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AI-Enabled Precision Public Health in Africa: Targeting Infectious Diseases Through Data-Driven Interventions

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Abstract

Infectious diseases remain a major public health and socio-economic challenge in the globe especially in Africa where issues such as environmental pollution, disease transmission, unequal healthcare access and resource limitations contribute to persistent disease vulnerability. The traditional public health approaches used in tackling infectious disease usually follows the generalized interventions which often overlook demographic, environmental, and socio-economic differences that causes disease risk across populations. Due to this, the use of precision public health (PPH) alongside artificial intelligence (AI) creates an opportunity that ensures that community at high risk are identified and prioritized during interventions. This review paper critically examines how AI contributes to PPH for infectious disease control and resource optimization in Africa through a systematic synthesis of literature published between 2005 and 2026. The Findings shows that machine learning, deep learning, and geospatial analytics can integrate epidemiological, climate, genomic, mobility, and social determinants data to support population risk stratification, targeted vaccination, precision vector control, and optimized healthcare resource allocation. These integrations have the potential to improve intervention efficiency, strengthen health equity, and maximize the impact of limited public health resources. However, translating these into a routine practice in Africa is quite challenging because of issues like fragmented data ecosystems, inadequate digital infrastructure, algorithmic bias, and weak governance policies. The study therefore concludes that while AI-enabled PPH offers significant potential to transform infectious disease management in Africa, its successful implementation will require sustained investment in key areas such as digital health infrastructure, workforce, and transparent governance systems.

Keywords: Africa, Artificial intelligence, Precision public health, Infectious disease control, Risk stratification, Healthcare optimization

1. Introduction

1.1 Infectious Disease Burden and Surveillance Gaps in Africa

Till date, Africa continues to experience a disproportionately high burden of infectious diseases, with recurrent outbreaks threatening healthcare systems, economic development, and population well-being (Omosigho et al., 2023). Diseases such as malaria, tuberculosis, cholera, Ebola virus disease, dengue fever, and emerging zoonotic infections remain persistent public health concerns across the continent. According to global public health estimates, Africa records more than 140 disease outbreaks annually (Africa CDC, 2026), reflecting the continent's heightened vulnerability to epidemic and pandemic threats (WHO, 2023; Fallah et al., 2024). Multiple structural and environmental factors contribute to this burden, including rapid urbanization, climate variability, weak healthcare infrastructure, poverty, population displacement, and limited disease surveillance capacity (Hassan et al., 2024; Vidona et al., 2024).

Despite substantial advances in epidemiology and public health governance globally, infectious disease control systems in many African countries remain largely reactive rather than predictive (Nkengasong & Mankoula, 2020). Conventional surveillance approaches often rely on delayed reporting systems, fragmented healthcare databases, and generalized interventions applied uniformly across populations (Nsubuga et al., 2024; Kruk et al., 2018). This leads to delay in outbreak detection, interventions, and inefficient distribution of healthcare resources during epidemic emergencies (Kruk et al., 2018;).

The growing availability of digital technologies and large-scale health data has created new opportunities for strengthening infectious disease management through data-driven public health systems (WHO, 2021a; Nkengasong & Mankoula, 2020). In particular, Artificial Intelligence (AI) has emerged as a transformative technological tool capable of processing vast quantities of heterogeneous data and generating predictive insights that support more proactive outbreak prevention and public health responses (Riley et al., 2011; Jiang et al., 2017).

Within this evolving landscape, the concept of precision public health has gained increasing attention. Precision public health (PPH) refers to the application of advanced analytics and targeted intervention strategies to deliver the right intervention to the right population at the right time (Khoury et al., 2016; WHO Africa, 2025). It diverges from traditional broad approaches by identifying at-risk populations and critical intervention moments (WHO Africa, 2025; Modi et al., 2024). Through AI-driven predictive modeling and geospatial analysis, PPH can enhance localized surveillance, resource distribution, and outbreak readiness (Rajendran et al., 2024; Naumova, 2022). This approach holds particular significance in Africa, where healthcare resources are limited and disease transmission is highly localized.

Against this background, this paper critically explores the impact of AI-enabled PPH on infectious disease burdens in Africa. Specifically, it explores AI technologies supporting risk stratification, intervention optimization, and resource allocation, while critically evaluating implementation challenges, ethical considerations, and future opportunities for strengthening infectious disease control and health equity.

1.2 Pattern and key drivers of infectious disease outbreak

The distribution of infectious diseases in Africa is uneven and clustered, influenced by ecological and socio-economic factors (Monden et al., 2026; Agyarko et al., 2025). Disease transmission concentrates in hotspots shaped by environmental conditions, vector habitats, sanitation, and human settlements (Monden et al., 2026). For instance, malaria thrives in tropical regions with heavy rainfall, while cholera outbreaks occur in crowded areas lacking clean water (WHO, 2023; 4). Seasonal variability also impacts outbreaks; heavy rain enhances mosquito breeding and water contamination, while drought can lead to population displacement and increased disease risk (Agyarko et al., 2025).

Therefore, infectious disease patterns in Africa are closely tied to environmental changes and climatic factors (Shi et al., 2026). Hence, the transmission dynamics of infectious diseases in Africa are strongly influenced by certain drivers such as environmental, climatic, demographic, and socio-economic factors (Monden et al., 2026; Chala & Hamde, 2021; Redding et al., 2019) (Table 1). Pathogen spread is shaped by complex interactions between ecological conditions, human mobility, urbanization, and healthcare accessibility (Baker et al., 2022).

Out of all these drivers, climate variability remains one of the most important determinants of infectious disease transmission (Shi et al., 2026). Vector-borne diseases such as malaria and dengue fever are highly sensitive to environmental conditions that influence mosquito populations and transmission intensity (Al-Manji et al., 2025).

It is also important to note that, environmental degradation and land-use change additionally increase the risk of zoonotic spillover events (Agyarko et al., 2025). Deforestation, mining activities, agricultural expansion, and encroachment into wildlife habitats intensify interactions between humans and animal reservoirs, increasing the likelihood of emerging infectious diseases (Monden et al., 2026; Agyarko et al., 2025).

Table 1. Epidemiological Patterns and Drivers of Major Infectious Disease Outbreaks in Africa

Disease	Transmission Mode	Key Drivers	Spatial Pattern	Temporal Pattern	Epidemiological Significance
Malaria	Vector-borne (Anopheles mosquitoes)	Rainfall, humidity, stagnant water, temperature	Sub-Saharan endemic zones	Seasonal peaks (rainy seasons)	High endemic burden with recurrent outbreaks
Cholera	Water-borne	Poor sanitation, flooding, unsafe water	Urban slums, displaced populations, coastal areas	Sudden epidemic spikes	Rapid outbreak escalation and high transmission risk
Tuberculosis	Airborne	Overcrowding, HIV prevalence, poor ventilation	Urban informal settlements, prisons	Persistent endemic	Chronic transmission with periodic surges
Ebola Virus Disease	Zoonotic and human contact	Wildlife exposure, deforestation, mobility	Central & West African forest zones	Sporadic outbreaks	High fatality, localized explosive epidemics
Dengue Fever	Vector-borne (Aedes mosquitoes)	Urbanization, warm climate, water storage	Urban/peri-urban coastal cities	Seasonal outbreaks	Increasing urban epidemic risk
Meningitis	Airborne droplets	Dry winds, dust, overcrowding	Sahel “meningitis belt”	Cyclical dry-season epidemics	Large regional epidemic waves
Lassa Fever	Zoonotic (rodent-borne)	Rodent infestation, poor housing	West Africa	Seasonal spikes	Endemic with periodic outbreaks

Source: *Developed by the authors based on evidence synthesized from the literature reviewed in this study including Monden et al. (2026), Chala & Hamde, (2021), Redding et al. (2019) and other studies.*

1.3 Limitations of one-size-fits-all public health approaches

Traditional public health programs frequently adopt broad population-level strategies that assume relatively uniform disease risk across communities (McGladrey et al., 2025). While such approaches have contributed significantly to disease control, they often fail to account for the substantial epidemiological diversity that exists across African populations (Kuate, 2014). Uniform allocation of interventions such as vaccination campaigns, vector control programs, and disease surveillance activities may therefore, result in inefficient use of limited resources, with low-risk areas receiving unnecessary attention while high-risk communities remain underserved. In addition, one-size-fits-all kind of interventions usually overlook important local determinants of disease transmission, including environmental conditions, socioeconomic factors, healthcare accessibility, and population mobility patterns. As a result, public health authorities may struggle to identify emerging hotspots, prioritize vulnerable populations, and deploy resources effectively (Lakatos et al., 2026). In low-resource settings where healthcare personnel, diagnostics, and medical supplies are limited, the inefficiencies associated with blanket public health approaches can significantly reduce intervention effectiveness and exacerbate existing health disparities (Gómez-Pérez et al., 2024).

1.4 Need for Precision Public Health

The considerable differences in disease risk, healthcare access, environmental exposure and social determinants of health across African populations in diverse countries highlights the need for more PPH strategies. Generalized (one-size-fit-all) interventions often fail to account for local differences in disease transmission and population vulnerability, leading to inefficient resource utilization and persistent health disparities. PPH addresses these challenges by using data-driven approaches to identify who is most at risk, where interventions are needed, and how resources can be allocated most effectively. By combining advanced analytics with targeted intervention planning, precision public health offers a practical framework for improving infectious disease prevention, healthcare optimization, and health equity across diverse African settings.

2. Methodology

This study used a structured narrative review with a systematic literature search to synthesize current evidence on the application of artificial intelligence in precision public health for infectious disease control in Africa.

Literature published between 2005 and 2026 was retrieved from different search engines including PubMed/MEDLINE, Scopus, Web of Science, ScienceDirect, IEEE Xplore, and Google Scholar using combinations of keywords such as *artificial intelligence*, *machine learning*, *precision public health*, *infectious diseases*, *Africa*, *risk stratification*, *geospatial analytics*, *resource allocation*, *digital health*, *vaccination*, *vector control*, and *decision support systems*. Boolean operators ("AND" and "OR") were used to refine the search strategy.

Studies were included if they examined AI applications for population-level infectious disease prevention, intervention planning, or healthcare optimization in African settings or had direct relevance to Africa.

