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Harnessing Artificial Intelligence for Public Health Surveillance in Africa: Current Applications, Challenges, and Opportunities: A Scoping Review

Author: Edet, John Etim[1]

Co – Authors: Adamu Ishaka Akyala[2], Edward, Agbo Omudu[3], Ikaiddi, Anthony Asukwo[4], Epelle, Jake[5], Etimedet, Etieno[6], Olatinwo, Islamiyyat Adekemi[7], Azuka, Chinwe Grace[8], Abah, Michael Idoko[9], Edem, Philip Asuquo[10], Oluwagbohun, Oluwakemi[11]

[1,2,7,9,11]Global Health and Infectious Diseases Control Institute, Nasarawa State University, Keffi, Nasarawa State, Nigeria.

[3]Department of Biological Science, Benue State University, Makurdi, Benue State, Nigeria

[4]Department of Chemistry, Georgia State University, USA

[5]TAF Africa (NGO).

[6]Department of Nursing Science, Amadu Bello University, Zaria, Nigeria

[8]World Health Organization

[10]Department of Geology, University of Calabar, Calabar, Niger

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ABSTRACT

Background: Artificial Intelligence (AI) is increasingly revolutionizing public health surveillance, particularly in regions with constrained healthcare infrastructure. This scoping review examines the application of AI in public health surveillance across Africa, identifying existing implementations, challenges, and opportunities. AI technologies such as machine learning, natural language processing, and predictive analytics enhance epidemic intelligence by analyzing vast datasets from diverse sources, including electronic health records, social media, and environmental sensors. These AI-driven tools provide early warnings for outbreaks, improve disease surveillance, and facilitate timely public health responses.

Methods: A systematic search of databases, including Pubmed, Google Scholar, Researchgate, Web of Science, Scopus, Scientific Research, African Journal of Health Informatics, International Journal of Infectious Diseases, ScienceDirect, African Journal of Biotechnology, PloS One, The Lancet, JMIMR, BMJ, and BMC. The search covers publications from January 2010 to February 2025, spanning for 15 years. A total of 1411 articles. An additional 44 records were identified through other sources after removing 201 duplicates; 1254 unique articles were screened based on titles and abstracts. One thousand one hundred and twenty-seven (1127) records were excluded as they did not meet the inclusion criteria. Then, 127 full-text articles were assessed for eligibility, and 54 full-text articles were excluded for various reasons: study in non-African location (52) Not focused on AI applications (12), challenges and opportunities, Insufficient Data (9) Finally, 54 studies were included in the qualitative synthesis.

Results: Following a rigorous selection process, 54 studies were included in the qualitative synthesis. Most studies (83.33%) were published as peer-reviewed journal articles, while technical reports and theses were less common, with five (9.26%) and four (7.41%) studies, respectively. The primary focus of these studies varied: 39 (72.22%) explored AI applications in disease detection and prediction, 25 (46.30%) examined AI applications in disease surveillance, 18 (33.33%) highlighted challenges in AI adoption for healthcare, and 15 (27.78%) focused on real-time surveillance and reporting in Africa. Findings reveal that AI is actively utilized in African public health systems for disease prediction, outbreak surveillance, and resource allocation. However, several challenges hinder its full potential, including inadequate infrastructure, data privacy concerns, limited access to high-quality datasets, and a shortage of AI-trained healthcare professionals. Despite these barriers, AI presents great opportunities for strengthening health security in Africa by improving diagnostic accuracy, optimizing healthcare interventions, and enhancing real-time epidemiological analysis.

Conclusion: Artificial intelligence presents a transformative opportunity for health surveillance in Africa, particularly in diagnostics and disease prediction. AI-powered tools, such as mobile diagnostic applications and predictive models, enhance healthcare accessibility in resource-limited settings by analyzing vast datasets for early disease detection. Successful implementations, including AI-driven malaria mapping and tuberculosis detection through chest X-ray analysis, HIV, cholera, Ebola, measles, Zika virus, and malaria, enabling targeted screening interventions, personalized treatment plans, and efficient resource allocation, demonstrate AI's potential to improve public health outcomes. Despite challenges such as infrastructure limitations and data privacy concerns, AI continues to revolutionize disease monitoring and response. By leveraging machine learning for targeted interventions and efficient resource allocation, AI holds promise for a future of more proactive and effective healthcare across the continent of Africa.

Keywords: Artificial Intelligence, Machine Learning, Public Health Surveillance, Africa, Epidemiological Modeling, Disease Detection.

INTRODUCTION

Artificial intelligence (AI), defined as the replication of human cognitive processes through machines, encompasses technologies such as machine learning, natural language processing, and robotics. (Russell & Norvig, 2016). Artificial Intelligence can be described as the simulation of the human mind to make computers think and act like humans by performing tasks like learning and problem-solving (Zhang & Lu, 2021). The use of artificial intelligence (AI) to generate automated early warnings in epidemic surveillance by harnessing vast open-source data with minimal human intervention has the potential to be both revolutionary and highly sustainable. AI can overcome the challenges faced by weak health systems by detecting epidemic signals much earlier than traditional surveillance. AI-based digital surveillance is an adjunct to—not a replacement of—traditional surveillance and can trigger early investigation, diagnostics and responses at the regional level. Several current epidemic intelligence systems including ProMED-mail, HealthMap, Epidemic Intelligence from Open Sources, BlueDot, Metabiota, the Global Bio surveillance Portal, Epitweetr and EPIWATCH exist for public health surveillance (MacIntyre et al.). Artificial intelligence (AI) refers to the process in which computers, rather than human intelligence, perform tasks, such as early warning of an epidemic.

The application of artificial intelligence (AI) to healthcare in Africa has the potential to transform productivity, diagnosis, disease surveillance, and resource allocation by improving accuracy and efficiency. (Alaran et al.). AI-driven tools can analyze vast medical data, enabling early disease detection, accurate diagnoses, and personalized treatment. AI's exceptional capabilities in pattern recognition, predictive analytics, and decision-making can enable the development of systems that can analyze complex medical data at a scale and precision beyond human capacity. This, in turn, can augment early disease detection and facilitate accurate diagnoses. (Dhanjal).

AI's ability to analyze vast datasets from diverse sources such as electronic health records, social media, environmental sensors, and genomic data enables the identification of patterns and anomalies indicative of disease outbreaks. Machine learning techniques, including random forests, support vector machines, and deep learning models, have shown remarkable success in providing quicker and more accurate predictions compared to conventional methods (Wahl et al.).

Artificial Intelligence (AI) is revolutionizing various fields, including public health surveil- lance. In Africa, where health systems frequently encounter challenges such as limited re- sources, inadequate infrastructure, failed health information systems and a shortage of skilled health professionals, AI offers a transformative opportunity. (Tshimula et al., 2024b).

Artificial intelligence is transforming healthcare in Africa, particularly in resource-limited regions, by improving diagnostics, treatment, and overall healthcare operations. AI-driven solutions, such as mobile-based diagnostics and precision medicine, help overcome accessibility and resource constraints. However, its full potential is limited by challenges, including inadequate infrastructure, data privacy concerns, and gaps in healthcare training, which must be addressed to maximize its impact (Oladipo et al., 2024).

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Research Questions

The scoping review aims to address this overarching question:

What are the existing applications of artificial intelligence (AI) in public health surveillance in Africa? The review explores the following sub-questions:

1. What AI technologies (e.g., machine learning, natural language processing, computer vision) are most commonly applied in public health surveillance?
2. Which diseases or health conditions are most frequently monitored or predicted using AI-based surveillance systems in Africa?
3. What are the main technical challenges in implementing AI for public health surveillance in Africa?
4. What are the potential opportunities for AI to improve disease surveillance and health security in Africa?

Objectives of the Study

The main objective is to harness artificial intelligence for public health surveillance in Africa: The specific objectives of this study are to:

Examine the current AI applications in disease surveillance, challenges, and opportunities in Africa

METHODOLOGY

Study Design

This study follows a scoping review methodology, which is designed to map the existing literature on the Harnessing Artificial Intelligence for Public Health Surveillance in Africa: Current Applications, Challenges, and Opportunities. A scoping review is suitable for examining broad research questions where the literature is diverse in terms of study designs and interventions. The methodology follows the guidelines of the Arksey and O'Malley framework.[18] with enhancements from Levac et al.[19] and the Joanna Briggs Institute (JBI) manual for scoping reviews.[20]

Eligibility Criteria

Inclusion Criteria

Studies are included in the review based on the following criteria:

Population/Setting: Studies focused on public health surveillance in African countries, research covering infectious disease monitoring, outbreak detection, epidemiological modeling, or health data analysis using AI.

Intervention/Technology: Studies that explicitly discuss Artificial Intelligence (AI) technologies such as Machine Learning (ML), Deep Learning, Natural Language Processing (NLP), Computer Vision, and Predictive Analytics in public health surveillance.

Study Design: Peer-reviewed quantitative, qualitative, and mixed-methods studies, systematic reviews, and reports from 2010 to 2025, and Government or health organization reports if they provide substantial AI-driven surveillance data.

Time Frame: Publications from the last 10 – 15 years (to capture recent AI advancements).

Language: Studies published in English or French (as they are widely used in African research contexts).

Outcomes of Interest: Discussion of applications, benefits, challenges, and opportunities of AI in public health surveillance.

