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Technical Brief: Gavi Digital Health Information to Digital Health Strategy: Artificial Intelligence & Machine Learning for Immunisation

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Executive Summary

As part of its efforts to explore building on the foundation of the Digital Health Information Strategy into a broader Digital Health Strategy, Gavi, The Vaccine Alliance has highlighted the need to document the current state of artificial intelligence (AI) and machine learning or (ML) or AI/ML for immunisation service planning, delivery, supply chain management, social behaviour communication, and monitoring. This technical brief aims to provide a framework that Gavi and stakeholders can use to help countries prioritise AI/ML for engagement and investment. The integration of AI/ML into immunisation programs presents transformative potential, which can benefit broader primary healthcare (PHC).

The possibilities are only beginning to be explored and come with both significant opportunities and potential risks that need to be anticipated and mitigated. The opportunities include improving equity through more systematic identification of gaps in immunisation service coverage, optimisation of service delivery strategies and locations, and automation of alerts and reminders for individuals and caregivers to receive timely vaccination. They also include the ability to systematically support health workers and individuals with decision support through virtual assistants or chatbots. The risks are largely grouped into algorithmic bias, data bias, and dependence on poor-quality data. The result is poor generalisability and relevance of algorithms developed in the United States and elsewhere to health systems in low and middle income countries, especially where Gavi works. Additional potential for bias may exist in country data sets to the most at-risk populations that Gavi is seeking to reach with immunisation services. There is also significant effort needed to test and validate outputs to ensure accuracy, relevance, and fairness. In addition, human-agency administration for accountability, responsibility, error management, and redress is an often overlooked but important discipline crucial for AI.

AI, encompassing a range of technologies such as Natural Language Processing (NLP) and Generative AI (GenAI), can automate trend identification, facilitate predictive analytics, and support data-driven decision-making. It can also simplify the analysis and synthesis of large volumes of qualitative data. Case studies and research efforts illustrate early experimentations in diverse applications of AI in immunisation. From developing ML models for predicting vaccine demand and route optimisation to utilizing geospatial technologies for microplanning, AI's role is expanding. While these use cases have largely been based on household surveys and geospatial data, there are increasing opportunities for broader applications to leverage operational data from health information systems used to support routine immunisation, supply chain, and immunisation campaigns. In broader health, relevant research shows that ML algorithms have been used to classify drugs successfully, predict fetal health outcomes, and identify disease patterns from unstructured medical records. These approaches can be carefully adapted and tested to improve immunisation programs. The enablers needed for successful adoption include supportive data policies and governance with guidance on what AI can and cannot be used for with appropriate ethical considerations, including ethical considerations for children's data. Availability of high-quality representative data, strong digital infrastructure, interoperability, and multi-stakeholder collaboration for the successful implementation of AI in immunisation are important.

This Gavi Digital Health Technical Brief presents a semi-systematic review and analysis of published literature and implementation reports complemented by insights from key informants on the applications, benefits and risks of AI/ML for immunisation programming. It highlights their capacity to enhance vaccine coverage, optimise supply chains, and predict disease outbreaks, while also discussing potential risks that must be addressed. The following are recommendations to guide investment consideration in AI/ML for immunisation within Gavi programs.

Key Recommendations

- Promote the generation of **high-quality, relevant, and applicable data in the right volumes** in Gavi-supported digital health information initiatives, research, and surveys as a foundational precursor to investment in AI/ML.
- Support Gavi countries to **establish data governance and supportive data infrastructure to leverage the potential** that AI/ML offers in the areas of optimisation of immunisation services and resources, service delivery monitoring, disease outbreak surveillance, and human resource distribution and supervision.
- **Evaluate existing AI/ML for immunisation interventions**, including applications that use household survey data, supply chain forecasting and prediction, and chatbots to ascertain the impact on coverage and demand, effectiveness, and equity, including systematic documentation of potential biases.
- Support priority Gavi countries with **catalytic support through Gavi Alliance members or other partners** for the systematic use case, adaptation, testing, and fairness audits in prioritised applications of AI/ML for immunisation using household surveys, supply chain data, geospatial data, and conversational chatbots.
- Support Gavi countries to **experiment, evaluate, and implement AI/ML systems using operational/ administrative data** from digital health information systems and other digital health interventions for immunisation service delivery for AI/ML through human-in-the-loop approaches.
- **Increase advocacy** to Gavi-supported countries to prioritize enablers essential for AI/ML application (e.g., infrastructure, literacy, and equity-enabled regulation, all necessary for collecting quality immunisation data).
- Develop an internal Gavi policy (ie. AI code of conduct) that guides the **ethical and responsible application of AI** for immunisation and other health programs.

Background

Artificial Intelligence and Machine Learning Overview

In the last few years, the rise of Generative AI (Gen AI) with the recent launch of ChatGPT by OpenAI has brought the revolutionary power of Machine Learning (ML) and Artificial Intelligence (AI) across many sectors, including health, into focus. Artificial Intelligence (AI) is a broad field at the intersection of computer and statistical sciences that deals with creating intelligent agents using computing algorithms (Columbia Engineering, 2024) (Weng, 2015). Intelligent agents learn, reason, and act autonomously. Algorithms are a set of rules, procedures, or instructions for solving a problem in a finite number of steps (Hill, 2016). Machine Learning (ML) is how AI algorithms are developed to learn and infer from data without being explicitly configured (Bi et al., 2019). The most popular form of AI in health is virtual assistants, which fall in the realm of Natural Language Processing (NLP), which helps generate basic-text or basic recommendation texts (Hall et al., 2022). Large Language Models (LLMs) are advanced NLP technologies that are able to process human-like text based on training received from vast databases of language information, like the Generative Pre-trained Transformers (GPT) (Yao et al., 2024). The AI application that makes it possible to generate various types of content – text, imagery, audio, video, and other synthetic data forms is referred to as Generative AI (GenAI) (IBM Research, 2024)(García-Peñalvo & Vázquez-Ingelmo, 2023). By leveraging AI, it may be possible to address some health program challenges, providing more timely, accurate, and actionable insights for better health outcomes (Jiang et al., 2017). AI systems themselves depend on high-quality representative data to extract insights. When they are automated and applied to routine information processes, they can help mitigate quality issues introduced during the Human translation/insight-extraction process. In addition, AI can potentially improve decision-making, enhanced analysis, increased efficiency & productivity, fraud detection, and more, ultimately leading to greater progress on the immunisation mission.