3. Concept of Precision Public Health

3.1 Definition and Evolution from Traditional Public Health

Precision Public Health (PPH) is an emerging approach in modern healthcare that combines advanced data analytics, epidemiology, and digital technologies to deliver the right intervention to the right population at the right time (Khoury et al., 2016). PPH emphasizes targeted and context-specific strategies based on localized risk factors and population characteristics unlike traditional public health systems, which often rely on generalized population-wide interventions, such as mass vaccination campaigns, nationwide vector-control programs, or generalized disease prevention strategies (Rajendran et al., 2024; Naumova, 2022). While these interventions achieved important public health gains, they frequently assumed that populations faced similar levels of exposure and vulnerability. In reality, infectious disease transmission varies considerably across geographic regions, socio-economic conditions, environmental settings, and demographic groups (WHO, 2024a). Consequently, uniform interventions may fail to adequately address localized transmission hotspots or vulnerable populations.

The emergence of precision public health reflects a shift from reactive and generalized disease management toward predictive and targeted healthcare delivery (Khoury et al., 2016). The concept evolved from precision medicine, while Precision medicine focuses on tailoring diagnosis, treatment, and prevention strategies to individual patients based on factors such as genetic characteristics, biomarkers, and clinical profile (Khoury et al., 2016; Naumova, 2022), PPH extends to entire populations by identifying high-risk population, and integrating epidemiological data, environmental information, demographic indicators, mobility patterns, and digital surveillance systems to improve decision-making at community and regional levels (Rajendran et al., 2024; Naumova, 2022). Table 2 gives the clear differences between precision medicine and precision public health.

Table 2: Comparison of Precision Medicine and Precision Public Health

Features	Precision medicine	Precision public health
Primary focus	Individual patient	Population groups and communities
Main objective	Personalized diagnosis and treatment	Targeted prevention and intervention
Data sources	Genomic, clinical, biomarker data	Epidemiological, environmental, mobility, genomic, and social data
Unit of intervention	Individual	Population or community
Key outcome	Improved patient care	Improved population health outcomes
Role of AI	Personalized risk prediction and treatment optimization	Risk stratification, intervention targeting, and resource allocation
Relevance to Africa	Personalized clinical care	Infectious disease control and healthcare optimization

Source: *Developed by the authors based on evidence synthesized from the literature reviewed in this study including Khoury et al. (2026), WHO Africa et al. (2025), Rajendran et al. (2024), Naumova, (2022) and other studies.*

Advances in AI, machine learning, geospatial analytics, and digital epidemiology has accelerated the development of precision public health systems (Ristevski & Chen, 2018; Jiang et al., 2017). These technologies enable the analysis of large and complex datasets that traditional epidemiological methods often struggle to process effectively. Through AI-powered analytics, public health authorities can identify emerging disease patterns, forecast outbreaks, and deploy interventions more strategically (Villanueva-Miranda et al., 2025).

In Africa, the transition towards precision public health is particularly important due to the continent's diverse epidemiological environments and uneven healthcare infrastructure (WHO

Africa, 2025). Diseases such as malaria, cholera, Ebola, and tuberculosis often demonstrate highly localized transmission patterns influenced by climate conditions, population density, sanitation infrastructure, and mobility networks (Agyarko et al., 2025). As a result, targeted approaches are increasingly recognized as more effective and economically sustainable than blanket interventions (Khoury et al., 2016).

3.2 Risk Stratification and Targeted Interventions

Risk stratification is fundamental to precision public health, categorizing populations by disease susceptibility and transmission risk using diverse datasets and predictive analytics (Velmovitsky et al., 2021). This approach targets individuals at risk, identifies concentrated transmission areas, and pinpoints critical intervention windows (De Manuel-Keenoy et al., 2023). AI-enhanced systems play a pivotal role, utilizing machine learning to analyze multifaceted data such as climate, epidemiological records, and socio-economic indicators, generating detailed risk profiles for communities (Jiang et al., 2017; Ristevski & Chen, 2018). These models can recognize transmission hotspots, predict outbreaks, and anticipate disease spread more accurately than traditional statistical methods. By identifying these high-risk zones, public health authorities can deploy interventions more systematically (Velmovitsky et al., 2021; De Manuel-Keenoy et al., 2023). Targeted interventions include localized vaccination drives, focused vector control, targeted drug distribution, and community-specific health education, concentrating limited healthcare resources in areas most impacted by disease transmission (Khoury et al., 2016).

3.3 Relevance of Precision Public Health (PPH) to Low-Resource Settings like Africa

In low-resource settings, such as many African countries, the relevance of PPH is particularly significant due to constraints in healthcare funding, laboratory infrastructure, and medical supplies (Thokala et al., 2025). In addition, traditional blanket approaches (one-size-fits-all) can be financially burdensome and lead to inefficiencies. Hence, Precision public health allows for resource concentration in high-risk areas, making interventions more sustainable and effective (Khoury et al., 2016).

PPH also improves healthcare access for underserved populations through satellite data, mobile technologies, and geospatial analytics, tracking disease risks even in remote areas lacking formal healthcare (Ristevski & Chen, 2018). This is particularly advantageous in rural African communities where delayed outbreak detection can lead to increased mortality. Enhanced cost-effectiveness is another benefit, as public health authorities can deploy resources based on actual demand rather than generalized distribution, minimizing operational waste and fortifying system resilience during emergencies.

4. AI Techniques Supporting Precision Public Health (PPH) Interventions

4.1 Machine Learning for Population Risk Stratification

Machine learning (ML) is one of the most important AI techniques needed in PPH for the identification and stratification of populations. Risk stratification involves using diverse datasets to categorize individuals or population groups into different risk categories according to their likelihood of experiencing a disease, adverse health outcome, or health-related event (Velmovitsky et al., 2021; 2). Unlike traditional epidemiological methods, ML algorithms can process large volumes of demographic, behavioral, environmental, genomic, and clinical data simultaneously to identify complex patterns associated with disease risk (Roberts et al., 2024). Integrating epidemiological records, healthcare utilization data, demographic characteristics, environmental variables, and social determinants enables machine learning models such as random forests, support vector machines, and neural networks to identify communities vulnerable to diseases such as malaria, tuberculosis, cholera, and HIV/AIDS (Table 3) (Abhadiomhen et al., 2024; Lokonon et al., 2026). These predictive capabilities assist health authorities in prioritizing interventions and efficiently allocating resources through targeted vaccination campaigns and community outreach (Edet et al., 2025). However, the effectiveness of these models relies on data quality and fairness, and poorly designed algorithms risk reinforcing health inequities among underserved populations (Birdi et al., 2024).

Table 3. Machine Learning for Population Risk Stratification and Benefits in PPH

Data Type	**AI Purpose**	**Precision Public Health Benefit**
Epidemiological data	Risk stratification	Targeted vaccination and screening programs
Healthcare utilization data	Identification of underserved populations	Strategic deployment of healthcare resources
Demographic data	Vulnerability assessment	Prioritized interventions for high-risk groups
Social determinants of health	Community risk profiling	Targeted outreach and health education
Environmental data	Disease hotspot identification	Precision vector-control interventions
Integrated datasets	Population-level risk assessment	Resource allocation and healthcare optimization

Source: *Developed by the authors based on evidence synthesized from the literature reviewed in this study including Robert et al. (2024), Abhadiomhen et al. (2024), Lokonon et al. (2026), and other studies.*

4.2 AI for Identifying High-Risk Communities (Geospatial Risk Mapping)

Geospatial risk mapping combines AI with geographic information systems (GIS), remote sensing technologies, climate data, epidemiological records, population density information, and socioeconomic indicators to identify communities that are disproportionately vulnerable to disease outbreaks and other health threats (Rajendran et al., 2024; Nusrat et al., 2024). These analyses provide a more detailed understanding of disease distribution across different geographical locations Traditional public health approaches often rely on aggregated regional statistics, which may mask localized hotspots of disease transmission (Dufitimana et al., 2025). AI enhances geospatial carry out analyses by identifying subtle spatial relationships and risk factors that might otherwise remain undetected (Diriba et al., 2024). According to Beard et al. (2018) and Rajendran et al. (2024)**,** machine learning models can combine rainfall patterns, temperature variations, population density, and historical disease incidence to identify areas at elevated risk of malaria or dengue outbreaks, while flood and sanitation data can be used to identify areas vulnerable to cholera outbreaks. Such risk maps enable public health authorities to prioritize high-risk locations for vaccination campaigns, vector-control measures, disease screening programs, and community health interventions. Geospatial risk mapping also supports healthcare optimization by identifying underserved populations with limited healthcare access (Isiagi et al., 2024; Cuadros et al., 2025). This information allows policymakers to strategically deploy healthcare workers, diagnostic services, medicines, and preventive resources to areas where they are most needed. As indicated in Table 4, geospatial risk mapping supports targeted prevention strategies and improves the efficiency of precision public health responses.

Table 4. Data Sources Used in Geospatial Risk Mapping and PPH interventions

Data Type	**AI Purpose**	**Precision Public Health Intervention Enabled**
Disease surveillance data	Identification of disease hotspots	Targeted vaccination and outbreak response
Population density data	Identification of high-transmission communities	Prioritized screening and prevention programs
Climate and environmental data	Mapping of environmentally suitable transmission zones	Precision vector control and environmental interventions
Mobility data	Identification of transmission corridors	Strategic placement of screening and healthcare services
Socioeconomic indicators	Detection of vulnerable populations	Resource prioritization and targeted community outreach

Source: *Developed by the authors based on evidence synthesized from the literature reviewed in this study including Isiagi et al. (2024), Beard et al. (2018), Rajendran et al. (2024), and other studies.*

4.3 Geospatial AI for Precision Intervention Planning

Geospatial AI extends beyond risk identification by supporting precision intervention planning. The primary goal of Precision Public Health (PPH) is to deliver the right intervention to the right population at the right time, and geospatial AI provides the analytical foundation for achieving this objective (Khoury et al., 2016). By integrating spatial, environmental, epidemiological, and population-level data, these technologies enable more targeted and effective public health actions (Roberts et al., 2024; Rajendran et al., 2024).

Using advanced spatial analytics, AI systems can evaluate disease distribution, healthcare accessibility, environmental exposures, and population movement patterns to determine where interventions will have the greatest impact (Villanueva-Miranda et al., 2025). For example, during infectious disease outbreaks, geospatial AI can identify optimal locations for vaccination campaigns, testing centers, vector-control programs, or health education initiatives. Such targeted approaches improve intervention effectiveness while reducing unnecessary resource expenditure (Beard et al., 2018; Rajendran et al., 2024). These technologies also facilitate scenario modelling, allowing public health officials to simulate the potential outcomes of alternative intervention strategies before implementation (Ahuja, 2026). Such predictive capabilities improve decision quality and support more efficient use of limited public health resources. In addition, geospatial AI can strengthen emergency preparedness by identifying populations that may be difficult to reach during disease outbreaks because of geographic isolation or inadequate infrastructure (Clark et al., 2025; Beard et al., 2018).

