Implementing AI in Tanzanian Health Supply Chain

JSI

inSupplyHealth

MACRO-EYES

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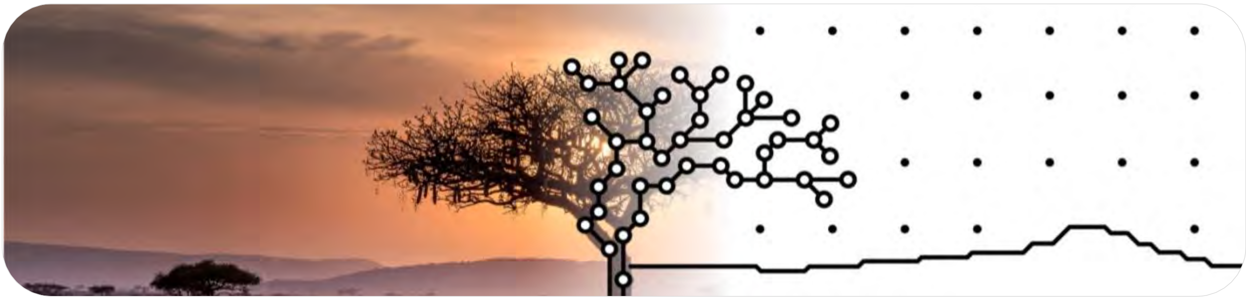

Preface

Artificial Intelligence (AI) solutions are becoming increasingly popular globally as their positive impact on a wide range of domains continues to expand. Tanzania has spent the last decade investing in strengthening health data collection systems and communications technology, priming the country to begin deploying AI solutions in health supply chains.

This report aims to be the central guide used by Tanzania and other middle- and low-income countries in assessing the potential benefits of Artificial Intelligence-based technologies, the country's readiness to integrate such technologies and their ability to prepare for success upon implementation by following a *Theory of Change/Theory of Action* framework.

This report will provide ideas from a wide variety of stakeholders on: How a country can select the right technologies to implement at the right time and with the right partner. How a country can ensure AI readiness, not only for a short period of time, but long-term.

Acknowledgements

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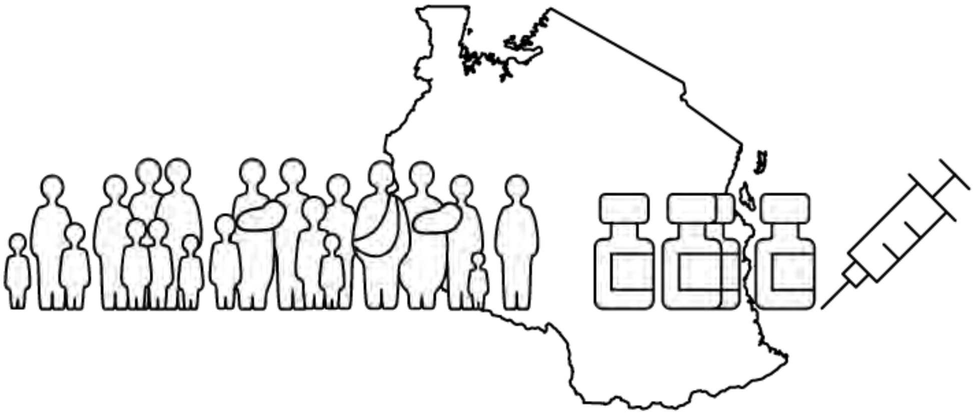
This report was written by Johnna Sundberg, Machine Learning Scientist and Emma Delmotte, Senior Partnerships Manager, of Macro-Eyes. Harrison Mariki, Senior Advisor, of inSupply Health and Jacqueline Minja, Supply Chain Analyst of John Snow, Inc. contributed greatly to the content of this report by organizing workshops, surveys, webinars, and interviews, with key stakeholders in Tanzania, providing feedback on report content, contributing their ideas and technical expertise, and developing the *Theory of Change/ Theory of Action* framework for this document.

Many thanks are extended to the broader Macro-Eyes and inSupply Health teams for their technical inputs and feedback. Additional gratitude is expressed towards our workshop participants for their contributions and feedback on the *Theory of Change/Theory of Action* framework.



Executive Summary

AI solutions are powerful technologies with demonstrated positive impact across healthcare and other domains, even when data and technical infrastructure are limited. The AI revolution has also reached Tanzania, and through a **Theory of Change/Theory of Action framework** developed with health supply chain stakeholders we demonstrate that the Tanzanian government has invested in many of the required preconditions to begin integrating AI technologies into existing health systems and map out several use cases where AI can have immediate impact.

Overview of Artificial Intelligence

AI readiness captures the ability of an organization to gain value from investing in Artificial Intelligence. The rise in the popularity of AI coincides with a global increase in AI readiness.

There has been an exponential increase in data globally, resulting in more powerful AI algorithms. Concurrently, the cost of building AI models has decreased substantially through easily accessible and affordable computational power.

Both of these factors mean that AI has transformed every sector of the economy, leading to claims that AI is the **"new electricity."**[1]

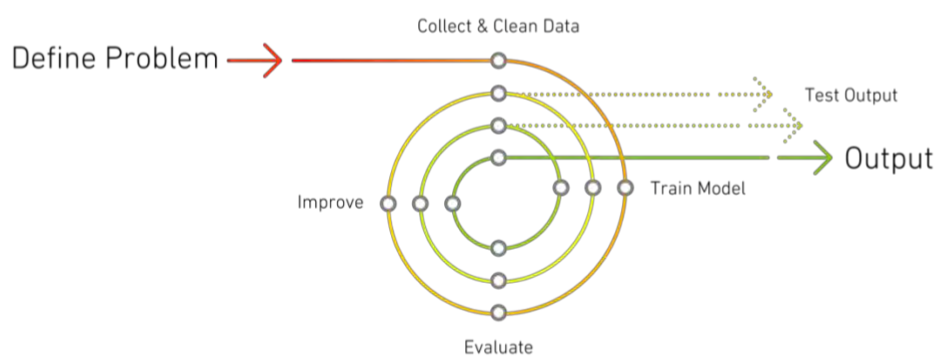
Within the healthcare industry, AI is projected to have the potential to radically cut healthcare costs by changing healthcare from reactive to

[1] Lynch, S. (2019). Andrew Ng: Why AI is the New Electricity. [online] Insights by Stanford Business. Available at: www.gsb.stanford.edu.

proactive by providing earlier diagnoses, precision medicine, and efficient treatment and follow-up.[2] Additionally, AI is used to optimize allocation of scarce health resources further improving outcomes and access.

AI has had such a large impact because of its ability to predict the future much more accurately than traditional statistical models. AI models capture complicated relationships and leverage both tabular and unstructured data such as satellite imagery and text data.

Even with limited data, AI solutions can still be explored and even perform well given their ability to leverage non-tabular data sources. AI does not require perfect, countrywide data. AI has been used even in situations of limited and/or imperfect data. The best way to determine if data is usable is to begin working with an AI team.



The AI process is a highly iterative process. It begins by defining the problem statement, or by framing the problem that AI will solve. Then, the AI team will collect and process data and use this data to develop AI models. Next, the AI team will work with stakeholders to evaluate models against historical benchmarks and by piloting the technologies when necessary. If the model performs well, the model will be deployed into the preferred system. AI solutions can integrate seamlessly into existing systems and interfaces.

Throughout this iterative process, AI algorithms are continuously evaluated. Monitoring and evaluation (M&E) are central to the machine learning development process. AI solutions are rigorously tested and evaluated to ensure that they are performing better than the baseline and continue to improve over time.

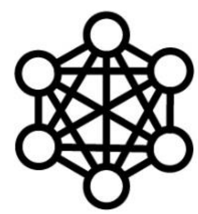
[2] Bohr, A., & Memarzadeh, K. (2020). The rise of Artificial Intelligence in healthcare applications. *Artificial Intelligence in Healthcare*, 25–60. https://doi.org/10.1016/B978-0-12-818438-7.00002-2

Theory of Change/Theory of Action for Tanzanian Health Supply Chains

In order to develop the Theory of Change/Theory of Action framework, a series of workshops were hosted with stakeholders from organizations representing the whole supply chain, including government, private suppliers, non-governmental organizations and academia. The Theory of Change/Theory of Action was created during the workshop series with participants' input.

The ultimate goals of deploying AI in health supply chains are to increase access and equity to healthcare by enabling AI solutions and empowering stakeholders to use them. In order to meet this goal, stakeholders identified five key preconditions: technical infrastructure, policy and strategy, knowledge and skills, partnerships, and financial resources.

Technical Infrastructure. The Tanzanian government, like many other LMIC countries, has implemented electronic health systems that are now collecting thousands of data points daily. The government has also invested in computing infrastructure that allows for data to remain completely in-country during the development and deployment of AI technologies. Tanzania can deploy AI using these systems and can continue to improve AI readiness by scaling and improving interoperability of existing systems.



Policy & Strategy. Following the success of the 2013-2018 National Health e-Strategy, the Tanzania MoHCDGEC released the 2019-2024 Digital Health Strategy (DHS) which comprehensively outlines steps Tanzania can take to create a supportive digital environment for AI solutions. Stakeholders identified additional needs including policies to safeguard data and more specific guidance on using AI within the health sector.

Knowledge & Skills. In-country organizations such as Tanzania AI Lab are working to promote AI for social impact and develop the capacity of local AI developers; however, stakeholders expressed interest in government-led activities including 'hackathon' workshops, learning sessions with other countries, and incorporating ML skills in continuous education plans.

TanzanAILab

Partnerships. The Tanzanian government has a long track record of successful partnerships for digital health solutions. Partners can be non-governmental organizations, independent AI experts, private sector companies, locally and abroad, to ensure the priority is to ensure Tanzania has access to the best knowledge in the world when it comes to AI. Stakeholders recommended that partners provide ongoing technical

assistance to build local capacity and that clear data approval processes are developed to support partners developing AI solutions.

Tanzania's investments in the preconditions demonstrate that Tanzania is ready to begin considering AI technologies to bolster supply chain efficiency and improve health outcomes.

Use Cases for Implementing AI in the Tanzania Health Supply Chain

In the workshops and through external research, several use cases were identified where Tanzania can immediately begin implementing and deploying AI solutions.

One key area identified by stakeholders is improved health supply forecasting. AI technologies have proven to be more successful than traditional forecasting methods. Macro-Eyes is developing forecasting technology for the Tanzanian health supply chain that reduces forecasting error to less than three for every 100 vials of vaccine delivered to health facilities. This use case meets needs from healthcare workers, public suppliers, ministry of health officials, and implementing partners.

Another key use case is improving supply chain routing, which meets needs from healthcare workers, public suppliers, private suppliers, and Ministry of Health officials. For example, Logistimo developed a Vehicle Routing and Scheduling product to identify optimal delivery routes but also schedule deliveries accordingly in order to produce a routing that can be agile to demand shifts. Logistimo deployed this technology as part of their end-to-end product suite in Uganda, leading to 90% availability of stock.[3]

Improving health supply chains also includes the patient. In order to meet their needs, Babylon Health built an AI-based chatbot called the "Symptom Checker". The app educates patients about their health and gives them recommended steps based on their individual needs. Empowering patients to take initiative can help manage demand at already busy clinics and

[3] Logistimo website (2019). Uganda GAVI VLMD. Available at: https://www.logistimo.com/uganda (Accessed 17 May 2021)

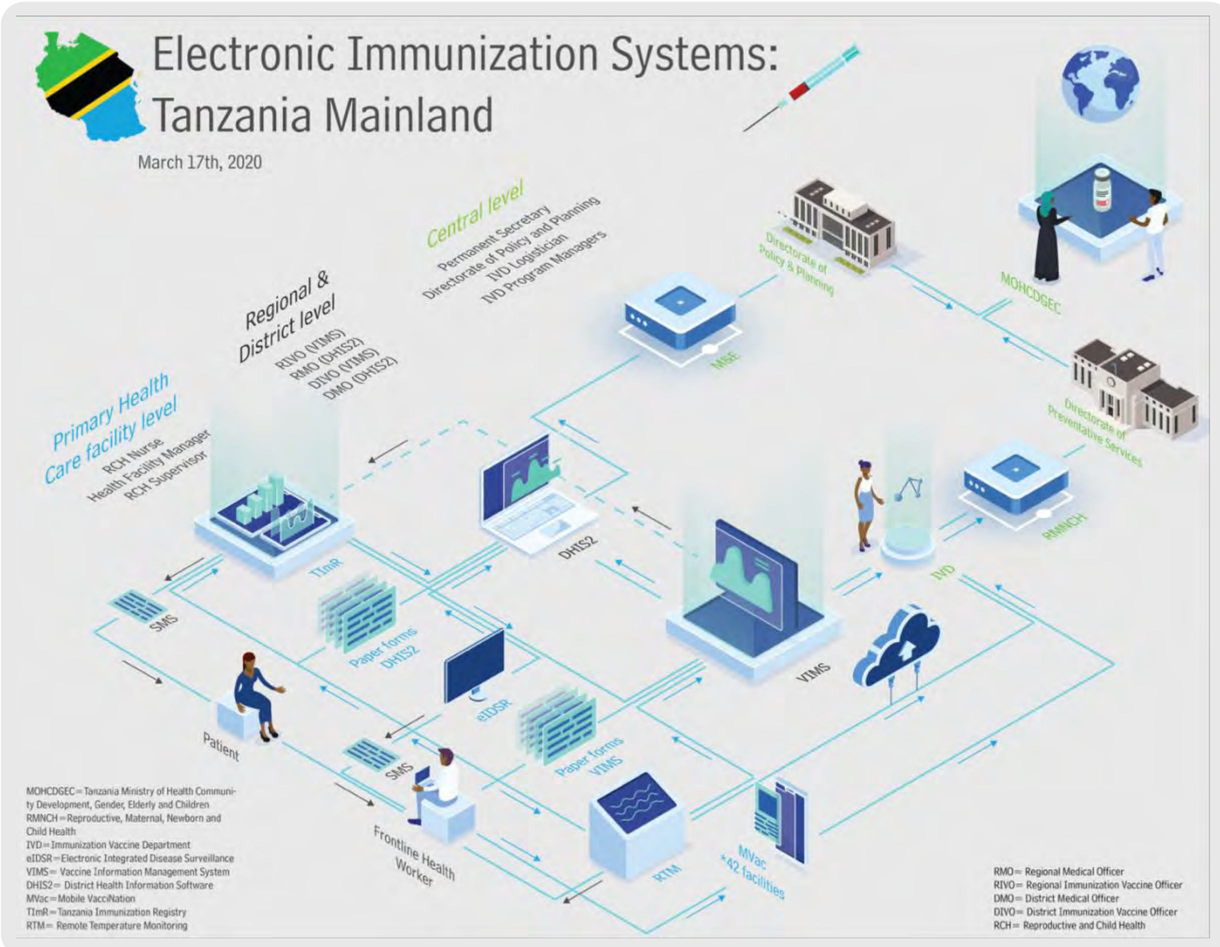
improve forecasts. This technology can help meet the needs of not only patients, but also healthcare workers.

AI can bolster supply chains by mining information directly from health care worker texts to improve both demand and supply forecasting, automating inventory counting for better visibility and traceability, and predict health system infrastructure to show where investment is needed. These powerful solutions are all available today and can be quickly integrated and implemented into Tanzania's health supply chain.

Conclusion

AI solutions are powerful technologies with demonstrated positive impact across healthcare and other domains. Per the Theory of Change/Theory of Action, AI technologies can be used to improve health service delivery and increase population health.

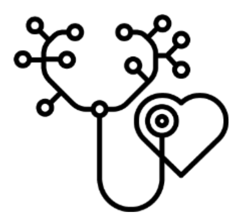
The Tanzanian government has heavily invested in the preconditions to AI technologies. Tanzanian health policymakers should consider developing national AI strategies to guide investment in strategic partnerships to begin implementing AI technologies.


Electronic Immunization Systems:
Tanzania Mainland
March 17th, 2020
Central level
Permanent Secretary
Directorate of Policy and Planning
IVD Logistician
IVD Program Managers
Regional &
District level
RIVO (VIMS)
RMO (DHIS2)
DIVO (VIMS)
DMO (DHIS2)
Primary Health
Care facility level
RCH Nurse
Health Facility Manager
RCH Supervisor
Directorate of
Policy & Planning
MOHCDGEC
Directorate of
Preventative Services
MSE
RMNCH
IVD
DHIS2
TImR
VIMS
SMS
Paper forms
DHIS2
eIDSR
Patient
SMS
Paper forms
VIMS
Frontline Health
Worker
RTM
MVac
+42 facilities
MOHCDGEC=Tanzania Ministry of Health Community Development, Gender, Elderly and Children
RMNCH=Reproductive, Maternal, Newborn and Child Health
IVD=Immunization Vaccine Department
eIDSR=Electronic Integrated Disease Surveillance
VIMS= Vaccine Information Management System
DHIS2= District Health Information Software
MVac=Mobile VacciNation
TImR=Tanzania Immunization Registry
RTM= Remote Temperature Monitoring
RMO= Regional Medical Officer
RIVO= Regional Immunization Vaccine Officer
DMO= District Medical Officer
DIVO= District Immunization Vaccine Officer
RCH= Reproductive and Child Health

Introduction

Artificial Intelligence (AI) technology is becoming increasingly popular globally as its positive impact on a wide range of domains continues to expand. The past decade has led to an explosion of new data sources and less expensive computing resources democratizing the proliferation of AI.

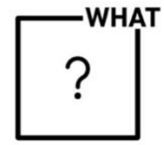
AI technologies have been deployed in almost every country in the world and are being used in a variety of private and public sector applications, including health supply chains.



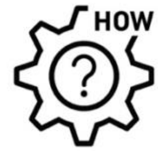
Health systems collect vast amounts of data through systems primed for AI integration. AI technologies have improved medical supply forecasting, predicted disease outbreaks, optimized supply routes, and estimated health system infrastructure.

The AI and data revolution have also reached Tanzania. The Tanzanian government has implemented many health systems in the last decade that are now collecting thousands of data points daily – more than enough data to begin implementing AI solutions. The government has also invested in internet and computing resources that empower data sovereignty - allowing for data to remain completely in-country during the development and deployment of AI technologies.

The goal of this document is to accelerate intelligent dialogue on how the Tanzanian government can begin implementing AI health supply chains. We use a Theory of Change/Theory of Action (ToC/ToA) framework to document the proposed changes.