AI/ML for Immunisation Current and Potential Applications

Immunisation programs are benefiting from digitalization. As a result, there is now significantly more data that can be leveraged for AI/ML applications. However, there are considerations related to data quality and representativeness that need to be accounted for as part of any application process. Research from other health areas suggests that immunisation stakeholders may gain from integrating AI into its mission of improving access to vaccines and reducing disease globally (Jiang et al., 2017). While this holds true, there are important considerations necessary to ensure investment in AI for immunisation programs yields the desired result. AI can help synthesize large amounts of data and automate trend identification for data-driven decision-making (Jiang et al., 2017).

Key opportunities in Gavi-supported countries where AI/ML is already being tested and/or may be applicable, include:

- Optimising vaccine demand, and forecasting
- Identifying zero-dose children through missed settlements
- Optimising vaccine distribution channels to ensure better targeting of immunisation programs
- Optimizing vaccine supply routes for efficient and timely deliveries
- Microplanning and vaccination strategy planning
- Immunisation campaign planning
- Outbreak prediction to inform targeted immunisation campaigns
- Non-disruptive training and supervision program support
- Precise demand forecasting based on historical demand-supply data to prevent vaccine shortages or wastage
- Managing and synthesizing technical information from reports, evaluations, publications, and other documents to accessible forms.

Each of these areas have some early evidence and/or parallels in other health domains and are well positioned for optimisation through targeted application of AI/ML for immunisation.

DEFINITIONS

"**Artificial Intelligence** is the field of developing computers and robots that are capable of behaving in ways that both mimic and go beyond human capabilities."
— *Columbia Engineering. (2024). Artificial Intelligence (AI) vs Machine Learning. https://ai.engineering.columbia.edu/ai-vs-machine-learning/*

For example, using historic datasets about distance, truck capacity, duration, etc. and a set of rules or model developed through Machine Learning to recommend optimal routes for vaccine stock

"**Machine Learning** is the use and development of computer systems that are able to learn and adapt without following explicit instructions, by using algorithms and statistical models to analyze and draw inferences from patterns in data."
— *Oxford Language Dictionary. (2024)*

For example, testing and assessing the outputs of data on adverse reactions to immunization based on demographics, geographic location, etc. to observed emerging patterns that can serve as the basis for AI models.

"**Generative AI** refers to deep-learning models that can generate high-quality text, images, and other content based on the data they were trained on."
— *IBM Research. (2024) https://research.ibm.com/blog/what-is-generative-AI*

For example, preloading vaccination schedules, loading, and up-to-date information with responses to engage a virtual assistant or chatbot to respond to questions for caregivers, vaccinators, supervisors, and EPI managers.

"**Data Science** is the study of data to extract meaningful insights for business. It is a multidisciplinary approach that combines principles and practices from the fields of mathematics, statistics, artificial intelligence, and computer engineering to analyze large amounts of data."
— *AWS. (2024) https://aws.amazon.com/what-is/data-science/*

For example, using dashboards to show immunization coverage rates against targets on a map to monitor performance during an immunization campaign to inform corrective action.

Review of frameworks, literature and experiences

A semi-systematic literature search and analysis of scholarly literature, augmented with a gray literature search on Alliance member websites, was conducted [see Appendix A for details on the methods, search strategy, and PRISMA diagram with the search and analysis results]. Similarly, a search was conducted on the websites of key Gavi Alliance members and relevant organizations as listed below to identify current use cases, namely being documented and/or implemented by WHO, UNICEF, Gavi, UNFPA, and Africa CDC. Forty-five articles on AI/ML for immunisation or broader PHC were included, and full-text analysis was used to extract the evidence of the current application of AI/ML for immunisation and other PHC areas. We also reviewed two reports on AI/ML for health and current applications of AI for immunisation. Websites of two interventions referenced in literature that use AI were also reviewed. Similarly, key informant interviews were conducted with 15 professionals who have researched, funded, or participated in AI for health programs and initiatives. Responses were used to validate and complement the findings of the literature review.

The evidence and examples of AI for immunization and PHC programs in the literature show that there are immense research efforts in the field of AI in immunisation and healthcare. Three main themes emerged from our analysis: 1) the use of AI to optimise immunisation systems; 2) improving vaccine demand and addressing mis/disinformation; and 3) improving health worker training and enhancing the quality of service delivery. AI-enabled vaccine supply chain optimization, though not in published literature is promising.

System optimization: Enhanced disease surveillance using survey data

Multiple research studies show that health security and enhanced disease surveillance can benefit from AI-enabled disease surveillance. One study in Bangladesh used the Bangladesh Demographic and Health Survey (BDHS) data from 2007, 2011, and 2018 to predict measles vaccine uptake. In this study, the measles vaccine was the dependent variable, and Independent variables include residence, education, religion, wealth index, husband education, working, sex of child, sex of household head, age, household number, first birth age, birth order, antenatal visits (Hasan et al., 2021). The main findings from this research were that it used minimal attributes from the child and family members to achieve 80% accuracy, and the data source code is also publicly available. Similarly, Dong et al. used data from the georeferenced Nigeria Demographic and Health Survey (NDHS) 2018 to model survey stratification and clustering to improve measles coverage estimates and provide more precise maps (Dong & Wakefield, 2021). While the methods used in this research are similar to those used for AI modeling, this research does not clearly state if this was traditional data modeling or AI modeling.

In addition, other research tests or validates new or existing ML models. For instance, Ru et al. compare two extreme gradient boosting (XGBoosting) and Logistic regression algorithms for predicting measles outbreaks in the US using sociodemographic data, population statistics, measles vaccination coverage and exemption policies, health care access, international air travel volume, and country of origin. They used aggregate survey data from 2014 and 2018 data for training and the 2019 survey data for testing (Ru et al., 2023). This further strengthens the interest in using survey data for AI-based disease surveillance.