Consequently, geospatial AI strengthens evidence-based planning by ensuring that interventions are tailored to local conditions and population needs. This targeted approach enhances the effectiveness of disease prevention and control programmes while maximizing the use of limited public health resources, particularly in low-resource settings common across many parts of Africa (Roberts et al., 2024; Rajendran et al., 2024).

4.4 AI-Assisted Public Health Decision-Making

AI-assisted decision-support systems are increasingly enhancing public health planning by transforming large and complex datasets into actionable recommendations for intervention design, resource allocation, and healthcare optimization (WHO, 2021a). Public health decisions often require the integration of epidemiological, environmental, demographic, mobility, and healthcare system data (Mendes et al., 2025). AI provides the analytical capacity needed to evaluate these diverse information sources simultaneously and support evidence-based decision-making (Campbell et al., 2026). Within a precision public health framework, AI-assisted decision-support systems can help policymakers determine where interventions should be implemented, which populations should be prioritized, and how limited healthcare resources can be allocated most effectively (Khoury et al., 2016).

Furthermore, AI systems can continuously analyze newly available data and adjust recommendations as disease patterns evolve (Chen et al., 2024). This dynamic capability enhances responsiveness and supports adaptive public health planning. Nevertheless, AI should complement rather than replace human expertise because public health professionals remain responsible for evaluating recommendations, considering ethical implications, and ensuring that interventions align with local priorities, equity considerations, and community needs (Mittelstadt et al., 2016).

4.5 AI for Personalized and Community-Level Prevention Strategies

One of the most transformative contributions of AI to Precision Public Health is its ability to support both personalized and community-level prevention strategies. Traditional public health interventions often target entire populations using uniform approaches. In contrast, AI enables interventions to be tailored according to the specific characteristics, behaviors, and risk profiles of individuals and communities (Roberts et al., 2024).

At the individual level, AI can analyze health records, behavioral patterns, genetic information, and environmental exposures to identify people who may benefit from targeted preventive measures (Dinc & Ardic, 2025). At the community level, AI can identify neighborhoods with elevated disease risk and recommend interventions such as vaccination campaigns, health education programs, screening initiatives, or environmental modifications (WHO, 2021b). These applications support the goals of precision public health by enabling more targeted and effective prevention efforts based on the specific needs of populations and individuals (Khoury et al., 2016).

The integration of AI into prevention strategies also facilitates continuous monitoring and adaptation (WHO, 2021b). As new data become available, AI systems can update risk assessments and modify recommendations accordingly which improves responsiveness and increases the effectiveness of prevention programs (Chen et al., 2024). Nevertheless, successful implementation requires careful attention to data privacy, ethical governance, and equity to ensure that AI-driven interventions benefit all population groups fairly and inclusively (Floridi et al., 2018).

5. Data ecosystems supporting Precision Public Health

Artificial intelligence (AI)-enabled precision public health majorly depends on the availability and integration of diverse data ecosystems that capture the biological, environmental, demographic, and social determinants of infectious disease transmission. Unlike traditional public health approaches that often rely on aggregated population-level statistics (Canfell et al., 2022), precision public health utilizes multidimensional datasets to identify high-risk populations and predict localized disease risks for optimize intervention delivery (Roberts et al., 2024).

5.1 Epidemiological and Clinical data

Epidemiological and clinical records form the central operational foundation of AI-driven precision public health (Nkengasong & Mankoula, 2020). These datasets include disease incidence and prevalence records, laboratory-confirmed cases, hospitalization data, mortality records, immunization coverage reports, and electronic health records (EHRs) (Vargas-Santiago et al., 2025). When integrated into machine learning models, such data enable the identification of disease hotspots, emerging outbreaks, and populations at elevated risk of infection (Idahor et al., 2025). Beyond their usage in disease surveillance, epidemiological data support intervention targeting and resource allocation. AI systems can identify districts with low vaccination coverage, communities experiencing increasing disease incidence, or healthcare facilities facing rising patient loads. This information as shown in Table 5, enables public health authorities to prioritize vaccine deployment, diagnostic services, healthcare personnel, and treatment resources in areas with the greatest need (Ogundipe et al., 2025).

Table 5. Epidemiological and Clinical Datasets Supporting AI-Enabled Precision Public Health in Africa

Data Source	**AI use of dataset**	**Precision public health Application**	**Public Health Outcome**
Electronic Health Records (EHRs)	Identification of vulnerable populations and disease patterns	Personalized and community-level intervention planning	Improved healthcare delivery and patient outcomes
Laboratory Reports	Early identification of emerging outbreaks	Rapid response and targeted containment measures	Reduced outbreak severity and spread
Disease incidence and prevalence records	Hotspot detection and risk stratification	Targeted vaccination, screening, and treatment campaigns in high-risk communities	Reduced disease transmission and improved intervention efficiency
Hospital Admission Data	Healthcare demand forecasting	Strategic deployment of healthcare personnel, diagnostics, and medicines	Enhanced health system preparedness and resource utilization
Mortality and morbidity data	Identification of high-burden populations	Prioritization of healthcare investments and intervention programs	Improved population health outcomes
Immunization coverage data	Detection of under-immunized populations	Targeted vaccination campaigns and catch-up immunization programs	Increased vaccine coverage and reduced susceptibility
Antimicrobial resistance surveillance data	Detection of resistance patterns	Targeted antimicrobial stewardship and treatment optimization	Reduced spread of drug-resistant infections

Source: *Developed by the authors based on evidence synthesized from the literature reviewed in this study including WHO Africa et al. (2025), Idahor et al. (2021), Khoury et al. (2016,) Ogundipe et al. (2025) Rajendran et al. (2024), Naumova, (2022) and other studies.*

5.2 Climate and Environmental Datasets

Climate and environmental datasets are important for AI-enabled PPH systems, particularly in Africa, where many infectious diseases such as malaria, dengue, rift valley fever, and cholera, are sensitive to ecological conditions affecting pathogen survival and human exposure (Ristevski & Chen, 2018; Inam, 2025). As seen in Table 6, AI systems increasingly utilize rainfall patterns, temperature, humidity, vegetation indices, land-use data, flooding information, and satellite imagery to generate spatial risk maps that identify areas vulnerable to disease outbreaks (Edet et al., 2025; MacIntyre et al., 2023). Integrating these variables into AI models enhances disease prediction accuracy and outbreak readiness before they escalate (Idahor et al., 2025). However, the value of these datasets extends beyond outbreak prediction to targeted public health interventions. For example, malaria risk maps generated from climate data can guide the deployment of insecticide-treated bed nets, indoor residual spraying campaigns, and seasonal malaria chemoprevention programs (Yahouedo et al., 2026). Similarly, AI-informed environmental surveillance can identify flood-prone communities at increased risk of cholera outbreaks, allowing authorities to prioritize sanitation interventions, oral cholera vaccination campaigns, and emergency preparedness measures (Amisu et al., 2024). Consequently, climate and environmental datasets serve as critical components of precision intervention planning and resource optimization.

Table 6. Climate and Environmental Datasets Supporting AI-Enabled Precision Public Health Intervention in Africa

Data Source	**AI use of dataset**	**Precision public health Application**	**Public Health Outcome**
Rainfall data	Prediction of vector breeding conditions and disease transmission risk	Identification of malaria, Rift Valley fever, and dengue hotspots	Reduced vector-borne disease transmission and improved intervention efficiency
Temperature data	Modeling pathogen and vector survival patterns	Detection of areas with favorable conditions for vector proliferation	Improved outbreak prevention and resource allocation
Humidity data	Assessment of environmental suitability for disease vectors	Identification of high-risk transmission zones	Enhanced disease prevention and reduced operational costs
Flooding and hydrological data	Prediction of waterborne disease outbreaks	Identification of communities vulnerable to cholera and other enteric diseases	Reduced outbreak severity and improved community resilience
Vegetation indices (NDVI, EVI)	Mapping ecological conditions favorable for vectors	Delineation of malaria and arboviral disease risk areas	Improved targeting of disease control programs
Water quality and surface water data	Detection of conditions associated with waterborne disease transmission	Identification of high-risk communities lacking safe water access	Reduced burden of cholera and other waterborne diseases
Air quality and climatic anomaly data	Identification of environmental stressors influencing disease vulnerability	Monitoring areas susceptible to climate-sensitive infectious diseases	Strengthened outbreak preparedness

Land-use and land-cover data	Detection of environmental changes associated with disease emergence	Identification of areas affected by deforestation, irrigation, or urbanization	Reduced emergence of environmentally driven infectious diseases

Source: *Developed by the authors based on evidence synthesized from the literature reviewed in this study including WHO Africa et al. (2025), Edet et al. (2025), MacIntyre et al. (2023) Idahor et al. (2025), Rajendran et al. (2024), Amisu et al (2024) and other studies.*

5.3 Human Mobility and Transportation Data

Human mobility patterns significantly influence infectious disease transmission by facilitating the movement of pathogens across communities, districts, and national borders (Tatem et al., 2012; Lessani et al., 2024). Data derived from mobile phone records, transportation networks, migration statistics, refugee movements, and population density surveys provide valuable insights into how diseases spread within and between populations (Table 7). AI systems uses these datasets to identify transmission corridors, high-risk mobility networks, and populations vulnerable to disease importation or exportation (Lessani et al., 2024; Ye et al., 2025). Such information enables precision public health interventions by guiding the strategic placement of screening stations, vaccination campaigns, contact tracing teams, and healthcare resources (Adams et al., 2022;). During outbreaks of Ebola, COVID-19, and cholera, mobility-informed AI models have supported targeted containment measures and improved allocation of outbreak response resources (Villanueva-Miranda et al., 2025). Demographic characteristics such as age distribution, household size, urbanization levels, and population density further enhance AI-driven risk stratification, enabling interventions to be tailored to specific population groups and geographic locations (Faye et al., 2026).