Exclusion Criteria

Geographic Scope: Studies that focus on AI in public health surveillance outside of Africa without an African context.

Technology Scope: Studies on general health informatics, electronic health records, or telemedicine without a focus on AI-driven surveillance.

Study Type: Opinion pieces, editorials, abstracts without full-text availability, and non-peer-reviewed articles (unless they provide significant insights).

Language Restrictions: Studies published in languages other than English or French (if translation is unavailable).

Irrelevant Focus: Papers that discuss AI in health without a direct link to surveillance, outbreak detection, or epidemiological monitoring.

Search Strategy

A comprehensive literature search is conducted across the following databases: Pubmed, Google Scholar, Medline, Web of Science, Scopus, Scientific Research, African Journal of Health Informatics, International Journal of Infectious Diseases, ScienceDirect, American Journal of Public Health Research, Researchgate, African Journal of Biotechnology, PloS One, The Lancet, JMIMR (Journal of Medical Internet Research), BMJ (British Medical Journal) and BMC (BioMed Central). The search covers publications from January 2010 to February 2025. The search terms will include combinations of keywords, and Medical Subject Headings terms include: “Artificial Intelligence (AI)”, Machine Learning, Public Health Surveillance, “Africa”, “Current Application”, “Challenges”, “AI Opportunities”, “AI application in Healthcare”. “AI Applications “Disease Detection” Disease Prediction”. The search strategy is customised for each database, and Boolean operators (AND, OR) are used to refine searches. References of selected articles are hand-searched for additional relevant studies.

Study Selection Process

The study selection process consists of three steps:

Initial Screening: Titles and abstracts of the identified studies are screened for relevance and eligibility. Articles that pass the initial screening are reviewed in full. Discrepancies in the inclusion decision are resolved.

Data Extraction

A standardized data extraction is developed and used to extract key information from each included study. It captures Study characteristics (author, year, location), AI Applications in Disease Detection and Prediction, challenges and opportunities, AI application in Healthcare in Africa, Machine Learning, and Predictions Models. Data are charted into a table that summarizes the key characteristics of each included study. The chart consists of Author(s), year, Study setting (country), Intervention description, and Conclusion (Intervention Success)

Data Analysis and Synthesis

A descriptive analytical approach will be applied to map the findings of the included studies. The data synthesis

will involve both quantitative summaries (e.g., frequency of specific intervention types) and qualitative thematic analysis (to identify common themes and patterns across studies). The findings of this scoping review will be reported following the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews) guidelines. A flowchart will be used to display the study selection process, and the results will be presented both narratively and in tables, summarizing key findings.

Ethical Considerations

Since this scoping review involves secondary data analysis of publicly available research, no formal ethical approval is required. However, all studies are handled according to standard ethical guidelines for conducting literature reviews, ensuring that data is reported accurately and objectively.

RESULTS

Study Selection Process

Figure 1 represents the PRISMA flow chart of the selected articles for this review. Records identified through database searching across Pubmed, Google Scholar, Medline, Web of Science, Scopus, Scientific Research, African Journal of Health Informatics, International Journal of Infectious Diseases, ScienceDirect, American Journal of Public Health Research, Researchgate, African Journal of Biotechnology, PloS One, The Lancet, JMIMR, BMJ and BMC (BioMed Central) totalled 1411 articles. An additional 44 records were identified through other sources after removing 201 duplicates; 1254 unique articles were screened based on titles and abstracts. One thousand one hundred and twenty-seven (1127) records were excluded as they did not meet the inclusion criteria. Then, 127 full-text articles were assessed for eligibility, and 54 full-text articles were excluded for various reasons: study in non-African location (52) Not focused on AI applications (12), challenges and opportunities, Insufficient Data (9) Finally, 54 studies were included in the qualitative synthesis.

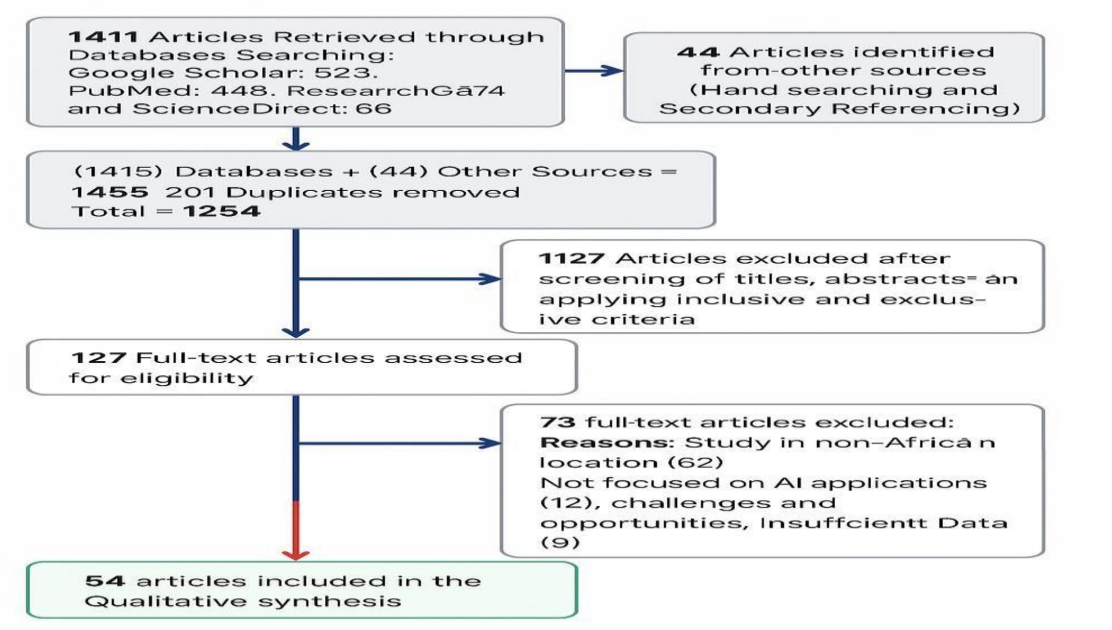

Figure 1 PRISMA Flow Chart of Selected Articles for the Scoping Review

Study Characteristics

Most of the studies (83.33%) were published as journal articles, reflecting peer-reviewed sources. Publications with technical reports and theses are less common, with only five study each (9.26%) theses are less common, with four study (7. 41%) reported in these formats.

Thirty-nine studies (72.22%) focused on AI Applications in Disease Detection and Prediction in Africa. Twenty five studies (46.30%) were on AI Applications in Disease Surveillance in Africa: Opportunities. Eighteen studies (33.33%) highlighted the challenges of AI Application in healthcare in Africa and fifteen studies (27.78%) focused on AI Applications in Real-time Surveillance and Reporting in Africa.

Table 1. Characteristics of included studies (n=54)

Reported variables	Frequency (n=54)	%
Literature sources		
Journal Articles	45	83.33
Technical Reports	5	9.26

Thesis	4	7.41
Themes		
AI Applications in Disease Detection and Prediction in Africa	39	72.22
AI Applications in Disease Surveillance in Africa: Opportunities	25	46.30
Challenges of AI Application in Healthcare in Africa	18	33.33
AI Applications in Real-time Surveillance and Reporting in Africa	15	27.78

Which diseases or health conditions are most frequently monitored and predicted using AI-based surveillance systems in Africa?

The integration of AI-driven predictive models into public health systems can significantly im- prove disease outbreak preparedness and response, ultimately save lives and reduce the disease burden. While there are numerous public health concerns in Africa, this paper focuses exclusively on the following: HIV, cholera, Ebola, measles, tuberculosis, influenza, Zika virus, COVID-19, malaria, and poliovirus.

HIV Detection and Prediction

Mutai et al. (2021) utilized machine learning algorithms to identify HIV predictors using socio- behavioral data from the Population-based HIV Impact Assessment (PHIA) surveys conducted in four sub-Saharan African countries. Their study applied the XGBoost algorithm, which significantly improved the identification of HIV-positive individuals.

The use of the XGBoost algorithm with socio-behavioural-driven data at substantially identifying HIV predictors and predicting individuals at high risk of infection for targeted screening. (Mutai et al., 2021b). In the context of HIV detection and prediction, AI has demonstrated significant promise in sub- Saharan Africa. Studies leveraging algorithms like XGBoost and artificial neural networks have achieved high accuracy in identifying HIV-positive individuals and predicting drug resistance mutations (Mutai et al., 2021; Ebulue et al., 2024a). This capability is crucial for developing personalized treatment plans and optimizing the allocation of healthcare resources.

The Machine Learning (ML) models have shown promise in identifying patterns and trends in HIV data, enabling more accurate predictions and targeted interventions. ML insights into HIV outbreak predictions leverage various data sources, including demographic, epidemiological, and behavioural data. (Charles Chukwudalu Ebulue et al., 2024).

