper, the term AI represents technologies that are ML-dependent.

The key difference between traditional statistical modeling and AI-based predictions is whether humans need to specify the relationship between the input data and the outcome of interest in advance.

Using algorithms that allow computers to learn directly from data means that patterns in data can be used to inform predictions without relying on a static model. This can be advantageous because it enables insights to be drawn across more complex datasets that often may seem to have no relation with each other, with more variables, than would otherwise be possible to input into a traditional approach. This can sometimes lead to more precise results than traditional methods; sometimes it can facilitate learning and better understanding of the drivers of behaviors or complex events. Further, once AI models are developed, they can be automated to analyze data in real-time, adjusting for new patterns that may emerge and enable timely insights that may not otherwise be apparent. Table 2 summarizes the key differences between traditional and AI-powered predictive analytics.

* <https://www.gartner.com/en/information-technology/glossary/predictive-analytics-2>

** AI Primer | NetHope Solutions Center

Table 2: Traditional vs. AI-driven Predictive Analytics

	Traditional Predictive Analytics	AI-driven Predictive Analytics
Technology	<ol style="list-style-type: none"> 1. Limited computational power based on past technologies and software 2. Unable to combine and analyze disparate data sources 	<ol style="list-style-type: none"> 1. Enhanced computational capacities based on current and evolving technologies and software 2. Offers an approach to analyze large and unstructured data stored in disparate systems
Data	Requires historical data	Capable of analyzing both historical and real-time data
Methodology	Classical statistical methods requiring humans to define relationships between input and output variables	Use algorithms that allow computers to learn from data, without pre-defining relationships between input and output variables
Application	Results can be used to support human decision-making	Generates a range of insights that can be used to assist human decision-making, as well as autonomously make decisions (if desired)



It is important to note that AI-driven predictions also have distinct risks from traditional methods. Since predictions will be driven by patterns in the data, it is especially important to understand and be aware of biases and spurious associations that may be embedded in the input data. Worse still, these biases could be amplified by the AI models, leading to unintended outputs that often harm the most vulnerable communities, deepening the digital divide, rather than addressing it. For instance, data representativeness is a major concern when deploying AI-based solutions in LMICs. Efforts like ImageNet, an image data set with more than 14 million images, attempt to “clean” the data by removing categories that may appear offensive*. The ability to automate predictive models means there is potential to quickly scale solutions that may be flawed, thus rigorous evaluation and responsible deployment is critical for AI applications. Moreover, governments and other stakeholders engaged in this space need to have transparent conversations to develop practices and procedures to minimize bias in AI**.

As the volume of healthcare data continues to increase, it will be difficult for decision-makers to analyze and digest the massive amount of available information using traditional methods.

Globally, it is estimated that the volume of healthcare data will reach 2,314 exabytes or enough tablets to stretch nearly a third of the way to the moon.¹³ Furthermore, much of the data is stored in disparate systems and databases, creating numerous silos and under-utilized data. Leveraging AI’s ability to analyze a combination of complex and disparate data sources (i.e. climate, behavioral patterns, health, demographics) faster than traditional analytical approaches can help decision-makers to save time and resources, maximize available data, and effectively make data-driven decisions. Section 3 identifies three benefits of AI-driven solutions, and how new insights derived from AI-powered predictions can address factors associated with health system inefficiencies.