Another approach evaluated in the literature to understand the state of ML for immunisation was its use to analyze a million death study survey data for six VPD disease areas – Pneumonia, diarrhea, malaria, meningitis, measles, and fever of unknown origin to determine the cause of death in India (Idicula-Thomas et al., 2021). These disease areas constituted 13,216 of the 18,826 unique childhood deaths at ages 1-59 months during the period 2004 to 2013. As over 70% of deaths were caused by the six VPDs, the combination of signs/symptoms presented by the deceased individuals was then used to Cause of Death (CoD) diagnosis. While verbal autopsy has been proven effective, even for this study, automated classification of parameters captured from verbal autopsy using AI improves the classification of cause of death.

These approaches of AI/ML align with Gavi's priority to better leverage data to improve surveillance of Vaccine-preventable diseases (VPDs) as an entry point to assess the strength of coverage of immunisation programs.

Optimising supply chains / intelligent supply chains

Supply chain optimisation is a known use case for AI/ML – especially for route optimisation, capacity/volume planning, and drug classification. The Indian government, for instance, through UNDP support, implemented the Electronic Vaccine Intelligence Network (eVIN), a smartphone and cloud-enabled platform for increased vaccine availability (UNDP, 2024). The eVIN platform supports all 733 districts of all 36 states and union districts in India, with nearly 25,000 temperature loggers helping achieve 80% reduction in instances of vaccine stock-outs. Alfred Addy noted that eVIN "… uses AI algorithms to track real-time data on vaccine stocks, storage temperatures, and distribution across the country" (Addy, 2021). The eVIN system was adopted in Indonesia in 2018 after its first launch in India in 2015, reducing vaccine stockouts by 55% (Ong & Wee, 2020). Similar to this, Zipline uses AI-enabled algorithms to optimize routes for blood delivery, which is transferable to immunization.

Informants also indicate that algorithms have been built to clean Family Planning (FP) and Maternal Newborn and ChildHealth (MNCH) data. These applications tested in Kenya, include a built-in human-in-the-loop and for approval of cleaned data. Key informants noted being able to use longer-series of data, unlike before AI-based analysis and forecasting were used. Informants also said that

> *teams were now able to meet deadlines ahead of schedule for the first time, addressing the manual, laborious process to improve forecasting for immunisation supply chain management strengthening.*

If properly configured with data aligned to Gavi's Target Software Strategy and EMS device strategy, AI-enabled supply chain system can improve conformance to these standards.

Optimizing geospatial service location and microplanning

Optimising immunisation service planning through the use of geospatial data is one of the more prioritised use cases as it has the greatest implications for the identification and reach of Zero-dose children. Ramos & Peramo developed an ML model for data processing, shortest route analysis, and automatic land-use categorization (Ramos & Peramo, 2024). They utilized Geographic Information System (GIS) technology and artificial intelligence (AI) to map current hospital distribution and evaluate the spatial availability of healthcare services in the Philippines. The geospatial mapping was defined in the boundaries of Olongapo City in the Philippines using road data from OpenStreetMap and QGIS. Informants think this will enhance traditional digital GIS-based microplanning by using information from the health facility level to inform planning at a higher level. An informant indicated that,

> *…digital micro-planning for identifying and mornitoring zero dose app with settlement maps make them more interactive, accessible, and help show outbreaks…*

A similar use case is the application of AI-enabled health systems to facilitate better location of laboratories. Chowdary et al. developed a model for Laboratory location with focusing on India (Chowdary et al., 2023). Inputs include geospatial estimates, census, line list of settlements, line-list of settlements that overlap with other facilities. Outputs could be the number of sessions, immunisation needs, locations, and strategies for reaching settlements. Gavi should explore this as an important area of exploration, testing, evaluation, and investment.

Vaccine demand and addressing mis/disinformation

AI-enabled Conversational agents like Chatbots hold great potential for immunisation programming Information in multiple languages. Simon et. al., in a pilot randomised control study found that AI-enabled chatbots help improve COVID 19 behavior amongst 59 culturally and linguistically diverse population (Baal et al., 2023). This use case can be easily transferable to routine immunization. Also, the the PROMPTS program in Eswatini and Ghana used AI-enabled two-way SMS messaging to reach over 2 million pregnant women with life-saving health messages (Jacaranda Health, 2023). Programs like this can easily be expanded to immunisation. Similar, the intervention deployed by Reach Digital Health in South Africa uses both SMS and WhatsApp to reach millions of mothers with AI-enabled two-way messages. According to an informant,

> *the service also provides access to a text-based helpdesk that recieves over 20,000 queries a month, with more than 1200 queries per day at peak times, and AI enables ease of resolution with three help desk operators acting as the human in the loop component at the end of the query flow.*

The program is now being expanded to include immunisation in Mozambique for immunisation schedule reminder tracking as part of a broader maternal health messaging program.

This model was also extensively used during the COVID-19 pandemic for social listening and demand generation, as outlined in this review article (Hall et al., 2022). Demographic and conversational data and Laboratory test data can also feed into analytics that lead to optimized data-based action. Similarly, Bolongaita et al. developed and validated an ML algorithm for adverse vaccine events in Ethiopia, leveraging real-time surveillance data to monitor EHRs for signs of adverse events following immunisation (Bolongaita et al., 2022). The diseases monitored include rotavirus, diarrhea, human papillomavirus (HPV), measles, and pneumonia and their corresponding vaccines. The study found that socio-economic factors are determinants of incidents and mortality.

These uses of operational / administrative data from digital health information systems and direct-to-client outreach with human-in-the-loop approaches offer potential promise for better targeting of immunisation messaging and services in real-time as part of Gavi's prioritization to strengthen vaccine confidence and demand.

Leveraging administrative and service delivery data for clinical decision support, service delivery prioritisation, and human resources distribution

One of the most promising areas in the use of AI/ML is to leverage operational, administrative, and service delivery data to support more targeted approaches to clinical decision support. While no papers were identified that focused directly on immunisation, applications in HIV provide useful insights into how operational and administrative data from electronic medical records (EMRs) are being used to support clinical decision-making. Romero et. al., found that AI Clinical Decision Support (CDS) effective from a pre-post AI CDS implementation survey of physicians in three primary healthcare outpatient clinics (Romero-Brufau et al., 2020). In Zimbabwe, the HIV status prediction model was integrated into the electronic medical records to predict the HIV status of Men having sex with Men (MSM) (Chingombe et al., 2022). The data used was collected in a prevalence study in 2018 targeting 1538 MSM from two provinces in Zimbabwe. Multiple ML models were applied to these datasets, showing the potential application in other clinical health areas, including immunisation.