Table 7. **Human Mobility and Transportation Data Sources for AI-Enabled Precision Public Health Intervention in Africa**

Mobility Data Source	**AI use of dataset**	**Precision public health Application**	**Public Health Outcome**
Mobile phone call detail records (CDRs)	Analysis of population movement patterns	Strategic placement of vaccination teams, screening stations, and outbreak response units	Improved outbreak containment and resource allocation
Transportation network data	Identification of transmission corridors	Prioritized surveillance and intervention along high-risk travel routes	Reduced geographic spread of infectious diseases
Migration and refugee movement data	Vulnerability and displacement risk assessment	Targeted healthcare services for displaced populations	Improved access to healthcare among vulnerable groups
Population density data	Identification of transmission hotspots	Prioritized vaccination, vector control, and disease prevention programs	More efficient intervention deployment
Urbanization and settlement data	Risk mapping of informal settlements and underserved communities	Targeted health outreach and disease prevention campaigns	Reduced health disparities
Age and population structure data	Identification of high-risk	Age-specific vaccination and prevention strategies	Improved intervention effectiveness

	demographic groups		
Cross-border mobility data	Monitoring transnational disease spread	Strengthened regional surveillance and border health interventions	Enhanced epidemic preparedness and control

Source: *Developed by the authors based on evidence synthesized from the literature reviewed in this study including Lessani et al. (2024), Ye et al. (2025), Adams et al. (2022), Khoury et al. (2026), WHO Africa et al. (2025), Rajendran et al. (2024), Naumova, (2022) and other studies.*

5.4 Genomic and Pathogen Sequencing Data

Recent genomic sequencing advancements have revolutionized infectious disease control by providing detailed information on pathogen evolution, transmission pathways, and antimicrobial resistance (Gardy & Loman, 2018). AI systems can rapidly analyze large genomic datasets to identify mutations associated with increased transmissibility, virulence, or drug resistance, generating actionable insights for public health decision-making (Sundermann et al., 2026; O'Connor & McVeigh, 2025). Within a precision public health framework, genomic data support targeted interventions rather than merely tracking pathogen evolution. AI-assisted genomic surveillance can identify emerging drug-resistant strains, enabling healthcare systems to prioritize antimicrobial stewardship programs, adapt treatment guidelines, and strengthen surveillance in high-risk communities (Ayesiga et al., 2025a; Kajumbula et al., 2024). Genomic analysis also supports vaccine strategy optimization by identifying circulating variants and informing decisions regarding vaccine deployment and effectiveness monitoring (Bentley & Lo, 2021). By linking molecular epidemiology with population-level surveillance, AI-enabled genomic systems improve the precision of infectious disease interventions across African settings (Dada et al., 2024). In Table 8**,** genomic and pathogen sequencing data support AI-enabled public health systems by enabling outbreak tracing, mutation detection, antimicrobial resistance monitoring, and improved vaccine development strategies.

Table 8. Genomic and Pathogen Sequencing Dataset for AI-Enabled Precision Public Health Intervention in Africa

Data Source	**AI use of dataset**	**Precision public health Application**	**Public Health Outcome**
Whole-genome pathogen sequencing	Identification of transmission chains and outbreak clusters	Targeted outbreak investigation and containment strategies	Improved disease control efficiency
Antimicrobial resistance (AMR) genomic data	Detection of resistance-associated mutations	Precision antimicrobial stewardship and treatment selection	Reduced treatment failure and AMR spread
Viral variant sequencing data	Identification of emerging variants of concern	Targeted vaccine deployment and effectiveness monitoring	Enhanced vaccine program effectiveness
Phylogenetic surveillance data	Mapping pathogen evolution and spread	Prioritization of high-risk areas for intervention	Improved outbreak response planning
Genomic surveillance databases	Real-time monitoring of pathogen diversity	Strengthened disease surveillance and preparedness systems	Faster detection of emerging threats

Multi-pathogen sequencing datasets	Detection of co-circulating pathogens	Integrated disease management strategies	More efficient use of healthcare resources

Source: *Developed by the authors based on evidence synthesized from the literature reviewed in this study including Gardy & Loman, (2018), Khoury et al. (2016), Topol (2019), Ayesiga et al. (2025a), WHO Africa et al. (2025), Rajendran et al. (2024), Naumova, (2022) and other studies.*

5.5 Socio-Economic and Demographic Indicators

Infectious disease risk is shaped not only by biological factors but also by social, economic, and environmental conditions (Noppert et al., 2023; Hassan et al., 2024). Data relating to poverty, education, housing quality, sanitation access, healthcare availability, employment, and population density provide critical insights into community vulnerability and health inequities as illustrated in Table 9. AI models increasingly incorporate these social determinants of health to identify populations at heightened risk of infectious disease exposure and poor health outcomes. For example, communities characterized by overcrowding, inadequate sanitation, and limited healthcare access are more susceptible to diseases such as cholera, tuberculosis, and neglected tropical diseases (Ramin, 2009; Chen et al., 2025; Siamalube et al., 2025). Integrating social determinant data into AI systems enables public health authorities to prioritize vulnerable populations for targeted vaccination, screening programs, vector control interventions, and healthcare resource allocation (Davis et al., 2025). This approach promotes equity by ensuring that interventions reach populations with the greatest need.

Table 9. Social Determinants of Health Supporting AI-Enabled Precision Public Health

Social determinant	**AI use of dataset**	**Precision public health Application**	**Public Health Outcome**
Poverty and income data	Vulnerability mapping	Targeted healthcare subsidies, vaccination programs, and treatment support	Improved healthcare equity
Education and literacy levels	Identification of health information gaps	Tailored health education and risk communication campaigns	Increased community awareness and preventive behavior
Housing conditions and overcrowding	Identification of high-transmission environments	Prioritized screening, vaccination, and infection prevention interventions	Reduced disease transmission
Water, sanitation, and hygiene (WASH) indicators	Cholera and waterborne disease risk assessment	Targeted sanitation improvements and WASH interventions	Reduced outbreak occurrence
Healthcare accessibility data	Identification of underserved communities	Deployment of mobile clinics and outreach services	Improved healthcare access
Employment and occupational data	Identification of occupational exposure risks	Targeted workplace health interventions and disease prevention programs	Reduced occupational disease burden

Geographic remoteness indicators	Mapping healthcare access gaps	Prioritized allocation of healthcare resources and telehealth services	Enhanced service coverage in remote areas

Source: *Developed by the authors based on evidence synthesized from the literature reviewed in this study including Khoury et al. (2026), WHO Africa et al. (2025), Rajendran et al. (2024), Naumova, (2022), Ramin, (2009), Chen et al. (2025), Siamalube et al. (2025), Davis et al. (2025) and other studies.*

5.6 Behavioural and Lifestyle Data

Behavioural and lifestyle data provide additional insights into factors influencing infectious disease transmission and intervention effectiveness (Miller, 2015). These datasets may include healthcare-seeking behaviour, vaccination uptake, treatment adherence, sanitation practices, mobile health application usage, social media interactions, and community perceptions of disease risk (Graham et al., 2024; Chakraborty et al., 2025).

As seen in Table 10, AI systems can analyze these data to identify behavioural patterns that contribute to disease vulnerability or intervention failure. For example, machine learning algorithms can detect communities with low vaccine acceptance, poor adherence to tuberculosis or HIV treatment, or limited engagement with preventive healthcare services. Such insights allow health authorities to design targeted health education campaigns, behavioural interventions, adherence support programs, and community engagement strategies (Obeagu et al., 2025; Gallego et al., 2024). By integrating behavioural and lifestyle information with epidemiological and environmental datasets, AI strengthens the ability of precision public health systems to deliver interventions that are both context-specific and population-centered (Chen et al., 2024).

Table 10. Behavioural and Lifestyle Dataset Supporting Precision Public Health Intervention in Africa

Data Source	**AI use of dataset**	**Precision public health Application**	**Public Health Outcome**
Vaccination uptake records	Identification of vaccine hesitancy clusters	Targeted vaccination promotion campaigns	Increased vaccine acceptance and coverage
Healthcare-seeking behaviour data	Detection of delayed care-seeking patterns	Community outreach and health education interventions	Earlier diagnosis and treatment
Treatment adherence records	Prediction of treatment interruption risk	Targeted adherence support for HIV, TB, and chronic infectious diseases	Improved treatment outcomes
Social media and online health discussions	Monitoring public perceptions and misinformation	Precision risk communication and misinformation management	Increased trust and community engagement
Mobile health (mHealth) application data	Monitoring health-related behaviours	Personalized health reminders and preventive interventions	Improved preventive health practices

Community survey data	Identification of behavioural risk factors	Targeted behavioural change interventions	Reduced disease vulnerability
Sanitation and hygiene behaviour data	Detection of practices associated with disease transmission	Community-level hygiene promotion programs	Reduced risk of waterborne and enteric diseases

Source: *Developed by the authors based on evidence synthesized from the literature reviewed in this study including Graham et al. (2024), Obeagu et al. (2025), Gallego et al. (2024), Khoury et al. (2026), WHO Africa et al. (2025), Rajendran et al. (2024), Naumova, (2022) and other studies.*

In summary, this section established that epidemiological, environmental, mobility, genomic, social, and behavioural data ecosystems provide the foundation for AI-enabled precision public health in Africa (Table 11). Through the integration of these diverse datasets, AI systems can identify high-risk populations and locations, support targeted interventions, optimize resource allocation, and enhance healthcare delivery. Rather than focusing solely on disease prediction, these data ecosystems enable a shift toward proactive, equitable, and evidence-driven infectious disease control strategies that can maximize the impact of limited public health resources in Africa.

Table 11. Behavioural and Lifestyle Dataset Supporting Precision Public Health Intervention in Africa

Data Ecosystem	**AI use of dataset**	**Precision public health Intervention Enabled**	**Expected Impact**
Epidemiological and clinical data	Risk stratification and disease burden assessment	Targeted vaccination, screening, and treatment programs	Improved intervention efficiency
Climate and environmental data	Hotspot mapping and environmental risk assessment	Precision vector control and environmental interventions	Reduced transmission risk
Human mobility and demographic data	Transmission corridor analysis	Targeted surveillance, screening, and outbreak containment	Enhanced epidemic control
Genomic and sequencing data	Variant and resistance detection	Precision treatment, antimicrobial stewardship, and vaccine optimization	Improved disease management
Social determinants of health	Vulnerability assessment	Resource prioritization and equitable healthcare delivery	Reduced health disparities
Behavioural and lifestyle data	Behaviour prediction and intervention tailoring	Targeted health education, adherence support, and community engagement	Improved intervention uptake

Source: *Authors' compilation from reviewed literatures*

6. AI for Intervention Optimization and Resource Allocation in PPH Africa

This section looks at how AI is being used to optimize intervention delivery, allocate scarce resources, and integrate precision approaches into the existing health systems across African countries (Figure 1).