Chikusi, et al., (2022) presents the Machine Learning model results to predict and visualise HIV index testing. The development process followed the Agile Software development methodology. The data was collected from Kilimanjaro, Arusha and Manyara regions in Tanzania. A total of 6346 samples and 11 features were collected. Then, the dataset was divided into training sets of 5075 samples and a testing set of 1270 samples (80/20). The datasets were run into Random Forest (RF), XGBoost, and Artificial Neural Networks (ANN) algorithms. The results of the evaluation, by Mean Absolute Errors (MAE), showed that; RF MAE (1.1261), XGBoost MAE (1.2340), and ANN MAE (1.1268.); whereby the RF appeared to have the best result compared to the other two algorithms. The study presents the results of the developed ML model that can help experts make predictions and produce up-to-date data visualization that is readable and understandable. In addition, the developed ML model can predict the number of HIV Index testing using partner notification information to identify people who are at risk to contract HIV AIDS. Hence, help decision-makers to come out with a good intervention strategy towards ending HIV AIDS in the societies.

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Machine learning in HIV/AIDS had applied as follows: Machine learning to identify HIV predictors for screening (Mutai et al., 2021b). Singh et al., used ML in the prediction of patient-specific current CD4 cell count to determine the progression of human immunodeficiency. A regression model predicting actual CD4 cell counts and a classification model predicting if a patient's CD4 cell count is less than 200 was built using a support vector machine and neural network. The most accurate regression and classification model took as input the viral load, time, and genome and produced a correlation of co-efficient of 0.9 and an accuracy of 95%, respectively, proving that a CD4 cell count measure may be accurately predicted using machine learning on genotype, viral load and time. Singh et al., (2016), prediction of new HIV infection in China by using internet search Zhang et al., (2018), predicting default from HIV service in Mozambique (*Machine Learning for Predicting Default from HIV Services in Mozambique*, 2018), Another area is improving HIV case findings Chikusi et al., (2022).

Ebulue et al. (2024a) proposed a novel clinical, behavioral, and laboratory data from 2016 to 2018. Three classification algorithms were eval- uated: logistic regression, random forest, and Ad- a Boost. The study found that the model's predic- tive accuracy, measured by the area under the curve (AUC), ranged from 0.69 for retention to 0.76 for VL suppression. The predictors included prior late visits, the number of prior VL tests, and the dura- tion on treatment. The results indicated that ma- chine learning could effectively identify patients at risk of disengagement and unsuppressed VL. This capability could potentially improve targeted inter- ventions and resource allocation in HIV treatment programs.

ML models have shown promise in identifying patterns and trends in HIV data, enabling more accurate predictions and targeted interventions. ML insights into HIV outbreak predictions leverage various data sources, including demographic, epidemiological, and behavioural data. By analysing these data, ML algorithms can identify high-risk populations and geographical areas susceptible to HIV transmission. This information is crucial for public health authorities to allocate resources efficiently and implement preventive measures effectively. Charles Chukwudalu Ebulue et al., (2024).

The findings from Alie et al., (2024) indicate that the J48 decision tree algorithm, when combined with demographic and health-related data, is a highly effective tool for identifying potential predictors of HIV testing. This approach allows us to accurately predict which adolescents are at a high risk of infection, enabling the implementation of targeted screening strategies for early detection and intervention. To improve the testing status of adolescents in the country, we recommend considering demographic factors such as age, age at first sexual encounter, exposure to family planning, recent sexual activity, and other identified predictors.

Tuberculosis Detection

The application of AI extends beyond infectious disease surveillance to real-time monitoring of various health conditions. For instance, AI-powered tools have been used in influenza surveillance, integrating Google search data with historical illness data to improve prediction accuracy. Google search patterns with Artificial Intelligence (AI) techniques for timely influenza-like illness (ILI) forecasting for each of the nine South African provinces. In South Africa, Google search data has been recently studied for ILI surveillance at the national level. (Olukanmi et al.).

In sub-Saharan Africa, AI has shown consider- able promise in improving TB detection and man- agement. Various machine learning models were developed to predict TB incidences and drug re- sistance, and boost diagnosis accuracy through computer-aided detection systems (Siamba et al., 2023;

We applied Autoregressive Integrated Moving Average (ARIMA), and hybrid ARIMA models to predict and forecast TB incidences among children in Homa Bay and Turkana Counties in Kenya. The ARIMA, and hybrid models were used to predict and forecast monthly TB cases reported in the Treatment Information from Basic Unit (TIBU) system by health facilities in Homa Bay and Turkana Counties between 2012 and 2021. (Siamba et al., 2023; Qin et al., 2024; Oloko-Oba and Viriri, 2022).

In a study that investigated the performance of the targeted next-generation sequencing (tNGS)-based Oxford Nanopore Diagnostics AmPORE TB assay, recently approved by the World Health Organization (WHO) as tuberculosis (TB) diagnostic test for the detection of drug resistance on respiratory specimens. A total of 104 DNA samples from Xpert MTB/RIF-positive TB sputum specimens were tested using the AmPORE TB kit, with the GenoScreen Deeplex Myc-TB as a comparative tNGS assay. For AmPORE TB, DNA samples were divided into five sequencing runs on the MinION device. Data analysis was performed using proprietary software. The WHO catalog of mutations was used for drug resistance interpretation. The assay achieved a high validity rate of 98% (102/104 DNA samples), homogeneous mean reads coverage across TB-positive specimens, and 100% positive and negative agreements for detecting mutations associated with resistance to rifampicin, pyrazinamide, fluoroquinolones, ethambutol, and capreomycin compared with Deeplex Myc-TB. The main discrepancies for the remaining drugs were attributable to the different assay panel designs. The AmPORE TB turnaround time was approximately 5–6 hours from extracted DNA to tNGS reporting for batches of 22 DNA samples. The AmPORE TB assay drastically reduced the time to tNGS reporting from days to hours and showed good performance for drug-resistant TB profiling compared with Deeplex Myc-TB. IMPORTANCE Targeted next-generation sequencing (tNGS) of Mycobacterium tuberculosis provides comprehensive resistance predictions matched to new multidrug-resistant/rifampicin-resistant tuberculosis regimens and received World Health Organization approval for clinical use in respiratory samples in 2024. The advanced version of the Oxford Nanopore Diagnostics AmPORE TB tNGS kit was evaluated in this study for the first time and demonstrated good performance, flexibility, and faster turnaround time compared with the existing solutions. Schwab et al., (2025).

Ojugo and Nwankwo (2021) developed a decision-making framework using Bayesian networks for predicting TB cases with high accuracy, focusing on modeling social networks and implicit suggestion algorithms for medical diagnosis in Nigeria to address problematic TB cases.

A retrospective analysis of the data generated from an Active Case Finding (ACF) intervention program in four southwestern states in Nigeria was conducted by Abiola Alege et al., (2024). Wards (the smallest administrative level in Nigeria) were further subdivided into smaller population clusters. ACF sites and their respective TB screening outputs were mapped to these population clusters. This data were then combined with open-source high-resolution contextual data to train a Bayesian inference model. The model predicted TB positivity rates on the community level (population cluster level), and these were visualised on a customised geoportal for use by the local teams to identify communities at high risk of TB transmission and plan ACF interventions. The TB positivity yield (proportion) observed at model-predicted hotspots was compared with the yield obtained at other sites identified based on aggregated notification data. The result indicates that the yield in population clusters that were predicted to have high TB positivity rates by the model was at least 1.75 times higher (p-value < 0.001) than the yield in other locations in all four states. The community-level Bayesian predictive model has the potential to guide ACF implementers to high-TB-positivity areas for finding undiagnosed TB in the communities, thus improving the efficiency of interventions. (Abiola Alege et al., 2024).

Artificial intelligence (AI) applications based on advanced deep learning methods in image recognition tasks can increase efficiency in the monitoring of medication adherence through automation. AI has sparsely been evaluated for the monitoring of medication adherence in clinical settings. However, AI has the potential to transform the way health care is delivered even in limited-resource settings such as Africa. Diagnostic properties and discriminative performance from internal cross-validation were moderate to high in the binary classification tasks with 4 selected automated deep learning models. The sensitivity ranged from 92.8 to 95.8%, specificity from 43.5 to 55.4%, F1 -score from 0.91 to 0.92, precision from 88% to 90.1%, and AUC from 0.78 to 0.85. The 3D ResNet model had the highest precision, AUC, and speed. All 4 deep learning models showed comparable diagnostic properties and discriminative performance. The findings serve as a reasonable proof of concept to support the potential application of AI in the binary classification of video frames to predict medication adherence. Sekandi et al., (2023).

A deterministic mathematical epidemic model developed by Oshinubi et al. (2023) to study the impact of TB in East Africa highlights the impor- tance of vaccination and treatment strategies. The model's simulations showed that increasing vacci- nation and treatment availability significantly re- duces TB prevalence, and supported the effective- ness of public health measures in controlling TB outbreaks.

Gichuhi et al., (2023) in a study used machine learning to predict tuberculosis treatment non-adherence in Uganda, analyzing records of 838 patients. Five classification algorithms were tested, with support vector machines (SVM) achieving the highest accuracy (91.28%) and AdaBoost performing best based on AUC. Key predictive factors included tuberculosis type, GeneXpert results, antiretroviral status, health facility ownership, and patient demographics. Machine learning proved effective in identifying at-risk patients, suggesting its potential as a screening tool for targeted TB program interventions.

Cholera outbreaks

Cholera outbreaks continue to pose a major public health challenge in Africa, especially in regions with poor sanitation and limited access to clean water. Researchers have explored the application of machine learning techniques to predict and monitor cholera outbreaks, with notable successes.