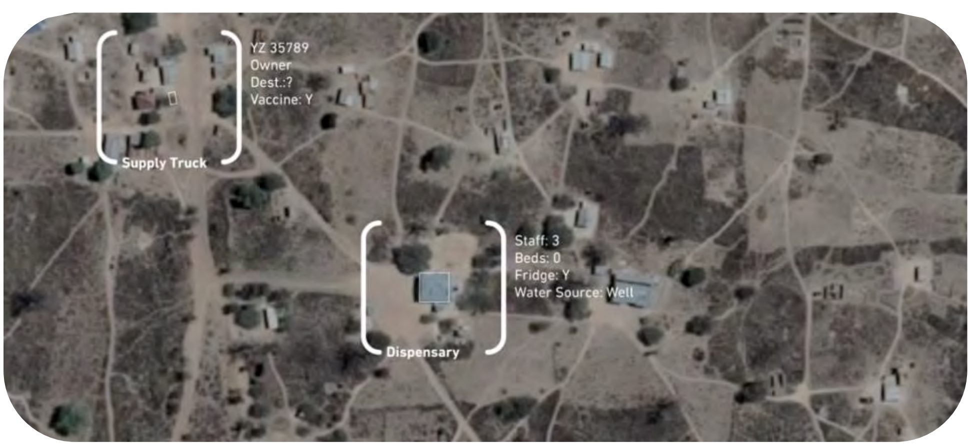
The ToC/ToA framework was successfully used to guide implementation of new health interventions in the past and is familiar to key health supply chain decision-makers in Tanzania. These tools allow for the careful documentation of the **what, how, and who** for change.

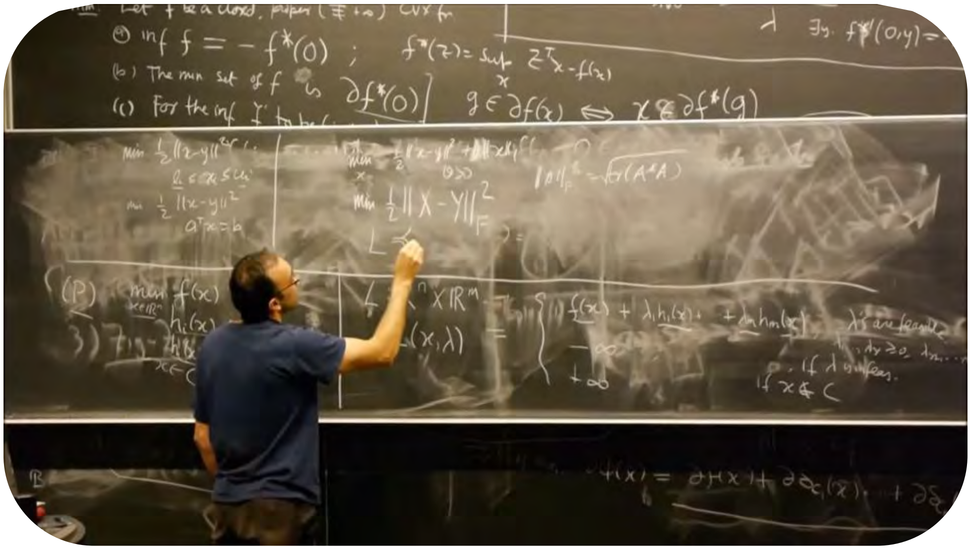


The content of this document, including the ToC/ToA, were developed through collaborative workshops with key stakeholders in Tanzanian health supply chains and expert informant interviews.

The document also draws extensively on the experiences of **Macro-Eyes, John Snow Inc (JSI),** and **inSupply Health** building and implementing technology solutions in the Tanzanian health system.

We begin this document with an **overview of AI and machine learning (ML**) for health supply chain decision-makers, including estimated time requirements for deploying AI solutions. Supply chains are the foundation of strong health systems and a good foundation for understanding the potential of AI. Next, we present **the outputs of the ToC/ToA.** Lastly, we end with a discussion on **how Tanzania can leverage AI/ML** to improve the Tanzanian health supply chains.





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CHIEF AI OFFICER
MACRO-EYES

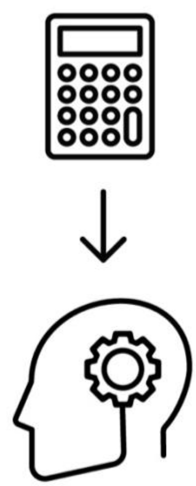
Overview of Artificial Intelligence and Machine Learning

Section Summary

Artificial Intelligence (AI), and its subfield machine learning (ML), have become increasingly popular over the past decade as the technology has become more powerful, resilient, readily available and understood for operational users.

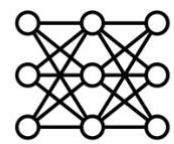
AI has proven its potential for impact across almost all domains globally in real world application. AI and ML technologies are developed using sophisticated mathematics that uncover non-linear, complex relationships between many different variables, making them dynamic, resilient, and often more predictive than traditional statistical and M&E methods – even with little or poor-quality data. The latter notion may sound controversial in the context of historical discussions of AI which suggest a need for reams (a lot) of highly curated data – the field is advancing rapidly, and we will address this in the coming pages.

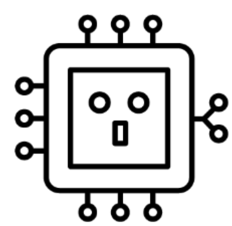
Today, many safeguards exist to ensure machine learning preserves data privacy and creates sustainable impact for good.



Objectives

- Define AI and differentiate between AI and ML.
- Discuss why AI has increased over past decade, in all sectors, on every continent.
- Provide an overview of the ML development process.
- Enumerate key questions and concerns for decision-makers in AI development:
    - Do I have enough data? **Is my data good enough?**
    - How do I ensure **my data is secure?**
    - How can **I evaluate the machine learning model?**
    - How do I ensure my **ML models are ethical and unbiased?**





AI has been referred to as "the new electricity."

Over the last decade, the field of Artificial Intelligence (AI) has begun to revolutionize global society with its transformational impact realized across industries. Due to its powerful potential across domains, AI has been referred to as "the new electricity."[4]

AI is driving rapid global economic evolution, much like electricity in the twentieth century. AI has been adopted into the daily operations of many major companies and governments and those adopting with the greatest rigor are quickly taking command of their markets. The majority of the planet's population interacts with an AI-algorithm on a daily basis, whether via social media, internet searches, ride-share apps, or even product purchases from multinational corporations. In some senses AI is mundane.

Both private and public sector entities worldwide are adopting AI to generate value. According to the 2020 State of AI report by McKinsey, a global management consulting firm, over half of companies surveyed are currently using AI. Although AI use was lower in lower-income and middle-income countries (LMICs), many companies in these countries are beginning to adopt AI, demonstrating the global potential of AI technologies.[5]

[4] Lynch, S. (2019). Andrew Ng: Why AI is the New Electricity. [online] Insights by Stanford Business. Available at: www.gsb.stanford.edu.

[5] McKinsey and Company. *The state of AI in 2020 | McKinsey*. Available at: mckinsey.com.

In fact, governments and organizations located within LMICs often have an advantage when deploying AI as they typically have more streamlined systems that facilitate faster AI implementation.[6] LMICs are rich environments for rapid growth in advanced technologies. There is opportunity for these countries to leapfrog the already archaic systems that burden the growth of wealthy countries that have become mired in overly complex systems and infrastructure which are underperforming. This has happened before with mobile phones and mobile banking which adopted more rapidly in LMIC and bypassed the costly infrastructure of brick-and-mortar banks and expansive telephone wires.

This proliferation of AI over the last decade has been fueled by lower costs of computing, data storage, and increasing data collection. As new data sources become available and deploying AI technology more accessible to non-technical users, AI use will continue to expand.

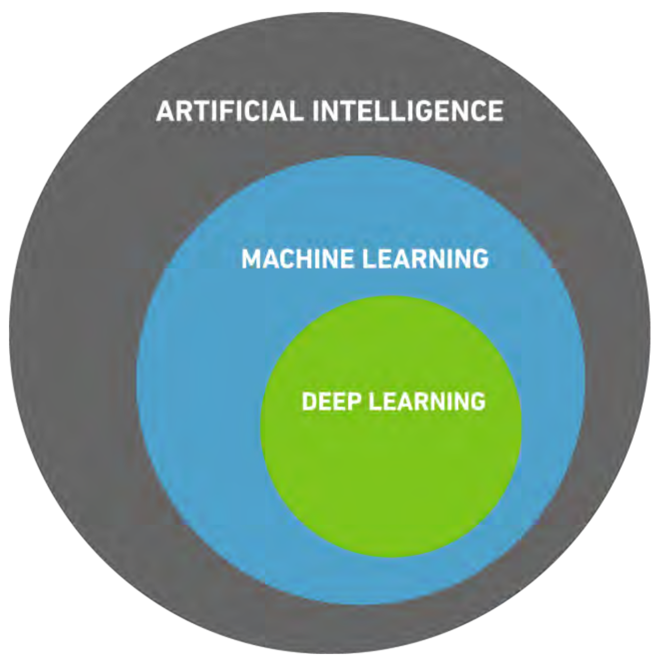
In order to ground discussion on how AI can improve Tanzania's health supply chain, this guide will first present the significance of AI through a discussion on why AI adoption has recently increased across fields and the impact AI has had both globally and within Tanzania.

DEFINING ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

Artificial Intelligence is an academic discipline founded in the early 1950s.

Machine Learning is the study of algorithms that learn by experience. It's been gaining momentum since the 1980s and is a subfield of AI.

Deep Learning is a newer subfield of machine learning using neural networks. It's been very successful in certain areas (image, video, text and audio processing).



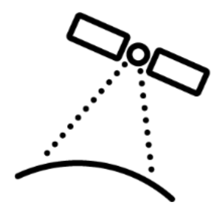
[6] Broadband Commission for Sustainable Development (2020). *Reimagining Global Health through Artificial Intelligence: The Roadmap to AI Maturity*.

Increasing Global AI-Readiness

AI readiness captures the ability of an organization to gain value from investing in Artificial Intelligence. The rise in the popularity of AI coincides with a global increase in AI readiness.

The first pillar of foundational AI readiness is data. Over the last decade, many organizations and institutions have transitioned to electronic records and are now collecting vast amounts of data on the populations they serve.

Meanwhile, as internet access has expanded globally, user populations have grown, resulting in an exponential increase in the amount of data worldwide that is used to train powerful AI algorithms. This aggregation of public data has been made interpretable by the concurrent advances in ML. Another democratized global data set is satellite imagery which has seen dramatic improvements over the past decade, enabling insights in even the most remote corners of the world.



In order to use large amounts of data, AI needs adequate computer processing power. Training advanced AI algorithms is resource-intensive and, historically, has been prohibitively expensive. Today, AI can be trained using servers hosted remotely, making AI significantly more cost-effective and accessible.

For example, Amazon Web Servers (AWS) was an early driver in making AI processing power more available and affordable: it is now possible to train a powerful model on an AWS server for less than $100USD.

Increasingly, governments and private companies have invested in building remote servers and data centers outside of the US and Europe to protect data sovereignty. This has had varied success in increasing data security, but has led to increased capacity in-country and is an opportunity for economic growth.

How much data do I need to implement AI? Is my data good enough?

AI algorithms are powered by data, so naturally the first concern many potential AI-users ask is whether or not they have enough data to create meaningful models.

"You do not have to wait to have perfect data.
You can start and then iteratively improve."
-Dr. Suvrit Sra, Massachusetts Institute of Technology

There is no easy rule of thumb to help answer this question. Even in cases of limited historical or geographical data reach, there are still many other sources of data available. For example, WorldPop has demographic estimates for almost every country in the world derived from satellite imagery, survey data, and census data.

Other non-traditional sources of data can also strengthen the predictive power of AI models. For example, researchers have successfully been able to predict the spread of disease using news data. Dynamic, AI-powered supply chain models are able to ingest publicly available news data as inputs in order to predict the increase in demand for critical medical supplies and where these supplies are needed.

Machine learning can even help evaluate data quality by determining if there are anomalies or inconsistencies within the dataset. This quality checking is a key part of the machine learning process that the machine learning team undertakes to improve predictive performance.

Is the data I have high-quality enough?

Historical data collected using paper forms and later entered into electronic data systems is often prone to error. Higher-quality electronically recorded data is frequently not available countrywide. **Machine learning scientists can still use machine learning methods as perfect data is not necessary.**

For example, in situations where high-quality data exists in some health systems or geographical areas but not others, the machine learning team can work to 'transfer' the knowledge learned from the high-quality data to the low-quality data. In other cases, the machine learning team can look for supplemental publicly available data or even learn from the model errors.

The best way to know if you have enough or good enough data is to explore implementing AI. An AI partner will be able to quickly determine the feasibility of a project.

Globally, including in Tanzania, AI readiness has substantially increased over the past decade. In the 'Preconditions to AI in Tanzania' section of this report, we have tailored specific components of AI readiness into the four different preconditions, or precursors to AI use. We have distilled the list to those elements most relevant to the Tanzanian AI context. We then explore how Tanzania has met or exceeded the necessary preconditions to implement AI.

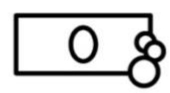
Multi-Sector Impact of Artificial Intelligence

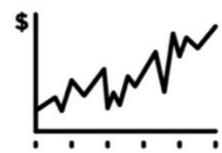
The impact of AI has reverberated across all business sectors worldwide. The earliest adopters constitute the most foundational components of our society – the places where resilience is imperative. Governments, non-profits, companies, and multilateral institutions have successfully deployed AI on every continent across many industries.

Finance

AI builds strong economies. One of the first industries to be transformed by AI was the finance sector. AI technologies were immediately exploited to help traders make stronger investment decisions, and these early adopters earned billions of dollars more in profit than competitors who were slower to adopt AI technology.

Many different types of AI are currently being used by the finance industry in order to make predictions about the market, such as using natural language processing, or AI technologies that attempt to understand human language, to track sentiment in news articles, and computer vision to analyze satellite imagery of ocean freighters, both employing deep learning to improve forecasting over traditional econometric techniques.





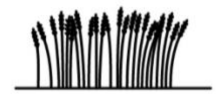
Trading rooms were once dominated by human traders interacting, human to human. Today, only an estimated 10% of financial trades in the United States are still being executed by human traders.[7] The vast majority are computers (AI) speaking to computers (AI).

In addition to the securities industry, business and consumer lenders have adopted AI into their operations all over the world. Many organizations in sub-Saharan Africa are using credit-worthiness predictions to lend to consumers who have no credit history. These companies can extend credit to millions of people who otherwise would not have access to financing.

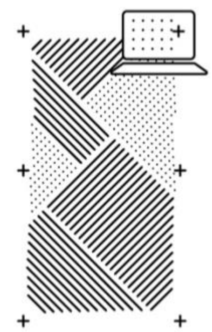
[7] Wigglesworth, R. (2019). *Volatility: How 'Algos' Changed the Rhythm of the Market*. Financial Times. Available at: www.ft.com.

Agriculture & Food Systems

AI puts food on the table. AI has been deployed by the agriculture industry in order to sustainably increase yields and decrease costs. For example, some applications have included fertilizer application optimization, disease and pest detection, weed control, and prediction of planting and harvest windows. By 2030, AI technologies are forecasted to generate up to $70 billion in additional income for farmers, including smallholder farmers. Farmers in developing countries can increase yields by an additional 250-500 million tons simply by accessing mobile services that employ AI to optimize farming decisions.[8]



Precision agriculture collects data throughout planting fields using sensors and satellite imagery, and then deploys Artificial Intelligence algorithms to recommend optimal inputs. Agricultural fields do not have homogenous soil composition, so different subsections of fields will require different nutrients and support different crops. Precision agriculture allows farmers to increase yields by optimizing the use of field sections. Companies such as Ujuzi Kilimo in Kenya and Zenvus in Nigeria are working to bring the power of machine learning to smallholder farmers throughout sub-Saharan Africa.



Healthcare

AI helps us live healthier and longer. Similar to agriculture and finance, almost every facet of health systems and care delivery has been touched by AI. ML algorithms are being deployed to optimize patient scheduling, inform clinical decision-making and diagnostics, research new drug and vaccines, optimize supply chains and even plan human resourcing at service locations.

In LMICs, AI can play a role in improving health systems, for example, by reducing acute health workforce shortages, strengthening public health surveillance systems, improving health service delivery, and reducing health disinformation.[9,10] In Tanzania, Dr. Elsa's Afya-Tek was developed to

ELSAHEALTH

[8] Sanghvi, S., et al. (2018). *Innovation with a Purpose: The Role of Technology Innovation in Accelerating Food Systems Transformation*. World Economic Forum. In collaboration with McKinsey & Company.

[9] Schwalbe, N. and Wahl, B. (2020). Artificial intelligence and the future of global health. *The Lancet*, 395(10236), pp.1579–1586.

[10] Broadband Commission for Sustainable Development (2020). *Reimagining Global Health through Artificial Intelligence: The Roadmap to AI Maturity*. pp.1–129.

improve diagnostics using AI-powered decision support tools for primary care providers.[11]

AI has also transformed the health supply chain sector, fundamentally changing "best practices" and creating more responsive and flexible supply chains. In the final section of this report, we expand on the application of AI in healthcare with a specific focus on health supply chains in Tanzania.

The examples in Fig. 1 touch on only a handful of the many industries AI has impacted in the last ten years. Over the next decade, AI will become more powerful, be deployed in new situations, and achieve ever greater impact.

Figure 1. Examples of AI Applications in Africa

INDUSTRY	COUNTRY	NAME	AI USE CASE
Agriculture	Nigeria	Zenvus	Precision farming
Agriculture	Kenya	UjuziKilimo	Precision farming
Agriculture	Nigeria, Kenya	HelloTractor	Farm input credit
Agriculture	Multiple	Pula Advisors	Smallholder crop insurance
Agriculture	Kenya	Apollo Agriculture	Farm input credit
Agriculture	Uganda	Farmers Companion App	Pest detection
Agriculture	Kenya	Safaricom	Farm input credit
Finance	Kenya	Tala	Consumer credit
Finance	Multiple	Branch	Consumer credit
Finance	South Africa	Lulalend	Business lending
Finance	Multiple	Teller	Customer service chatbot
Finance	Tanzania	MiPango App	Consumer credit
Marketing	South Africa	Xineoh	Predictive customer engagement
Health	Rwanda	Rwandan Ministry of ICT and Innovation	Robotic COVID screening
Health	Tanzania	Dr. Elsa	Diagnostic aid chatbot
Energy	Multiple	Azuri Systems	Energy consumption optimization
Social Services	South Africa	rAInbow	Domestic violence chatbot-
Social Services	South Africa / Rwanda	harambee	Job matching between employers and youth

[11] Turner, B. (2020). *Tanzania's digital doctor learns to speak Swahili*. Financial Times. Available at: www.ft.com.

Missed Opportunities and Future Direction of AI in Healthcare

AI has had proven positive impact across many sectors, but like any new technology there have been notable examples where deployment of AI has failed to meet performance standards. This section will cover a handful of these cases as well as what is being done to avoid these errors in the future.

IBM Watson's first Oncology Deployment

IBM Watson is an AI supercomputer that analyzes text data to answer questions posed by users on a wide range of topics. The product has proven to be very successful in personalizing customer experience[12] and has even won the US trivia show Jeopardy!

Watson was promised to be able to use the same technology to process medical literature and patient records – including often complex and unorganized doctor notes – to support clinical decision-making and personalize cancer treatment plans.