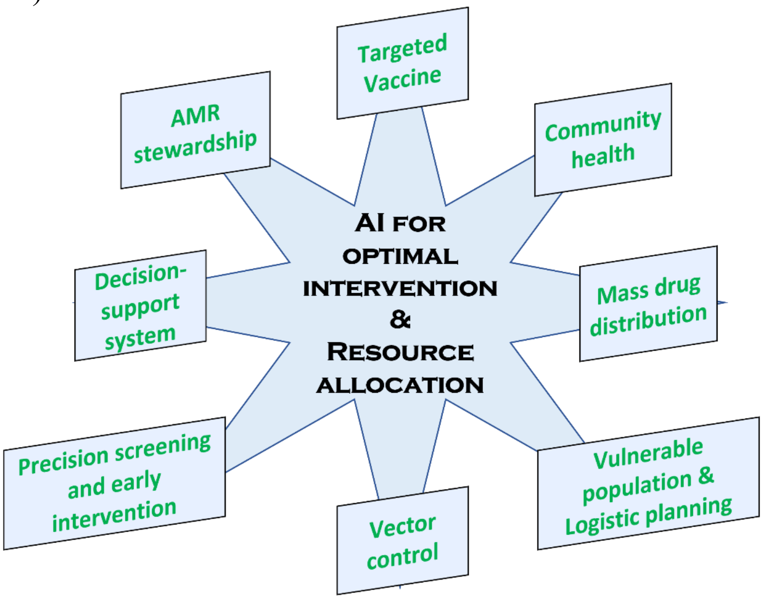

Figure 1: Diagram showing the central role of AI in optimizing public health interventions and healthcare resource allocation within the PPH framework (AMR: antimicrobial resistance).

6.1 Targeted Vaccination and Drug Distribution Strategies

Vaccine-preventable diseases is known to be one of the major causes of morbidity and mortality in Africa, especially among children and underserved populations in areas where access to healthcare and infrastructural is challenges (Olutuase et al., 2022; Lubanga et al., 2024). Research shows that using AI within the PPH framework can help in vaccination distribution by utilizing machine learning models that combines epidemiological data with demographic, climatic, and mobility data, to identify communities at high risk of disease transmission (Musuka et al., 2026; Baiasu et al., 2026). This risk stratification method helps public health authorities focus on deploying vaccine to locations where they are more likely to achieve better health impact, especially when vaccine availability is limited. This will further promote equitable healthcare delivery (Alshaya et al., 2024; Okesanya et al., 2026). Geospatial AI tools, including CholeraMap, EWARS, Zzapp, and DHIS2, further strengthen this approach by producing detailed risk maps that highlight communities vulnerable to diseases such as cholera, measles, and malaria (Nusrat et al., 2024; Musuka et al., 2026). These maps not only identify areas of concern but also help to guide vaccination campaigns and other preventive measures (Nusrat et al., 2024; Musuka et al., 2026). In addition, these systems also help in address long-standing challenges in vaccine logistics across many African countries, such as vaccine stockouts, delayed deliveries, and cold-chain failures which continue to affect immunization programmes (Munasinghe & Halgamuge, 2023; Musa et al., 2025). By analysing past consumption patterns, disease trends, and anticipated demand, ML models can forecast vaccine requirements, support inventory management, and improve cold-chain planning (Aifuobhokhan et al., 2025). This enables health systems to respond more effectively to changing needs while reducing vaccine wastage and improving distribution efficiency (Ogundipe et al., 2025). As seen in various studies, several initiatives have demonstrated how these technologies can be translated into practice. In Rwanda, Viebeg Technologies uses AI to strengthen inventory management and improve the availability of essential medical supplies across healthcare facilities (African Development Bank, 2022; African Development Bank, 2024). Also, Zipline's drone delivery service has efficiently transported vaccines and medicines across multiple across Ghana, Rwanda, Nigeria, Kenya, and Côte d'Ivoire (Addy, 2023; Musa et al., 2025; FII, 2024).

The same principles are currently being applied to the distribution of essential medicines due to shortages of antimalarial drugs, antibiotics, and antiretroviral therapies in many African health systems, particularly in rural communities. Predictive AI models is being used to forecast medication demand, this help health facilities estimate future medicine demand based on seasonal disease patterns, population movement, and healthcare utilization, allowing stock levels to be adjusted before shortages occur (Park et al., 2025). AI is also improving the planning of mass drug administration (MDA) programmes for neglected tropical diseases and seasonal malaria prevention. By integrating demographic, epidemiological, and geospatial information, AI can identify communities with the greatest disease burden and the lowest treatment coverage, this enables programme managers to prioritize limited medicines and personnel to areas where they are likely to have the greatest public health impact (Hoefle-Bénard & Salloch, 2024; Sangare et al., 2026).

6.2 Precision Vector Control

Vector-borne diseases like malaria, dengue fever, and Rift Valley fever, continue to be a significant public health challenges across Africa despite decades of vector control (WHO, 2024a). According to the Malaria Atlas Project (MAP), interventions such as insecticide-treated nets (ITNs) and indoor residual spraying (IRS) have prevented an estimated 1.22 billion malaria cases and 3.5 million deaths across Africa since 2000, representing more than 77% of all malaria cases averted during this period (MAP/IVCC, 2025a; MAP/IVCC, 2025b). ITNs alone accounted for approximately 1.13 billion prevented cases, while IRS contributed to about 85 million additional cases averted (MAP/IVCC, 2025b). Despite this achievement of vector control, challenges such as insecticide spraying and distribution of insecticide-treated bed nets are still implemented uniformly without considering local transmission and environmental variations (Sami et al., 2022). This shows that there is the need for more precise, data-informed approaches that can better match vector control strategies to local epidemiological and environmental conditions. Studies in 19 sub-Saharan African countries reveal significant disparities in bed net use and malaria risk, with an overall prevalence of 24%, with Central Africa recording the highest prevalence at 26%, followed by West Africa at 25%, and East Africa at 20%, critically, 49.17% of households reported no bed net use (Yitageasu et al., 2025; Yitageasu & Demoze, 2026). AI-enabled PPH approaches can enhance vector control by utilizing geospatial mapping and predictive environmental analysis using machine learning to identify anopheles mosquito breeding hotspots based on environmental variables such as rainfall, temperature, humidity, vegetation indices, and land-use patterns to predict mosquito breeding hotspots and transmission zones (Rezvan et al., 2025; Okyere et al., 2025; Aduvukha et al., 2025), this allow malaria control programs to prioritize limited vector control resources, including ITNs, IRS, larval source management, and community engagement activities, in locations where interventions are expected to yield the greatest epidemiological impact (Kumar et al., 2025; Obeagu & Ogenyi, 2025).

6.3 AI-Guided Antimicrobial Stewardship and Drug Resistance Monitoring

Antimicrobial resistance (AMR) poses a significant threat in Africa due to antibiotic misuse and inadequate surveillance, jeopardizing medical advancements in combating infectious diseases. The WHO's 2024 Strategic and Technical Advisory Group has recognized Africa's AMR situation as a public health emergency (WHO 2024b). Sub-Saharan Africa faces alarming multidrug-resistance rates in major bacterial pathogens like *Escherichia coli*, Klebsiella pneumoniae, Staphylococcus aureus, Mycobacterium tuberculosis, and Salmonella enterica (Kariuki et al., 2022; Totaro et al., 2025). These pathogens show increased resistance to antibiotics, including third-generation cephalosporins and fluoroquinolones, severely restricting treatment options (Patra et al., 2025). Annually, AMR is responsible for over 250,000 deaths in Africa, compounded by complications from untreatable infections (Ayesiga et al., 2025b; Kariuki et al., 2022). The continent's lack of diagnostic capacity and weak antimicrobial stewardship leads to over-reliance on empirical treatments that may worsen resistance. AI presents transformative potential to bridge these gaps. With limited antimicrobial susceptibility testing (AST) and diagnostic resources, AI-driven antimicrobial stewardship programs that uses ML techniques can predict resistance patterns from sequencing data in sub-Saharan Africa and optimizing treatments (Lyimo, 2026). Preliminary studies in Kenya, Nigeria, and South Africa showcase the viability of ML-driven AMR predictions, although they lag behind similar research in Europe and North America (Ayesiga et al., 2025b; Nsubuga et al., 2024).

In tuberculosis, ML models have shown impressive predictive accuracy. A Ugandan study evaluated ten algorithms for predicting resistance to first-line anti-TB drugs, finding logistic regression particularly effective for rifampicin resistance, while boosting classifiers excelled in predicting other drug resistances (Babirye et al., 2024;). However, model generalizability poses challenges, as Ugandan logistic regression models did not perform well on South African data, indicating that regional resistance patterns and lineage variations affect performance (Babirye et al., 2024).

A proposed mini-framework for AI-enabled AMR interventions in sub-Saharan Africa includes four domains: (a) detecting resistance genes from whole-genome sequencing, (b) monitoring resistance trends geographically and temporally, (c) optimizing treatment through decision-support systems, and (d) integrating monitoring of antimicrobial prescribing and resistance patterns (Al Mazrouei et al., 2025; Peiffer-Smadja et al., 2024; Grand challenges, 2023).

6.4 Decision-Support Systems for Policymakers

Public health decision-making in Africa is frequently challenged by fragmented data systems, delayed reporting, and limited analytical capacity (Griffin et al., 2025). AI-powered decision-support systems represent a critical bridge between data analytics and policy action in African public health which can assist policymakers in synthesizing large and complex datasets into actionable insights for healthcare planning and intervention prioritization (Shaffer et al., 2018). These systems combine predictive analytics, geospatial visualization, and epidemiological modeling to support evidence-based decision-making (Ahmed et al., 2020).

Instead of the usual relying on general reports to make decision, these decision-support systems are currently being integrated into public health planning due to their ability to provide timely insights into disease burden, healthcare utilization patterns, vaccination coverage, and the availability of essential resources (Ogundipe et al., 2025; Oboli, 2026). This can further help policymakers to identify communities that at higher risk and direct preventive services, healthcare personnel, and other resources towards these areas (Ganatra et al., 2024; Hongoh et al., 2016). This AI-driven decision-support systems can therefore contribute to improving healthcare equity and reducing disparities in access to both preventive and curative health services.