Cholera remains a major public health issue in Nigeria due to poor sanitation, inadequate water quality, and climatic factors that facilitate outbreaks. Since the first epidemic in 1972, recurrent outbreaks have occurred, with the deadliest in 1991 causing over 7,000 deaths. Weak surveillance, limited diagnostic capacity, and reporting delays further worsen the crisis, leading to increased mortality and economic losses. According to Ibrahim et al., (2025) study that explores the use of artificial intelligence (AI) and machine learning (ML) to enhance outbreak detection and response. AI-driven predictive models, including random forests and convolutional neural networks (CNNs), can analyze diverse data sources to detect patterns and forecast outbreaks. Successful case studies from other cholera-endemic regions highlight AI's potential to transform Nigeria’s public health system by enabling early detection, improving resource allocation, and mitigating disease spread.

AI can forecast cholera outbreaks using various techniques to analyze meteorological, environmental, and health data. Historical cholera case data can be used to simulate epidemic trends and evaluate the risk factors. Data on water quality and sanitation can be integrated to understand the environmental triggers of cholera. For instance, by merging climatic data from Earth-orbiting satellites with AI approaches, a study employed ML algorithms to predict cholera outbreaks in the coastal regions of India with an 89% success rate. Artificial intelligence models can include meteorological variables, such as temperature, humidity, and rainfall, to gain a deeper understanding of the correlation between weather patterns and cholera epidemics (*Cholera Outbreaks Predicted Using Climate Data and AI*, 2020).

Zheng et al. (2022) analyzed outbreak data to predict and monitor cholera outbreaks across 25 countries, using data from the Global Task Force for Cholera Control's global cholera database, which integrates public and confidential surveillance reports from sources such as the World Health Organization (WHO), Médecins Sans Frontières (MSF), the Program for Monitoring Emerging Diseases, ReliefWeb, UNICEF, national ministries of health, and scientific literature. Focusing on cholera outbreaks in sub-Saharan Africa from January 2010 to January 2020, the study identified 999 outbreaks across 744 sub-national regions in 25 countries, reporting a total of 484,450 suspected cholera cases.

Kaseya et al., (2024) research emphasizes the importance of integrating climatic factors into cholera outbreak management strategies, advocating for a multisectoral approach and long-term investments in water, sanitation, and hygiene facilities to effectively address the disease.

Ebola Predictions

Hauwa Ahmad Amshi et al., (e2023b, develop a cholera outbreak risk prediction (CORP) model using machine learning and data science techniques. The model utilized nonnegative matrix factorization (NMF) for dimensionality reduction, synthetic minority oversampling technique (SMOTE) for data balancing, and density-based spatial clustering of applications with noise (DBSCAN) to remove outliers. Prediction was carried out using the extreme-gradient boost algorithm. The CORP model achieved high performance, with 99.62% accuracy, a Matthews correlation coefficient of 0.976, and an area under the curve of 99.2%, outperforming previous models. These findings suggest that the model could be a valuable tool for healthcare providers in predicting and mitigating cholera outbreaks in Nigeria.

In a 2019 study, Leo et al. linked seasonal weather changes to cholera outbreaks in Tanzania, achieving high prediction accuracy through a machine learning model that incorporated data from the Tanzania Meteorological Agency, Ministry of Health, and Dar es Salaam Water and Sewerage Authority.

Siettos et al., (2015) developed an agent-based model to analyze the epidemic dynamics of Ebola virus disease (EVD) in Liberia and Sierra Leone from May 27 to December 21, 2014. The model simulated disease spread using small-world transmission networks, adjusting network densities to reflect public health interventions and individual behavioral responses. Using official WHO case data, the researchers estimated key epidemiological variables via the Equation-Free approach. The study found that transmission networks in both countries had largely random structures, with network densities decreasing by approximately 19% over time due to interventions. The estimated effective reproductive number (Re) remained above 2.3 in both countries until mid-October. However, by late December, Re had dropped below 1 in Liberia, signaling epidemic saturation, while in Sierra Leone, it remained around 1.9, indicating continued transmission. Projections suggested that the epidemic in Liberia would fade by early March 2015, while Sierra Leone could see up to 18,000 cases and over 5,000 deaths. However, later data (December 21, 2014–January 18, 2015) suggested a decline in Sierra Leone's epidemic, with Re dropping to approximately 0.82, indicating remission.

Zhang et al. (2015) used large-scale simulations based on geodemographics to predict Ebola outbreaks, focusing on modeling the 2014 epidemic and intervention impacts, while also developing models to predict death likelihood during the 2014-16 outbreak. The research highlights the potential of artificial intelligence and machine learning for public health surveillance, especially in Africa, where outbreaks like Ebola can pose significant challenges.

Loubet et al., (2016) developed a predictive scoring model for Ebola virus disease (EVD) to improve triage accuracy during the 2014 outbreak in Nzérékoré, Guinea. Using a retrospective analysis of 145 suspected EVD cases admitted between December 2, 2014, and February 23, 2015, the study employed multivariate logistic regression to identify key clinical and epidemiological predictors. Fever above 38.5°C (OR = 18.1, 95% CI = 7.6–42.9) and anorexia (OR = 2.5, 95% CI = 1.1–6.1) were independently associated with EVD. The predictive score achieved an area under the curve of 0.85 (95% CI = 0.78–0.91), demonstrating improved specificity (85% vs. 41%) compared to the World Health Organization's algorithm. While requiring external validation, this model may aid in risk stratification and patient management in high-prevalence settings Loubet et al., (2016).

Genisca et al., (2022) developed the EVD Prognosis in Children (EPiC) model using machine learning to predict mortality in pediatric Ebola virus disease (EVD) patients. Analyzing retrospective data from the 2014–2016 West African EVD outbreak and externally validating it with data from the 2018–2020 Democratic Republic of the Congo epidemic, the study identified key mortality predictors, including younger age, lower PCR cycle threshold values, unexplained bleeding, respiratory distress, and gastrointestinal symptoms. The EPiC model achieved an AUC of 0.77 (95% CI: 0.74–0.81) in the derivation dataset and 0.76 (95% CI: 0.64–0.88) in the validation dataset. Incorporating peak aspartate aminotransferase (AST) or creatinine kinase (CK) within 48 hours of admission improved the AUC to 0.90 and 0.87, respectively. This novel EPiC prognostic model integrates clinical and biochemical markers to enhance early risk stratification in pediatric EVD cases. Genisca et al., (2022).

In Liberia and Sierra Leone, Colubri et al., (2018) developed a family of prognostic models for Ebola virus disease (EVD) using the largest published dataset of EVD patients, integrating these models into the *Ebola Care Guidelines* app to provide evidence-based supportive care recommendations. Applying multivariate logistic regression to 470 patients from five Ebola treatment units in Liberia and Sierra Leone (2014–2016), the models were validated using independent datasets from Sierra Leone. Viral load and age were the strongest predictors of mortality, with a parsimonious model including body temperature, bleeding, jaundice, dyspnea, dysphagia, and referral time at triage. The model achieved an AUC between 0.7 and 0.8 and an accuracy of 64%–74%, approximating expert clinical assessments. The study highlights the potential of machine learning and mHealth tools to enhance care in low-resource settings, demonstrating how harmonized datasets can improve prognostic modeling and clinical decision support Colubri et al., (2018).

Pigott et al., (2014) used species distribution models and environmental covariates to map the zoonotic transmission niche of Ebola virus disease (EVD) across Central and West Africa. Analyzing location data from zoonotic transmission events, as well as Ebola virus infections in bats and primates (1976–2014), the study identified key ecological factors—including vegetation, elevation, temperature, evapotranspiration, and reservoir bat distributions—defining the transmission niche, which spans 22 countries and is home to 22 million people. Despite the broad geographic risk, human outbreaks remain rare, highlighting the low probability of zoonotic spillover. However, rising population sizes and increased international connectivity suggest that human-to-human transmission dynamics in contemporary outbreaks may differ significantly from past patterns. (Pigott et al., (2014).

Measles Surveillance

AI is revolutionizing public health surveillance in Africa, offering tools like machine learning to enhance measles

surveillance and immunization strategies, leading to more accurate disease detection and prediction. Predictive Modeling - Machine learning algorithms, like random forest, can analyze complex data to predict measles outbreaks and identify high-risk populations, enabling targeted interventions and resource allocation. It is also used for enhanced surveillance as it can analyze data from various sources, including social media and health records, to detect early signs of outbreaks and track the spread of measles, improving the timeliness and accuracy of surveillance efforts. Optimized immunization strategies - Predictive models are being used to identify areas with low vaccination coverage and inform the planning of supplementary immunization activities (SIAs).

Alemayehu, (2024) utilized the XGBoost algorithm to predict measles vaccination dropout, achieving the highest accuracy (73.9%) and AUC (0.813) among tested classifiers. Key predictors included younger maternal age, specific religious affiliations (Jehovah's Witness/Adventist), low parental education, maternal unemployment, residence in Oromia and Somali regions, large family size, and older paternal age. The study found that the national measles dropout rate exceeded the recommended <10% threshold, emphasizing the need for targeted interventions. Recommended strategies include public awareness campaigns, health education, and partnerships with religious institutions and health workers to improve vaccination retention and overall coverage. (Alemayehu, 2024).