IBM Watson partnered with the University of Texas MD Cancer Center to execute this vision; however, the project was cancelled only a few years later. One hypothesis for the failure of IBM's initial foray into healthcare was that Watson was unable to easily digest and understand often complex and ambiguous doctor notes.[13]

IBM continued to pursue Watson's healthcare applications and through a partnership with Memorial Sloan Kettering Hospital launched Watson for Oncology; it has been deployed in hospitals worldwide with mixed success.

One criticism is that, because Watson was trained entirely by American doctors, the medical advice Watson gives is biased towards American treatment protocols.[14] Despite this bias, Watson is still incredibly useful at

[12] *Watson Success Stories*. IBM. Accessed May 2021.Available at: www.ibm.com.

[13] Strickland, E. (2017). *How IBM Overpromised and Underdelivered on AI in Health Care*. IEEE Spectrum. Available at: IEEE.org.

[14] Ross, C. (2017). *IBM pitched its Watson supercomputer as a evolution in cancer care. It's nowhere close.* Stat News. Available at: statnews.com.

hospitals without oncology specialists – one hospital in Mongolia without any cancer doctors followed Watson's recommendations in all cases.[15]

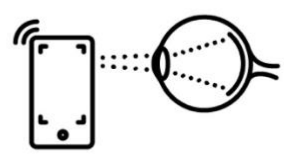
Furthermore, Watson is quickly able to find and recommend relevant medical literature based on patient charts. A recent study in China found that doctors agreed with Watson's recommendations in 73% of cases for cervical cancer patients, and common reasons when recommendations diverged included reimbursement complications and patient preferences.[16]

Although the early deployments of Watson in the healthcare industry were not scaled, IBM is continuing to improve both Watson for Oncology by localizing recommendations and improving its accuracy so that the technology may be confidently adopted by hospitals worldwide.

Google Health Retina Diagnostics

Google Health developed an AI-assisted diagnostics tool that used images of the eyes to detect diabetic retinopathy. In the lab, the algorithm Google developed was able to detect the disease at the same rate as specialists; however, deployment failed to match these initial benchmarks.[17]

Thailand has limited retinal specialists and a growing diabetic population, so Google Health developed an AI-assisted diagnostics tool to alleviate the overburdened healthcare system. In order to test the model, Google Health piloted the ML approach in 11 clinics, where they found substantial differences in diagnostic procedures across clinics, including some photos taken in fluorescent lighting contrary to standard practice, causing the ML algorithm to deem 21% of photos unusable.[18]



[15] Ibid.

[16] Zou, F. W., Tang, Y. F., Liu, C. Y., Ma, J. A., & Hu, C. H. (2020). Concordance Study Between IBM Watson for Oncology and Real Clinical Practice for Cervical Cancer Patients in China: A Retrospective Analysis. *Frontiers in genetics*, *11*, 200. https://doi.org/10.3389/fgene.2020.00200

[17] Beede, E., Baylor, E., Hersch, F., Iurchenko, A., Wilcox, L., Ruamviboonsuk, P., & Vardoulakis, L. M. (2020). A Human-Centered Evaluation of a Deep Learning System Deployed in Clinics for the Detection of Diabetic Retinopathy. *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. doi:10.1145/3313831.3376718

[18] Ibid.

In order to improve deployment performance, Google Health began providing real-time feedback to nurses on the quality of their photos. This again proved to be unfeasible in practice as nurses faced long patient queues and could not afford to spend an additional minute waiting for an image to upload in conditions of poor internet connectivity.[19] Next, Google Health tried to get nurses to turn off overhead lights, but as many examination rooms were multi-use this again proved impractical.

Despite these initial challenges, the Google Health team has pivoted to holding workshops at future sites to help the staff identify and address implementation challenges. Google's efforts have shown that stakeholders need to be included early on to identify deployment challenges and ensure that technologies will work in local contexts.

Future of AI in Healthcare

Although historically AI in healthcare faced deployment challenges, it remains one of the fastest growing sectors of AI. The US healthcare market is projected to expand over 11x its estimated 2014 market by 2021.[20]

AI is estimated to have the potential to cut healthcare costs by radically changing healthcare from reactive to proactive by providing earlier diagnoses, precision medicine, and efficient treatment and follow-up.[21] Top research companies such as Google, Amazon, and IBM are continuing to expand their healthcare offerings and invest in these future applications of AI in healthcare.

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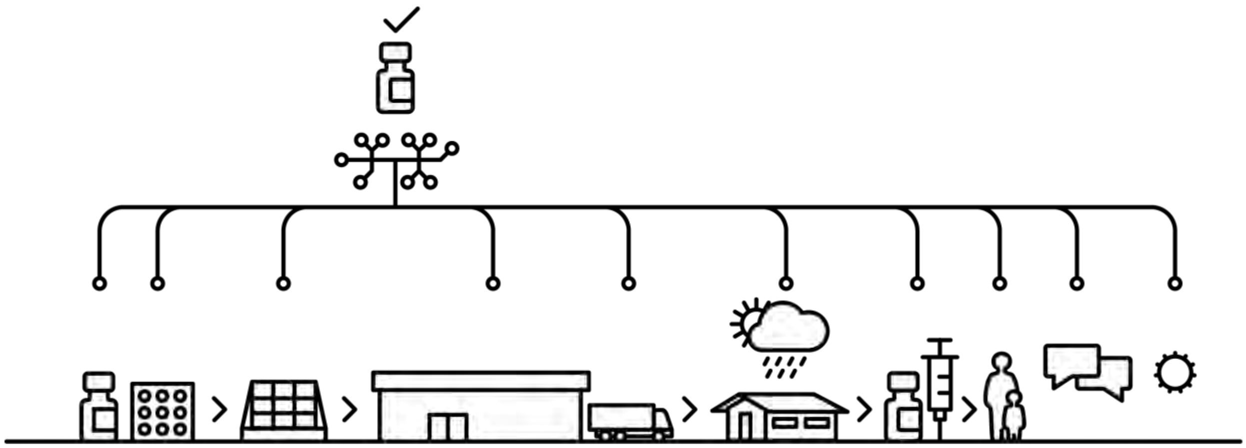
[19] Ibid.

[20] Collier, M, & Fu, R., & Yin, L. *Artificial Intelligence: Healthcare's new nervous system*. Accenture. Accessed May 2021, Available at: Accenture.com

[21] Bohr, A., & Memarzadeh, K. (2020). The rise of Artificial Intelligence in healthcare applications. *Artificial Intelligence in Healthcare*, 25–60. https://doi.org/10.1016/B978-0-12-818438-7.00002-2



Going Deeper:

Technical Overview of AI for Supply Chain Leaders

AI technologies are machines that learn and produce intelligent decisions. Foundationally, AI is rooted in mathematics. AI generates an output that the user defines by discovering mathematical relationships between input data.

This output can take on many forms. For example, it can be a number sent back to a database, an image, a paragraph of text, or even the steps a self-driving car takes to successfully navigate a street. Although these outputs are very different, they are all built by applying advanced mathematics to a set of input data.

Within this document, all examples cited use machine learning technical principles; therefore, this section will focus specifically on machine learning, rather than AI.

It is important to note that AI is often used interchangeably with ML, as ML is currently the dominant implementation of AI.

How Does AI Compare To Traditional Statistical Techniques?

Complex systems cannot be given simple models. Machine learning generally outperforms statistical models when predicting the future, due to its ability to capture complicated relationships and leverage both tabular and unstructured (i.e., non-tabular) data such as satellite imagery.

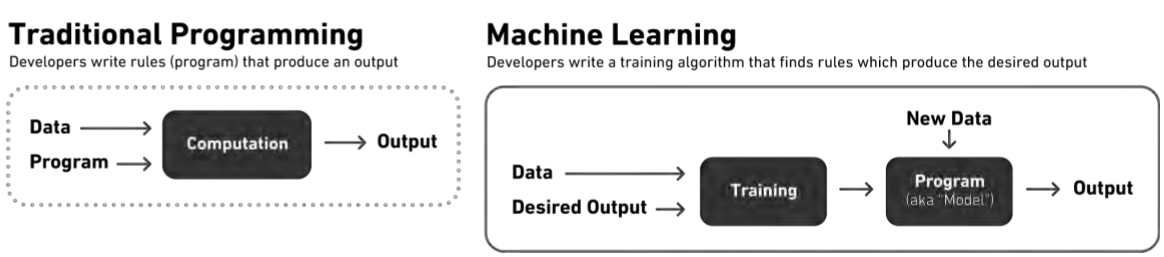
Statistical methods are often used for retrospective analysis to model past events and identify causal relationships. For example, in Monitoring & Evaluation (M&E) statistical models such as differences-in-differences are frequently used to evaluate the effect of an intervention.

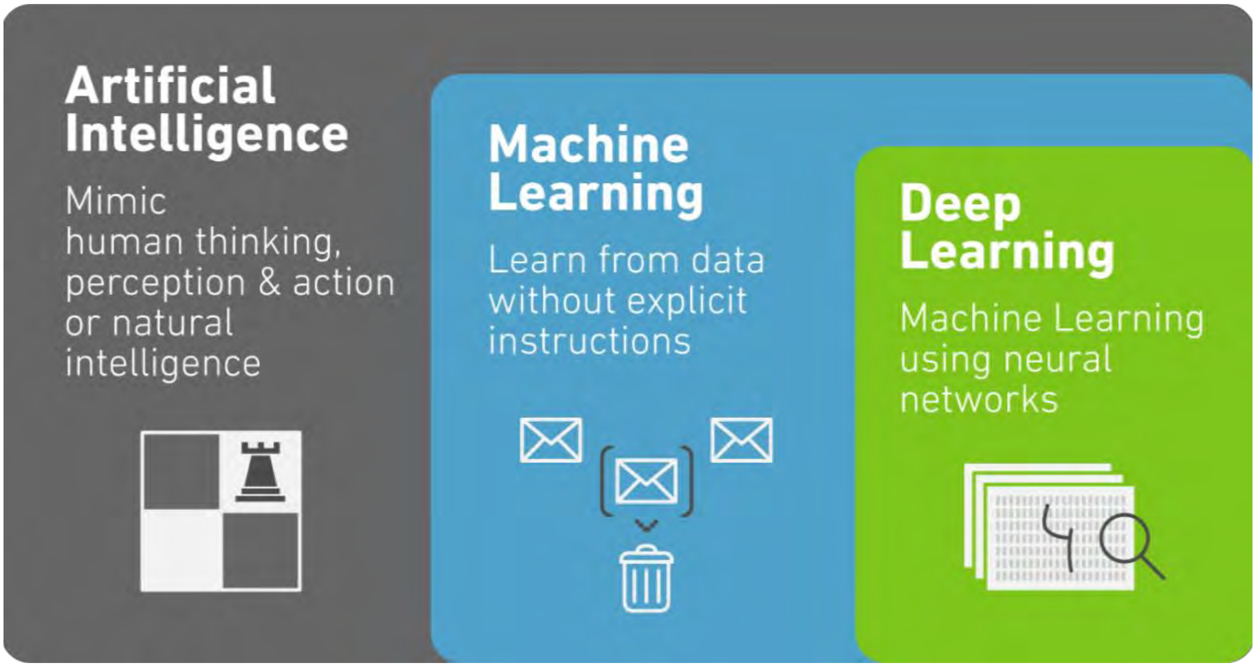
Statistical methods uncover linear relationships between variables. The resulting models are static, are rarely updated after they have been built and are often poor at predicting the future. Statistical techniques are limited to using tabular data as input, while machine learning models can use both tabular and non-tabular data.

Machine learning algorithms are able to discover non-linear relationships between input data elements. This discovery process becomes rather powerful when looking to predict a value that does not directly correlate with the input data or in cases when one is limited by poor quality data.

These non-linear relationships become stronger and more robust predictors the more data is available. In cases with large quantities of data (over a thousand data points), machine learning generally outperforms statistical models.

Machine learning scientists usually compare the results of machine learning algorithms and traditional statistical methods on the same dataset. Traditional statistical models are typically less computationally expensive than machine learning models; therefore, it is important to deploy a machine learning model only when it outperforms statistical models.



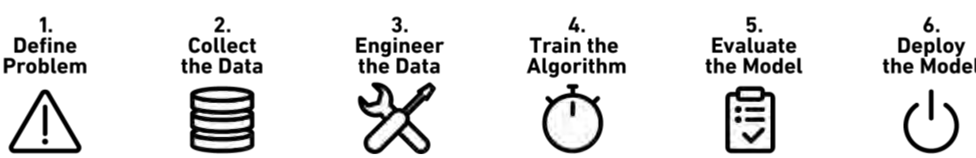


Relationship between AI, ML, and Deep Learning

Building Machine Learning Models

The machine learning development process is **iterative.** Throughout the development process, performance is constantly evaluated and new data sources are added. Even after the model is deployed, changes in context or availability of new data create opportunities for improvement. The development process is neither linear nor terminal.

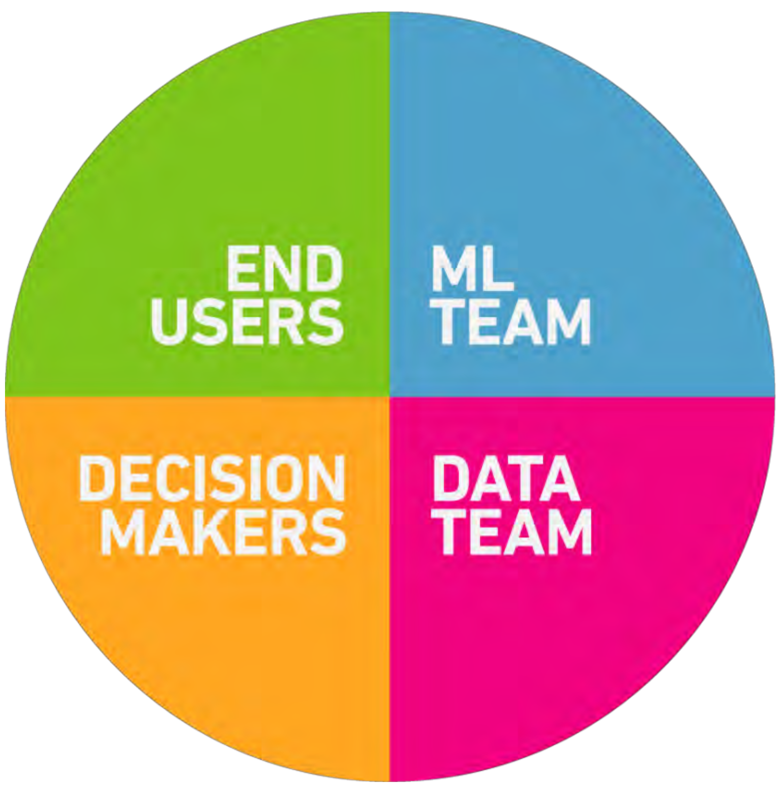
In machine learning, **there are six general phases** to creating a model, although, as we noted above, these phases can occur concurrently and are iterative. The following sections detail the end-to-end machine learning process beginning with defining the goal of the machine learning project and ending with deployment of the model.



At the beginning of each section, estimated time requirements by stakeholder are displayed in order to give a clearer picture of which stakeholders are involved at what stage of the machine learning process.

There are four major groups of stakeholders:

- **Machine learning team:** Machine learning scientists and machine learning engineers who will build and deploy the model.
- **Decision makers**: Decision makers and project management guide overall vision and provide context to the machine learning team.
- **Data engineering team:** Data engineers and analysts managing the databases and product interfaces the machine learning team will both draw data from and send predictions back to. For internal teams, these roles may overlap with the machine learning team.
- **End users:** The end users of the data product. This role can overlap with decision-makers depending on the machine learning use case.



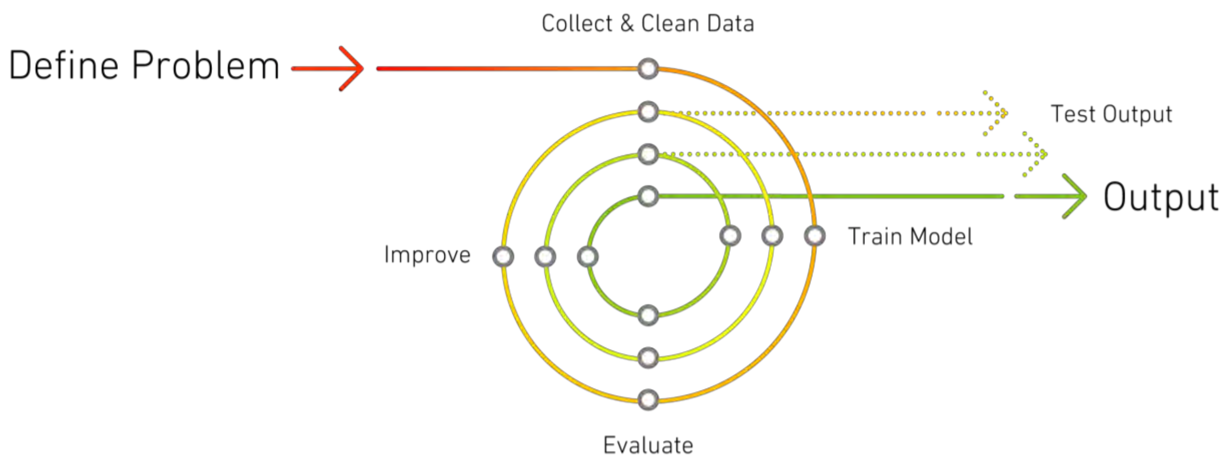
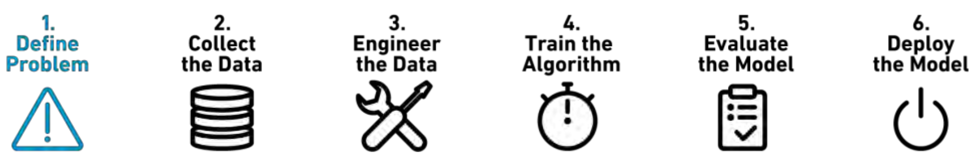


Figure 3. The Machine Learning Process



1. DEFINING THE MACHINE LEARNING PROBLEM STATEMENT

The first step is to define the problem by deciding what you are trying to predict and how it will be used by the end users. For example, will the project create a new product, or integrate into existing systems?

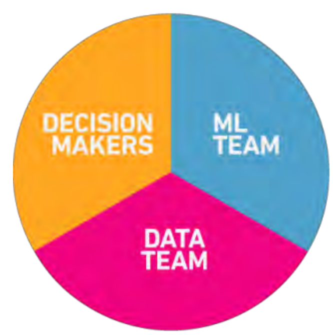
All stakeholders should be involved at this point to make sure that the project is set off in the right direction and there is a clear vision of the project's anticipated outcome.

A machine learning problem statement should be straightforward and allow for evaluation against existing processes. Some potential problem statements for improving health supply chains are listed below:

- Reduce drug wastage in health clinics through more accurate supply forecasting.
- Increase access to medical equipment in areas with high need through more accurate demand forecasting.
- Reduce stock-outs by building proactive facility-to-facility distributions.