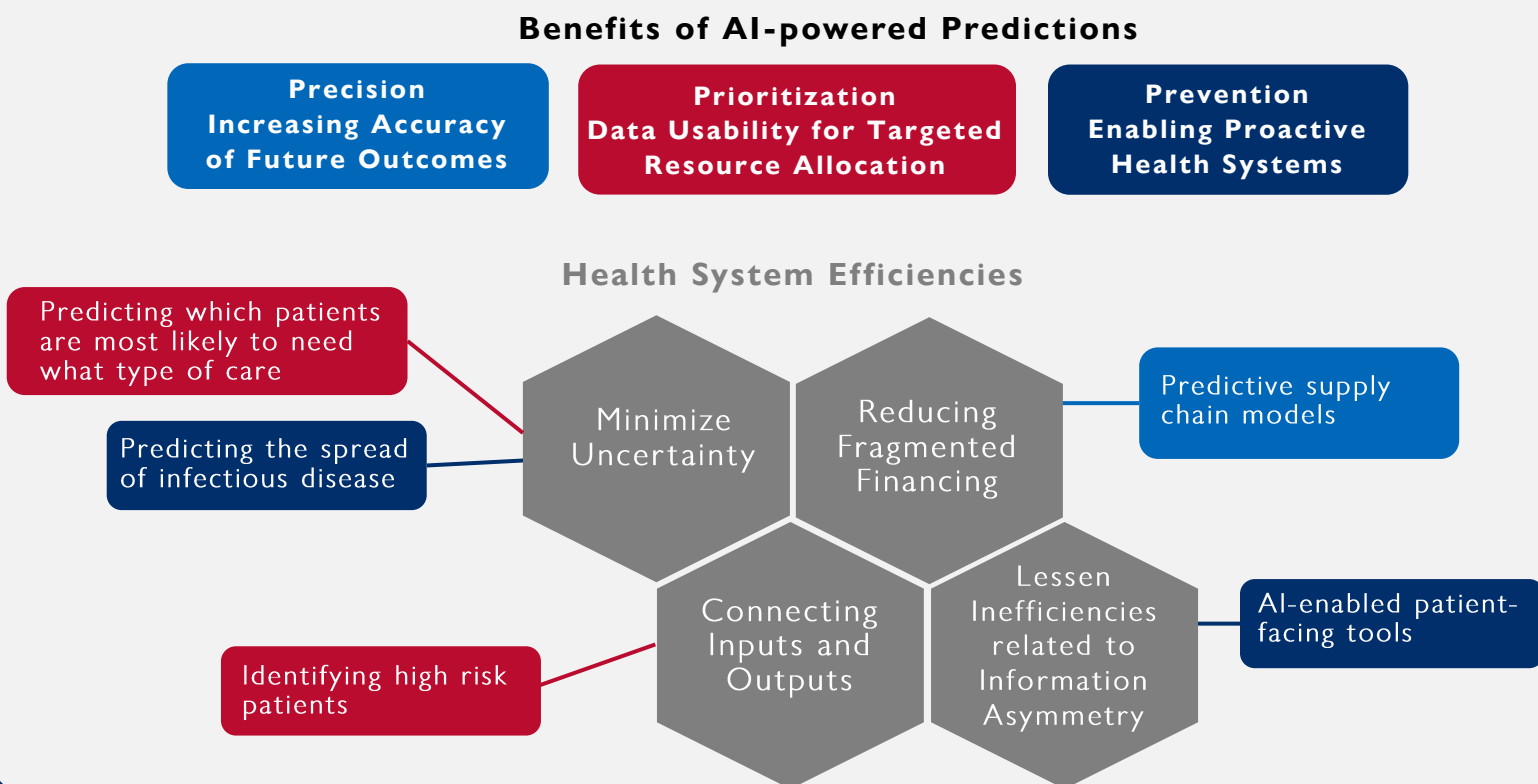
* ImageNet (image-net.org)

** IBM Proposes Artificial Intelligence Rules to Ease Bias Concerns - Bloomberg

3. Using AI-driven Predictions to Improve Efficiency

Often, decision-makers base their decisions on anecdotes or data that lack the level of detail to fully understand the root causes behind systemic supply and demand issue. By analyzing historical and real-time data, AI-driven predictions can offer new interpretations of unexamined data – resulting in a more holistic assessment of a given issue. Notably, information generated from AI-powered predictions have the potential to support data-driven decision-making by: 1) more *precisely* predicting individual and system-level demand, use, and provision of health services, 2) improving the *prioritization* and the allocation of resources based on demand and efficacy, and 3) generating timely insights that enable decision-makers to *prepare* for system-level issues and public health events (expected and unexpected). The figure below offers a conceptual framework that illustrates the relationship between the benefits of AI-driven predictions and improved health system efficiency (Figure 1).

Figure 1: Using AI-driven Predictions to Improve Health System Efficiency



It is important to note that the “3Ps” – Precision, Prioritization, and Prevention – mentioned above are interrelated, with improvements in one area strengthening the other.

The following three sections expand on the 3Ps by providing examples of AI use cases*, and how new information from AI-driven predictions can address many of the factors associated with health system inefficiency, as described in Section 1.1.

3.1 Precision: Increasing Accuracy of Future Outcomes

Diagnostic errors can be costly for the healthcare system and dangerous for patients. One study found that medical errors cost the United States USD 19.5 billion in 2008.¹⁴ To mitigate potential patient harm and reduce the costs associated with misdiagnosis, hospitals and other health facilities are relying on AI-enabled clinical decision support (CDS) tools** that allow health workers to produce faster and more accurate diagnoses. AI-enabled CDS solutions have also been used in LMICs with promising results. Studies have shown that many of the AI-powered diagnostic interventions in LMICs reported “either high sensitivity, specificity, or high accuracy (>85 percent for all), or non-inferiority to comparator diagnostic tools”.⁴ Examples include diagnostic interventions using AI to precisely diagnose tuberculosis¹⁵, malaria¹⁶, and cervical cancer¹⁷.