Several key informants also identified HIV/AIDS as the program with the highest area of application of AI and ML for clinical decision support. Informants believe that the high uptake of AI for HIV is because that is where the greatest uptake of EMR investment has been in LMICs, which in turn makes available data used to build and test the AI models. A respondent highlighted,

…the objective of using AI application is to improve clinical outcome based on theory of change so that psychosocial support can be provided proactively to avoid treatment stoppage...

Data from mature immunisation registries like the ZM-EIR in Sindh, Pakistan, are playing a key role in personalized surveillance by applying ML to millions of mother and child health records (Siddiqi et al., 2021). Another example of such application at the primary healthcare level can also be found with the study by Kumar et. al., that used an ML learning approach to model gestational diabetes risk classification (Kumar et al., 2022). The research setting was of 909 Singaporean pregnant women living the UK.

Diagnostic aids using computer vision and Large Language Models (LLM) hold great potential for early warning systems and other computer vision applications like rash identification (Glock et al., 2021), and informants highlighted vaccine vile counting using computer vision. Informants indicated that “Computer vision and LLM have been used for supportive supervision”.

AI-enabled self-testing for Malaria, HIV, and COVID is also now being considered by some Gavi partners. There are areas that this can apply to immunisation, for instance,

determining if an injection entered an arm to confirm the certainty of a vaccine outreach using image recognition and based on Computer vision and vision with Large Language Models.

In addition, key informants highlighted countries such as Rwanda, South Africa, DRC, Cote D’Ivoire, Uganda, Benin, Nigeria, Kenya, Burundi, Sierra Leone, and Ethiopia that are experimenting with AI.

In addition, the combined use of data from multiple data sources can support health service optimisation and human resource distribution. In India, Prabhune et al. developed and validated an ML model for easy access to primary health facilities in India using geospatial, demographic, and health utilization data (Prabhune et al., 2024). The model classifies villages based on accessibility and classifies PHCs based on their utilization. The model also helps identify underutilized and overutilized health facilities. The model successfully optimizes human resource allocation based on demand burden and accessibility, considered a systematic approach to addressing human resource shortage. The model was validated using data from the demographic influence index from the 2011 census, the mortality index from e-Janam for 2016 to 2019, and the footfall index for all villages for 2018 to 2020. The model was applied to 903 villages in Karnataka and 59 PHCs. The PHCs were classified as high burden and low burden to aid allocation. The methods here are important for Gavi in addressing shortages in vaccination and optimizing and automated allocation to areas of greatest need to support the reallocation of resources in real or near real-time.

In the literature, AI has enabled human resource manpower allocation and optimization (Bhat et al., 2024). AI-enabled training of health workers via gamification or plain information-enabled targeted capacity building was highlighted by a few informants as having immense potential. An example application will address health automated responses to frequently asked questions (FAQ), as well as chatbots. Others are AI-enabled gamified health worker capacity building. Automatically translating the training materials into a game with a bank of randomized questions that lead to different stages implementable via workflows but can potentially allow an AI system to select paths based on the player’s responses.

Predictive risk analytics for vaccine-preventable diseases

AI can facilitate predictive analytics for vaccine demand and disease outbreaks by analyzing survey data. Examples of such analysis of survey data have been used in Nigeria (Dong & Wakefield, 2021), Bangladesh (Hasan et al., 2021), and India (Idicula-Thomas et al., 2021). In Bangladesh, AI-driven models have been utilized to predict vaccine uptake based on socio-demographic factors, helping to identify areas with low immunisation coverage and enabling targeted interventions (Hasan et al., 2021). Similarly, in Nigeria, Bayesian Geostatistical models using Demographic and Health Survey data have been employed to generate small-area estimates of measles vaccine coverage, facilitating more precise and effective immunisation strategies (Dong & Wakefield, 2021). In the United States, machine learning approaches have been applied to predict measles outbreaks by analyzing sociodemographic data, vaccination coverage, and exemption policies. These predictive models help public health officials preemptively address potential outbreaks, thereby reducing the incidence of vaccine-preventable diseases (Ru et al., 2023).

In addition, Rocha tested survey data on six ML algorithms to ascertain the risk of preterm birth in Brazil (Rocha et al., 2021). This population-based study analyzed data from 3.8 million mothers with live births distributed over nearly 4,000 Brazilian municipalities. The important variables for predicting preterm week of delivery were the number of previous deliveries through cesarian-section, number of prenatal consultations, age of mother, availability of ultrasound, the proportion of primary care teams in the municipality.

Similarly, Boland et al. used AI/ML to analyze ICD-9 coded pharmacological drug dataset of 5,658 pregnant women in New York with congenial anomaly (Boland et al., 2017). The study was able to identify categories of drugs that can be considered harmful or safe. The live Rubella vaccine was one of those classified as harmful and increased risk of fetal loss, which the study indicated was consistent with existing literature on exposure during early pregnancy. This is relevant to Gavi’s programming on Rubella vaccines and other priority risk analyses.

Key Considerations & Recommendations

While the literature on the application of AI in public health in general and immunisation in particular is growing, the two areas that are the farthest along are the use of AI to analyze household or other health survey data and the use of AI for micro-planning. All the others are still in the experimentation pilot or testing stages. Minimal evidence exists in scholarly literature of the current implementation of AI for health and for immunisation. Information from respondents shows the increasing potential of AI/ML in health and immunisation. Models help predict areas and populations at risk, aiding in targeted measles vaccination campaigns (Cutts et al., 2020). In Nigeria, the cost-effectiveness of using data from consumables, direct labor, indirect labor, supply chain, infrastructure, and transport cost groupings was equally evaluated (Zimmermann et al., 2019).