6.5 Resource Prioritization for Vulnerable Populations and Logistics Planning

The scarcity of healthcare resources remains one of the major barriers faced by most of the African countries when it comes to infectious disease control. Some of these resources are healthcare workers, diagnostic facilities, transportation networks, and financial resources (WHO Africa, 2026; Adjei et al., 2026). Because of this, the use of AI provides an opportunity to improve how scarce resources are identified, prioritized, and distributed. By analysing information from climatic conditions, population movement, environmental factors, and previous disease patterns, machine learning models can help estimate where healthcare needs are likely to be most needed (Ogundipe et al., 2025). These predictions can help health authorities to plan ahead and direct essential supplies, diagnostic services, healthcare personnel, and emergency response resources to communities where they are most urgently required (PHB, 2026). In addition, AI can also improve the logistic aspects of healthcare delivery by supporting transportation routes, warehouse management, and coordination of medical supply chains (Ogundipe et al., 2025).

A key principle of PPH is ensuring that vulnerable groups, who often experience the greatest impact from infectious diseases, are not overlooked during resource allocation. These groups may include people living in remote rural areas, refugees, internally displaced populations, urban slum communities, pregnant women, and individuals with underlying chronic illness (Tomás Júnior et al., 2026; Dahab et al., 2020). AI-powered vulnerability mapping can help public health agencies direct interventions toward these populations while minimizing inefficiencies in resource distribution (PHB, 2026).

6.6 AI-Guided Community Health Interventions

One of health groups that plays an important role in healthcare delivery across Africa is the Community health workers (CHWs). This set of workers are found particularly in rural communities where access to formal healthcare facilities is limited. However, CHWs faces challenges such as high workloads which can affect the effectiveness of community-based interventions (Idriss-Wheeler et al., 2024; Ahmed et al., 2026). To solve these challenges, AI-enabled systems provide new opportunities to strengthen CHW programmes by supporting workforce deployment, prioritizing tasks, and guiding intervention planning according to local health needs (Hodges et al., 2025).

AI-guided community health interventions are an important component of PPH because they allow healthcare activities to be used according to the specific needs, risks, and social contexts of different communities (Ibitoye et al., 2025). By analysing epidemiological, environmental, and population-level data, AI models can help identify communities requiring increased attention and support the targeted deployment of CHWs for activities such as vaccination campaigns, disease prevention education, active case finding, and treatment follow-up (Sheer et al., 2022; Faye et al., 2026).

In addition, mobile AI applications can assist frontline workers by supporting symptom assessment, clinical decision-making, patient monitoring, and referral processes (Igwama et al., 2024). AI-assisted task shifting strategies can further support redistribution of healthcare responsibilities among frontline health workers (Mbouamba Yankam et al., 2023, Chinkhumba, 2026). For example, AI-powered diagnostic tools for tuberculosis screening and malaria detection can assist non-specialist healthcare workers in in identifying suspected cases and initiating appropriate referral or treatment pathways (Obi et al., 2024; Lindblade et al., 2025). Hence, by combining human expertise with AI-supported decision-making, these approaches can improve CHWs healthcare efficiency, reduce pressure on overstretched health systems, and ensure that essential interventions reach communities that need them most.

6.7 AI for Precision Screening and Early Intervention

Early identification of diseases is another major reason for persistent infectious diseases in Africa. To address this, the intervention of AI screening enables faster identification of individuals who may require further investigation or early treatment especially for diseases like the Tuberculosis (TB) and HIV co-infection. The WHO recommends the use of AI-based Computer-Aided Detection (CAD) systems for TB screening, particularly through the analysis of digital chest X-rays (WHO, 2025a; Moodley et al., 2022). In African, CAD technologies have improved screening efficiency in routine healthcare facilities and high-risk environments such as correctional facilities, where they have identified additional TB cases that may have been missed through symptom-based screening alone (Velen et al., 2022; Moodley et al., 2022). Economic assessments from Nigeria further suggest that AI-enabled chest X-ray screening can be a cost-effective, especially in areas where asymptomatic TB contributes significantly to ongoing transmission (Garg et al., 2025). These cases showed that improving early case identification can lead to timely treatment initiation, reduce disease spread, and improve patient outcomes (Nivethitha et al., 2025; WHO, 2025a).

Also, AI is also expanding precision approaches for HIV prevention and related health interventions. Predictive models have been used in Uganda and Tanzania to identify individuals and communities with increased HIV risk, allowing prevention programmes to better target limited resources (Sah et al., 2025; Cherezov et al., 2025). This means that precision delivery of pre-exposure prophylaxis (PrEP) to individuals that needs them is possible. It will also improve adherence monitoring, and help prioritize cervical cancer screening among women living with HIV, who face increased risk of cervical disease (Mengistie et al., 2026). Similarly, in malaria control programmes, AI models that integrate environmental, demographic, and epidemiological information can identify communities requiring intensified screening, preventive treatment, and outreach activities (Kumar et al., 2025).

Overall, AI-driven precision screening shifts infectious disease management from broad, reactive testing approaches toward more targeted strategies that focus on populations and locations where early intervention can have the greatest impact. When integrated with existing healthcare systems and community-based programmes, these technologies can strengthen disease detection, improve resource allocation, and support more equitable delivery of preventive and curative services across Africa.

7. Challenges to AI-Enabled Precision Public Health in Africa

7.1 Data Quality and Representation Challenges

For an AI system to be effective, it depends largely on the quality, accuracy, and completeness of data. However, this is not so in many African countries where data required to support these systems remain not only fragmented but also difficult to use due to paper-based records, inconsistent reporting systems, and weak digital integration (Nsubuga et al., 2006). These limitations can affect the accuracy of risk stratification resulting in the misidentification of high-risk populations. This can lead to directing interventions to inappropriate locations or populations while vulnerable communities remain unreached (Khoury et al., 2016). It is therefore necessary to improve data quality and interoperability in order to enhance the effectiveness and equity of AI systems that support equitable and effective PPH interventions.

7.2 Digital Infrastructure Limitations

For successful application of AI in PPH there is need for a strong digital infrastructure that can support effective data collection, integration, analysis, and communication between different level of the health system. However, many African countries continue to face different digital infrastructural challenges such as unstable internet connectivity, limited digital technology access, inadequate computing capacity, and unreliable electricity supply (Katurura & Cilliers, 2018; Mensah et al., 2023). These limitations can or have restricted timely health data collection and processing of health information, thereby reducing the ability of AI systems to provide useful insights for intervention planning and decision-making (Labrique et al., 2018). Addressing these infrastructure challenges through investment in digital health systems, affordable connectivity, and sustainable technology solutions will be important for ensuring that AI-enabled precision public health benefits are accessible across different populations and geographical settings.

7.3 Algorithmic Bias and Equity Concerns

The issue of algorithmic bias occurs when AI systems produce inaccurate results due to the fact that the datasets used for training do not adequately represent the populations where these systems are applied. Many existing AI models in Africa were developed using datasets from high-income countries, which in reality do not capture the unique environmental, genetic, socioeconomic, and healthcare characteristics of African populations (Obermeyer et al., 2019). This will usually lead to inaccurate risk predictions and also influence decisions about who receives healthcare resources, preventive interventions, or disease monitoring. In PPH, such errors can have serious consequences because inaccurate targeting may unintentionally exclude communities that already experience limited healthcare access. If this is not addressed, the AI systems may reproduce or worsen existing health inequalities rather than reduce them (Char et al., 2018; Obermeyer et al., 2019). The major sources of algorithmic bias affecting AI-enabled PPH implementation are summarized in Table 12.

Table 12: Sources of Algorithmic Bias and Effects

Source	Effect on AI model	Consequence
Missing rural data	Biased risk estimates	Underserved communities excluded from interventions
Non-African training datasets	Reduced local validity	Misallocation of healthcare resources
Historical inequities	Skewed vulnerability assessment	Reinforcement of health disparities

Source: Developed by the authors based on evidence synthesized from the literature reviewed in this study including Obermeyer et al. (2019), Khoury et al. (2016) and other studies.

7.4 Ethical and Governance Challenges

Another major challenge of AI-enabled PPH implementation is the ethical and governance framework. This framework is responsible for upholding transparency, accountability, privacy protection, and public trust (Khoury et al., 2016). It is well known that PPH requires access and integration of diverse datasets in order to provide valuable insights for targeted interventions, this access usually raises concerns regarding data ownership, informed consent, and confidentiality (Mittelstadt & Floridi, 2016).

In many African settings, regulatory frameworks for digital health data governance are still developing, and differences in policies between countries may create challenges for responsible AI implementation across the continent. Weak governance structures can reduce public confidence and limit community willingness to participate in AI-supported health programmes (Floridi et al., 2018). Furthermore, using AI systems to guide decisions about resource allocation and intervention priorities introduces ethical questions regarding the fairness, transparency, and accountability. In fact, most communities may not want to accept AI-driven interventions if they perceive the systems as unfair, discriminatory, or lacking human oversight (Khoury et al., 2016; Aranda-Jan et al., 2014).

To ensure AI transparency, equity and acceptance, it is important to involve communities, healthcare professionals, policymakers, and technology developers in the development process. This will not only build trust but also help address real health priorities rather than simply introducing new technologies. Strong ethical frameworks and regulatory guidance will ultimately determine whether AI-enabled PPH can benefit populations most affected by infectious diseases, particularly underserved and vulnerable communities.

8. Practical Applications (Case-studies) of Precision Public Health in Africa

This section examines case studies where AI-enabled precision public health (PPH) approaches have been deployed to address Africa's most pressing infectious disease.

8.1 Malaria Intervention Targeting: AI-Identified High-Risk Zones Using Climate Data

Malaria remains one of Africa’s most persistent infectious disease challenges, accounting for approximately 95% (265 million cases) of global malaria cases and 95% of malaria-related deaths (579,000 deaths) reported worldwide in 2023 (WHO, 2025b). However, malaria transmission is not evenly distributed across populations or geographical areas. Differences in climate conditions, mosquito ecology, population characteristics, and human behaviour create variation in malaria risk, making uniform intervention approaches less effective (Sadoine et al., 2024). This has increased the need for PPH strategies that can identify where and when interventions are most urgently required. Recent studies have showed that AI and machine learning models are increasingly being used to combine satellite-derived environmental information with epidemiological data in order to identify malaria risk patterns and guide targeted control activities (Obeagu & Ogenyi, 2025). In Tanzania, for example, predictive models incorporating climatic factors such as rainfall, temperature, and humidity are being evaluated for district-level malaria forecasting (Obeagu & Ogenyi, 2025; Lutambi et al., 2025). These models generate seasonal risk maps that can support decisions on when and where to implement interventions such as indoor residual spraying (IRS), community awareness campaigns, and other preventive measures (Hoek et al., 2024). Studies indicates that, predictions generated one to two months before peak transmission periods have shown good agreement with observed malaria trends, allowing health authorities to prepare supplies, position healthcare resources, and strengthen response activities before case numbers increase (Obeagu & Ogenyi, 2025).