From overburdened clinicians to task shifting, health workers in sub-Saharan Africa can benefit greatly from augmented intelligence and AI-enabled CDS tools, at least for certain diseases and interventions where there is a sufficiently strong evidence base and quality data.

Improving diagnostic accuracy helps reduce uncertainty by improving the accuracy of information about disease prevalence – allowing for better planning for treatment needs. Other examples of increased precision include use cases like AI-enabled optimization of health operations***. These AI-powered tools have the potential to precisely predict “what will likely happen” by optimizing back-end processes in health system planning. AI technologies like predictive supply chain models have been shown to more accurately forecast vaccine utilization than current methods.¹⁸ By improving demand forecasting, AI-driven predictions can minimize the uncertainty factor that makes efficient resource allocation such a difficult task for decision-makers. Moreover, donors and governments can use this information to better plan and budget for future activities – giving stakeholders an opportunity to coordinate resources and reduce fragmented financing.

* Examples and definitions of AI use cases from the report “Reimagining Global Health through Artificial Intelligence: The Roadmap to AI Maturity” served as the basis for the purposes of this paper.

** AI-enabled CDS solutions are examples of AI-enabled clinical care pathways (AI use cases that support existing and new clinical workflows). Working Group on Digital and AI in Health Reimagining Global Health through Artificial Intelligence: The Roadmap to AI Maturity (broadbandcommission.org)

*** AI-enabled optimization of health operations refers to the use of AI technologies to optimize and improve the performance of back-end processes and procedures. Working Group on Digital and AI in Health Reimagining Global Health through Artificial Intelligence: The Roadmap to AI Maturity (broadbandcommission.org)

3.2 Prioritization: Improving Data Usability for Targeted Resource Allocation

Issues like fragmented information systems and poor data quality add to the already difficult task of determining the best approach for allocating limited resources across the health system. Knowing how to best prioritize and strategically distribute resources based on need, hinges on a comprehensive understanding of the different environmental and human factors that impact demand of health services.

AI use cases that optimize health system operations by filling data gaps, and improving data quality can help consolidate data silos, and provide decision-makers with a holistic view of all data related to a given health issue.

Applications like remote sensing and satellite imagery analysis can quickly gather information that may be out of date or missing from other systems. For example, satellite images can provide proxy estimations of household wealth, population density, or flood risk. To assist with digitizing data, optical character recognition uses AI to digitize hand-written text, speeding up the digitization of paper-based records. AI can also be used to improve data quality, for example, by developing approaches to quickly identify problematic data to remove from analysis and better target data quality improvement efforts*. These types of applications can accelerate the process of filling information gaps and consolidating data silos, resulting in improved data usability and a foundation for more targeted resource allocation.

AI use cases that can help segment populations, identify high risk patients, and enable health workers to anticipate those most likely to benefit from intervention can also help prioritize limited resources in ways that maximize their impact or optimize the link between inputs to outputs. Examples include the use of AI to predict patients most likely to be HIV positive so that testing services can be targeted to them; predicting which patients are most likely to miss appointments in order to target follow-up and adherence support**; and predicting which patients are most likely to need what type of care, thus enabling health workers to better provide differentiated, targeted treatment***. These kinds of interventions can minimize uncertainty – enabling health workers to better prioritize and identify true risks and needs of patients, as well as reduce the duplication and waste of resources.

* <https://www.datakind.org/blog/strengthening-frontline-health-systems-with-data-science-ai-updates-from-our-first-cohort-of-project>

** https://icap.columbia.edu/wp-content/uploads/OpCon-Mozambique_Final-Report_FINAL.pdf

*** <https://www.datakind.org/blog/strengthening-frontline-health-systems-with-data-science-ai-updates-from-our-first-cohort-of-project>

3.3 Prevention: Enabling Proactive Health Systems

Preventing and reducing the burden of disease is one strategy to improve efficiency by minimizing the resources or inputs needed. AI use cases that can predict risk factors for different diseases or forecast emerging disease outbreaks have the potential to reduce healthcare costs. For instance, AI-enabled patient-facing tools* like health apps that use chatbots to communicate with the user, give patients an opportunity to better understand their symptoms. Patients can then determine whether to seek health services or change their behavior to reduce their risk for chronic conditions. These technologies can also minimize the progression of chronic diseases by alerting patients and providers on health issues.