Overall, AI has the potential to impact how zero-dose and under-immunized children are identified and reached, help quick response to outbreaks, enhance quality and vaccine safety, and facilitate optimized resource allocation and supportive supervision. There is also promising research on the application of AI for clinical decision support (CDS) in electronic health records (EHR) for HIV management, which holds potential for adaptation in electronic immunisation information systems and registries. AI-enabled CDS systems have been shown to enhance patient care by providing real-time, evidence-based recommendations to healthcare providers. For example, AI frameworks have been developed to predict health outcomes and guide treatment plans for HIV patients, which can be similarly applied to manage immunisation schedules and monitor vaccine safety (Romero-Brufau et al., 2020). Emerging research on AI-driven human resource allocation at primary healthcare facilities also presents opportunities for immunisation services. Studies have developed machine learning models to optimize the allocation of healthcare workers, ensuring that resources are effectively distributed based on demand and utilization patterns. Such models can be adapted to optimize the deployment of immunisation teams, enhancing the efficiency and reach of vaccination programs (Bhat et al., 2024).

Prioritised enablers for AI/ML

Key inhibiting factors identified while developing this technical brief include an inadequately mature digital health ecosystem to support AI/ML applications in health and immunisation; poor digital infrastructure to collect quality data inhibits data availability (for example, electricity, server farms, and connectivity); building models can be data and processor-intensive, and few countries have data centers.

A recent WHO report on AI for reproductive health highlighted the need for better data governance in AI for sexual and reproductive health programs (WHO, 2024). The Health Data Governance Principles was recently launched with endorsements from several development organizations (Health Data Governance Principles, 2023). The principle addresses protecting individuals and communities, building trust in data systems, ensuring data security, promoting health systems and services, promoting data sharing and interoperability, facilitating additional innovation using health data, promoting equitable benefits from health data, and establishing appropriate data rights and ownership. Each of these Eight principles has core elements to enable operationalization. Before this, there were other frameworks, like the Organization for Economic Co-operation and Development (OECD) health data governance framework, which provides guidelines for the management of health data to ensure privacy, security, transparency, accountability, and cross-border data flow (OECD, 2017). Other general data guidelines and regulations are the European General Data Protection Regulation (GDPR) and the US Health Insurance Portability and Accountability Act (HIPPA). Addressing the lawfulness, fairness, transparency, purpose, storage limit, accountability and privacy rules, and breach notification. Several countries where Gavi works already have National Data Governance regulations and Acts, that mirror these guidelines.

The WHO guideline on Ethical Issues in Public Health Surveillance provides ethical guidance to ensure public health surveillance is conducted in manner that respects individual rights (WHO, 2017). The America Medical Association (AMA) Code of Medical Ethics provides a framework for medical professionals to conduct themselves, including when using AI (AMA, 2024). There are also country specific Codes of medical ethics that can apply.

Digital literacy remains a major challenge in most of the countries where Gavi works. This is crucial for progress in the application of AI/ML at scale. Also, limited policies and regulations (guardrails) are available to manage AI in most countries. For example, most countries do not even have adequate data governance mechanisms in place. Questions of how technology can be used? Who is accountable? Who decides if the AI/ML system works? Reverse regulation and data sovereignty issues remain as many countries continue to attempt to enforce regulation to limit cross-border health data sharing and storage. An informant noted,

> *Sovereignty is an important issue, as exemplified in Rwanda and India where Governments demand to own the model algorithms…*

In addition,

> *The costs of… current LLMs conversational models are also prohibitively high for many countries where Gavi works. The question remains on long-term sustainability.*

While not reflected in the literature of the application of AI/ML in LMICs for immunisation, gender and racial bias of widely adopted and used LLMs is of concern and should be proactively addressed through the development of systematic transparent approaches to evaluation of algorthmic bias and data representativeness. To address these concerns, greater representation by gender and diverse ethnic, cultural, and linguistic backgrounds is needed in governance, algorithm development, and datasets.

The successful implementation of AI/ML applications in immunisation programs hinges on several key enablers, which collectively ensure the effectiveness, efficiency, and ethical deployment of these technologies. Inequitable use of AI can significantly affect children and other vulnerable groups. For instance, data consent procedures may apply differently for different age groups (particularly children), so also is data privacy concerns. Similarly, when soliciting public opinion on AI-related programs, children's perspectives from parents and teachers should be critical (UNICEF, 2021). The traditional consent (or informed consent) mechanisms for data capture may be linked to digital literacy in environments where Gavi works, and should be optimized. Several key informants identified

> “ *high-quality data availability* ”

as essential for the success of AI models. As one key informant said,

> “ *…Bad data will give a very bad AI model...* ”

Dependable data governance and infrastructure that supports the collection, storage, and processing of large datasets is critical for AI/ML applications. This includes the capacity to handle real-time data inputs from various sources needed for health service optimisation and disease surveillance. Building human capacity, providing training, and maintaining a workforce that is proficient in computing systems are essential for design and use of AI/ML and data science systems. Much of the capacity and innovation in AI/ML is coming from the private sector and academia, creating a need for greater collaboration between the public, private, and academic institutions and stakeholders.

Recommendations

The ability for Gavi-supported countries to effectively adopt AI/ML for immunisation hinges on strong leadersip and guidance at the national level that can then enable effective sub-national contributions of quality data and use of the outputs generated through AI/ML for better service delivery, disease surveillance, and increased vaccine confidence and demand.

National governments need to strengthen their existing data governance mechanisms to promote the availability of high-quality data and address potential privacy concerns, sovereignty, potential for bias, or equity issues. As such, the following recommendations are proposed.

- Gavi and development stakeholders should support governments to systematically adopt and apply proven health data governance frameworks by:
  - Domesticating broader national data regulations and guidelines into the health sector with the lens of health data principles
  - Identify an AI use case (preferably Immunization or Primary healthcare) and apply the health data governance principles and document level of compliance through stakeholder collaboration.
  - Promote, prioritize, and support Policies that enhance local capacity to understand, interpret, regulate, and use ethical AI/ML models.
- Gavi should leverage internal AI and data-related policies for its immunization programs and support for AI for immunization and health programs.
- Gavi should ensure that supported interventions using (or leveraging AI) adhere to the principles of digital development, particularly designing with the users and local communities, including training datasets where applicable.
- High quality data from multiple sources (beyond immunization) are essential for higher accuracy decision making for immunisation, thus stressing the important of policy and data infrastructure that fosters interoperability for integrated health systems strengthening.
- Governments should review existing regulations that limit AI/ML programs (like unfavourable data sovereignty requirements as highlighted by few informants).
- Governments should ensure that deployed AI/ML applications in health are equitable by design with strong representation by gender and diverse ethnic groups in governance, model development, data sets, and output validation and evaluation.
- Governments need to establish appropriately skilled oversight teams to oversee AI/ML for health who can work on immunisation use cases. These teams need to have knowledge of ML/AI model design, interpretation, review, evaluation, validation, and performance.
- Governments should explore greater collaboration with the private sector and academia, where much of the capacity and innovation in AI/ML for health is happening

Conclusion

The integration of Artificial Intelligence (AI) and Machine Learning (ML) in immunisation programs represents a pivotal advancement in public health. By leveraging these technologies, significant strides can be made in vaccine coverage, outbreak prediction, optimisation of immunisation service delivery, and more targeted vaccine demand and uptake. The evidence presented in this technical brief underscores the transformative potential of AI/ML in enhancing the efficiency and effectiveness of immunisation programs.