DEFINE ML PROBLEM

ML TEAM	33%
DATA TEAM	33%
DECISION MAKERS	33%
END USERS	0%



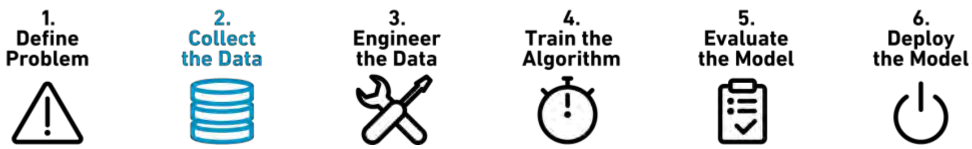
- Reduce Lost-To-Follow-Ups (LTFU) by Identifying patients in treatment likely to become LTFU.
- Identify clinics with access to power sources improve access to care.

A well-defined problem statement will give direction to the machine learning team throughout the machine learning process, increasing the chances the project will succeed.

CASE STUDY: Deciding Where to Integrate Vaccine Supply Predictions into Tanzania's Health Information Systems

During the problem statement phase, Macro-Eyes worked with decision-makers in the Tanzanian ICT department, National Immunization and Vaccine Development department, inSupply Health, and PATH in order to understand where best to place a vaccine immunization prediction.

Through this process, Macro-Eyes, PATH, and inSupply Health undertook a mapping exercise of Tanzanian immunization systems where it became apparent that the prediction should be integrated into VIMs to be used by the District Immunization Vaccination Officials (DIVOs) who have final decision-making power over vaccine supply allocation to facilities.



2. COLLECTING THE INPUT DATA

After the problem statement is defined, the machine learning team will continue to hold conversations with stakeholders to understand what data is available and how it is collected. The team will then liaise with the data team to set up a secure environment with access to the necessary data to build the model.

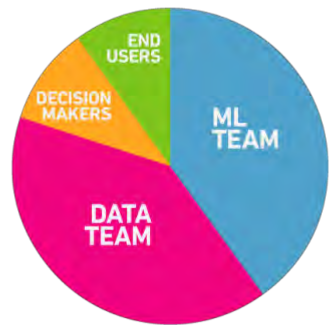
The machine learning team will lead conversations with end users and decision-makers to gain a better understanding of both the context around the problem statement and also how the data was collected.

The machine learning team also may ask decision-makers and end users for hypotheses on why certain events happen; for example, their observations on why young women are at risk of dropping out of HIV/AIDs therapy.

These conversations can help guide the machine learning team to collect relevant external data that may be correlated with the outcome and also understand any biases or other inconsistencies in the data to be corrected.

COLLECT INPUT DATA

ML TEAM	40%
DATA TEAM	40%
DECISION MAKERS	10%
END USERS	10%



Common publicly available data sources for Machine Learning in Tanzania

Many sources of publicly available data exist for Tanzania – and for much of the world through increased participation in the public internet. Publicly available data is free for anyone to access and use in accordance with the data's terms of use. Below are samples of openly available and commonly used public data sources in LMICs:

- Demographic and Health Survey Data
- WorldPop Demographic Estimates
- Facebook Data for Good Demographic Estimates
- Food and Agricultural Organization Gridded Livestock of the World
- Climate Hazard InfraRed Precipitation with Satellite Data
- NASA Vegetation Index from MODIS Satellite
- Open Street Map Points of Interest
- Social media, such as Twitter data

2. Collect the Data

How to Protect Health Data During the Machine Learning Process?

Health data is extremely sensitive and allowing more people to access data may increase the risk the data is exposed. There are ways to mitigate the danger of a data leak that have proven effective for organizations accustomed to working with sensitive data.

The first step to ensure data protection is to have a strong data governance policy all staff and partners must abide by that is updated as needed by security experts. Below are some common ways that organizations protect their data even when working with external machine learning teams:

1. **Restrict data access to secure environments.** The machine learning team can be restricted to accessing data only from a secure server in Tanzania. This means that although the machine learning team can work with and view the data, they will not download and store any sensitive data to their personal machines. It is also recommended to log and track any access and actions taken on the virtual machine to monitor for unanticipated activity.

2. **Ensure data is exchanged via secure communication.** Secure Sockets Layer (SSL) encryption protects data in transit from one location to another. SSL eliminates the risk of a data breach occurring during data transfer.

3. **Encrypt data at rest.** Encrypting data at its endpoint reduces the risk of exposing sensitive data in the event of an outside breach

4. **Remove sensitive personal identifying information**. Second, the data team may remove any personal identifying information, such as names, addresses, telephone numbers, and ID numbers. The data team can also bin ages and other numeric personal data to further protect individuals. This means that even in the case of a breach, individuals will not be able to be identified from the data.

5. **Masking.** Lastly, it is possible to mask the data so the machine learning team never has access to the true values of a dataset. Although this approach can improve security, machine learning performance will likely decrease. Understanding context and creating new features that better capture the realities on the ground is critical to the machine learning process; and uncovering and bolstering these relationships is much more difficult with masked data. In addition, masking can create deployment issues as the data needs to be masked in the exact same way as the original dataset.

3. ENGINEERING THE INPUT DATA

During the engineering, or preprocessing, phase, the machine learning team — or a savvy data engineering team – must prepare the data into a machine learning-ready format. The data that machine learning algorithms use must be numeric, be combined into one source, and not contain any missing values.

While handling the data, the machine learning team will have questions for the data team. For example, it is crucial to determine if missing values are equivalent to zeros, are missing at random, or are missing for a certain reason (such as an interviewee declining to respond to a question), as this information may hold predictive value that must be engineered appropriately.

ENGINEER INPUT DATA

ML TEAM	90%
DATA TEAM	10%
DECISION MAKERS	0%
END USERS	0%

What Machine Learning Tools Exist For Non-Machine Learning Scientists?

Technology companies are developing new products to make machine learning technologies more accessible to users without a computer science or data science background.

For example, **AutoML products** will autonomously create hundreds of machine learning features from datasets, feed these inputs to different algorithms, and visually represent the results to help the user decide which model is best. These packages are generally geared towards developers or data analysts with experience in programming but limited background in machine learning.

One drawback of AutoML products is that the responsibility for managing model performance and deployment lies entirely in-house. Issues that may need an expert to detect and fix, such as bias, may go unnoticed. It is important to consider the overall risk of a project when determining whether or not to use these tools or consult external experts.

During this phase the machine learning team may also create new features, or data points, from the collected data.

For example, if the machine learning team is working with time series data, such as drug utilization, the machine learning team may create features that describe historical utilization such as the average amount utilized in the past month, three months, and six months.

This creation process is driven by the earlier conversations held with the data team, end users, and decision-makers in order to engineer features that will meaningfully improve predictive performance. These are contextually derived features that link data sets with operational realities.

4. TRAINING THE MACHINE LEARNING ALGORITHM

Before training, or configuring, the machine learning model, the machine learning team first splits the data into two or more distinct datasets. The first portion of data is the largest – typically 70-85% of overall data – and is used for training the machine learning algorithm.

The remaining data is reserved for the evaluation phase in order to provide an unbiased approximation of the model's performance. This can be a single test set, or multiple tests sets based on availability.

Next, the machine learning team chooses which algorithm(s) to use and uses the training dataset to learn the algorithm parameters. There are scores of algorithms to choose from.

Scientists at top research companies, such as Google, will frequently use proprietary algorithms, while other machine learning teams will favor tried-and-tested, open-source algorithms that have proven to be successful on a wide variety of tasks.

The team will also set the algorithm settings, or hyperparameters, during training, to obtain the best possible performance on the training dataset. There is no one-size-fits all approach to machine learning. The exact hyperparameter settings and the choice of algorithm are both primarily dependent on the data.

It is the machine learning team's responsibility to discover the algorithm and hyperparameter combinations that perform best on the data. The highest eschelon – though rare – empowers a set of available algorithms to self-optimize without human intervention. This would enable rapid scalability.

TRAIN ML ALGORITHM

ML TEAM	100%
DATA TEAM	0%
DECISION MAKERS	0%
END USERS	0%

**4.
Train the Algorithm**

Task	Popular Algorithm Choices
Classification (Supervised learning) • Predicting health facilities with a shortage of qualified medical personnel • Predicting drugs that are counterfeit	• Tree-based ensemble models (e.g., Random Forest Classifier, XGBoost Classifier, ADA Boost Classifier) • Neural networks
Regression (Supervised learning) • Forecasting next period drug utilization • Predicting next period demand	• Neural networks • Tree-based ensemble models
Grouping (Unsupervised learning) • Discovering facility-to-facility networks • Creating groupings of the population to track group health needs	• K-means/medians clustering • Spectral clustering • Graph neural networks

Figure 4. Common types of machine learning algorithms

Within machine learning, there are two principal learning methods: **supervised and unsupervised learning**. These methods determine the choice of algorithm.

Supervised learning is used when the prediction targets ('y' variables) are known. For example, both sales forecasting and identifying objects in images are examples of supervised algorithms. In sales forecasting, the total volume of sales each period is the target.

In image classification, the machine learning team will manually create the target by labelling the images with the object they contain. The machine learning algorithms will use the input data to find mathematical relationships that are best able to predict these targets.

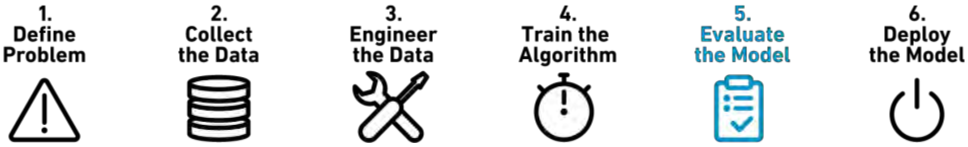
Unsupervised learning is used when the predictive target is unknown. A common application of unsupervised machine learning is clustering, or grouping, data points into similar segments.

An example is the way companies group customers to understand various segments of their customer base. Unsupervised algorithms will use the input data to minimize differences *within* clusters and maximize differences *between* clusters in order to create clusters that are distinguished and as homogenous as possible.

Common issues for machine learning algorithms

- **Underfitting**: Underfitting occurs when machine learning fails to adequately model complex relationships between features. An underfit model does poorly even on the training dataset and usually stems from using a biased algorithm. Choosing a more flexible model can overcome this problem provided there is sufficient data.
- **Overfitting**: Overfitting occurs when the machine learning algorithm performs well during training, but poorly during evaluation. Overfitting can also occur if the algorithm is tuned specifically to perform well on the test set, for example by refitting the algorithm multiple times to achieve a good result on the test set.

  Overfitting is dangerous because the performance of the algorithm after deployment will be worse than expected.
- **Data imbalance:** Data imbalance occurs when the target variable proportions are not balanced. For example, if machine learning were deployed to predict refrigerators that need maintenance this dataset would likely be imbalanced because most often refrigerators do not need maintenance. If the imbalance changes over time, this presents another complication to the process. Luckily, there are specific tools the machine learning team can use to correct imbalance.



5. EVALUATING THE MACHINE LEARNING MODEL

After training the machine learning model, it is crucial to understand how well the model will perform on both unseen data and an appropriate comparison. Like other global health programs that use M&E, machine learning models must also be rigorously assessed and compared to a baseline. Users will also need time after the initial assessment by the ML team to better ascertain performance and benefits.

The ML team evaluates the model by selecting the model that performed best on the training dataset and then testing the same model against the reserved set of test data created during the model training step. This is to ensure that the model is able to perform well even on new data and to give realistic expectations of performance.

In addition to evaluating the model on a test set of data, it is also important to understand how the machine learning output compares to the existing decision-making process or baseline. For example, if a model is designed to forecast contraception utilization to decrease stock-outs, the machine learning team may count the total number of stock-outs that occurred in the test set of data and determine if the model correctly predicted an increase in use in the period preceding the stock out.

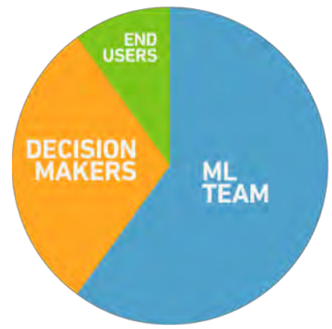
Alternatively, if a model is predicting counterfeit medicine, then the machine learning team may compare the correct predictions of the model to how many counterfeit medicines passed initial inspections. It is crucial for the machine learning team to work with decision-makers to understand which benchmark to use and clearly communicate the results of the machine learning process.

It is critical for the machine learning team to present the results of the work to decision-makers and end users. These stakeholders will immediately be able to give feedback on the results and gaining their trust in the results of the model will be crucial to the success of the project overall. This effort reinforces the models in ground truth context – making AI truly operational.

If the model still performs well with the test dataset and the project leaders are satisfied with the performance relative to the benchmark, then the model

EVALUATE ML MODEL

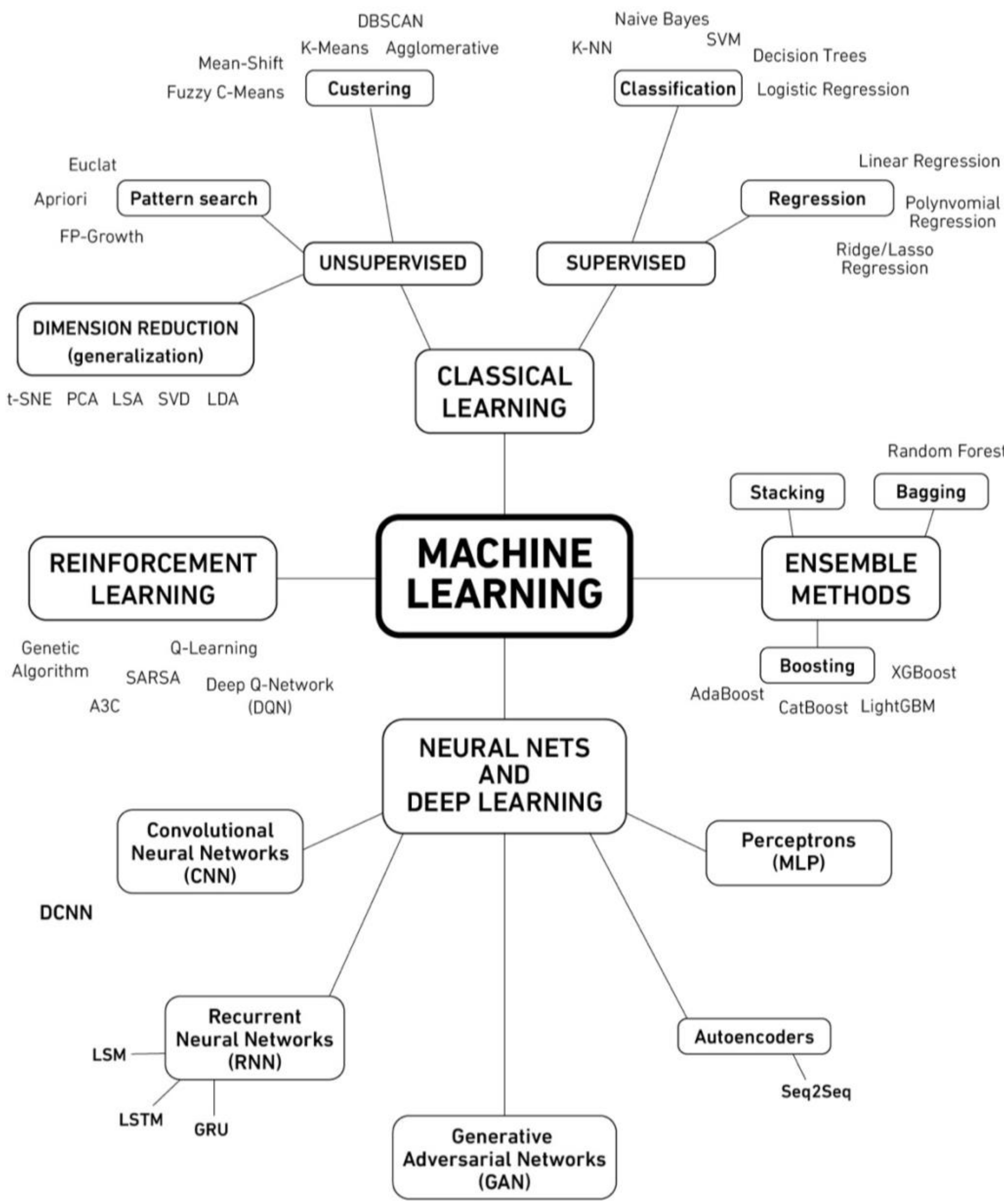
ML TEAM	60%
DATA TEAM	0%
DECISION MAKERS	30%
END USERS	10%



5. Evaluate the Model

is ready to be deployed for further assessment by the decision-makers and end users.

After an initial pilot period (retrospective or prospective), the decision-makers can decide whether or not to deploy the model based on both its performance during the pilot and end user feedback.



Common Machine Learning Evaluation Metrics

Task	Metric	Definition
Classification	Accuracy	The percentage of cases the machine learning model guesses correctly. Accuracy can be a misleading metric when working with imbalance data. For example, if the target class only occurs 20% of the time the model could guess that it never occurs and achieve 80% accuracy.
	Precision	The percentage of cases that the model guessed as part of a class were actually part of that class. If a model predicted that 50 drugs were likely counterfeit, and out of those 50 only 25 were, then the precision would be 50%.
	Recall	The percentage of cases that the model guessed as part of a class out of the overall cases of that class. Taking the example for precision, if there were 30 counterfeit drugs in the dataset and the model correctly identified 25, then recall would be 83%.
Regression	R^2	Measurement of how well the model is correctly able to predict values ranging from 0 to 100%. At 0%, the predictions do not have any value; At 100%, the predictions are perfect.
	Mean Absolute Error	The average error among all predictions. The lower the average error, generally the more predictive the model.
	Root Mean Squared Error	Similar to mean absolute error, except the mathematics of root mean squared error decrease the influence of outliers. It is important to compare both the mean absolute error and root mean squared error in order to receive a more holistic understanding of model performance.
	Fraction Error	Measures how far each predicted value is from the actual values. The lower the fraction error, the more predictive the model.

1. Define Problem | 2. Collect the Data | 3. Engineer the Data | 4. Train the Algorithm | 5. Evaluate the Model | 6. Deploy the Model

6. DEPLOYING THE MACHINE LEARNING MODEL

After the model is developed and tested, the next step is to deploy the machine learning model. Machine learning can be integrated into existing systems and the machine learning team will work with the data team to send the predictions through a secure application programming interface (API). By using an API, the machine learning model does not need to access the database directly and protects the original data in the database. This can have varying levels of visibility into the data and the stakeholders should work with the ML partners on determining the best approach to meet security needs. The more access the ML team has to the data, the better the solution will be.

DEPLOY ML MODEL

ML TEAM	25%
DATA TEAM	25%
DECISION MAKERS	25%
END USERS	25%

First, the model is stored either on a server or a computer and given access through a secure API to both the input data and final output location. For example, if the output is a new entry in a database to later be displayed on an interface or dashboard, the machine learning model will send the prediction to the database through a secure API.