Solutions like AI-enabled patient-facing tools can minimize inefficiency issues related to information asymmetry by equipping patients with knowledge and empowering them to take ownership of their healthcare journey.

Furthermore, these AI use cases can prevent system-related challenges by advising patients on when and where to seek healthcare. This reduces overcrowding at health facilities and allows for the efficient distribution of resources for health.

AI technologies can also be used to prevent disease at the population level by predicting epidemiological patterns and hotspots. For instance, AI-enabled population health solutions can predict the spread of infectious disease and reduce uncertainty about the next emerging threat. These tools can analyze large and disparate data sources such as satellite images, call detail records, and social media data in real-time, giving decision-makers the most current information about a given situation. One study found that using data from social networking sites like Twitter is an efficient resource for preventing outbreaks, and can be an effective and faster tool for disease surveillance than traditional methods.¹⁹

* Working Group on Digital and AI in Health Reimagining Global Health through Artificial Intelligence: The Roadmap to AI Maturity (broadbandcommission.org)

4. Case Studies

AI-based solutions for health are still in the early stages of development and deployment in LMICs. The following four examples were selected for their potential for wide-scale deployment in other countries. The case studies highlight how insights generated from AI-powered predictions can facilitate strategic decision-making and strengthen the resource allocation process.

4.1 Case Study: Leveraging ML models to predict vaccine utilization

Problem: Globally, childhood immunization programs are one of the more successful and cost-effective public health measures. One study found that the estimated return on investment for vaccines is more than 16 times the costs across 94 LMICs.²⁰ The challenge, however, is implementing vaccination programs that maximize immunization coverage. Current methods for predicting utilization rates rely on outdated data (e.g. population census) and technology (e.g. low-dimensional demand forecasting models) – making it difficult for decision-makers to appropriately allocate vaccines to health facilities. Hence, the sub-optimal distribution of vaccines contributes to issues like stock-outs and vaccine wastage.

AI-based Solution: Cooperative Human Artificial Intelligence Network (CHAIN), an AI-enabled enterprise software developed by Macro-eyes, addresses many of the performance issues associated with supply chain management.

By leveraging ML algorithms, they have been able to create a predictive supply chain model capable of precisely forecasting vaccine utilization at granular levels.

Using a combination of publicly available data (e.g. electronic immunization registries) and real-time feedback from frontline health workers, Macro-eyes can predict vaccine utilization at the facility, district, and regional level for weeks and months in advance.

Benefit of AI: The biggest benefit of using AI-powered predictive analytics is the ability to fill in key data gaps related to where and when vaccines need to be distributed based on demand. Initially piloted in Tanzania, CHAIN has been able to outperform current models with an average forecasting fraction error nearly 18 times less compared to the existing system.¹⁸ By reducing uncertainty and precisely predicting vaccine utilization rates, health officials can appropriately prioritize health facilities – lowering the likelihood of stock-outs and wastage.

4.2 Case Study: Harnessing AI technologies to produce hyper-localized population data

Problem: Primary data collection is an expensive and time-intensive exercise. Limited resources and infrastructure compound the challenges of data collection in sub-Saharan Africa. Hence, robust, localized population data are few and far between – leaving decision-makers to make resource allocation decisions with incomplete information. This contributes to the misallocation of scarce resources, and amplifies the difficult task of proactively preparing for health system emergencies like public health events.

AI-based Solution: Fraym, a geospatial analysis firm, leverages AI technologies to produce hyper-local information about emerging disease hotspots and trends.

By considering other health determinants like climate and socioeconomic factors, Fraym's algorithms provide a comprehensive approach to addressing health challenges.

Fraym recently partnered with the World Bank to create various high-resolution maps highlighting different risk factors for COVID-19 in Pakistan. Using geotagged household survey data (Demographic and Health Survey 2018), coupled with satellite imagery, Fraym was able to identify risk of exposure and disease transmission at the provincial, district, and neighborhood level*.

* Fraym Partners with the World Bank - Three ways geospatial data can help Pakistan During COVID-19 - Fraym

Benefit of AI: The benefit of combining geospatial techniques with AI technologies is the ability to produce a more accurate understanding of population data and community characteristics, without the need to invest in primary data collection.

Insights generated from Fraym’s analyses can be used for targeted disease control and prevention.