In Kenya, malaria programmes have explored the use of drones combined with AI-based image recognition to analyse high-resolution aerial images and identify environmental features associated with *Anopheles* mosquito breeding, including water bodies and suitable vegetation areas. These approaches have demonstrated improved detection of breeding sites compared with conventional assessment methods, enabling more focused vector control activities (Nyambo et al., 2026; Minakshi et al., 2020). Similarly, Nigeria has developed AI-enhanced mobile health platforms that allow real-time malaria tracking, reducing reporting delays significantly and enabling quicker distributions of diagnostic tests and antimalaria treatments (Obeagu & Ogenyi, 2025; ICT Works 2024**).** This system merges mobile technology with predictive analytics, creating an efficient surveillance-to-action workflow (Ogwu & Izah, 2025). These risk maps enable malaria control programs to prioritize limited vector-control resources and preventive interventions in communities where they are likely to have the greatest impact.

8.2 Cholera Risk Mitigation Strategies: AI-Guided Sanitation and Intervention Prioritization

Cholera is a pressing public health issue in Africa due to issues like poor sanitation and limited access to clean water. According to Kaseya et al., (2024), between January 2023 to January 2024, 19 African countries reported approximately 252,934 cholera cases and 4,187 deaths, which showed the continuing impact of the disease across the continent with southern Africa notably impacted (Kaseya et al., 2024). The persistence of cholera outbreaks is influenced by multiple factors such as water scarcity, poor sanitation coverage, population displacement, rapid urban expansion, vulnerable living conditions, and climate-related changes that affect rainfall patterns and water availability (Charnley et al., 2022; Lippi et al., 2016; Christaki et al., 2020).

Conventionally, cholera treatment usually intensify after outbreaks are detected rather than before transmission becomes widespread (Mohamed et al., 2025), leading to ineffective control measures, especially in low-income area. Hence, AI-enabled PPH provides an opportunity to shift cholera management towards a more preventive and targeted approach. By integrating environmental, climatic, demographic, and water, sanitation, and hygiene (WASH) data, AI-based models can help identify communities at increased risk and guide the prioritization of interventions before outbreaks escalate (Akingbola et al., 2025).

Emerging initiatives by UNICEF demonstrate the potential of these approaches in practice. UNICEF has incorporated AI-supported predictive analytics into WASH planning activities in African countries to improve the identification of areas requiring targeted water and sanitation interventions (UNICEF, 2026). Overall, AI-driven risk maps can guide sanitation investments, prioritize oral cholera vaccination campaigns, and support targeted deployment of water treatment resources in high-risk communities.

8.3 Mobility-Informed Ebola Containment Strategies

The 2014–2016 West African Ebola outbreak demonstrated how human movement patterns can influence the spread of infectious diseases and highlighted the importance of incorporating mobility information into outbreak response strategies. Research showed that the epidemic affected Guinea, Liberia, and Sierra Leone, resulting in more than 11,000 deaths and placing significant pressure on already limited public health systems (WHO, 2026a; Ohimain & Silas-Olu, 2021). During this outbreak, mobile phone call detail records (CDRs) became an important source of information for understanding population movement, particularly the movement of people between outbreak hotspots and surrounding communities (Peak et al., 2018; Wesolowski et al., 2014).

Analysis of Orange Telecom CDR data was used in generating movement maps for Senegal and Côte d'Ivoire, this same approach was also used in other affected West African countries (Wesolowski et al., 2014). These mobility patterns were useful to researchers in estimating potential transmission pathways, anticipate areas at risk, and support decisions on where healthcare resources and response teams should be prioritized (Peak et al., 2018; Wesolowski et al., 2014). Importantly, these approaches provided evidence for targeted response planning instead of the broad measures such as unnecessary travel restrictions. Another important example is the Surveillance and Outbreak Response Management System (SORMAS), developed after Ebola experienced in Nigeria. SORMAS improved communication between frontline health workers and public health coordination centres by enabling timely reporting, case monitoring, and response management. Its flexible design also allowed adaptation for other outbreaks, including COVID-19 (Fähnrich et al., 2015; World Bank, 2023).

However, challenges remain in utilizing mobility data, examples are: inconsistent network coverage in rural areas, disparities in phone ownership, and the complexities of informal phone sharing (Wesolowski et al., 2012). Thus, combining digital mobility data with traditional epidemiological methods and community reporting is essential for effective containment strategies.

8.4 AI-Assisted Tuberculosis Screening

Tuberculosis (TB) remains a leading cause of infectious disease mortality in Africa, particularly among individuals living with HIV/AIDS and populations with limited healthcare access (Abraham et al., 2024; WHO 2026b). Delayed diagnosis and inadequate screening contribute substantially to continued transmission and poor treatment outcomes. AI-assisted precision screening approaches have therefore become increasingly important for improving early TB detection and expanding diagnostic access in underserved communities. A TB prevalence survey in South Africa revealed that 57.8% of confirmed TB cases lacked typical symptoms (Pillay et al., 2021), which would lead to missed diagnoses using the WHO-recommended symptom screening (Mendelsohn et al., 2025). Incorporating chest X-ray (CXR) screenings could significantly enhance TB detection, although access remains limited for at-risk populations (Abraham et al., 2024). Digital chest X-ray (dCXR) combined with computer-aided detection (CAD) employs AI to interpret images and identify TB indications effectively (Hansun et al., 2023; Qin et al., 2019, 2021). CAD systems uses machine learning and deep learning algorithms which analyses chest radiographs with high sensitivity and specificity for TB detection (Qin et al., 2019, 2021).

The WHO now advises using dCXR+AI in high TB burden regions, having approved six CAD software products for TB detection in June 2025 (WHO, 2025a). Evaluations of CAD tools in Africa show improved accuracy, with CAD4TB version 7 outperforming version 6, achieving a ROC curve of 0.865 against 0.833 (Nzimande et al., 2025). However, both versions showed diminished performance in those aged 60 and above and individuals with a history of TB, highlighting the need for local calibration and performance monitoring (Nzimande et al., 2025). The Stop TB Partnership's Introducing New Tools Project facilitated the deployment of CAD in seven countries, including Uganda, screening over 430,000 people and identifying nearly 14,000 with TB (Stop TB Partnership 2025a, 2025b). Community screenings using dCXR+AI promote active case finding, easing the testing burden for asymptomatic individuals with non-suggestive results (Frederick et al., 2025). Precision public health approaches also facilitate targeted TB screening by identifying populations at increased risk based on demographic, clinical, and socio-economic factors (Koura et al., 2025). AI systems integrating HIV prevalence, malnutrition rates, overcrowding indicators, and healthcare utilization data can prioritize communities requiring intensified TB screening and treatment support (Chaoui et al., 2026). Such targeted screening strategies improve healthcare efficiency while reducing diagnostic delays and transmission risk.

8.5 HIV/AIDS: AI for Precision PrEP Targeting, Viral Load Monitoring, and Adherence Prediction

HIV has been known to place a significant public health burden on Africa, particularly in sub-Saharan Africa, which accounts for roughly two-thirds of people affected by this virus global.

Although pre-exposure prophylaxis (PrEP) can reduce the risk of HIV acquisition by 40–90%, its uptake and long-term adherence remain suboptimal in many low- and middle-income countries (UNAIDS, 2025; Orlando et al., 2025).

With the emergence of PPH alongside AI, there is opportunity to make HIV prevention programmes more targeted by identifying individuals and communities that would benefit most from preventive and/or treatment interventions. Evidence supporting this solution is on the increase according to a scoping review covering ten studies from 2019 to 2025 which showed that, predictive models can improve PrEP targeting, strengthen adherence monitoring, and support more efficient use of healthcare resources. Most of the studies reviewed relied on demographic and behavioural information and reported predictive accuracies of approximately 70% for identifying HIV risk (Pam et al., 2025; Terefe et al., 2025). AI also has another important role after treatment has been initiated and this role is to ensure patients adherence to treatment. This is because poor adherence to antiretroviral therapy (ART) remains one of the leading causes of treatment failure and ongoing HIV transmission in Africa. Therefore, ML models are increasingly being used to identify individuals who are most likely to experience adherence challenges before treatment failure occurs. In Ethiopia, research showed that seven ML algorithms were evaluated using data from 4,640 adults receiving ART, with the gradient boosting model achieving an accuracy of 0.78 in predicting treatment adherence, the result enables healthcare providers to identify patients who may benefit from additional counselling and follow-up before adherence declines (Yeneakal et al., 2025). Similar result was also reported from the International Center for Child Health and Development (ICHAD, 2025) targeting adolescents living with HIV in sub-Saharan Africa. Researchers at ICHAD developed a model that accurately identified 80% of those at risk of non-adherence while minimizing false alarms. This helps healthcare providers focus on individuals needing support, counselling, and community follow-up on (ICHAD, 2025).

Aside from prevention and adherence monitoring, AI is also used for viral load monitoring needed for the management of HIV. AI-enabled decision-support systems developed in Ethiopia have demonstrated the ability to predict treatment response and identify patients with previously stable viral suppression who may be at risk of unexpected viral rebound, allowing earlier clinical review and intervention (Seboka et al., 2023). Digital twin technologies are also beginning to provide a virtual platform for exploring individualized treatment scenarios before clinical decisions are made (Sah et al., 2025). These applications show how AI can strengthen HIV programmes by supporting targeted prevention, improving treatment monitoring, and helping healthcare providers deliver more timely and efficient interventions.

8.6 Rigorous Evaluation of Case-studies and Real-World Effectiveness

Despite the current applications and case studies of AL-enabled PPH as discussed above, transiting from pilot projects to widespread application requires careful evaluation of whether these technologies deliver meaningful benefits under real-world healthcare conditions such as impact effectiveness, cost-effectiveness, and health system impact, especially in Africa (Figure 2). As noted in previous sections, most of the current research on AI in African public health is fragmented, with much of the research focusing on algorithm development and validation rather than long-term impact, scalability, and practical use in low-income countries where there are limited resources.