Key findings indicate that AI-driven models utilizing household surveys and geospatial data have been particularly successful in predictive analytics and microplanning. Notable examples from Bangladesh, Nigeria, and the USA demonstrate the effectiveness of these approaches in identifying under-immunized populations and optimizing vaccine distribution. Furthermore, the application of AI in verbal autopsies in India highlights the potential for AI to improve diagnostic accuracy and health outcomes. The promising research on AI/ML for clinical decision support in electronic health records (EHR) for HIV management suggests that similar systems could be adapted for electronic immunisation information systems and registries. Additionally, emerging studies on AI-driven human resource allocation at primary health care (PHC) facilities indicate potential applications for optimizing immunisation team deployments.

To fully realize the benefits of AI in immunisation, several key enablers must be addressed. These include data governance, high-quality data availability, strong digital and data infrastructure, interoperability of systems, stakeholder collaboration, and a skilled workforce. Additionally, ethical considerations, regulatory frameworks, and community engagement are crucial for the responsible and effective use of AI/ML. AI/ML has the potential to revolutionize immunisation programs by providing timely, accurate, and actionable insights and advancing efforts to increase health equity. As these technologies continue to evolve, it is imperative to invest in the necessary infrastructure, governance, and partnerships to ensure their successful implementation. The recommendations provided in this brief offer a roadmap for leveraging AI/ML to enhance immunisation services, ultimately contributing to improved public health outcomes worldwide.

Appendix A
Literature Review Methodology

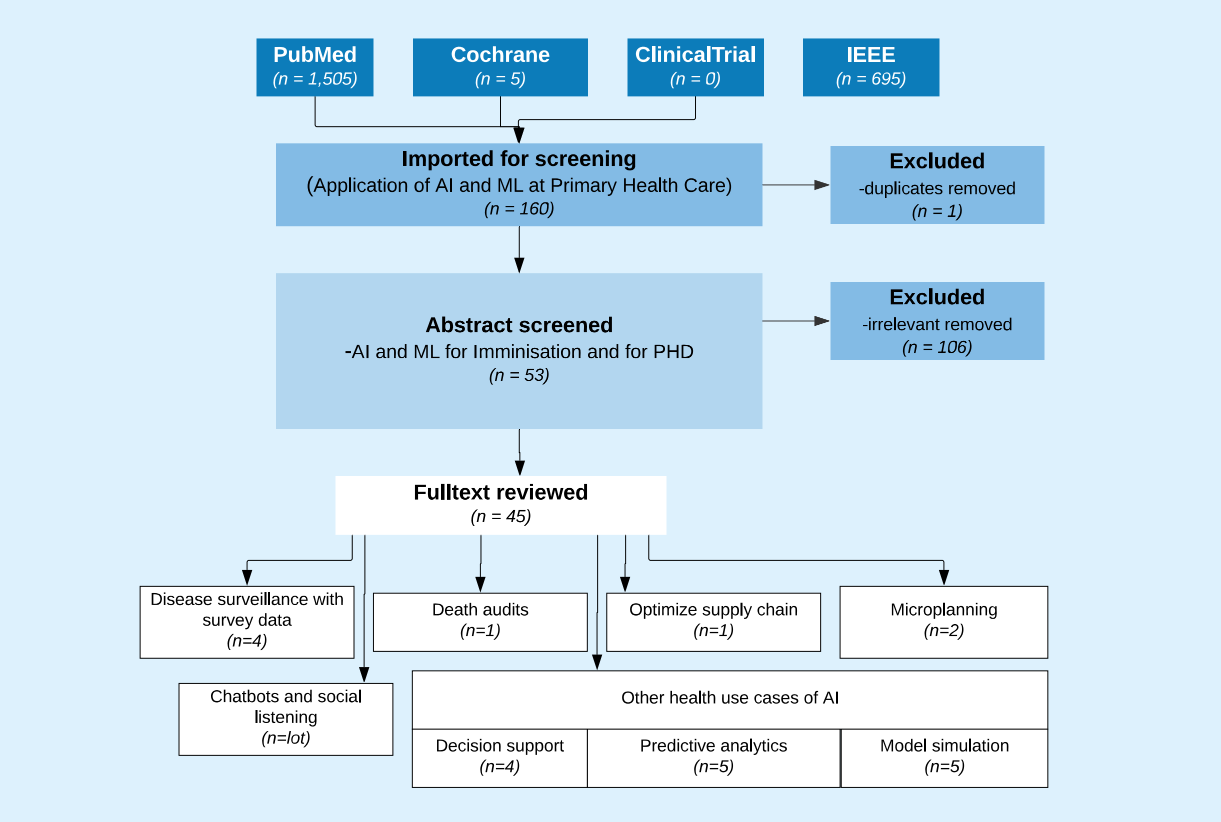
The literature review used the following boolean search terms aimed at identifying public articles covering the domain of interest.

("measles" OR "rubella" OR "polio" OR "DPT" OR "PHC" OR "primary health care") AND ("predictive analytic" OR "machine learning" OR "ML" OR "deep learning" OR "Artificial Intelligence" OR "AI" OR "LLM" OR "Large Language Model").*

The literature review process is as in table:

AI in Health tools					
	PubMed	Cochrane	ClinicalTrials	IEEE	TOTAL
Search Result	1,505	5	0	695	2,205
Title screened	83	0	0	77	160
De-duplication					159
Abstract					63
FullText review					45

Figure 1: PRISMA Diagram of the systematic literature search



The search was conducted in the following databases PubMed, Cochrane, ClinicalTrials.Gov, OpenGray, and IEEE. Similarly, a search will also be conducted on the websites of key alliance members and relevant organizations as listed below to identify missed use cases: WHO, UNICEF, Gavi, UNFPA, and Africa CDC. The inclusion and exclusion criteria are as in the PRISMA diagram, with irrelevant articles representing articles not specifically focused on the application of ML/AI for immunization or PHC programs.