Moreover, it can minimize the disconnect between inputs and outputs by supporting health systems to “do the right things in the right place”. It also supports strategic decision-making by helping decision-makers prioritize certain areas of the country – resulting in a more targeted and tailored prevention strategy. Being prepared for expected and unexpected events can also help governments systematically prioritize and allocate public resources.

4.3 Case Study: AI-based solutions to improve frontline health worker performance

Problem: Children under five years old in sub-Saharan Africa are especially vulnerable to dying from preventable diseases like diarrhea*. In response, the World Health Organization (WHO) and the United Nations Children’s Fund (UNICEF) developed the Integrated Management of Childhood Illness (IMCI) strategy – an integrated approach to improving child health. One component of IMCI focuses on improving the case management skills of frontline health workers. The challenge, however, is getting frontline health workers to consistently use the IMCI protocol as part of their clinical consultations. Typically, the protocol is available as a paper-based document, making it difficult for routine use across all health facilities.

AI-based Solution: Since 2009, Terre des hommes foundation (Tdh) has been leading the Integrated eDiagnosis Approach (leDA) project in Burkina Faso. In collaboration with the Ministry of Health, leDA has been working to improve the consistent use of IMCI guidelines by deploying tablets with digital versions of the protocol.

* <https://www.un.org/sustainabledevelopment/health/>

The goal is to assist frontline health workers with correctly managing and treating childhood illnesses by streamlining the use of IMCI, as well as the data entry process from paper-based to electronic forms. leDA is one of the few digital interventions at scale in the region, with 67 percent of all health centers in Burkina Faso involved. Over the years, the project has been able to amass a database with over five million consultations.

Recognizing the volume of digitized data as an opportunity to analyze previously unexamined questions, Tdh has taken leDA one step further by partnering with the Cloudera Foundation to incorporate AI-powered predictive analytics.

The main objectives for the AI phase of the project include the use of algorithms to identify irregularities in the consultation data to improve health worker performance, as well as leverage AI-driven analyses to predict disease outbreak.

Benefit of AI: Currently, the AI-based component of the project is in the research phase. At the same time, preliminary findings have been promising. By leveraging insights generated from AI-powered predictions, the project has been able to precisely detect the most common errors in real-time – enabling them to anticipate the types of clinical irregularities made by each frontline health worker*. This has allowed them to provide continuous individualized feedback – preventing and decreasing the number of mistakes and inefficient use of resources. Additionally, by integrating their database with other health information systems like DHIS2, leDA has given Ministry of Health officials a more holistic understanding of health worker performance issues at the facility level. Efforts like Tdh highlight the potential to incorporate AI-based solutions to existing digital health projects in LMICs.

4.4 Case Study: Using Natural Language Processing to reduce maternal mortality

Problem: Maternal mortality continues to be a major concern in Kenya**. Many of these deaths are preventable, and related to pregnancy and childbirth issues. According to the Kenya Ministry of Health, 33 percent of maternal deaths could have been avoided by timely care-seeking behaviors***. A lack of awareness and limited knowledge about the danger signs associated with pregnancy and

* How we're improving healthcare for children in Burkina Faso - Cloudera Foundation Blog

** It's Time to Take Maternal Mortality in Kenya Seriously – FXB Center for Health & Human Rights | Harvard University

*** CEMD-Summary-of-findings-Sept-3-FINAL.pdf (familyhealth.go.ke)

childbirth, as well as prenatal/postpartum care, make it challenging for women to determine whether and when to seek health services.

AI-based Solution: Jacaranda Health, a nonprofit organization, is working to reduce maternal mortality for low-income mothers in Kenya. Spurred in part by the high penetration of mobile phones, Jacaranda Health has implemented a low-cost digital solution (PROMPTS) where they send text messages to women, covering topics like danger signs related to pregnancy and family planning – leading to an increase in care-seeking behaviors. For instance, women who received family planning messages were 1.85 times more likely to access services compared to controls.²¹ The digital platform also includes a help desk function that allows mothers to send questions about a particular concern or to seek general pregnancy advice. To improve the efficiency and timeliness of responses, the project has integrated an AI-based triage system that prioritizes messages based on medical need to ensure that all questions are answered in an organized, equitable, and timely manner. Specifically, the AI-based triage system uses natural language processing to read and analyze thousands of messages per day for urgency and prioritization. These messages are then answered by agents – maintaining a human-in-the-loop system – who then recommend next steps like nutrition advice or schedule referrals for urgent and emergency issues*.