Next, the organization must decide how frequently the model should be run by considering two factors: cost and availability of data. The more often the model is run, the more computer processing time is used, thus increasing costs. If the model is run before all input data is entered, the model's predictions may fail. The data team and machine learning team will work together to decide the optimal frequency given these considerations.

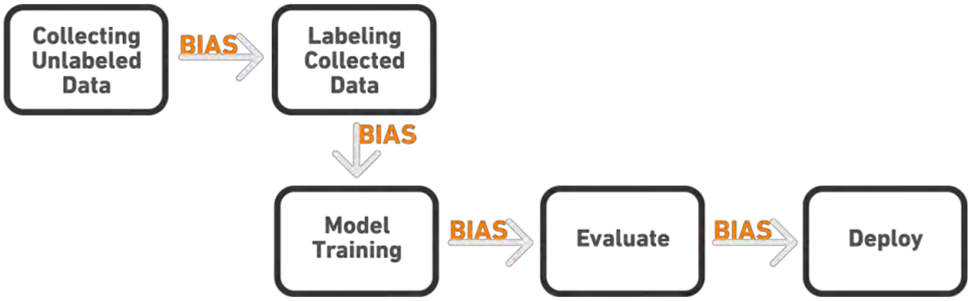
6. Deploy the Model

The machine learning team and decision-makers will work together to train end users on how to use and interpret the model's predictions. Although the predictions should be intuitive and seamlessly integrate into existing workflows, the machine learning team should describe how the model works (what inputs it is using, what is its output) in order to build trust and understanding among end users.

Lastly, the machine learning team must monitor the model's performance. Over time external influences, such as new policy, can change the mathematical relationships discovered by the machine learning model. This will cause the model's performance to decay.

If performance begins to deteriorate, the model should be retrained by a machine learning team.

As mentioned at the beginning of this section, the machine learning process is **iterative**. Machine learning performance will in most cases degrade over time. It is important to constantly re-evaluate the model and re-train if necessary.

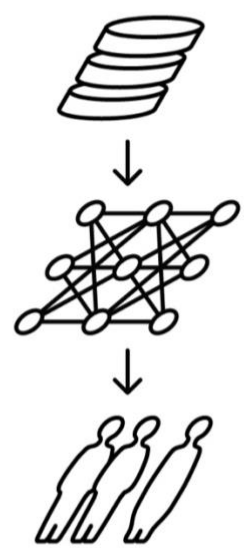


Risk of bias in Machine Learning

Ethical Considerations for Machine Learning

There exist multiple levels of risk when deciding to deploy or not deploy machine learning models. First, there is risk in not using machine learning models that may improve outcomes. Second, there is the risk that it does not result in equitable outcomes across different groups even if the model is accurate overall.

The role of the machine learning team is to give decision-makers the information they need to understand the trade-offs between accuracy and fairness in order to assess risk.[22]



Bias in machine learning output is a result of bias in the underlying data the model uses for predictions, and the humans that create the model and/or collected the data – rather than the model or data on its own. AI is not biased; it is the human participants that are biased which is an opportunity to use AI to illuminate and correct that bias.

In order to assess bias, the machine learning team will work with the data team to understand *how* the data was collected and thoroughly evaluate the data for differences in outcomes between protected groups.

> **bias is defined as "the systematic preferences of a group or groups over others," while fairness is defined as "just or equitable treatment across individuals and/or groups."**
>
> *- Exploring Fairness in International Development, MIT D-Lab*

[22] Sra, Suvrit (2021). Interview by Johnna Sundberg.

For example, if machine learning is employed to aid decision-makers in determining where to open new health clinics, the machine learning team will likely use national population estimates to help identify where unmet healthcare demand exists.

It is critical that the team monitors for any bias that may exist in population estimates, such as potential underrepresentation of disadvantaged groups, and transparently reports these biases and any corrections made during the machine learning process to decision-makers.

The machine learning team can also evaluate the results of the model across different groups in order to assess the equity of outcomes. For example, certain health facilities may be overallocated resources with regard to their catchment populations because other facility catchment populations may not seek healthcare as often or seek healthcare at different locations.

It is important for the machine learning team to clearly communicate to decision-makers where supply may decrease or increase as a result of model predictions. In this scenario, decision-makers can decide to both deploy the algorithm to improve supply chain efficiency and create interventions to help populations not utilizing healthcare access the healthcare they need.

Bias that exists in input data will be reflected in machine learning output. This does not mean that machine learning should not be used, but rather that the machine learning team needs to be transparent with decision-makers about where bias exists and inform decision-makers on the trade-offs between adjusting for bias and model accuracy.

It is incumbent upon the decision-makers to decide how to balance accuracy and fairness in outcomes. It is an opportunity to use ML to make the bias visible and addressable.

Confirmation Bias

Interpretation Bias

Prediction Bias

Information Bias

FURTHER READING

Machine learning in International Development

- USAID: Reflecting the Past, Shaping the Future: Making AI Work in International Development
- USAID/Vital Wave: Managing Machine Learning Projects in International Development

Data Security

- ICRC Humanitarian Data Handbook

Fairness and Ethics in ML

- MIT d-Lab Exploring Fairness and Bias in International Development

Key Takeaways

- **AI is everywhere.** AI has been deployed in many different contexts and industries, including agriculture, health, and finance, in both LMICs and wealthier countries. This illustrates how AI can be useful even with more limited data and technical infrastructure.
- **ML is a subset of AI.** There is a slightly nuanced difference to the definitions of AI and ML. ML is the most common implementation of AI and both are used interchangeably.
- **AI/ML algorithms are mathematics.** Unlike traditional statistics, AI/ML algorithms are able to capture non-linear combinations of interactions between different inputs which makes them incredibly powerful even in situations with little data.
- **Data is no longer a limitation.** Even with limited data, ML/AI solutions can still be explored! There has been a proliferation of publicly available data, and data from non-traditional sources (e.g., data outside of databases) may still be predictive and useful for the problem statement at hand.
- **Algorithms are continuously evaluated.** M&E is part of the machine learning development process. AI solutions are rigorously tested and evaluated to ensure that they are performing better than the baseline.
- **AI can be complementary.** AI solutions can integrate seamlessly into existing systems and interfaces. They do not necessarily have to be standalone solutions.

THEORY OF CHANGE - STRUCTURE

STRATEGIC PLANNING		EFFECTS		
INPUTS	ACTIVITIES	OUTPUTS	OUTCOMES	IMPACT

Successful Implementation of Artificial Intelligence: Theory of Change and Theory of Action Framework

Section Summary

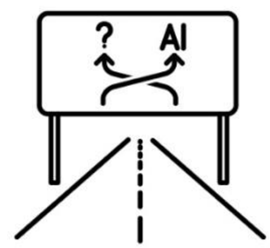
Theory of Action/Theory of Change (ToC/ToA) frameworks have proven to be useful tools for demonstrating pathways and benefits of change. One core component of the ToC/ToA framework is defining and measuring progress against preconditions, or necessary conditions for change.

Tanzania has spent the last decade implementing data collection systems, creating data use policy, and forming strategic partnerships demonstrating substantial progress on each of the preconditions to AI use.

Tanzania is now ready to begin considering how to deploy AI and MoHCDGEC can begin considering items from ToA developed in collaborative workshops with a variety of stakeholders.

Objectives:

- **Provide rationale for choice** of Theory of Change/Theory of Action Framework.
- Discuss **collaborative development process** of the Theory of Change/Theory of Action.
- Show how AI/ML technology **can positively be adapted in health supply chains via the Theory of Change.**
- **Introduce Theory of Action** in the context of integrating AI into health supply chains.



Theory of Change/Theory of Action (ToC/ToA) frameworks have long been used to map the pathways of programmatic change. The ToC is a tool used to document *how* change is expected to occur. The ToC answers the questions: *what* is the change, and *why* is it occurring? The ToC is a living tool that adapts as programmatic context changes.

The ToA framework is a complementary tool designed to answer the questions: *what* are the steps for the change to occur and *by whom?* The ToA is designed to capture the specific mechanisms through which the activities in the ToC are executed.

Many programs have successfully used the ToC/ToA frameworks to demonstrate potential impact and measure actual versus expected impact, and Tanzania is leading the way.

We adopted this framework to demonstrate how AI/ML can be beneficial to Tanzanian health supply chains.

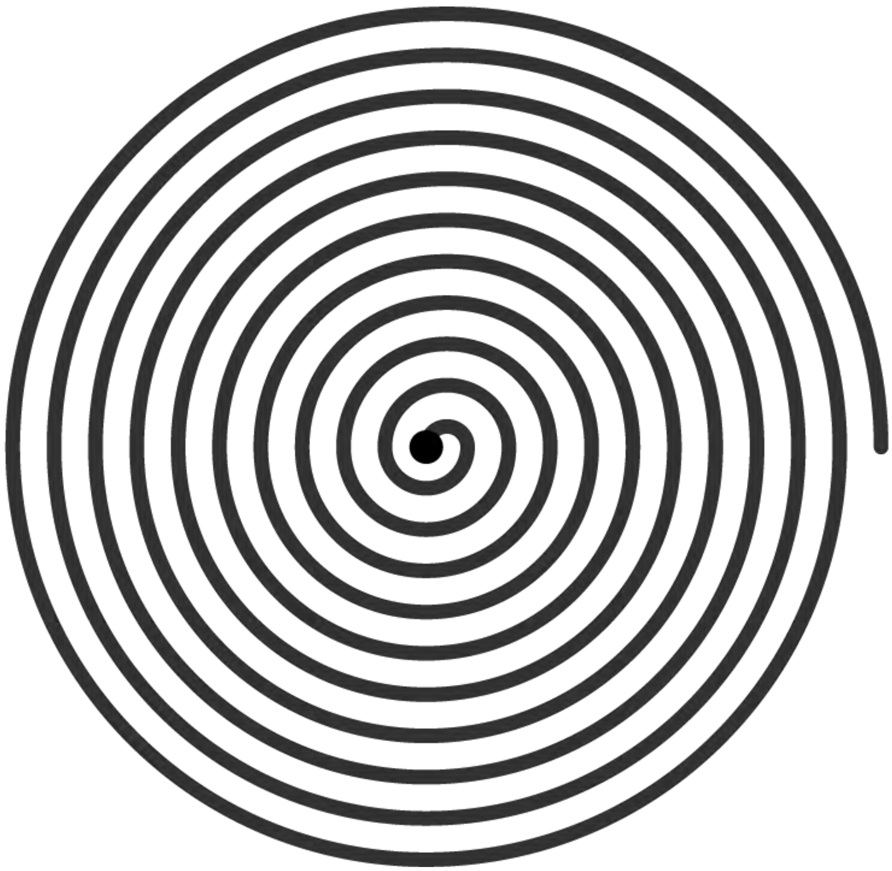
This section will discuss the development of the Toc/ToA framework, followed by the complete ToC/ToA framework itself.

ToC/ToA Development Process

The first draft of the ToC/ToA was developed collaboratively with a diverse network of stakeholders in a workshop held on November 3, 2020, in Dar-es-Salaam. The group included health supply chain experts from academia, the social sector and the Ministry of Health to ensure as many diverse opinions and ideas as possible were represented.

The outputs of these initial frameworks were then combined and refined by the authors of this document, and final inputs were taken into consideration during follow on consultative workshops with the President's Office of Regional Administration and Local Government (PORALG), AI practitioners, the Tanzanian AI community, and private health supply chain stakeholders in addition to the group from the first meeting.

It is important to note that this ToC/ToA is not an exhaustive list of all potential change pathways and benefits of AI/ML, but rather initial conclusions from the workshop participants. The spirit of the ToC/ToA is dynamic, and as these technologies as well as the AI context in Tanzania continue to evolve the ToC/ToA should be updated to maintain its relevancy.



The Essence of the Theory of Change is to make a plan working backwards from a goal, outcome or impact. A Theory of Action Plan is by nature iterative.

Theory of Change for Implementing AI/ML in Health Supply Chains

The purpose of this ToC is to outline the high-level pathway to implementing AI in Tanzanian health supply chains. The ToC contains both the final vision and also necessary precursors to implementing AI in Tanzania.

In this Theory of Change, we begin first with the end goal of this process, or the final vision agreed upon by workshop participants. After, we present a description of the needs identified by the stakeholders that must be met before implementing AI in health supply chains. These need statements are then grouped into preconditions, or necessary conditions, to boost AI use in health supply chains in Tanzania.

Figure 6. Theory of Change for AI/ML in Health Supply Chains in Tanzania

<table>
<tr><th>Stakeholder Needs
"We need to…"</th><th>Preconditions
for AI Change</th><th colspan="3">End Goal</th></tr>
<tr><td>build trust in the people and tools providing AI solutions.</td><td rowspan="7">Elements that must be in place to trigger pathways to achieve end goal.</td><td rowspan="3">Enabling environment to support AI/ML solutions.</td><td rowspan="7">A responsive and integrated supply chain with prediction, automation and data visibility to ensure 100% health commodity availability</td><td rowspan="3">Improved access: health commodities are available to all in need</td></tr>
<tr><td>know the technical infrastructure required to implement AI.</td></tr>
<tr><td>support technical infrastructure that enables AI.</td></tr>
<tr><td>understand the benefits for using AI.</td><td rowspan="4">Empowered, skilled, and motivated stakeholders to use AI/ML solutions.</td><td rowspan="4">Improved equity: Supply chains are optimized and responsive to needs of all population segments</td></tr>
<tr><td>understand the risks of using AI.</td></tr>
<tr><td>know what our responsibilities are for implementing AI.</td></tr>
<tr><td>clear policies and guidelines to inform AI use.</td></tr>
</table>

Intended Goal. The final column in Figure 6 displays the intended outcome of implementing the steps highlighted in this document: **improving health access and equity by employing AI solutions.** AI has been successfully deployed in many contexts to improve efficiency, reduce wastage, and reduce costs. Successful implementation of AI in Tanzania health supply chains can lead to similar benefits.

Preconditions for AI/ML. The preconditions for AI/ML deployment build on the concept of AI readiness previously discussed and are tailored to the

Tanzanian context based on the feedback of stakeholder needs and expert input.

A full discussion of the preconditions for AI current progress in meeting these preconditions is discussed in the next section of this guidebook.

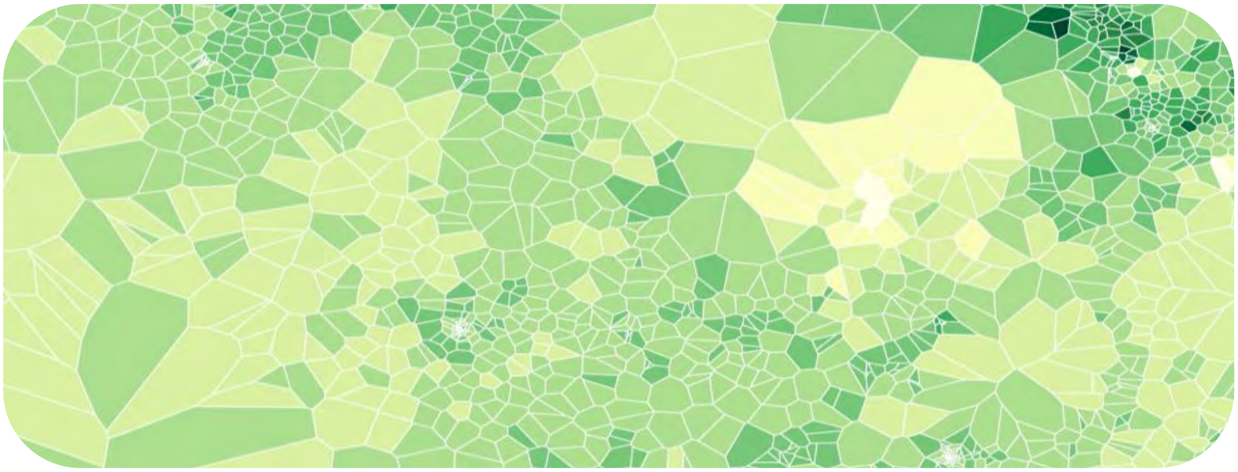
Stakeholder Needs. The first column in Figure 6 lists the needs stakeholders identified during the workshops. These needs, as well as expert feedback, were then used to identify the ML preconditions.

Many stakeholders expressed a need to better understand the technology, including what is required to implement AI, how AI can integrate with existing systems, what impact to expect from AI and how to mitigate risks of AI deployment. These needs are grouped under the **'Knowledge/Skills'** precondition.

Additionally, stakeholders expressed concern about the quality of data and technical infrastructure. Tanzania has made impressive investments in digital infrastructure over the past decade, and a further exploration of these technologies and whether these are sufficient or required for AI use is presented in the **'Technology'** precondition.

Stakeholders were also concerned about vetting potential partners and enabling AI/ML partnerships to succeed, and the potential cost of building/procuring AI technology "out-of-house". Partnerships are a critical component to enable AI use and capacity building within Tanzania and are discussed more thoroughly in the **'Partnerships'** section. There is too little AI expertise in the world for every country have dedicated technology developers. To get best in class, we must think at greater scale.

Finally, stakeholders mentioned a need for clear guidance and regulation on AI use. Many expressed concerns regarding data security and ownership. An enabling policy environment can help address both these concerns. These are discussed more under the **'Policy'** precondition.



Theory of Action for Implementing AI in Health Supply Chains

Tanzania's AI-readiness has substantially increased over the last decade due to new investments in technological infrastructure and creation of data use policies. This section will explore the main preconditions to AI use, discuss Tanzania's progression within each of these preconditions, and present key next steps from the Theory of Action framework.

For full ToA recommendations, refer to ToC/ToA companion document.

Figure 7. Preconditions of AI Use in Tanzania

Precondition	Definition
Technical Infrastructure	Data collection systems and infrastructure necessary for AI use
Policy & Strategy	Governance and vision on data access, privacy, and ownership to guide internal officials and external partners
Knowledge & Skills	Competencies needed to successfully implement AI by all stakeholders
Partnerships	Strategic agreements to facilitate AI/ML use
Financial	Financial resources that provide the means needed to follow through on AI use.

Figure 8. Stages of Theory of Action Interventions

Stages	Definition
INSTILL	The actions or interventions that support **establishing the foundation** of a particular enabling environment in a specific jurisdiction and sub-group of people.
SCALE	The actions or interventions **to expand solutions** to new levels of the health system, new users or new geographies.
SUSTAIN	The actions or interventions that focus on macro, **system-level changes** that help permanently embed solutions across multiple levels of the health system, multiple geographies and multiple teams.

Technical Infrastructure

Tanzania has invested in national electronic data collection systems that have greatly improved the quality and quantity of data within the country. Tanzania is now collecting thousands of datapoints every day that describe the health system and supply chain from an array of health information systems.

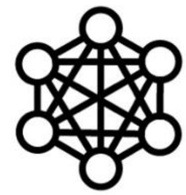


Figure 9 lists data collection systems that have been scaled or have plans to scale nationally, within Zanzibar, or on the mainland. There are many other data collection systems operating sub-nationally or used by partners. The smaller scale of these systems, although potentially AI ready, would limit the scope of any AI application and thus is not the focus of this report.