In Ghana, Gyebi et al., (2023) conducted a study comparing five machine learning classification techniques with a traditional method for predicting measles cases in Ghana found that the random forest (RF) model demonstrated superior performance. Using an analytical cross-sectional design, the RF model achieved the highest sensitivity (0.88), specificity (0.96), ROC (0.92), and overall accuracy (0.92). The findings suggest that machine learning, particularly the RF model, can serve as an effective tool for early measles detection, improving disease control efforts.

An analysis of Uganda’s measles case-based surveillance (CBS) system from 2012 to 2015 found suboptimal effectiveness, with only 72% of suspected cases having blood samples collected for laboratory confirmation—below the WHO-recommended 80% threshold. Among 6,974 investigated cases, 14% tested measles-specific IgM positive, with a positive predictive value (PPV) of 8.6%, indicating a decline in true measles cases. The study recommends strengthening surveillance efforts to improve case confirmation and support measles elimination goals. (Nsubuga et al., 2017)

Leung & Ferrari, (2024) developed a dynamic model to simulate measles surveillance, incorporating suspected case reporting and limited diagnostic testing to estimate reporting rates and annual incidence. Results showed that unbiased incidence estimates could be achieved at moderate vaccination levels, even with low testing proportions, though lower test sensitivity (<90%) introduced slight bias at high vaccination levels. Frequent estimation of measles prevalence among suspected cases was necessary to maintain accuracy. The study suggests that integrating routine diagnostic confirmation with suspected case surveillance can enhance measles incidence estimation, supporting improved disease monitoring and control efforts.

Thakkar et al., (2024) developed a Somalia-specific measles transmission model using epidemiological data, including case-based surveillance, vaccine registries, and serological surveys, to evaluate the impact of measles vaccination campaigns since 2018. Analysis showed that among the 10 million doses administered, one in five vaccinated individuals was a susceptible child. A counterfactual analysis estimated that the 2019–2020 campaigns prevented over 10,000 deaths. These findings highlight the critical role of vaccination efforts in reducing measles susceptibility and mortality in Somalia's fragile healthcare setting.

In Nigeria, James et al.'s (2022) study, which investigated the impact of vaccination and hospitalization on measles transmission, likely found that vaccination significantly reduces measles transmission, while hospitalization, though important for managing severe cases, has a less direct impact on the overall spread of the disease.

A deterministic mathematical model was developed to study measles transmission dynamics in Nigeria, incorporating real-world data from the Nigeria Centre for Disease Control (NCDC) for 2020. The model determined the basic reproduction number (R_0), demonstrating that when $R_0 < 1$, the disease-free equilibrium is stable, while $R_0 > 1$ leads to an endemic equilibrium under specific stability conditions. Analysis showed that combined control strategies, including vaccination and hospitalization, were more effective in reducing infection peaks than single interventions. This study provides valuable insights into measles epidemiology and control measures in Nigeria. (James Peter et al., 2022).

Szusz et al., (2010) reviewed of measles epidemiology in low-income countries analyzed age-stratified case reporting and seroprevalence studies, focusing on data necessary for dynamic transmission modeling. Findings indicate that peak measles attack rates occur earlier in Africa (age 1) and India (ages 1–2) than in pre-vaccination developed countries, with around 60% seropositivity by age 2. The force of infection declined with age in some Indian studies but not in African studies, suggesting potential overestimation of immunity thresholds needed for eradication. Population density showed a possible correlation with the basic reproductive number (R_0), which varied significantly across settings. The study highlights the feasibility of dynamic measles models for low-income countries but emphasizes the need for more country-specific data to enhance measles control strategies.

An analysis of the 2012 measles outbreak in Cameroon, which recorded over 14,000 cases, examined the spatio-temporal dynamics of disease transmission using Ministry of Health data. Comparing multiple multivariate time-series models, the study identified the power law model, which incorporates long-distance population movement, as the best representation of measles spread. Findings revealed that movement between health districts within departments contributed to 7.6% of cases, while inter-department and inter-region movements accounted for 16.0% and 16.7%, respectively. At finer geographic resolutions, long-distance mobility explained up to 29.7% of transmission at the health district level. The study underscores the significant role of population mobility in measles dynamics and highlights the need to account for mobility and vaccination coverage heterogeneity in measles control strategies in Cameroon. (Parpia et al., 2020).

In Nigeria, Akinbobola & S. Hamisu, (2018) carried out a study analyzing the impact of weather variables on measles incidence in Kano, Nigeria (1997–2012) found that temperature and relative humidity significantly influence disease transmission. Using Spearman rank correlation, Poisson regression, and ARIMA models, the researchers identified a high-risk temperature window of 38–40°C and relative humidity of 19–30%, with peak measles cases occurring in April and May. The Poisson model incorporating all weather variables best fit the data, while ARIMA (0,0,1) was optimal based on Bayesian information criteria. Wind speed was not a limiting factor for measles transmission. The study underscores the role of climate in measles dynamics and recommends integrating weather considerations into disease prevention strategies.

A study applying an Artificial Neural Network (ANN) model to analyze measles immunization coverage in Nigeria (1984–2019) projected a significant decline from 51% in 2020 to approximately 23% by 2030. The

ANN (12,12,1) model demonstrated stability based on residuals and forecast evaluation criteria (Error, MSE, and MAE). These findings highlight the urgent need for the Nigerian government to strengthen child health surveillance and immunization programs to prevent a resurgence of measles.

In Uganda, a study by Bishai et al., (2011) evaluating the cost-effectiveness of Supplemental Immunization Activities (SIAs) for measles control in Uganda (2010–2050) integrated a dynamic stochastic measles transmission model with a cost model. It compared maintaining routine first-dose measles-containing vaccine (MCV1) coverage at 68% with and without triennial SIAs covering 95% of children aged 12–59 months. The model estimated an incremental cost-effectiveness ratio (ICER) of $1.50 per Disability Adjusted Life Year (DALY) averted, demonstrating that SIAs reduce outbreak frequency and severity. These findings support SIAs as a cost-effective public health intervention in sub-Saharan Africa.

Takudzwa et al., (2021) applied Artificial Neural Networks (ANN) approach to analyze child immunization trends in Burkina Faso. The employed data covers the period 1985-2020 and the out-of-sample period ranges over the period 2021-2025. The residuals and forecast evaluation criteria (Error, MSE and MAE) of the applied model indicate that the model is quite stable. The results of the study indicate that it is possible to win the war against the scourge of measles in the country. A 3-fold policy recommendation has been suggested in order to help public health policy makers in controlling the disease in the country.

A systematic review and meta-analysis assessed the impact and cost-effectiveness of measles vaccination strategies in low- and middle-income countries (LMICs). The study analyzed 44 articles, including 14 in the meta-analysis, using a random-effects model. Findings indicated that interventions such as vaccination reminders, cash incentives, community engagement, and health education significantly increased measles vaccination coverage (RR 1.19, 95% CI 1.10–1.27) and improved timeliness. Cost-effective strategies included geographically informed microplanning, unrestricted vial opening, supplementary immunization activities, and outreach programs. The study highlights the importance of context-specific approaches to enhance measles vaccination outcomes in LMICs. (Kiddus Yitbarek et al., 2025).

Hasan et al., (2021) study utilized nationally representative demographic and health survey data applied an ensemble machine learning (ML) approach to classify measles vaccine utilization and identify key predictive factors. Various imputation techniques addressed missing data, and feature selection methods determined crucial attributes for vaccination prediction. Optimized ML models, including Naïve Bayes, random forest, decision tree, XGBoost, and LightGBM, were assessed, with LightGBM achieving the highest individual precision (79.90%) and AUC (77.80%). An ensemble of LightGBM and XGBoost further improved performance (precision: 84.60%, AUC: 80.0%). The study highlights the effectiveness of a minimal attribute-based ML model for predicting vaccine uptake, providing a tool for early detection and policy intervention to improve measles immunization rates.

Table 2: Summary of AI Applications in Disease Detection and Prediction

Authors	Model	Disease	Country	Application	Case Study Description
Mutai et al., 2021	XGBoost algorithm	HIV	Sub-Sahara Africa	HIV Identification	Use of machine learning techniques to identify HIV predictors for screening in sub-Saharan Africa
Charles Chukwudalu Ebulue et al., (2024)	Machine Learning	HIV	Sub-Saharan Africa	HIV Outbreak Predictions	Machine learning insights into HIV outbreak predictions in Sub-Saharan Africa
Chikusi (2022)	Random Forest, XGBoost, ANN	HIV	Tanzania	HIV index testing	Improved prediction and visualization of HIV index testing using machine learning models.
Singh et al., (2016)	Machine Learning	HIV	South Africa	Predict current CD4 cell count	Applying machine learning to predict patient-specific current CD4 cell count in order to determine the progression