Benefit of AI: By integrating an AI-powered component to their digital health platform, Jacaranda Health has been able to quickly scan and respond to messages from mothers – allowing them to optimize program effectiveness, while minimizing costs.

The AI-based triage system has allowed agents to respond to urgent questions within two hours, giving women the timely response necessary to act quickly, as well as prevent emergency situations**.

More importantly, the project has been able to empower women by equipping them with knowledge about prenatal and postpartum care – minimizing the inefficiency issues related to information asymmetry. This has increased the likelihood for women to seek medical care when pregnant, and has improved maternal health metrics like antenatal care (ANC) visits. For instance, health facilities participating in PROMPTS have shown a 20 percent increase in mothers completing four ANC visits compared to non-participating facilities***.

* How Jacaranda Health is getting help for mothers in Kenya faster using Natural Language Processing - Ai Kenya

** PROMPTS — Jacaranda Health

*** PROMPTS — Jacaranda Health

5. Considerations for Optimizing AI-driven Predictions in Decision-Making

The previous sections have highlighted how new insights generated from AI-powered predictions can be used to strengthen the resource allocation process, and improve health system efficiency. There are, however, several foundational elements that need to be in place before countries can successfully and optimally leverage AI-driven analytics.

As a subset of digital technologies, AI-based solutions require a robust digital ecosystem, with many of the eHealth building blocks from the International Telecommunication Union (ITU) and WHO's National eHealth Strategy Toolkit* in place, to fully deliver on its potential.

Rather than providing an exhaustive list of recommendations for creating an enabling environment for AI, this paper builds on the U.S. Agency for International Development's *A Vision for Action in Digital Health***. In short, the paper focuses on three areas that countries need to consider when using AI-powered predictions in decision-making. First, data **governance** is a critical component of ensuring the availability, access, and effective use of good quality data. Second, countries need to cultivate local **capacity** to collect, analyze, and routinely make data-driven decisions. Third, digital **investments** should create an enabling environment for AI technologies, while at the same time, stay consistent with national digital health strategies, prioritize global goods, and support the broader digital ecosystem transformation (Figure 2).

Figure 2: Summary of Key Considerations



* National eHealth Strategy Toolkit | WHO | Regional Office for Africa

** A Vision for Action in Digital Health (usaid.gov)

5.1 Governance

Data, in many ways, functions as the fuel that give algorithms the ability to extract value and generate new insights for the users. Without robust and quality data, it will be difficult to fully harness the power of AI-driven predictions. As AI-based tools for health continue to gain prominence, the importance of data will only increase. Countries need to act now to ensure that the collection, storage, and use of data promotes responsible deployment and will strengthen the integrity of future AI applications. Policymakers should consider: 1) applying a governance perspective that promotes data protection rights, 2) promoting a culture of responsible data sharing across stakeholders, sectors, and geographies, and 3) establishing a data quality improvement strategy.

Apply a governance perspective that promotes data protection rights:

Policies that protect sensitive health data and user rights are necessary to garner public trust, which is vital for large-scale adoption of AI-based solutions. Fears around data breaches and mishandling of personal information will only increase as the availability of digitized data continues to grow. The commoditization of individual health data can have negative human rights impacts. Policymakers will need to apply a governance perspective that benefits the public, as their constituents demand more data protection and privacy rights. The European Union has introduced regulations for entities collecting and using personal data*. South Africa has also implemented data privacy laws that protect consumers by requiring the secure and local storage of personal information**. These policies will have significant implications on how health data for AI applications can be collected, used, and shared within and across borders – as well as on the practices of organizations seeking to use health information. It will be important for governments to ensure that all parties involved understand and capable of adhering to these policies, along with the opportunity to contribute to the development of sound practices as they continue to evolve.

* Data protection in the EU | European Commission ([european-council.europa.eu](https://european-council.europa.eu/media/en/press-communications/infographic/infographic_data-protection-in-the-eu-2018-2019))

** South Africa's new data privacy laws take effect tomorrow – What you need to know ([mybroadband.co.za](https://mybroadband.co.za/news/industry/101124/south-africa-s-new-data-privacy-laws-take-effect-tomorrow-what-you-need-to-know))

Promote a culture of data sharing across stakeholders: One of the benefits of AI technologies is the ability to analyze large volumes of disparate and incomplete data. Access to data is critical for AI algorithms to generate useful information. The challenge, however, is the limited opportunities for the private sector, researchers, and other stakeholders to share and collaborate across and within sectors. Issues like data ownership, data silos, and proprietary data contribute to the challenges surrounding data sharing – leading to fragmentation and under-utilized data.