Appendix B
Costing for ML/AI investment for Immunization & PHC

The integration of Artificial Intelligence (AI) into immunization programs and broader health systems holds imense potential for enhancing healthcare delivery, improving efficiency, and ensuring equitable access to healthcare services. In 2018, Gartner forcasted the Enterprise AI market will hit $3.9 trillion by 2022 (Wheatley, 2018). The surge in values of NVIDIA, OpenAI, and the sub-sequent AI-race in recent years is a testament to this potential. The question that often arises relates to how an enterprise like Gavi can adequately cost and budget for an AI intervention in its programs. The cost associated with AI investment is multifaceted. Due to the many different dimensions of AI investments, it can prove difficult to standardize the cost metrics for deploying AI in an immunization program. Also, information on the cost of AI programs in healthcare is difficult to obtain. As there are currently no guidance on costing for AI systems which Gavi can relly on. David Hall, in his medium blog post, categorised AI cost as a combination of data cost, computing cost, and people cost.

The cost of AI implementation varies significantly across different dimensions and is influenced by different features. This appendix has included factors to consider when considering investment in an AI system in healthcare, the requisite state of readiness for AI investment, the state of digital health enablers, illustrative budgets using two use cases, and potential cost drivers.

Factors Influencing volume of AI investment in Immunization Programs

1. **Features, Dataset Sizes, and Types:** The complexity and capabilities of an AI system are significantly dictated by the features it offers and the data it processes. For instance, a simple chatbot can be free or really cheap, while a fully-fine-tuned AI model can be prohibitively expensive, especially for contexts where Gavi works. Larger datasets, especially those requiring real-time analysis, such as those sourcing data from longitudinal data systems, demand more computational resources and sophisticated sometimes algorithms, which can escalate costs significantly. Similarly, the type of data - whether structured or unstructured, longitudinal or aggregate, text or image, or even video impacts the preprocessing steps and the complexity of the models needed. All adding to the eventual costs of the investment intervention. For instance, a model using multi-year survey data alone will cost much less compared to one that uses imaging data from an MRI machine.
2. **Domain of Application:** The domain of interest also impacts the eventual costs, in this case, health domain, specifically immunization and PHC, for tracking, outbreak prediction, or vaccine distribution logistics determines the required customization of the AI models. Tailored solutions often require additional development time and domain expertise, leading to higher costs (Kishore, 2024).

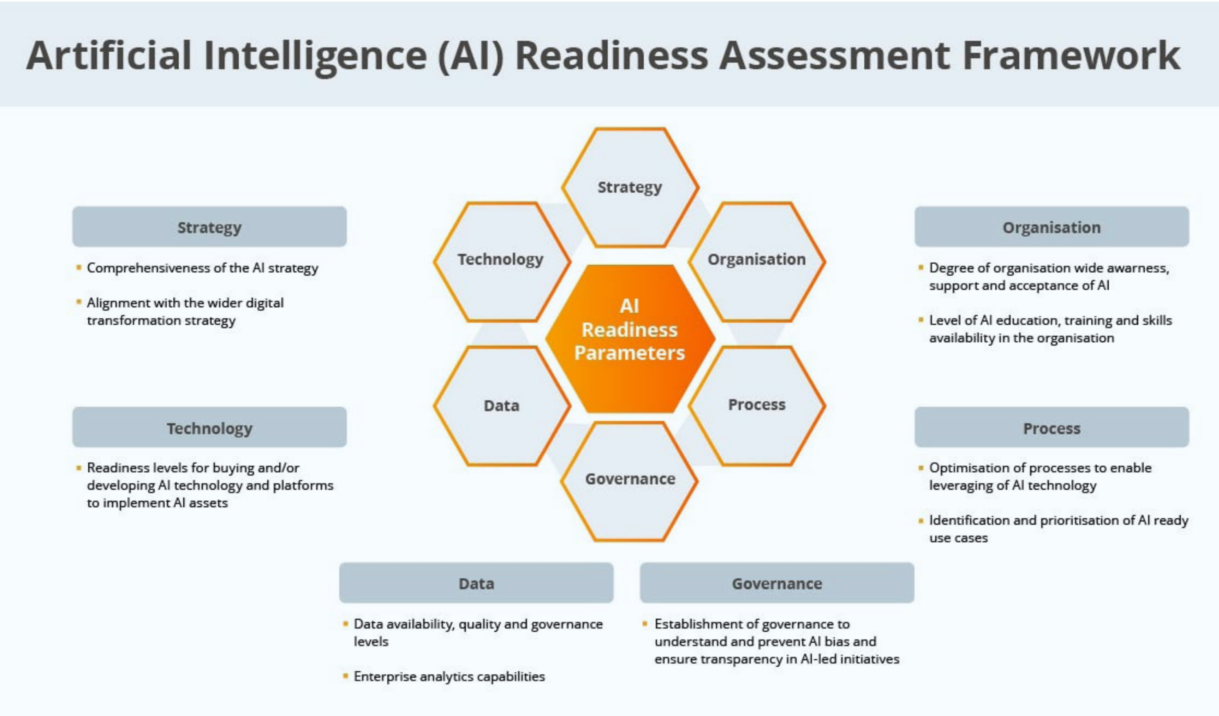
3. **Geographic Considerations:** The cost of deployment of an AI system with the same features will be different from geography to geography depending on the state of readiness of the required enabling environments. Also, deployment in diverse geographic regions can influence costs due to varying data availability, lack of uniformity in context, infrastructure maturity, and healthcare policies. For instance, deploying AI solutions in rural or low-resource settings, similar to where Gavi works, might necessitate additional investments in infrastructure and in some cases digital systems to support data collection and analysis capabilities.
4. **Hardware Requirements and Software Architecture:** The choice of hardware is pivotal and depends on the processing needs of the AI applications. High-frequency data collection and processing tasks might require advanced servers or cloud services, significantly impacting initial and operational expenses. Specialized hardware costs for AI systems can range from $5 to $100,000 (Hillaman Curtis, 2022). Moreover, the software architecture plays a crucial role in the eventual cost. For instance, hosted service vs self-managed systems will vary in costing needs.
5. **Data Source and Frequency:** The sources from which data is collected (e.g., electronic immunization registry (EIR), national health management information systems (NHMIS), mult-year surveys, other data sources), and the frequency of data updates require careful consideration. For instance, survey data collected every five years will require less burden and investment compared to EIR data collected at point of service. Similarly, this will differ for monthly HMIS data. So, high-frequency, real-time data collection systems involve more complex data management and storage solutions than systems that do not collect data in real-time, thus impacting the costs.
6. **Type of AI Application:** Different AI applications, from predictive analytics to decision support systems, each carry their own set of requirements and costs. Predictive analytics might require continuous data training and model tuning, while decision-support-enabled recommendation systems might need extensive user interface design and integration testing.
7. **Software, Data Science, and AI Expertise:** The level of expertise required to develop, deploy, and maintain AI systems can be a significant cost factor. For instance, the average salary of a machine learning engineer in the US is $160,791 (indeed, 2024). Costs like these are simply prohibitive, and in developing countries where Gavi works, finding the talent with the skill is difficult. As a result, hiring skilled professionals or training existing staff in AI technologies requires substantial investment, which can be ongoing depending on the system's complexity and support needs.
8. **AI Access Strategy:** Whether the AI system is deployed on-premises or through cloud-based services affects both initial and maintenance costs. Cloud-based solutions might reduce upfront hardware costs but can lead to higher long-term operational expenses due to service subscriptions and data storage fees. Similarly, whether the system is accessed via mobile or desktop or a combination of channels can potentially increase the cost and scale of the investment.