					of human immunodeficiency virus (HIV) infection
Alie & Negesse, (2024)	Machine learning	HIV	Ethiopia	HIV outbreak prediction	Machine learning prediction of adolescent HIV testing services in Ethiopia
Olukanmi et al. (2022)	Time series, machine learning, and deep learning methods	influenza-like illness	Sub-Sahara Africa	Timely influenza-like illness (ILI) forecasting	Leveraging Google Search Data and Artificial Intelligence Methods for Provincial-level Influenza Forecasting: A South African Case Study
Tshimula et al., (2024b)	Machine Learning	TB, malaria, HIV, Ebola & COVID-19.	Africa Continent	Applications of AI in public health surveillance across Africa continent	Artificial Intelligence for Public Health Surveillance in Africa: Applications and Opportunities
Siamba et al. (2023)	ARIMA, hybrid ARIMA	Tuberculosis	Kenya	TB incidence prediction	Applied ARIMA and hybrid ARIMA models to predict TB incidences among children, demonstrating significant under-reporting.
Schwab et al., (2025)	Targeted next-generation sequencing	TB	South Africa and Zambia	Predict drug-resistant tuberculosis	Field evaluation of nanopore targeted next-generation sequencing to predict drug-resistant tuberculosis from native sputum in South Africa and Zambia
Ojugo & Nwankwo, (2021)	Bayesian networks	TB	Nigeria	Detection and diagnosis of TB	Multi-Agent Bayesian Framework For Parametric Selection In The Detection And Diagnosis of Tuberculosis Contagion In Nigeria.
Abiola Alege et al., (2024)	Bayesian inference model	TB	Nigeria	TB Case finding	Effectiveness of Using AI-Driven Hotspot Mapping for Active Case Finding of Tuberculosis in Southwestern Nigeria.
Sekandi et al., (2023)	deep learning models	TB	Africa	Monitoring of Medication Adherence for TB	Application of Artificial Intelligence to the Monitoring of Medication Adherence for Tuberculosis Treatment in Africa: Algorithm Development and Validation
Kayode Oshinubi et al., (2023)	Deterministic mathematical epidemic model	TB	East Africa (Uganda & Rwanda)	TB Disease Impact	Mathematical Modelling of Tuberculosis Outbreak in an East African Country Incorporating Vaccination and Treatment
Oloko-Oba & Viriri, (2022	Deep Learning techniques	TB	South Africa	Diagnosis of TB	A Systematic Review of Deep Learning Techniques for Tuberculosis Detection from Chest Radiograph
Gichuhi et al. (2023)	SVM, classification algorithms	TB	Uganda	TB treatment non-adherence	Identified individual risk factors for TB treatment non-adherence using five classification algorithms, with SVM achieving highest accuracy.
Ibrahim et al., (2025)	Machine Learning	Cholera	Nigeria	Cholera detection and response	Leveraging AI for early cholera detection and response: transforming public health surveillance in Nigeria

Zheng et al. (2022)	Machine learning	Cholera	Sub-Saharan Africa	Cholera outbreak prediction	Analyzed outbreak data to predict and monitor cholera outbreaks across 25 countries.
Kaseya et al., (2024)	Machine learning	Cholera	Southern Africa	Cholera prevention and control	Climate change and malaria, dengue and cholera outbreaks in Africa: a call for concerted actions.
(Hauwa Ahmad Amshi et al., 2023b)	Machine Learning	Cholera	Nigeria	Predict Cholera	How can machine learning predict cholera: insights from experiments and design science for action research.
Leo, (2020)	XGBoost	Cholera	Tanzania	Cholera outbreak prediction	A reference machine learning model for prediction of cholera epidemics based-on seasonal weather changes linkages in Tanzania.
Siettos et al. (2015)	Agent-based simulations	Ebola	West Africa	Ebola epidemic dynamics	Modeling the 2014 Ebola Virus Epidemic – Agent-Based Simulations, Temporal Analysis and Future Predictions for Liberia and Sierra Leone.
Zhang et al. (2015)	Machine learning	Ebola	West Africa	Ebola outbreak prediction	Predicted Ebola outbreaks using large-scale simulations based on geodemographics.
Loubet et al., (2016)	Prediction Models	Ebola	Guinea	Ebola Outbreak Prediction	Development of a Prediction Model for Ebola Virus Disease: A Retrospective Study in Nzérékoré Ebola Treatment Center, Guinea.
Genisca et al., (2022)	Machine Learning	Ebola	Democratic Republic of the Congo	Ebola Survival Prediction	Constructing, validating, and updating machine learning models to predict survival in children with Ebola Virus Disease.
Colubri et al., (2018)	Machine-Learning prognostic models	Ebola	Liberia and Sierra Leone	Ebola death likelihood prediction	Machine-Learning prognostic models from the 2014-16 Ebola outbreak: data-harmonization challenges, validation strategies, and mHealth applications.
Pigott et al. (2014)	Species distribution models	Ebola	Central and West Africa	Ebola zoonotic niche mapping	Mapped the zoonotic niche of EVD across 22 countries, identifying at-risk regions.
Alemayehu, (2024)	Machine learning algorithms	measles	Ethiopia	Predict measles vaccination dropout	Machine learning algorithms for prediction of measles one vaccination dropout among 12-23 months children in Ethiopia
Gyebi et al., (2023)	Machine Learning Classifiers	Measles	Ghana	Predicting measles	Prediction of measles patients using machine learning classifiers: a comparative study
Nsubuga et al. (2017)	Case-based surveillance	Measles	Uganda	Measles surveillance evaluation	Assessed the effectiveness of measles surveillance, highlighting the need for robust data collection.
Leung and Ferrari (2024)	Dynamic model	Measles	Africa	Measles reporting rate	Combined clinical and diagnostic data to estimate measles incidence under

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				and incidence estimation	varying vaccination coverages.
Thakkar et al. (2024)	Transmission model	Measles	Somalia	Measles vaccination impact assessment	Evaluated the impact of vaccination campaigns on measles incidence and mortality.
Takudzwa et al., (2021)	ANN	Measles	Burkina Faso	Analyze child immunization trends	Forecasted child immunization rates using an ANN model.
(Kiddus Yitbarek et al., 2025)	Random-effects model	Measles	low-income and middle-income countries	Assessed the impact of measles vaccination strategies on vaccination rates	Impact of measles vaccination strategies on vaccination rates in low-income and middle-income countries: a systematic review and meta-analysis
James et al. (2022)	Deterministic model	Measles	Nigeria	Measles transmission dynamics	Studied the impact of vaccination and hospitalization rates on measles transmission.
Akinbobola and Hamisu (2018)	Poisson regression, ARIMA	Measles	Nigeria	Weather impact on measles incidence	Analyzed the relationship between weather variables and measles incidence.
Szusz et al. (2010)	Review	Measles	Low-income countries	Measles transmission modeling	Reviewed epidemiology data essential for dynamic models of measles transmission.
Bishai et al., (2011)	Dynamic stochastic model	Measles	Uganda	Cost-effectiveness of SIAs	Evaluated the cost-effectiveness of supplementary immunization activities.
Parpia et al. (2020)	Multivariate time-series models	Measles	Cameroon	Spatial dynamics of measles outbreak	Characterized spatial heterogeneity in vaccination coverage and transmission patterns.
Hasan et al., (2021)	Ensemble of Machine Learning Models	Measles	Bangladesh	Measles vaccine utilization and identify key predictive factors	Associating Measles Vaccine Uptake Classification and its Underlying Factors Using an Ensemble of Machine Learning Models.

Real-time surveillance and reporting

Fontes et al., (2022) *AI-Powered Surveillance Systems: Assessing Real-Time Facial Recognition and Public Health Surveillance Technologies* study examines the deployment of AI-driven surveillance systems, particularly real-time facial recognition (FRT) in public spaces and contact tracing applications for public health. These technologies aid law enforcement by tracking individual movements and predicting social behavior, making them valuable in addressing societal crises like crime and pandemics. The paper introduces a three-dimensional framework for evaluating these tools: (1) the **function dimension**, assessing data requirements for system effectiveness; (2) the **consent dimension**, addressing user autonomy and informed consent; and (3) the **societal dimension**, analyzing potential vulnerabilities and the political implications of data-driven surveillance.

While in its beginnings public health surveillance activities were focused on the mere monitoring of diseases and reporting of resulting deaths Gschwend et al., (2002), it has evolved into a "continuous, systematic collection, analysis and interpretation of health-related data" (World Health Organization, 2023), or dataveillance. Epidemiologic observations have since developed from typically individual and locally concentrated health-related event recordings to large-scale, structured and preventive data interpretation Fontes et al., (2022).

Influenza surveillance

Zékiba Tarnagda et al., (2014) study presents the first sentinel surveillance of influenza viruses in Burkina Faso, conducted from July 2010 to May 2012. Oropharyngeal swabs from 881 outpatients meeting WHO/CDC criteria for influenza-like illness (ILI) were analyzed using real-time RT-PCR. Influenza viruses were detected in 6.6% of cases, with equal distribution between influenza A and B. Among influenza A cases, 55.2% were A(H1N1)pdm09, and 44.8% were A(H3N2), with no seasonal A/H1N1 detected. Children aged 0–5 and 6–14 years were the most affected groups. Influenza circulation was observed during both the dry Harmattan season and the rainy season, peaking in January and August. This study provides the first confirmation of influenza A(H1N1) pdm09, A(H3N2), and influenza B circulation in Burkina Faso, contributing to regional influenza surveillance efforts.

In epidemic outbreak prediction and control, AI algorithms can analyze various data sources, such as disease surveillance data, social media feeds, and climate information, to predict and

track disease outbreaks. This enables early warning systems and targeted interventions to control the spread of diseases, such as influenza, dengue, or Ebola, by optimizing resource allocation and response strategies (Ogbaga, 2023).