Figure 9. National Tanzania Technical Health Data Information Systems

National Tanzania Technical Health Data Information Systems		
Name	**Description**	**Level of Data Collection**
DHIS2	In 2010, Tanzania began development of an electronic health information system to collect data on major health programs including maternal/child health, malaria, HIV/AIDs, and TB. The system was fully rolled out by 2014. [23]	Facility
Tanzania Immunization Registry (TiMR)	TiMR is an integrated stock management and electronic immunization registry first piloted in 2016 and currently scaling nationally.[24]	Patient / Facility
Vaccine Information Management System (VIMs)	VIMs is a module within the eLMIS system to implement vaccine and cold train equipment inventory management.	Facility / District
Electronic Integrated Disease Surveillance And Response (eIDSR)	The eIDSR system feeds into DHIS2 and includes disease surveillance for many high priority diseases, such as malaria, TB, and HIV/AIDs.[25]	Facility
Human Resources for Health Information Systems / Training Institution Information System (HRHIS / TIIS)	The HRHIS was developed and scaled nationally between 2009 and 2014 to collect and aggregate data on health facility staffing and trained health professional pipeline.[26]	Facility
Master Facility Registry (MFR)	In 2015, the MoHCDGEC launched the Master Facility Registry. The MFR is a publicly available database containing geographic location, basic infrastructure, services, and pandemic readiness for all health facilities in Tanzania.[27]	Facility

[23] Tanzania: Integrated Health Information Architecture - DHIS2 Documentation. (n.d.). [online] *DHIS2 Documentation*. Available at: docs.dhis2.org.

[24] Gilbert, S.S., Bulula, N., Yohana, E., Thompson, J., Beylerian, E., Werner, L. and Shearer, J.C. (2020). The impact of an integrated electronic immunization registry and logistics management information system (EIR-eLMIS) on vaccine availability in three regions in Tanzania: A pre-post and time-series analysis. *Vaccine*, 38(3), pp.562–569.

[25] Nkowane, Dr.B.M. (2019). *Streamlining and Strengthening the Disease Surveillance System in Tanzania: Disease Surveillance System Review, Asset Mapping, Gap Analysis, and Proposal of Strategies for Streamlining and Strengthening Disease Surveillance*. [online] John Snow Inc. Available at: jsi.com.

[26] Ishijima, H., Mapunda, M., Mndeme, M., Sukums, F. and Mlay, V.S. (2015). Challenges and opportunities for effective adoption of HRH information systems in developing countries: national rollout of HRHIS and TIIS in Tanzania. *Human Resources for Health*, [online] 13(48). Available at: researchgate.net.

[27] Darcy, N., Perera, S., Stanley, G., Rumisha, S., Assenga, K., Polycarp, F., Sijaona, A., Msechu, E., Mzeru, M., Kumalija, C., Kambenga, M., Mayala, B., Elias, M., Biondich, P., Kalungwa, Z., Mwamafupa, J., Kipilyango, N. and Teesdale, S. (2018). Case Study: The

National Tanzania Technical Health Data Information Systems		
Name	Description	Level of Data Collection
Medical Stores Department Logistics Management Information System (eLMIS)	Tanzania first began implementing its eLMIS system in 2011 and started scaling the platform in 2013 to track family planning, malaria, HIV, TB, and other medicines. Since then, the platform has been strengthened and new modules, such as VIMs, added.[28]	Facility
Nexleaf ColdTrace5 (CT5)	In early 2018, Tanzania began installing remote temperature monitoring into vaccine freezers to improve cold chain monitoring.[29]	Facilities, district vaccine stores
mSupply	ERP software for Zanzibar.	Zanzibar health facilities
Epicor9	ERP software for Tanzania mainland.	Medical Stores Department
Tanzania Facility Financial Accounting and Reporting System (FFAR)	In 2017, Tanzania launched a suite of financial platforms standardizing accounting practices and reporting across facilities.[30]	Facility
PlanRep	Along with FFAR, Tanzania also implemented an electronic planning and budgeting platform for local governments.[31]	Local Government Authorities
Government of Tanzania – Hospital Management Information System (GoT-HoMIS)	The GoT-HoMIS system manages service delivery and client information for hospitals. The GoT-HoMIS system was first launched in 2015. Specifically, it includes an electronic medical record module, laboratory information, medical supplies tracking, billing, and reporting forms.[32]	Hospitals
Care and	CTC2 is an EMR system for HIV/AIDs patients.	HIV/AIDs

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Tanzania Health Facility Registry. *Healthcare Policy and Reform*, [online] pp.339–368. Available at: www.researchgate.net.

[28] John Snow Inc. (n.d.). *Building Stronger Health Information Systems in Tanzania: A DECADE OF COLLABORATION AND LEARNING*. [online] John Snow, Inc. Available at: publications.jsi.com.

[29] Bulula, N. (2018). *You Can't Manage What You Can't See: Making Cold Chain Data Visible in Tanzania*. [online] John Snow, Inc. Available at: www.jsi.com.

[30] U.S. Embassy Dar es Salaam. (2017). *New Government of Tanzania Information Systems to Improve Delivery of Public Services*. [online] U.S. Embassy Tanzania. Available at: tz.usembassy.gov.

[31] Ibid.

[32] Health Data Collaborative. (2017). *Joint and Aligned Investment in Digital Health Information Systems*. [online] Health Data Collaborative and POIRAG. Available at: www.healthdatacollaborative.org.

National Tanzania Technical Health Data Information Systems		
Name	Description	Level of Data Collection
Treatment Center (CTC2/3)	CTC3 was implemented in late 2017 and serves as a data aggregation tool for multiple clinics.[33, 34]	clinics
Laboratory Information System (LIS)	The LIS tracks patient specimens and results. It was implemented in 2010.[35]	

Machine learning algorithms typically use electronic medical data (from Health Management Information Systems – HMIS) or electronic logistics data (from electronic Logistics Management Information Systems – eLMIS), among other types of data (such as publicly available data). Therefore, it is critical that the expansion of both those systems be ensured by the government of Tanzania so that machine learning algorithms can be fed more and more data from all levels of the supply chain.

In addition to many different primary data collection systems, Tanzania has invested in health information support systems to improve data accessibility and interoperability between data collection systems. These are the valuable links between otherwise siloed data sets.

Tanzania has invested in both proprietary and open-source software within the health supply chain creating the need for a bespoke interoperability layer leading to the "most advanced health information exchange in Sub-Saharan Africa."[36, 37]

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[33] PEPFAR (2019). *Tanzania Country Operational Plan COP 2019 Strategic Direction Summary*. [online] pp.1–109. Available at: www.state.gov.

[34] University of Dar es Salaam Computing Centre. (n.d.). *CTC Databases for National Aids Control Programme (NACP).* [online] UCC. Available at: www.ucc.co.tz.

[35] Monu, R. (2010). *Design and Implementation of a Basic Laboratory Information System for Resource-Limited Settings*. [online] pp.1–45. Available at: smartech.gatech.edu.

[36] Nsaghurwe, A., Dwivedi, V., Ndesanjo, W., Bams, H., Busiga, M., Nyella, E., Massawe, J.V., Smith, D., Onyejekwe, K., Metzger, J. and Taylor, P. (2020). *One country's journey to interoperability: Tanzania's experience developing a national health information exchange*. [online] Available at: www.researchsquare.com.

[37] Nsaghurwe, A. (2019). *Tanzania Deploys the Most Advanced Health Information Exchange in sub-Saharan Africa*. [online] Maternal Child Survival Program. Available at: www.mcsprogram.org.

Figure 10. Tanzania National Health Information Exchange (TzHIE) Support Systems

Name	Description
Health Information Mediator (openHIM)	Interoperability layer between HRHIS, eLMIS, DHIS2, VIMS, and Epicor9.[38]
National Health Data Repository	National standardized repository for health data
National Health Client Repository	National standardized repository for identifying patient information

The impressive effort behind the TzHIE has primed Tanzania to deploy AI to improve health supply chains at national scale. The synchronization of data at the national level means less upfront effort to collate and prepare data for AI.

AI technology can and should integrate into existing systems and interfaces whenever possible and beneficial. Tanzania has trained thousands of health supply chain workers – from frontline health care workers to Ministry of Health officials – to use these systems in their day-to-day work. An AI tool can seamlessly be built into interfaces that healthcare workers are already using accelerating adoption and impact. This mitigates change management requirements and dramatically increases the probability of a successful implementation.

The Tanzanian government and private companies have invested in connectivity infrastructure to ensure data sovereignty. AI practitioners can utilize servers within Tanzania to protect sensitive data and abide by local policies. These investments mean that AI models can be nationalized and run solely within Tanzania without data ever leaving Tanzania's borders.

Tanzania's public and private investments into improving data infrastructure have primed the country to consider AI solutions to improve health supply chain operations.

[38] Bagumhe, S.E. (2019). Implementing Interoperability Layer to Support Health Information Exchange in Tanzania. [online] Available at: www.researchgate.net.

List of National Tanzania Data Infrastructure

- National Internet Data Center
- Tigo Data Centre
- Vodacom Data Centers

TOA RECOMMENDED NEXT STEPS

Instill	Scale and Sustain
Continued scale up of facility Electronic Medical Records (EMRs) with universal patient and services identifiers	Systems with ability to determine expected clients and their medicines, health equipment, and services needed
Interoperability of systems for managing demand, supplies, and funds	Push mobile messages for healthcare and medicine tailored to individual patients using AI
Integration of other systems, including the Tanzania Bureau of Standards, Tanzania Medical Devices Authority, Business Registration and Licensing Agency, Tanzania Revenue Authority and Private Health Laboratory Board to show legitimacy of suppliers	Predictive analytics integrated in e-LMIS National and global quality management standards to include AI/ML components ICT infrastructure and devices at all levels
Updated geo-locations of all service delivery points	
Mapping of data collection systems for particular program/problem area	

Policy & Strategy

The facilitative policy and strategic government vision outlined in the 2013-2018 National Health e-Strategy led to an impressive expansion of digital health systems the previous decade. Following the success of the e-Strategy, the Tanzania MoHCDGEC released the 2019-2024 Digital Health Strategy (DHS).

The top stated goal and priority of the DHS is to strengthen digital health governance and leadership. Other goals include to expand ICT access and operational use as well as improve interoperability between systems. These activities will continue to strengthen Tanzania's AI readiness by creating a supportive digital environment.

However, there are likely policy changes that will need to occur as Tanzania continues investing in AI. In order to ensure successful AI implementation, government representatives must be involved to guide regulation change.[39] Policy must be built in a manner to generate a framework for the trust and accelerated adoption of AI technology. In addition, the Tanzania MoHCDGEC should begin considering adding a section on AI strategy to the DHS with input from technical experts, end users, and other supply chain stakeholders.[40]

TOA RECOMMENDED NEXT STEPS

Instill	**Scale and Sustain**
Policies to safeguard patient data, including privacy and ownership Adopt global guidance of use of AI in health sector Transparency around available data sources	Policies guiding AI-powered Targeted Digitized Information as part of patients & community outreach/communication programs Policies supporting e-Prescription information to be shared during dispensing/service delivery Support from regulatory bodies and policy makers

[39] AI Commons, Sahara Ventures and Tanzania AI Lab (n.d.). *Making Artificial Intelligence Solutions Work In Tanzania: Lessons From IdeaLab. AI Project.* Sahara Ventures.

[40] Yadav, Prashant. (2021). Interview by Johnna Sundberg and Emma Delmotte.

Knowledge & Skills

Knowledge of AI is not limited to the teams developing AI algorithms. In order for AI to be successfully implemented, awareness of what the AI is doing, what are its inputs and the expected outputs are critical to build trust among end users. Increasing AI literacy among all stakeholders is crucial to AI sustainability.

The Tanzania AI Lab is an organization working to build the government's confidence and trust in AI, as well as equip students with the technical skills and experience necessary to develop AI technologies. Local organizations like the AI Lab will be crucial to not only building Tanzania's AI expertise but also trust in AI.

This precondition will also be naturally strengthened through successful implementations of AI technology. With successful training and change management practices, stakeholders who use AI in core operations will begin to gain trust in the technology and confidence in expanding its use.

To make sure these preconditions are met, it is recommended that the Government of Tanzania establishes an inter-ministerial AI group[41] that can act as the AI expert body within Tanzania to support each Ministry's Technical Working Group, which will be running the AI technology implementation projects.

[41] Yadav, Prashant. (2021). Interview by Johnna Sundberg and Emma Delmotte.

TOA RECOMMENDED NEXT STEPS

Instill	Scale and Sustain
Community engagement of benefits of AI Share experience from other countries/ regions that have implemented AI Curriculum development for professionals and academic programs on how to use AI Internships and practicums through partnerships with implementing partners to ensure AI is applied cost-effectively in practice Workshops and hackathons for capacity-building	ML skills incorporated in pre-service training and continuous education plans for healthcare professionals Institutionalize AI agenda in academic plans and budget Engaging local institutions in order to build local capacity

Partnerships

The Tanzanian government has invested in strategic partnerships to develop its data system infrastructure, working with diverse partners such as international technology companies and regional NGOs such as inSupply.

The success of these implementations has shown that partnerships can be a powerful tool for the government to outsource the development of new technology while building capacity internally to manage that technology.

Although the Tanzanian government has formulated partnerships to build new technologies, AI in most uses will be an addition to an existing technology. Therefore, a collaborative policy environment for partnerships should be established with clear guidance and regulation concerning data sharing, privacy, and ownership of these systems.

Partners can be non-governmental organizations, independent AI experts, private sector companies, locally and abroad to ensure the priority is to ensure Tanzania has access to the best knowledge in the world when it comes to AI.

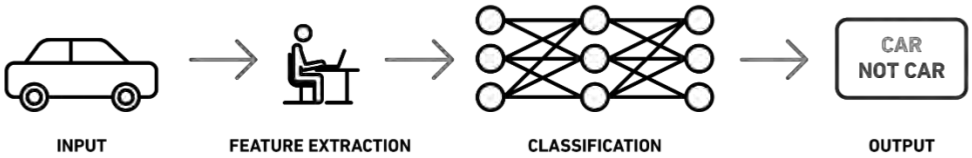
TOA RECOMMENDED NEXT STEPS

Instill	Scale and Sustain
Partnership with domain/subject matter experts for consultation AI skills outsourced while building local capacity Data approval for using data for co-creating working solution	Partnerships with solution providers to provide ongoing technical assistance Research agenda that is built with data owners and ministries Successful partnership exit strategies

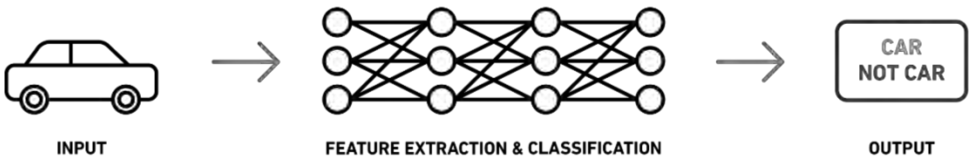
Key Takeaways

- Following the Theory of Change, AI can be used to improve health supply chain efficiency and performance ultimately improving health outcomes.
- Tanzania has invested heavily in the technology infrastructure required to begin implementing AI.
- Tanzania has strong guidelines on data use and developing new systems; however, new policy is needed to address AI-specific concerns such as data access and modifying existing systems.
- Organizations within Tanzania such as **inSupply Health/JSI** and the **Tanzania AI Lab** are working to develop AI skills among all health supply chain stakeholders.

Machine Learning



Deep Learning



Successful Implementation of Artificial Intelligence Technologies in the Tanzania Health Supply Chain

This section will act as a guide to the Government of Tanzania to identify which AI solutions can address Tanzania's specific needs and how to successfully implement them, based off the *Theory of Change/Theory of Action*.

Why integrate ML with supply chains?

The AI revolution reached the supply chain sector over the last 20 years, fundamentally changing the best practices leading to supply chains that are more responsive and flexible.[42]

Adopting AI in supply chains can lead to faster distribution, real-time adjustments to meet demand, greater tailoring to individual needs all leading to more accuracy and efficiency in the supply chain overall.[43] While AI has been deployed across verticals, it is in supply chain where it has consistently yielded the most impact in ROI financially and operationally.

AI can play a role in addressing health supply chain issues, especially in low- and middle-income countries, at a time when information technology infrastructure such as electronic Logistics Management Information Systems (eLMIS) and Health Management Information Systems (HMIS) are more and more advanced and increasingly available at all levels of the supply chain.[44]

According to Health Supply Chain Expert Dr. Prashant Yadav, Professor at the Global Center for Development, INSEAD and Harvard Medical School, AI is key to the success and optimization of health supply chains across the world. Supply Chain functions require "highly contextualized" knowledge of staff at lower levels of the supply chain to carry out the planning function. The opportunity that AI can bring is to render tacit knowledge at lower levels of the supply chain, codified and therefore available throughout the entire supply chain and inform supply planning decision-making.

The ability to plan accurately for commodities needs clearly depends on how well you can codify knowledge about demand at the lowest point, most knowledgeable point of the supply chain and "mimic human-like intelligence."[45]

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[42] Magner, M., Yadav, P. (2017). *Supply Chains of the Future.* [online] pp.1-40. Available at: wdi.umich.edu.

[43] McKinsey and Company. (2016). *Supply Chain 4.0 – the next-generation digital supply chain.* [online] McKinsey and Company. Available at: mckinsey.com.

[44] Schwalbe, N. and Wahl, B. (2020). Artificial intelligence and the future of global health. *The Lancet*, 395(10236), pp.1579–1586.

[45] Broadband Commission for Sustainable Development (2020). *Reimagining Global Health through Artificial Intelligence: The Roadmap to AI Maturity*. pp.1–129.

Opportunities for Supply Chain Improvements

Health supply chains are critical in preventing the spread of diseases.

Health supply chains have long been considered the backbone of healthcare – it is time to start thinking of them as the central nervous system. Investment is beginning to recognize this data-driven opportunity at the center of health.

Donors and governments increasingly invest in improvement projects to ensure supply chains not only meet demand, but meet it increasingly faster, at the highest quality and in the most transparent way possible.

With the introduction of modern Logistics Management Information Systems (LMIS), the physical, financial and information flows of supply chains have become increasingly traceable and enabled, in large part, to deliver the necessary products for patient care. However, these systems lack real capabilities in forecasting short and long-term demand.

This is where AI can help.