It is also important to note that the "pilot purgatory" phenomenon, where promising digital health initiatives fail to progress beyond initial testing phases, is particularly relevant in sub-Saharan Africa, where sustainability can be affected by infrastructure limitations, funding gaps, and workforce capacity constraints (Joseph, 2026). To address this challenge, AI interventions should incorporate evaluation frameworks such as RE-AIM (Reach, Effectiveness, Adoption, Implementation, and Maintenance) from the early stages of development. In addition, standardized reporting approaches, including CONSORT-AI and SPIRIT-AI, can improve transparency and allow meaningful comparison between studies (Ibrahim et al., 2021). Strengthening implementation science capacity will therefore be essential to generate reliable evidence, guide investment decisions, and ensure that AI-enabled precision public health solutions achieve lasting impact across African healthcare systems.

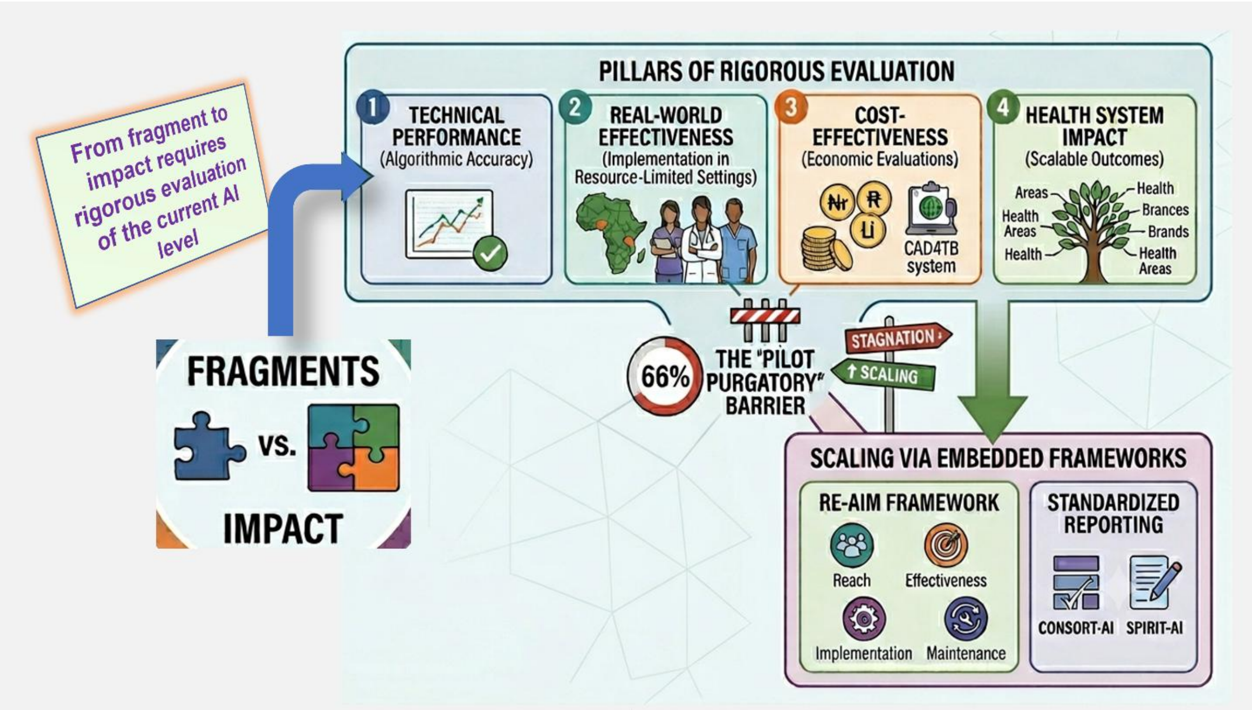

Figure 2: Diagram showing how current AI applications in precision public health should be rigorously evaluation from fragment data to actual impact

9. Future Directions for Precision Public Health in Africa

9.1 Integration of Genomics and AI

The integration of genomics with AI is an important opportunity for future direction for PPH in Africa. Genomic sequencing provides needed information about pathogen mutations, genetic variation, transmission patterns, and population health characteristics, all of which are important for designing disease control strategies (Gardy & Loman, 2018; Grubaugh et al., 2019). However, the bulky and complex nature of genomic data require advanced analytical approaches capable of identifying meaningful patterns within large datasets. Therefore, when combined with AI, these large genomic datasets can be analysed rapidly to not only identify biological patterns, but also provide understanding of disease transmission and support targeted public health interventions (Topol, 2019).

9.2 Capacity Building and Workforce Development

To establish a sustainable AI-enabled PPH in Africa, it is important to implement capacity building and workforce development in order to counter the challenge of shortage of healthcare personnels and professionals in data science, health informatics, and artificial intelligence (WHO, 2021a; Duggal et al., 2023). This can be achieve by strengthening technical education, interdisciplinary training, and digital literacy programs which will improve the ability of healthcare workers to manage and apply AI technologies effectively (Chan & Zary, 2019).

Collaboration between healthcare professionals, researchers, policymakers, and technology experts is also necessary to ensure successful implementation and long-term sustainability of AI systems (Topol, 2019).

9.3 Investment in Digital Health Infrastructure

Strong and continuous investment in digital health infrastructure is important for supporting AI-driven PPH systems across Africa. Reliable internet connectivity, interoperable electronic health systems, cloud computing platforms, and stable electricity supply are necessary for efficient data collection, storage, and analysis (WHO, 2021). These components are essential for enabling scalable and sustainable AI implementation in resource-constrained health systems (Table 13). Currently, infrastructure limitations are a major barrier to scaling AI applications in many African settings. Therefore, strengthening digital health infrastructure is needed to improve not only AI implementation but also broader healthcare system performance by enhancing data sharing, improving coordination between healthcare providers, and supporting more timely allocation of public health resources (WHO, 2021a; Aceto et al., 2018). Sustainable investment in digital systems will be essential for ensuring that AI-enabled PPH solutions can reach underserved populations and contribute to more equitable infectious disease control across the continent.

Table 13. Key Digital Health Infrastructure Components Supporting AI-Driven Public Health Systems

Infrastructure Component	Role in AI-Driven Public Health
Internet Connectivity	Enables real-time transmission of health data across facilities and regions
Electronic Health Systems	Facilitates digital collection, storage, and retrieval of patient and population health data
Cloud Computing Platforms	Supports large-scale data storage, integration, and AI processing
Stable Electricity Supply	Ensures uninterrupted operation of digital health technologies and networks
Interoperability Standards	Enables seamless data exchange between health information systems

Source: Developed by the authors from the literature reviews.

9.4 Community Engagement and Participatory Data Collection

Community engagement and participatory data collection are important for improving the relevance and accuracy of public health data. Involving communities in the design and implementation of health programmes enhances trust, strengthens local ownership, and ensures that interventions are responsive to community needs and realities (George et al., 2018). Such participatory approaches also promote shared decision-making between communities and health systems, which improves the acceptability and sustainability of public health interventions.

Participatory approaches such as mobile reporting systems and community health worker programs can improve the timeliness and completeness of health information, particularly in underserved regions (Labrique et al., 2018). Artificial intelligence–driven systems can further enhance healthcare decision-making by improving the accuracy, efficiency, and responsiveness of public health interventions (Khosravi et al., 2024).

9.5 AI for Equitable Healthcare Delivery

AI has significant potential to improve equitable healthcare delivery by identifying vulnerable populations and supporting targeted allocation of healthcare resources. By analysing demographic, environmental, and health data, AI systems can help reduce disparities between urban and rural communities and improve access to healthcare services. However, the effectiveness of these systems depends on the quality and representativeness of the underlying data. Evidence shows that population health algorithms may also reproduce or amplify existing inequities if not carefully designed. Obermeyer et al. (2019) highlight that biased proxy variables can lead to unequal identification of health needs, while Rajkomar et al. (2018) emphasize that model fairness depends on diverse data and robust design. In addition, fairness in machine learning involves inherent trade-offs that require ethical and policy considerations. These considerations are summarized in Table 14, which outlines key AI functions and associated health outcomes.

Table 14: AI Contribution to Equity in Healthcare

Function	Outcome
Population risk identification	Targeted intervention
Resource optimization	Reduced waste
Geographic mapping	Improved access
Decision support	Evidence-based planning

Source: Developed by the authors from the literature reviewed

9.6 Equitable and Sustainable AI Ecosystems

The development of equitable and sustainable AI ecosystems is essential for the long-term success of precision public health. In this context, sustainability and equity are not only technical requirements but also governance-driven principles that guide responsible AI design, deployment, and scaling. The Organisation for Economic Co-operation and Development (OECD, 2019) reinforces this by emphasizing that trustworthy AI systems must be grounded in fairness, transparency, accountability, and human-centered values to ensure inclusive and sustainable outcomes. Sustainable ecosystems therefore require strong governance frameworks, ethical standards, local expertise, and continuous financial investment (OECD, 2019; Floridi et al., 2018; Mittelstadt, 2019; WHO, 2021a). Governments, academic institutions, and private sector partners must collaborate to develop AI systems that are transparent, inclusive, and aligned with public health priorities, particularly in low- and middle-income settings (Jobin et al., 2019). Strengthening digital infrastructure, human capacity, and ethical governance will support resilient AI-enabled health systems capable of improving health outcomes across diverse populations (Topol, 2019; WHO, 2021a).

10. Conclusion

Till this present time, Africa continues to face a heavy burden of infectious diseases, and due to the different kind of populations, environments, and healthcare systems across the continent, the use of a single public health strategy is rarely effective. As discussed in this review paper, AI provides practical tools that can help public health personnel identify where disease risk is highest, prioritize vulnerable populations, and make better use of limited healthcare resources. Its applications in malaria, cholera, Ebola, tuberculosis, and HIV/AIDS showed that AI is valuable not only for predicting disease patterns but for supporting more targeted and timely interventions.

Despite these promising developments, the successful implementation of AI-enabled PPH is far from guaranteed as noted in this review, due to persistent challenges like poor-quality and

fragmented data, limited digital infrastructure, algorithmic bias, and weak governance frameworks in many African countries. To overcome these barriers, there is need for a strong investment in digital health systems, workforce training, and policies that promote transparency, fairness, and community trust.
On a final note, it is necessary to note that AI is only a decision-support tool and hence cannot replace public health expertise. When combined with local knowledge, sound public health practice, and sustained political commitment, AI has the potential to make infectious disease interventions more targeted, efficient, and equitable, contributing to stronger and more resilient health systems across Africa.

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Authors' Contribution

All authors contributed to the conceptualization, methodology, literature analysis, writing, review, and editing of the manuscript. All authors participated in manuscript preparation, critically revised the content, approved the final version, and accept responsibility for the integrity and accuracy of the work.

Competing Interest
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