Zika Virus Monitoring

In the realm of vector-borne diseases, AI has also been instrumental in monitoring and predict- ing the spread of Zika virus and malaria

Jiang et al.'s 2018 study used machine learning models (BPNN, GBM, and RF) to map the global transmission risk of Zika virus, identifying high-risk areas in Southeastern North America, Eastern South America, Central Africa, and Eastern Asia. The study employs machine learning techniques to map the global transmission risk of Zika virus, which has been linked to severe congenital abnormalities and is spreading rapidly due to increased global travel and trade. Three machine learning models—backward propagation neural network (BPNN), gradient boosting machine (GBM), and random forest (RF)—were used to predict outbreak probabilities by integrating high-dimensional covariate layers with recorded Zika infection data. High-risk regions were identified in Southeastern North America, Eastern South America, Central Africa, and Eastern Asia. Model performance was assessed using 50 modeling processes with a 10-fold cross-validation, where BPNN achieved the highest accuracy (AUC = 0.966), followed by GBM (AUC = 0.964) and RF (AUC = 0.963), with statistically significant differences between them ($p = 0.0258^*$ and $p = 0.0001^{***}$, respectively). The study also quantified prediction uncertainty, providing a more robust foundation for disease transmission forecasting and public health planning.

Caldwell et al., (2024), investigates the rarity of Zika virus (ZIKV) outbreaks in Africa despite its origin on the continent, examining the role of mosquito genetics and climate in shaping transmission risk. Using a modeling approach informed by empirical data, the researchers assessed ZIKV transmission suitability across Africa, integrating laboratory-derived mosquito infection data with seroprevalence surveys. Findings indicate that mosquito population genetics—specifically, the lower human-biting preference and reduced ZIKV susceptibility of the African *Aedes aegypti* subspecies—play a stronger role in limiting transmission than climate. The model explains 46% of the variation in historical ZIKV seroprevalence patterns. Climate and genetic projections suggest that by the end of the century, nearly 75% of Africa's largest urban centers could become suitable for ZIKV outbreaks. These results highlight the importance of genomic surveillance of mosquito populations to enhance outbreak prediction and preparedness, particularly in the context of urbanization and climate change.

Obore et al. (2019) reviewed the epidemiological evidence and distribution of Zika virus in Africa, highlighting its origins, spread, determinants, complications, and management strategies. They identified critical determinants of Zika virus spread, including climate, sociodemographic factors, and human density, and emphasized the importance of improving surveillance mechanisms and vector control. Over 87 countries reported Zika virus presence by 2019, with significant cases in Cabo Verde and Angola.

COVID-19 Tracking

Barhoumi et al., (2020), in order to aid policy decisions during the COVID-19 pandemic, the study proposes a machine learning approach to nowcast GDP growth in sub-Saharan Africa, a region where official statistics are released with considerable delays. It shows that machine learning methods provide nowcasts with lower root mean square errors than standard benchmarks used in the literature. Nowcasts imply that the COVID-19 crisis initially had a large adverse impact on the region.

Chimbunde et al., (2023), applied machine learning algorithms to predict ICU mortality among 392 COVID-19 patients in South Africa, using artificial neural networks (ANN) and random forest (RF) models. Key predictors of mortality identified across models included age, intubation status, comorbidities (asthma, diabetes, hypertension), oxygen saturation, and severity of symptoms. The ANN model demonstrated high predictive performance with an accuracy of 71%, precision of 83%, recall of 88%, and a Cohen's k-value of 0.75, while the RF model achieved a recall of 76% and precision of 87%. The study underscores the potential of machine learning to enhance ICU triage and optimize resource allocation in COVID-19 management, particularly in resource-limited settings.

In East Africa, Abegaz & Etikan, (2022) applied artificial intelligence-based ensemble modeling to predict COVID-19 mortality in East Africa using a two-year dataset. The research followed a three-step approach: sensitivity analysis, modeling of four single AI-driven models—adaptive neuro-fuzzy inference system (ANFIS), feedforward neural network (FFNN), support vector machine (SVM), and multiple linear regression (MLR)—and the development of four ensemble models. Performance evaluation showed that ANFIS (DC = 0.9273) outperformed FFNN (DC = 0.8586), SVM (DC = 0.8490), and MLR (DC = 0.7956). Non-linear ensemble methods demonstrated superior predictive accuracy, with the ANFIS ensemble model yielding the best performance. These findings highlight the effectiveness of ensemble models in predicting COVID-19 mortality and suggest their potential applicability to other global regions.

Malaria reporting

Artificial Intelligence is being used in Africa to improve malaria reporting and management by enabling faster, more accurate diagnosis, predicting outbreaks, and optimizing resource allocation through AI-powered surveillance systems and image analysis of blood samples as reviewed in different scholarly articles.

AI can be applied to disease intervention in the following areas:

1 **Early detection and diagnosis**: AI algorithms can analyze vast amounts of medical data, including patient records, medical images (such as X-rays, CT scans, and MRIs), and genetic information (Siddiq et al., 2009), to aid in early detection and diagnosis of diseases (Al-Antari, 2023). AI can help healthcare providers identify patterns and markers that may not be easily recognizable by humans (Meskó & Görög, 2020), leading to earlier intervention and improved patient outcomes.

2 **Precision medicine**: AI enables personalized treatment approaches by analyzing individual patient data, including genetic information, lifestyle factors, and medical history. This allows for tailored treatment plans and the identification of optimal drug therapies, leading to more effective interventions with reduced side effects (Kosorok & Laber, 2019).

3 **Drug discovery and development**: AI can accelerate the drug discovery process by analyzing vast amounts of scientific literature, biological data, and clinical trial result[34]s. Machine learning algorithms

can identify potential drug targets, predict the effectiveness of drug candidates, and optimize drug design, saving time and resources in the drug development pipeline (Mak et al., 2023).

4 Public health planning and resource allocation: AI can assist public health authorities in planning and allocating resources efficiently. By analyzing population health data, AI algorithms can identify disease hotspots, assess risk factors, and predict healthcare resource needs. This information helps policymakers make informed decisions about resource allocation, intervention strategies, and public health campaigns (Humphreys, 1998) (Feldstein et al., 2025).
5 Telemedicine and remote monitoring: AI technologies, combined with telemedicine platforms and wearable devices, enable remote monitoring of patients' health conditions. AI algorithms can analyze real-time patient data, detect abnormalities, and provide timely alerts to healthcare providers. This facilitates early intervention, reduces hospital visits, and improves patient outcomes, particularly for chronic diseases. (Field, 2012).
6 Disease surveillance and tracking: AI-powered systems can analyze large volumes of data from multiple sources, including electronic health records, social media, and environmental sensors, to track the spread of diseases, monitor population health trends, and provide real-time situational awareness to public health agencies (Feldman & Mishra, 2019; Rufino et al., 2023). This allows for prompt responses and targeted interventions.

Ogbaga, (2023). explores the potential impact of artificial intelligence (AI) in enhancing malaria interventions across Africa, highlighting its applications in outbreak prediction, diagnosis, personalized treatment, surveillance, resource allocation, and research innovation. Despite these benefits, challenges such as data limitations, infrastructure constraints, ethical concerns, and integration into healthcare systems hinder AI adoption. The study recommends strengthening data infrastructure, building local AI capacity, contextualizing models, addressing ethical issues, establishing evaluation frameworks, fostering collaboration, and securing sustainable funding. These strategies can facilitate the successful implementation of AI-driven malaria interventions, ultimately improving disease control and public health outcomes in Africa.

Muthoni Masinde, (2020), study presents a bibliometric analysis of 247 publications on predicting infectious diseases in Africa, sourced from the Web of Science core collection. Findings indicate a rise in scientific output over the past decade, driven by severe outbreaks, yet highlight the underrepresentation of African researchers in this domain. The United States emerges as the leading contributor and collaborator. Key research hotspots include malaria, disease modeling, classification, COVID-19, and cost-effectiveness, with weather-based prediction emerging as a growing trend. Notably, few studies have incorporated Fourth Industrial Revolution (4IR) technologies such as machine learning. The study underscores the need for integrating advanced predictive tools and interdisciplinary approaches to enhance disease forecasting in Africa, offering valuable insights for researchers, practitioners, and funding agencies.

Mariki et al. (2022) demonstrated the feasibility of using clinical symptoms and demographic data to predict malaria with high accuracy using machine learning, particularly in regions with limited access to parasitological tests.

Nkiruka et al., (2021), proposes a machine learning-based model for classifying malaria incidence using climate variability data across six Sub-Saharan African countries over 28 years. The model incorporates feature engineering to identify key climate factors, k-means clustering for outlier detection, and the XGBoost algorithm for classification. Findings indicate that non-seasonal variations in precipitation, temperature, and surface radiation significantly influence malaria outbreaks, though the strength of these associations varies by region. Comparative analysis demonstrates that the proposed model outperforms existing classification systems. This early detection mechanism offers valuable insights for public health authorities, enabling improved monitoring, prevention, and adaptive responses to malaria outbreaks driven by climate variability.

Poliovirus surveillance

AI-driven tools have revolutionized poliovirus surveillance in Africa and significantly improved the detection and reporting of acute flaccid paralysis.