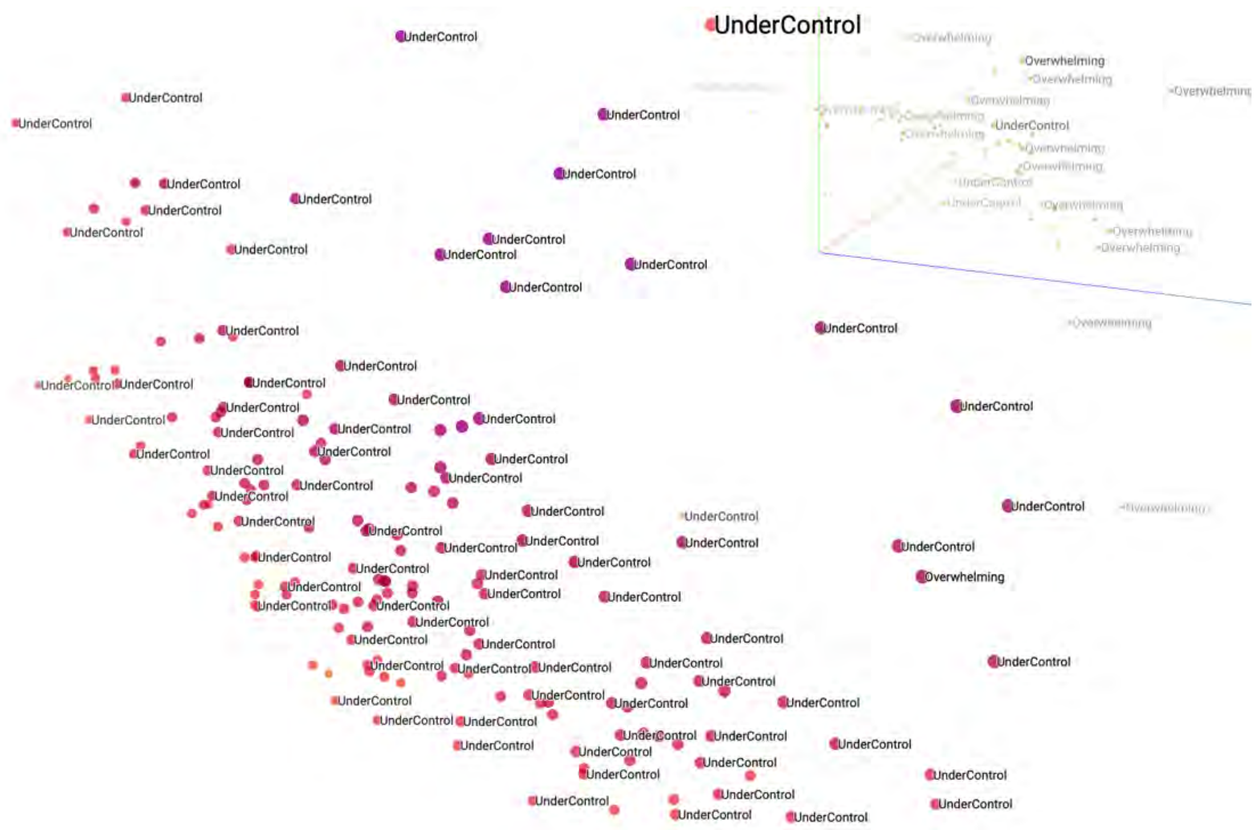


Figure 11. Language patterns in chats among front line health workers

Leveraging frontline workers' tacit knowledge upstream

One challenge ML technology can address is to enable the use of lower tier knowledge from healthcare workers to inform supply planning decision-making. This is ground truth from hyper local contextual experts – it is the fuel for precision. AI can be used to codify their knowledge and to make it usable.

For example, Health Management Information Systems that manage to record patient level data are unfortunately still operating at a level of granularity which is insufficient. They do not track week-to-week, day-to-day patient arrival, seasonal issues that may affect population health and other deep patient/population details.

The healthcare workers at the health facility level possess that knowledge. It remains with the worker and does not benefit higher levels of the supply chain as it should.

Precise and accurate supply chain planning can only happen when we have information from the last mile of the supply chain and "get that information organized as quantitatively as possible."[46] AI can help extract and use the frontline healthcare worker expertise through Expert-in-the-Loop ML technologies.

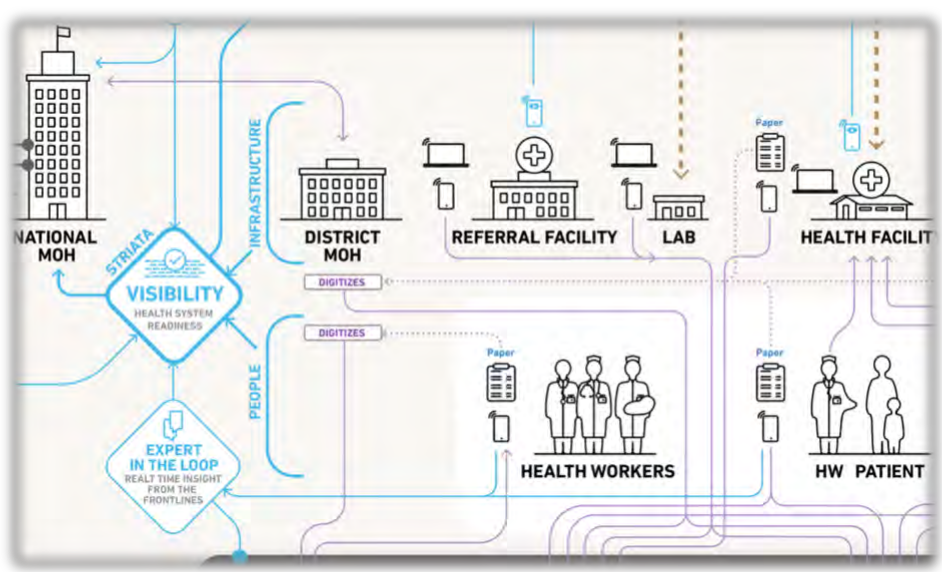
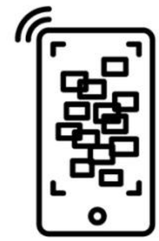


Figure 12. Expert-in-the Loop. Health workers provide real-time frontline insights.

[46] Yadav, Prashant. (2021). Interview by Johnna Sundberg and Emma Delmotte.

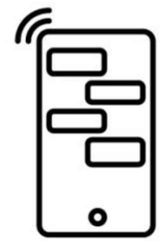
Optimizing delivery networks for speed and efficiency

Another example of an opportunity to boost efficiency exists in the health delivery logistics: a health care worker knows, by experience, which roads have the tendency to get blocked or encounter issues; for example, rising political conflict zones, and may know what alternative routes are safer and/or faster.



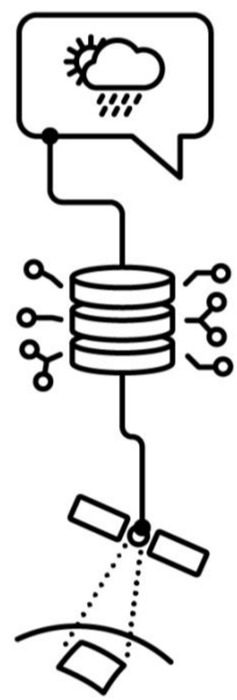
Once again, that tacit knowledge not being codified means this experienced-based knowledge is not available as a factor in decision-making at higher levels of the supply chain.

In addition to collecting and codifying data, AI technologies can feed on different types of publicly available data such as local radio or satellite imagery as well, to create better maps of the road network and to predict routes that may encounter issues.[47]



As Suvrit Sra, PhD Professor of AI at MIT states:

> *"Machine learning methods offer an automatic way to combine a variety of sources of information towards a common end goal of either predicting or maximizing efficiency or ensuring robustness.*
>
> *"Hard coded, typically used standard models cannot easily make use of rich, multi-modal sources of data and can also be non-robust because the moment their brittle assumptions are violated, their reliability is off.*
>
> *"Machine learning is the only method that allows for the collection of multiple sources of information. For instance, Machine Learning Speech Recognition methods can understand and collect data from local radios and computer vision technologies can understand and gather information from satellite imagery.*
>
> *This multi-modal data can then suggest to users which routes are operable at any point in time to reach his/her destination rapidly and in the safest way."* [48]



[47] Mees, A. (1989). Modelling Dynamical Systems from Real-World Data. *Measures of Complexity and Chaos,* 208(B), pp.345-348.

[48] Sra, Suvrit (2021). Interview by Johnna Sundberg and Emma Delmotte.

AI technology can predict routes that should be taken, that are operable and that will ensure a safe and rapid trip to the driver/health worker to his/her destination. Route optimization is also the foundation of carbon reduction across supply chains minimizing output through inefficient logistics.

Similarly, Logistimo developed a product that allows for vehicle routing and scheduling, as further detailed in a use case below.

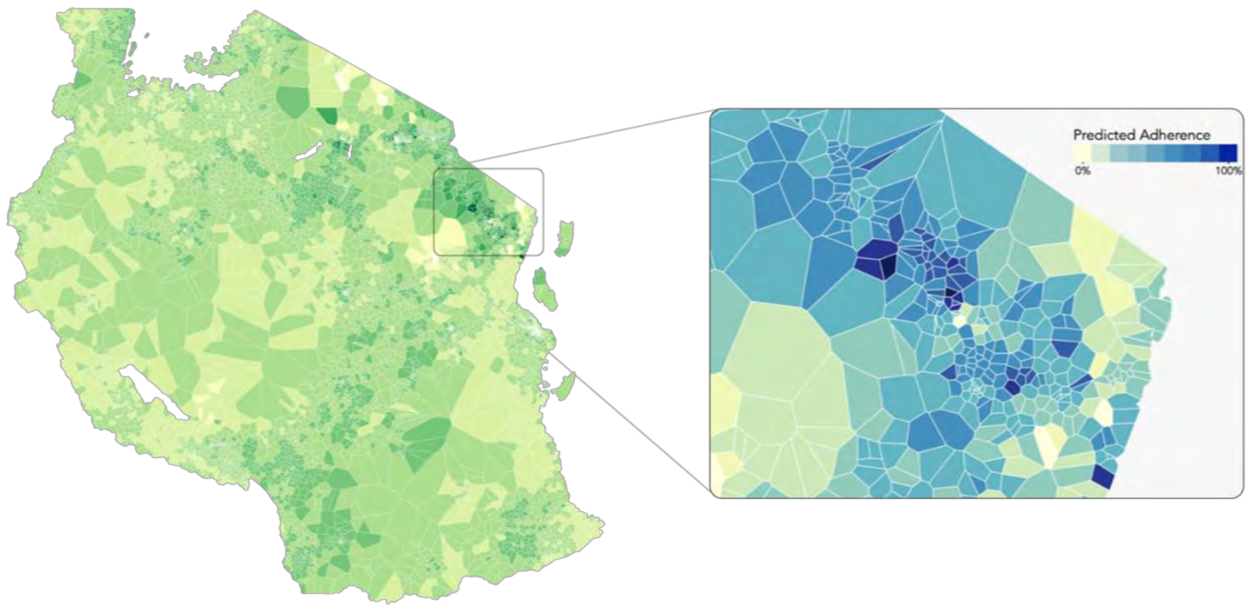


Figure 13. Predicted Treatment Adherence by Facility

Promoting patient and commodity transfers inter-facility to improve health service delivery

Another difficulty experienced in global health supply chains around the world are shortages of commodities and staff, leading to overcrowding of patients in waiting rooms or untreated patients.[49]

An accurate prediction of patient load can enable a more efficient system so that health facilities can timely re-assign patients to nearest health facilities or send needed commodity quantities to health facilities in need in the area.

[49] Mtonga, T. et al. (2019). Design and implementation of a clinical laboratory information system in a low-resource setting. *African Journal of Laboratory Medicine,* 8(1).

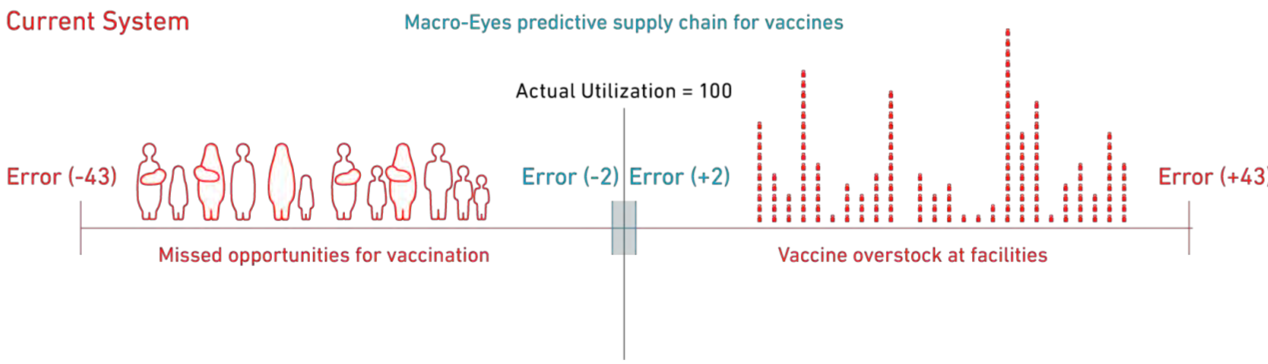
End-to-End AI Use Cases and Opportunity Areas in Tanzanian Health Supply Chains

Use Case 1: Predictive Supply Chain for Vaccines

TOA IDENTIFIED USER NEEDS

User	Need
Healthcare worker	I need to be able to anticipate surges in demand based on outbreaks, seasonal disease
Public supplier (medical stores)	I need to know demand from my customers well in advance to provide better customer care I need to be able to forecast and optimize stock levels across warehouses to minimize stock out and expiry
Ministry of Health	I need to eliminate the need to call lower levels for reports. I need to predict and prevent loss due to wastage.
Implementing partners	I need to be able to analyze data to give them information.

AI can be used to significantly improve the forecasting exercise in any supply chain, no matter the industry or geographic location. Currently, Tanzania uses a three-month rolling average to forecast utilization of vaccines. Historical data shows that this method is not optimal and leads to situations of stock-outs, and consequently emergency orders, and accumulation of expired products.



Macro-Eyes Predictive Supply Chain for Vaccines – Performance comparison

Machine learning has proven extremely successful at forecasting. One of the specific methods of machine learning that enables a more accurate forecast is to use cross-product training, or historical data of several products at the same time, instead of using historical data for only one product to predict utilization.[50] It is significantly more accurate even if one product's historical data has a substantial number of missing values.

The Macro-Eyes Predictive Supply Chain for Vaccines (PSCV) module is based on machine learning forecasting technology (Macro-Eyes' STRIATA Forecast product) and is able to predict utilization of vaccines with less than 2% error at the national level. This real-time, AI-powered forecasting algorithm learns over time from new data, remaining relevant to changes in Tanzania and its health systems.

The model uses and learns from publicly available data, health system data (when available), satellite imagery, atmospheric data, images and natural language inputs (when available). Precision forecasting means less wastage, lower cost, and more lives saved with the same resources. The model is 98.5 % accurate and cuts vaccine forecast misallocation by 96% (compared to legacy three-month rolling average forecasting method) by predicting utilization of vaccines across 3,500 facilities.

Macro-Eyes' STRIATA Forecast technology can be used with any medical commodities. Macro-Eyes is currently working closely with the Ministry of Health and its partners, PATH and inSupply Health, to deploy the model in the vaccines supply chain through integrating the model in existing systems

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[50] Zhu, X., et al. (2021) Demand Forecasting with Supply-Chain Information and machine learning: Evidence in the Pharmaceutical Industry. Production and Operations Management. In Press: https://doi.org/10.1111/poms.13426

(VIMS and TImR). The PSCV model (based off of STRIATA Forecast product is already built and tested).

To quantify the impact of the integration of the PSCV model in VIMS and TImR, Macro-Eyes conducted an analysis to calculate the potential reduction in mortality rate and supply chain costs enabled by a more accurate forecast.

Reduction in mortality rate

Assumption: 98.5% accurate predictions of utilization will at least lead to a vaccine coverage increase of 50% compared to current coverage predictions (% coverage predictions are provided by the Lives Saved Tool – LiST).

Macro-Eyes used LiST, developed by the Institute for International Programs (IIP) at Johns Hopkins Bloomberg School of Public Health and funded by the Bill & Melinda Gates Foundation to calculate the new mortality rate with this increased coverage.

Results:
14.3% reduction in mortality for women aged 15-49 years old and 0.8% reduction for children under 5, by 2027, in relation to the following vaccines:

- Tetanus (TT)
- Pneumococcal Conjugate Vaccine (PCV13)
- Bacillus Calmette-Guérin (BCG) – tuberculosis
- Poliomyelitis (OPV)
- Rotavirus (RV)
- Diphtheria Tetanus Pertussis Hepatitis B and Haemophilus Influenza (DTP-Hib-HepB)
- Measles and Rubella (MR)

ASSOCIATED WASTED COSTS

Legacy US$360,360

ML-based US$267,540

Excerpt from table below

Reduction in cost by more accurate forecasts

When forecasts are inaccurate, health workers tend to place larger orders to ensure that, if there is a peak in demand, no stock-outs will happen. This exercise certainly ensures patients can be vaccinated and therefore saves lives, but it also results in high wastage, especially at health facilities and warehouses at the mid-level of the supply chain.

Those financial losses can then lead to shortage of funds to buy commodities at a later stage and can have a snowball effect, putting patients' lives at risk. These order variances tend to also increase as they propagate to the upstream supply chain, portraying a distorted image of the demand at higher levels of the supply chain. This information distortion is referred to as the Bullwhip Effect.[51] This will often result in excessive distribution of commodities downstream and cause wastage.

Machine learning-based forecasting is more accurate and not only looks at historical order data to make predictions, but uses all sorts of different data sets, including publicly available data to predict the accurate utilization at facility level and enables the right provision of commodities to be sent downstream.

Because of data access limitations, Macro-Eyes was only able to calculate cost reduction for the Arusha region in Tanzania over one full year. Therefore, the following results only account for cost reduction estimates over one year for the Arusha region.

[51] Lee, H. et al. (1997). The Bullwhip Effect in supply chains. *MIT Sloan Management Review,* 38(3), pp. 93-102.

Results: based on historical data of previous utilization, we calculated that with more accurate forecasting, Tanzania healthcare supply chain workers will be able to significantly reduce the number of unnecessary vaccines being bought to only what is needed, based on accurate demand. The result is a 25.8% decrease in costs incurred by vaccine vial over ordering.

Cost Reduction Estimates for the Arusha region over one full year		
One year estimate based on available historical data from April 2018	Unnecessary vials bought (wastage/ buffer stock)	Associated **wasted** costs incurred
Based on **legacy** three-months rolling average forecasting method	17,160 vials	$US 360,360
With **ML-based** forecasting method	12,740 vials	$US 267,540

Use Case 2: Health system and Covid-19 readiness

TOA IDENTIFIED USER NEEDS

User	Need
Healthcare worker	I need to be able to anticipate surges in demand based on outbreaks, seasonal disease
Ministry of Health	I need to analyze data to uncover root cause of factors causing challenges or bringing success I need to eliminate the need of calling lower-levels for reports
Implementing partners	I need easy accessibility and real-time data insights to provide to different levels, such as Ministry, subnational, etc.