As AI-powered predictions depend heavily on the availability and access to data, policymakers need to promote a culture of responsible data sharing by establishing data exchanges and agreements with appropriate data protections.

Establish a data quality improvement strategy: Data integrity and quality algorithms need to be at the forefront of any AI-based solution. The performance of AI-powered predictions depends on the quality of the data and algorithms used to produce the new information. Ethical issues like bias and unfair outcomes can be unintentionally exacerbated when using poor quality and inaccurate data. Policymakers need to be able to trust the insights generated from AI-powered predictions to confidently apply those results in decision-making. Benchmarking efforts like the one initiated by ITU and WHO, provide the international framework to evaluate AI-based solutions.²² Similarly, policymakers should establish national frameworks to ensure the accountability of AI projects. These frameworks should require AI development teams to transparently share procedures that guarantee the continuous evaluation of AI-driven approaches. Importantly, it will be critical to include data quality improvement strategies that incentivize the collection and use of quality data to minimize misrepresentations of data.



5.2 Capacity

Building local capacity to collect, analyze, and use data, as well as design and maintain AI tools, is a critical component for long-term sustainability and large-scale adoption of AI-based solutions.

Given the danger for AI to exacerbate stereotypes or reinforce wrong conclusions, it is essential to cultivate homegrown AI algorithms and data collection that sufficiently represents the population it intends to benefit.

Investing in local human capital capable of contributing to the AI ecosystem can help mitigate some of the ethical issues like bias and accountability. As part of this process, countries should: 1) institutionalize data-driven decision-making at all levels of the health system, 2) foster research and innovation hubs, and 3) develop a roadmap that aligns AI technologies and the local workforce.

Institutionalize data-driven decision-making: New insights about the data are only useful if decision-makers at all levels of the health system have the capacity to digest, understand, and act based on the information generated from AI-powered predictions. Decision-makers need to incentivize, develop, and empower relevant staff to make data-driven decisions. Practices that create a culture of data-driven decision-making can help institutionalize and expand the use of data to inform the resource allocation process. For instance, incorporating data and analytics into routine organizational processes that bring together multi-disciplinary teams encourages critical thinking. To support these endeavors, countries need to establish an environment that supports the safe and secure sharing of data, as well as create government training and development opportunities to build proficiency in data skills.

Foster research and innovation hubs: Research and innovation hubs offer an opportunity for governments to leverage public and private sector resources to cultivate local talent by bridging the gap between higher education and industry. Building local technical skills and knowledge, strengthening research, and supporting responsible innovation can help address the various biases that come from out-of-context experiences, foster applications that are responsive to local needs, and ensure long-term sustainability of AI tools. Innovation hubs also provide a way to meaningfully engage young people. Opportunities such as internships and employment after graduation can incentivize young people to pursue professions that contribute to the AI ecosystem.

Develop a roadmap that aligns AI technologies and the workforce: As countries continue to adopt AI-driven approaches, it will be imperative for governments to identify the skills and knowledge needed to sustainably deploy AI. Policymakers should develop a national roadmap that outlines the AI goals and the necessary workforce to achieve those objectives. A feasibility assessment that examines the status of the workforce can help with this process by identifying current gaps and opportunities in the labor market. The roadmap should highlight the education and training needs to meet both near-term and long-term requirements.

5.3 Investments

Many of the same investments endorsed by the Principles of Donor Alignment for Digital Health* serve as prerequisites for numerous AI-based approaches. Strategies that promote long-term investments and sustained financing are necessary to fully realize the benefits of AI-powered predictions. Countries should: 1) prioritize digital investments that are aligned with national digital health strategies, promote the use of global goods, and have the potential to benefit multiple sectors, 2) proactively shape private sector investments, and 3) increase investments to routinely evaluate AI projects.

Prioritize digital investments that are aligned with national digital health strategies, promote global goods, and have potential to benefit multiple sectors: Investments in the digital ecosystem at large are necessary for many of the AI-based solutions to succeed at scale. Specific investments, however, may differ as countries display varying levels of digital maturity. Many countries have digital health strategies that should inform investments in strengthening digital ecosystems for AI.

Prioritizing digital investments that are consistent with national strategies and contribute to the broader development of a country's digital ecosystem help strengthen the overall digital infrastructure and mitigate further fragmentation.

This can create opportunities and resources that can be leveraged across multiple sectors and geographies. Moreover, countries taking a holistic digital ecosystem approach can take advantage of economies of scale and expect greater return on investment.²³ For instance, investing in national digital health architectures can strengthen interoperability between data systems, promote efficiencies, and create a foundation for future applications of AI.