9. **Number of Users:** The scale at which the AI system will be used also impacts cost, particularly if the system needs to support multiple users across different locations. Licensing fees, user training, and system support will be scaled accordingly, affecting the overall budget.

National Immunization Program Readiness for AI Investment

Evaluating a country's readiness for AI investment involves assessing the existing health system infrastructure, data management capabilities, and human resource skills. Readiness is critical to ensure that the introduction of AI technologies leads to expected improvements. Key readiness indicators include the current level of digitalization of the health system, the capacity for data integration across multiple health platforms, the availability of digitally skilled personnel to manage and analyze data or AI systems, and a ready IT infrastructure capable of supporting AI technologies. The Future Processing data team developed and presented a framework for AI readiness, as in the figure.

Figure 2: AI Readiness Assessment framework (FP Data Solutions Team, 2024)



Digital Health Enablers Relevant to AI for Immunization programs

For AI to be successfully integrated into national immunization programs, several digital health enablers are a prerequisite (GDHM, 2024):

- **Infrastructure:** Adequate computing hardware, electricity, and internet connectivity are essential for supporting AI functionalities, especially in remote or underserved areas.
- **Standards and Interoperability:** Countries need to ensure that AI tools can communicate with existing digital health systems through standardized protocols is crucial for seamless functionality.

- **Digital-Enabled Workforce:** Building capacity in AI and data annotation skills within the healthcare workforce is necessary to manage and maintain AI systems effectively.
- **Foundational Digital Registries:** Robust health data registries are crucial for training AI systems and facilitating their practical application in health programs including immunization.
- **Relevant Policy & Legislation:** Supportive policies and legislation that foster data governance, privacy, AI ethics, and security are foundational to the adoption and scaling of AI technologies.
- **Availability of Adequate Data Sources from Priority Digital Health Interventions:** The success of AI applications heavily relies on the availability and quality of data. For immunization programs, relevant data may include vaccination rates, stock levels, cold chain status, and outbreak tracking. Ensuring that these data are collected consistently and standardized for use across AI systems is critical for accurate and effective AI outputs. Organizations like Gavi should collaborate with an external AI specialist organizations rather than maintaining an AI team.

Illustrative Country Budget (using two use cases)

An illustrative budget for integrating AI into a national immunization program should consider initial setup costs, ongoing operational costs, and potential scaling costs. This budget must include investments in infrastructure, training, data management, software licensing, and possibly consultancy fees for expert guidance in implementation. The under-lying assumption is that an AI system already has a digital system deployed for routine data collection.

Use Case 1:

Subscription-based AI systems often cover broadly the GPU hardware costs, electricity, and network costs. This excludes the cost associated with collecting the data (or a section of the data) that will be used by the AI system. If there is a need for ongoing training and retraining of the model, there may be additional costs related to the AI engineers who will contribute to this endeavour. Included in the subscription is the cost for maintaining a robust cybersecurity measure and adequate local and international compliance. This licensing can range from $20 to $500 or 5,000 monthly, depending on usage metrics. For instance, in ChatGPT API-enabled scenarios, where pay-per-use is applied, the latest token costs can be assessed from https://openai.com/api/pricing/. It is expected that other LLMs are already introducing similar token-based pricing models.

Use Case 2:

In the second scenario, if Gavi does want to partner with an AI-focused organizations (eg. Like Exchange Design or Audrea) to invest in a special-purpose AI for a specific country's immunization program, all the factors described above have to be considered in the costing process. The cost will include data collection costs in addition to the application of AI on collected data to generate and apply the relevant insights. Key cost drivers in this AI implementation use case include:

- **Technology Acquisition:** Initial costs for purchasing AI software or custom development.
- **Infrastructure Upgrade:** Costs associated with upgrading existing digital health infrastructure to support AI functionalities.
- **Training and Capacity Building:** Expenses related to training staff to use and maintain AI systems.
- **Data Management:** Costs for data collection, storage, and analysis, including data privacy and security measures.
- **Maintenance and Upgrades:** Ongoing costs to ensure AI systems remain operational and up-to-date with the latest technology.

Conclusion

Investing in AI for immunization and broader health systems offers substantial potential to enhance health outcomes, streamline operations, and promote equitable health access. However, such investments must be carefully planned, with a clear understanding of the associated costs and readiness factors. By addressing these aspects comprehensively, Gavi, the Vaccine Alliance can support countries in making informed decisions that align with their health system capacities and goals, ensuring that investment in AI technologies are necessary and deliver their intended benefits without unintended consequences.

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