In addition to predicting demand-and-supply, predictive analytics can also be used to determine where, who, and when medical devices are needed.[52]

Macro-Eyes has devoted a decade to building predictive technology and has recently integrated it into a platform called STRIATA. STRIATA is a product running core Macro-Eyes AI, to continuously assess the health system as a whole and generate health facility readiness scores for COVID-19 in Sierra Leone. Through the application of multi-dimensional data (health data to satellite imagery to information scraped from the public internet including news), Macro-Eyes generated a “resiliency index” for the health system as a whole for Sierra Leone. The Macro-Eyes product STRIATA helps the country leaders assess available capacity of health facilities and identify where and when well-defined resources will save the most lives. In essence, STRIATA is able to:

- Use both unsupervised and supervised machine learning (ML) to predict COVID-19 readiness for each of Sierra Leone's 1,200+ health facilities.

[52] Ernst and Young (EY). (2019). A reinvented supply chain will be the backbone of decentralized healthcare, pp.1-12.

- Phenotype health facilities using graph neural networks to machine learn groups of health facilities that share common characteristics.
- Learn from various data sources (surveys, web data, imagery, DHIS2), link the data and generate, in near real-time, views into the state of infrastructure, human resources, materials and supplies and essential medicines.
- Use web scraping to detect changes at the health facility level and input this data into the ML algorithms.
- Use low resolution satellite imagery to understand shocks to the health system.
- Use high resolution satellite imagery to predict the state of electrification for health facilities across Sierra Leone.
- Predict emergency readiness with greater than 92% accuracy for health facilities in Tanzania.
- Remotely and continuously assess COVID readiness of every health facility in Sierra Leone.

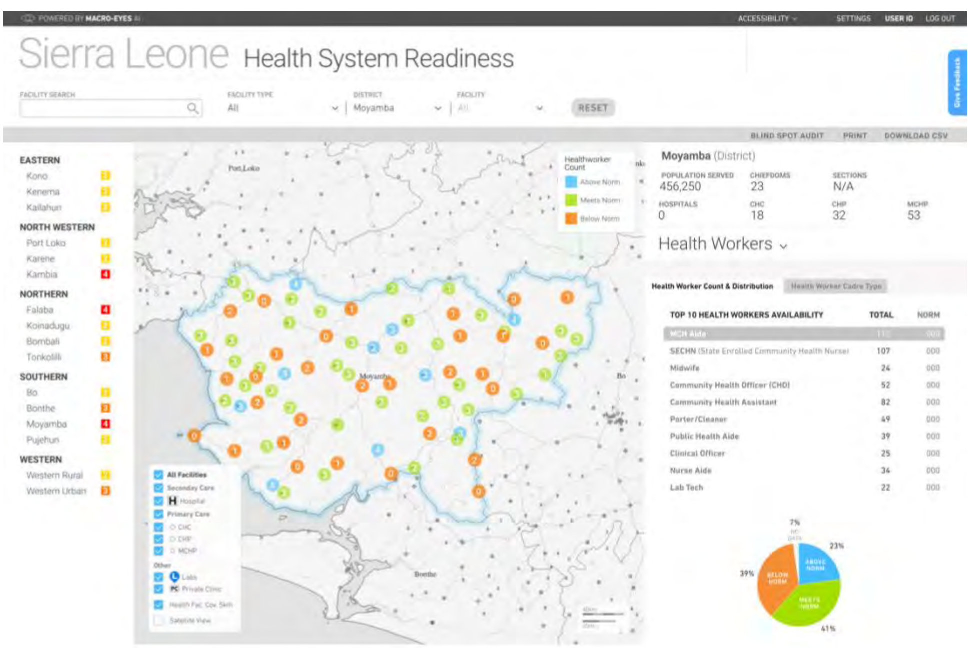

Figure 14. Health System Readiness Interface

Speed and precision will be the defining factor. Macro-Eyes technology anticipates shifts in demand, predict behavior, and remotely assess health system infrastructure – in challenging environments and very often without access to conventional data.

Use Case 3: Inventory management and auditing

TOA IDENTIFIED USER NEEDS

User	Need
Healthcare worker	I need to understand stock status to prevent wastage.
Ministry of Health	I need to track free and subsidized health commodities I need to triangulate information from different systems to overcome data quality issues
Implementing partners	I need ready to use information for decision-making
Private suppliers	I need to know real-time stock levels across public and private suppliers for better planning

AI can help to improve traceability of medical commodities. Lack of traceability and multiple opportunities within supply chains for product diversion can lead to both stock-outs and substandard drugs. Track and trace technology enables us to determine where each product is and where it came from.[53]

Despite the substantial benefits of the technology, cost and appropriate IT remain barriers to implementation today although countries using a LMIS have the potential to integrate track and trace technology within these existing systems.[54] AI can be used to enhance these efforts by predicting medicines that are bad or by bolstering quality assurance systems.

[53] Pisa, M., McCurdy D. (2019). *Improving Global Health Supply Chains through Traceability.* [online] Center for Global Development. Available at: www.cgdev.org.

[54] USAID Center for Innovation and Impact. (2019). Artificial intelligence in global health: defining a collective path forward, pp. 4-27.

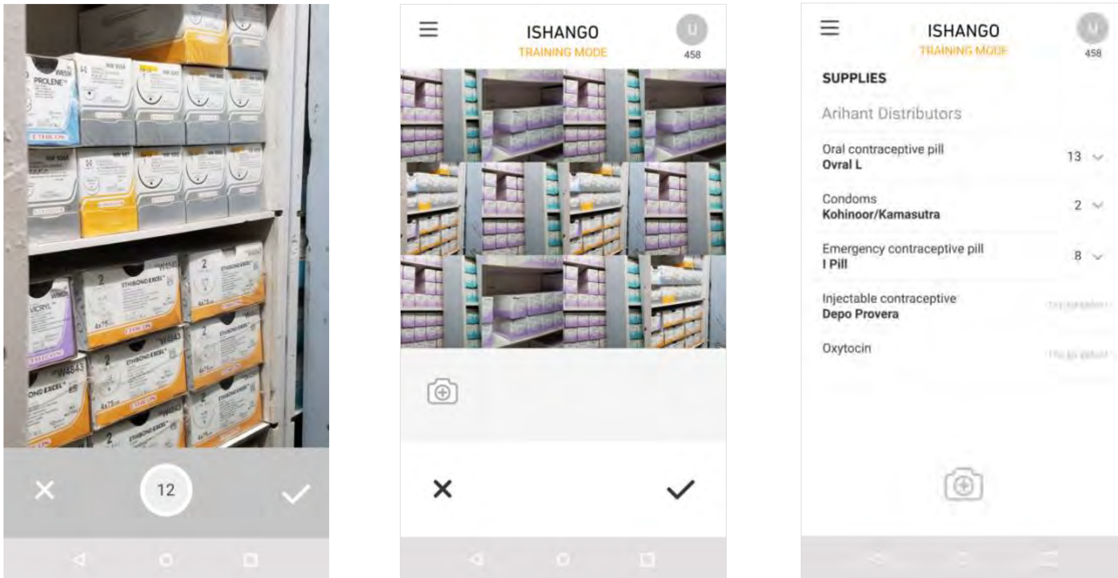

Figure 15. The Ishango application. User screenshots.

Through Ishango, the Macro-Eyes AI technology counts, catalogues, verifies and audits various health commodities.[55]

Ishango is a mobile application using computer vision to rapidly generate accurate counts. It is the first counting app with on-device AI to see, measure & report on the current state of infrastructure.

Running on a phone and extracting data by analyzing simple photographs, Ishango can be used to accurately count medications, vials, supplies and more from the point of service level to the supplier level with the snap of a picture. The technology works offline and at speed, delivering data over 50 times faster than counting by hand, with less than 2.5% error rate.

With funding from the Bill & Melinda Gates Foundation, Ishango was deployed by UNICEF in Nigeria and Zambia to count vials during and after mOPV2 mass vaccination campaigns.

[55] Pisa, M., McCurdy D. (2019). *Improving Global Health Supply Chains through Traceability.* [online] Center for Global Development. Available at: www.cgdev.org.

In India, Ishango was used by pharmaceutical partners to count and verify on-shelf family planning products.

Similarly, Logistimo offers an inventory management platform that automatically converts information from paper forms to electronic forms by only using a mobile phone. Platforms like Logistimo can help reduce forecasting error by eliminating errors from transferring data from paper to electronic format. Furthermore, the technology allows AI solutions to be integrated into supply chains that are still primarily paper-based.

Use Case 4: Logistimo's vehicle routing and scheduling product

Needs identified during the **Theory of Change/Theory of Action workshop series** held in 2020/2021:

TOA IDENTIFIED USER NEEDS

User	Need
Healthcare worker	I need my orders to be fulfilled on time and in full.
Public supplier (medical store)	I need efficient distribution systems to be able to deliver according to schedule.
Private suppliers	I need to have high order fulfilling rate to meet service-level agreements to win tenders.
PORLAG	I need to track the status of medical equipment, medicine, and non-medicine supplies.

Logistimo developed a vehicle routing and scheduling product to identify optimal delivery routes but also schedule deliveries accordingly in order to produce a routing that can be agile to demand shifts. Their solution also optimizes loads based on the available space left in the truck, vehicle location, storage location and pick-up points.

Logistimo deployed this technology as part of their end-to-end product suite in Uganda for FIT Uganda (Freight-In-Time) and UPS via GAVI (Global Alliance for Vaccine and Immunization) targeting the Uganda Health Supply Chain (including cold chain).

The result is that "Warehouse Managers have been able to streamline replenishment cycles and reduce costs," and improve "operational efficiency," leading to a consistent above 90% availability (or "in-stock").[56]

[56] Logistimo website (2019). Uganda GAVI VLMD. Available at: https://www.logistimo.com/uganda Accessed 17 May 2021)

Use Case 5: Expert-in-the-Loop

TOA IDENTIFIED USER NEEDS

User	**Need**
Healthcare worker	I need to anticipate surges in demand based on outbreaks, seasonal disease.
Public suppliers (medical stores)	I need to know demand from my customers well in advance to provide better customer care I need to be able to forecast and optimize stock levels across warehouses to minimize stock-outs and expiry

Macro-Eyes also developed an AI technology called "Expert-in-the-Loop" in the attempt to address the tacit knowledge challenge at the lower operational levels of the supply chain (please refer to section "Current Supply Chain Pain Points").

Frontline health workers are the world's foremost experts on the communities they serve: supply constraints, changes in demand, environment, rumors, staffing. Today, health workers are treated as mechanisms for data entry: "measure x," "record y." None of these data entry tasks take advantage of their unique insight or knowledge. The Expert-in-the-Loop AI solution's approach attempted to change how health systems learn from health workers.

Figure 16. Featured frontline health workers.

Macro-Eyes launched five Telegram group chats at health facilities in Mozambique in partnership with VillageReach in November 2019. Health workers were rarely asked direct questions, and were not told what to share. It was simply asked that they describe change in their environment that they deemed important.

On average, users shared about 46 messages, averaging 15 words per message. Macro-Eyes technology machine-learned insight into supply constraints, environmental conditions, the spread of rumors, COVID and catchment population adherence to social distancing and hand-washing. It demonstrated the possibility to correctly gauge the capacity for care, machine learned only from natural language.

In April 2020, 25% of messages were related to COVID-19. The Expert-in-the-Loop platform identified washing stations at all included facilities, social distancing was being done, but masks and adherence to stay at home orders were being followed with varying rigor from site to site. These insights contributed to a broader understanding of how diseases move and how existing (and potential similar) treatments may or may not be effective.

Understanding individual level facility resilience to environmental factors is crucial to accurately predicting both supply, demand and estimating the ability of a facility to meet required levels of capacity in real time. As Dr. Suvrit Sra states, you have to "let the data guide what mathematical models should bear used to overcome the limitations of hand-coded models (for example, those based on typically used, unrealistic statistical assumptions). When augmented with Expert-in-the-Loop Machine Learning methods, models can circumvent the difficulties posed by lack of pre-existing datasets." [57]

[57] Sra, Suvrit (2021). Interview by Johnna Sundberg and Emma Delmotte.

Use Case 6: Babylon Health Symptom Checker

TOA IDENTIFIED USER NEEDS

User	Need
Patient	I need information on health interventions, healthy living, and preventative measures.
Healthcare worker	I need to make accurate diagnosis and provide the right services.
Academician	I need exposure to challenge driven AI special projects for students.

The company Babylon Health built an AI-based chatbot called the "Symptom Checker." It can be downloaded by any individual and is built to guide the user to decide on next steps related to symptom(s) he or she is experiencing. It works in three steps:

1. The user enters any health symptoms he/she is experiencing into the application from a list the application provides. Depending on the symptoms selected, the app will ask for follow-up information.
2. The user is given recommended next steps. The app will indicate possible conditions and connect the user to a doctor if requested.
3. The user is then able to focus on his/her specific health need.

This state-of-the-art application was developed by Babylon's team of Research Scientists, Engineers and healthcare professionals.

The technology was built so it mimics a doctor's approach and builds upon four main pillars: a knowledge base (essentially a medical encyclopedia), health records (based on information from users that have accepted to share their data), Probabilistic Graphical Model (processing combinations of symptoms, diseases, and risk factors to help identify conditions which may match the information entered) and Simulations (What-if scenarios to help users estimate the impact of current diet, exercise, lifestyle on their health).

The technology behind Babylon Health has been published in more than 20 peer-reviewed papers. [58] The app is currently used by millions worldwide.[59]

[58] Babylon Health. Accessed May 2021. Available at: babylonhealth.com.

[59] Dawkins, D. *Britain's Billion Dollar Babylon Health App Set to Launch for 'Millions' of New Yorkers.* Forbes. May 5, 2020. Available at: forbes.com.

Investment Areas Critical to Accelerating the Use of ML in Health Supply Chains

Building trust in AI

Understanding the capabilities of AI and generating trust in the outputs of the machine learning models are essential for the sustainability of the solution. Therefore, engaging with Ministry Leaders from the onset to respectfully build trust into Artificial Intelligence technology is key.

AI institutions understand and have visibility into the performance and implementation processes – ensuring they are aware of how the model improves forecasting and ultimately impacts lives. The goal is that the AI technology seamlessly integrates itself to existing technology the country is already familiar with, minimizing the change management effort.

Demonstrating AI's impact

AI's impact can only be demonstrated when there is transparency. Therefore, it is important for any AI-expert working to implement AI in Tanzania to ensure that the impact of AI is being shared consistently across the Government, Ministry in charge and all other stakeholders involved.

For example, interfaces such as dashboards can be developed to enable the tracking of a machine learning model's accuracy. Such an interface is being developed for the Predictive Supply Chain for Vaccines model, comparing it against the legacy three-month rolling average forecasts and the actual utilization. This is a very simple and easy way to showcase the performance of a model.

Additionally, it is critical to determine the ROI of improved accuracy. There would be no use for any new technologies if they cannot primarily support the government in saving lives and saving costs in order to improve health outcomes in the long run.

Helping leaders understand their own AI-readiness

Prior to any new technology implementation, it is critical that the government takes the lead in assessing areas of the national health supply chain that are ready for Artificial Intelligence technologies. It is advised to set up a Technical Working Group (TWG) to follow-up on Artificial Intelligence technology implementations, impact and expansion to additional areas of the supply chain.

It is advised that these Technical Working Groups not only include Ministry officials from the Ministry of Health, but also from other Ministries within the Government, in-country partners involved in the technological systems currently in place in the country and that might be affected by the introduction of Artificial Intelligence, Independent AI-experts (such as University professors or young doctorate candidates) and companies.

As stated in the preconditions to AI readiness, the set-up of an inter-ministerial AI pole would be effective. Each Technical Working Group of AI projects can refer to this export pole and receive advisory services.[60,61]

The introduction of Artificial Intelligence in a country can only be successful if all active players are invited to the table and agree on objectives of the implementation and prepare for potential challenges.

Developing local expertise

The sustainability and viability of a solution powered by Artificial Intelligence relies on the capacity building done in-country to ensure self-reliance of Tanzania in terms of carrying out the AI solution in the long-term. It is observed that Governments are increasingly becoming the new funder for

[60] USAID Center for Innovation and Impact. (2019). Artificial intelligence in global health: defining a collective path forward, pp. 4-27.

[61] Yadav, Prashant. (2021). Interview by Johnna Sundberg and Emma Delmotte.

health, funded through both taxation and from philanthropic organizations.[62] Building AI capacity in-country should therefore be the priority.

Every country is at a different stage of capacity building:

1. How to use AI technology,
2. How to maintain AI technology, and
3. How to design and build AI technology.

The majority of the world is in stage 1, a subset is in stage 2, and a small few are in stage 3. Each stage takes time. Each stage requires focus and generates enormous value for countries.

At lower levels of the supply chain, it is recommended to prioritize in-person training. This is the reason why partnering with in-country AI experts and appointed Ministry officials is key. Not only does it ensure knowledge transfer to Tanzania, but it also ensures the country can build and keep knowledge to reach self-reliance in the long-term.

It is critical that health workers at the health facility level understand how the algorithm works and understand the data from which it learns. Broad understanding is important to build trust in the accuracy of the system, which increases the likelihood of broad and committed use.

Machine learning systems ultimately should benefit from input and observations from the frontlines of care – with trust, health workers will be willing to share what they notice, which very well might improve the performance of the system as a whole.

Additionally, it is also advised to partner with in-country partners such as non-governmental organizations involved in supporting the Ministry with the technical aspects of the electronic logistics and health systems of the national health supply chain. Tanzania is best known by Tanzanian people, and their knowledge should be a leading element of any new technology implementation in Tanzania.

[62] Magner, M., Yadav, P. (2017). *Supply Chains of the Future.* [online] pp.1-40. Available at: wdi.umich.edu.

Conclusion

Tanzania has robust data and technology foundations for sweeping impact from AI technology. AI solutions are powerful technologies with demonstrated positive impact across healthcare and other domains. Per the ToC, AI technologies can be used to improve health service delivery and increase population health. Accelerated impact of AI in Tanzania will be through investments in pilots, capacity building, and communication all aimed at developing trust and rapid adoption.

Tanzania has invested in many of the preconditions required to implement AI technologies. The last ten years the Tanzanian government has developed many new health data collection systems, invested in increasing interoperability between systems, and created new national health data exchanges. The Tanzanian government has successfully guided the implementation of these technologies through strategic partnerships and policy. These partnerships have in-turn have boosted local capacity to lead and implement data projects. The same strategies can be employed to implement AI in Tanzanian health supply chains and begin proactively leveraging the vast amounts of data being collected today.

AI technologies can be used to leverage frontline workers' knowledge to improve supply chain planning, optimize delivery networks to increase efficiency, and even facilitate proactive inter-facility commodity transfers to prevent stock-outs and wastage. AI can also be used for supply chain forecasting with much greater accuracy than traditional forecasting methods. For example, Macro-Eyes developed a model that has an error of less than 3 vials for every 100 vials of vaccine delivered.

AI technologies are powerful, and the Tanzanian government has heavily invested in the preconditions to AI technologies. Tanzanian health policymakers should consider developing national AI strategies to guide investment in strategic partnerships to begin implementing AI technologies.