* Digital Investment Principles | Donor Alignment Principles in Digital Health

Other investments to accelerate the adoption of AI include, but are not limited to: 1) local data warehouses for storing large volumes of data, 2) cloud computing to facilitate processing and data analysis, 3) management information systems for sufficient, high quality, machine-readable data, and 4) global goods – solutions that are open-source, adaptable, and reusable – should be emphasized to support long-term sustainability.

Proactively shape private sector investments: Governments need to proactively engage private sector firms already investing in sub-Saharan Africa.²⁴ Policymakers should develop policies that encourage private sector participation where it can strengthen country digital health systems and advance development objectives. These partnerships are necessary to bolster investments in human capital and infrastructure development to collect, manage, and maintain large sums of quality data, as well as the AI-based technologies that depend on it. It also offers an opportunity for governments and the private sector to identify mechanisms for better and more effective collaboration on sensitive issues like data ownership and storage. The challenge, however, will be for governments to develop policies that balance the needs of the public such as privacy and data security (especially for a sensitive area like health), while regulating the private sector without limiting growth and innovation.

Increase investments to routinely evaluate AI projects: Policymakers should consider establishing policies and procedures that support the routine assessment and evaluation of AI projects. To support this effort, governments need to coordinate with stakeholders like researchers and the private sector to increase investment in and transparency of rigorous evaluations of AI, and develop processes for sharing cost and impact data. Understanding the trade-offs and opportunity cost of investing in AI is critical, since AI-based solutions may not always be the best approach for a given problem. Findings from these evaluations can also help decision-makers assess whether the investments made in AI-driven approaches are worth scaling. Decision-makers interested in the details of such analyses can find additional information in the costing companion piece (see the report, “*Developing Economic Impact Assessment Methods to Identify the Costs of AI-powered Health Technology*”).

6. Conclusion

According to Gartner, AI augmentation is projected to “create USD 2.9 trillion of business value and 6.2 billion hours of worker productivity globally”.²⁵ The business case for AI-based solutions to improve efficiency is one of the main drivers for AI’s rapid adoption globally.

Despite the hype and promise surrounding AI technologies, it is important to note that AI is not a silver bullet for all healthcare challenges.

Many AI projects fail to deliver on the expectations and value initially promised. Gartner predicts that by 2022, “85 percent of AI projects will deliver erroneous outcomes due to bias in data, algorithms or the teams responsible for managing them”.²⁶ Additionally, AI is one tool among several digital health solutions for policymakers to consider when determining the best intervention for a given problem. Hence, AI-based interventions may not always be the most optimal solution depending on the maturity of the digital ecosystem.

Yet, the outlook for AI technologies to transform healthcare in sub-Saharan Africa is promising.

Without the legacy health systems found in many high-income countries, sub-Saharan Africa has the advantage to be nimble and flexible in their approach to adopting and deploying AI-based solutions. This will, however, require investments in the foundational digital health infrastructure. Furthermore, the growing youth population offers an opportunity for countries to grow and nurture local technical skills that are needed to successfully implement large-scale AI solutions for health.

With the pandemic threatening to derail decades of progress and advances in health, it is now more important than ever for LMICs to seriously assess the potential of digital technology and AI as part of their strategy to address healthcare challenges. If the pandemic has revealed anything, it is that emerging diseases do not discriminate nor respect state boundaries. The speed with which the global scientific community has rallied together to tackle one of the greatest public health emergencies in more than a century is partly due to the use of digital technologies like AI.

The mainstream acceptance of digital health like telemedicine, coupled with the additional resources allocated for COVID-19, provide a unique opportunity for countries in sub-Saharan Africa to invest and strengthen their digital ecosystem.

As digital health strategies are being drafted, countries need to consider how and where to integrate AI technologies and prioritize investments that create a foundation for the responsible use of AI-driven approaches in the post-pandemic era.

As the adoption of AI-enabled solutions is expected to rise exponentially into the 21st century, policymakers need to be forward thinking and consider the opportunity cost of AI. When used thoughtfully, AI can be a powerful tool to improve health system efficiency. By incorporating AI-driven analytics into the decision-making process, policymakers can rethink decades-old problems and strategically allocate resources across the health system based on new insights about the data. Moreover, AI-powered predictions have the potential to set the stage for intelligent and proactive health systems – those that meet the needs of all patients and ensure quality health for all.

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