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Ayana et al., 2024) study presents a deep learning-based approach to improve acute flaccid paralysis (AFP) surveillance in Ethiopia by leveraging transfer learning on mobile phone images collected by community key informants. A vision transformer model pretrained on the ImageNet dataset was utilized, outperforming convolutional neural networks and vision transformers trained from scratch. The proposed model achieved high accuracy, precision, recall, F1-score, and an AUC of 0.870 ± 0.01, significantly surpassing alternative models ($P < 0.001$). While the study highlights the potential of AI in bridging community reporting with health system response, it also identifies challenges related to image data quality. The research underscores the need for a dedicated platform for data storage and analysis to enhance future AFP surveillance efforts, contributing to global disease eradication strategies.

Dese et al., (2024) survey examines the role of artificial intelligence (AI) in enhancing acute flaccid paralysis (AFP) surveillance, a key strategy for early polio detection. Traditional AFP surveillance methods are resource-intensive and lack timeliness, whereas AI-driven approaches, including machine learning models, offer improved automation in case detection, outbreak prediction, and data analysis. Despite the growing interest in AI applications for AFP surveillance, a comprehensive review of the field is lacking. This paper consolidates key concepts, achievements, challenges, and future research directions, providing a framework for advancing AI-driven AFP surveillance. The findings contribute to optimizing surveillance efficiency, supporting timely responses to potential polio outbreaks, and strengthening global health security efforts.

In Nigeria, Touray et al., (2016) examines the use of GIS technology to track vaccination teams and improve settlement coverage in Nigeria, one of the three countries where polio remains endemic. Between 2012 and June 2015, GPS-enabled Android phones were distributed to immunization teams across multiple local government areas, allowing real-time tracking and performance assessment. The study found that GIS tracking improved geographic coverage, reduced the number of missed settlements, and supported microplan reviews and intervention strategies. These findings highlight the value of geospatial tools in optimizing polio eradication efforts.

Shuaib et al.'s 2018 study, "AVADAR (Auto-Visual AFP Detection and Reporting)", demonstrated the effectiveness of a novel SMS-based smartphone application in improving acute flaccid paralysis (AFP) surveillance in Nigeria, particularly in remote areas, by enhancing detection and reporting through community involvement and technology.

Table 3: Summary of AI Applications in Real-time Surveillance and Reporting

Zékiba Tarnagda et al., (2014)	Real-time RT-PCR	Influenza	Burkina Faso	Surveillance Improvement	Sentinel surveillance of influenza in Burkina Faso: identification of circulating strains during 2010–2012.
Jiang et al., (2018)	BPNN, GBM, RF	Zika Virus	Central Africa	Epidemic Mapping	Mapping probability of Zika epidemic outbreaks globally, identifying high-risk regions.
Caldwell et al. (2023)	Genetic Variation Model	Zika Virus	Africa	Outbreak Risk Projection	Investigated mosquito genetic variation and climate factors influencing Zika virus transmission patterns.
Obore et al., (2019)	ML Models	Zika Virus	Cabo Verde and Angola	Epidemic Mapping	Zika Virus in Africa: Epidemiology and Determinants.
Barhoumi et al. (2022)	Nowcasting Framework	COVID-19	Sub-Saharan Africa	Economic Activity Tracking	Developed framework to predict real-time economic activity using machine learning during the pandemic.
Chimbunde	ANN, RF	COVID-	South	ICU Mortality	Identified predictors of COVID-19

et al. (2023)		19	Africa	Prediction	ICU mortality using machine learning models.
Abegaz and Etikan (2022)	ANFIS, FFNN, SVM, MLR	COVID-19	East Africa	Mortality Prediction	AI-driven ensemble model to predict COVID-19 mortality, comparing several ML models.
Ogbaga, 2023)	ML Models	Malaria	Africa	Prediction of malaria fatality	Artificial Intelligence (AI)-Based Solution to Malaria Fatalities In Africa: An Exploratory Review.
Muthoni Masinde, (2020)	ML Models	Malaria	Africa	Malaria prediction	Africa's Malaria Epidemic Predictor: Application of Machine Learning on Malaria Incidence and Climate Data.
Mariki et al. (2022)	Random Forest	Malaria	Tanzania	Malaria Diagnosis	High accuracy in diagnosing malaria using demographic data and clinical symptoms.
Nkiruka et al. (2021)	XGBoost	Malaria	Sub-Saharan Africa	Climate-based Prediction	Classified malaria incidence based on climate variability, achieving high accuracy.
Ayana et al., (2024)	Deep Learning Model	Poliovirus	Ethiopia	AFP detection	Deep learning model meets community-based surveillance of acute flaccid paralysis.
Shuaib et al. (2018)	AVADAR System	Poliovirus	Nigeria	AFP Detection	Increased detection and reporting of AFP cases using machine learning and smartphone video analysis.
Dese et al., (2024)	AFP surveillance	Poliovirus	Ethiopia	AFP Detection	Leveraging Artificial Intelligence for Acute Flaccid Paralysis Surveillance.
Touray et al., (2016)	GIS, Spatial Analysis	Poliovirus	Nigeria	Tracking Vaccination	Tracking Vaccination Teams During Polio Campaigns in Northern Nigeria by Use of Geographic Information System Technology.

Opportunities for AI in Africa

The application of artificial intelligence (AI) to healthcare in Africa has the potential to transform productivity, diagnosis, disease surveillance, and resource allocation by improving accuracy and efficiency. (Alaran et al., 2025a).

The artificial intelligence (AI) era is rapidly reshaping numerous sectors including, education, agriculture, healthcare, and medicine. The application of deep learning algorithms, in AI is significantly enhancing the efficiency, diagnosis, and speed of treatment. (Kermany et al., 2018; Davenport & Kalakota, 2019).

According to Davenport & Kalakota, (2019), the complexity and rise of data in healthcare means that artificial intelligence (AI) will increasingly be applied within the field. Several types of AI are already being employed by payers and providers of care, and life sciences companies. The key categories of applications involve diagnosis and treatment recommendations, patient engagement and adherence, and administrative activities.

The high-income countries (HICs) and upper middle-income countries (UMICs) are adopting and making investments in further unleashing and optimizing the application of AI in several sectors such as wearable devices, telemedicine, precision medicine, genetic-based solutions, and drug discovery and development; all of which are aimed at building a robust approach to patient care worldwide. The World Health Organization's (WHO), Global Strategy on Digital Health recommended cross-country collaboration, to ensure equity, access, and affordability of improved medical care services and universal health coverage with a target year of between 2020 and 2025. (Alaran et al., 2025a).

Tshimula et al., (2024a), AI algorithms can analyze patient data and suggest personalized treatment plans, considering factors such as comorbidities, genetic in- formation, and local disease patterns. This support can improve the accuracy of diagnoses and treatment outcomes, especially in rural and underserved areas. Providing local health workers with AI tools improves the resilience and capability of healthcare systems to handle a wide range of health issues. Their study explores the application of AI in public health surveillance across Africa, highlighting its potential to address challenges such as resource constraints, inadequate infrastructure, and workforce shortages. Through case studies, the research demonstrates AI's ability to enhance disease detection, prediction, and response, optimize resource allocation, and support targeted public health interventions.

Forecasting and allocating healthcare resources

AI has been instrumental in enhancing healthcare and streamlining resource allocation with great efficacy and efficiency. It has effectively tackled the problem of imbalanced distribution of healthcare resources, which has been a significant contributor to health disparities and political discord. (Wu et al., 2023). For instance, predictive analytics can help forecast disease outbreaks, enabling proactive measures to be taken, such as stockpiling necessary medications and deploying healthcare workers to high-risk areas. AI is also capable of analyzing a vast range of data about healthcare supply chain logistics, usage patterns, and external factors like weather and economic conditions. The resulting models trained on these data can be used to predict potential shortages of medical supplies and equipment, thereby empowering healthcare organizations to take preemptive measures to mitigate the impact of these shortages and ensure continuity of care for their patients. Such measures may include adjusting procurement strategies, ordering additional supplies well in advance, or implementing conservation measures. Traditionally, the allocation of healthcare resources is determined by the supply-demand equation, logistics, and governance structure.

According to, (Lane et al., 2017), Using the COVID-19 response as an example, the severity of the pandemic can determine the healthcare resources required in each location, but the resources might not be distributed according to need. (Kang et al., 2020) In such cases, AI can be utilized to study supply-demand, logistics, and patient characteristics. Moreover, AI can facilitate better financial resource allocation by identifying cost-effective interventions and reducing waste. For example, by analyzing the outcomes of various treatment protocols, AI can help healthcare providers choose the most effective and efficient options, ultimately reducing healthcare costs and improving patient outcomes. (Davenport & Kalakota, 2019a), this is particularly important in resource-limited settings, where the efficient use of funds can make a significant difference in the quality and accessibility of healthcare services.

Diagnosis and treatment applications

Bush (2018) highlights the long-standing role of artificial intelligence (AI) in disease diagnosis and treatment, tracing its origins back to the 1970s with the development of MYCIN at Stanford University. MYCIN was an early AI system designed for diagnosing blood-borne bacterial infections, demonstrating the potential of AI in medical decision-making and laying the foundation for subsequent advancements in AI-driven healthcare solutions. This and other early rule-based systems showed promise for accurately diagnosing and treating disease, but were not adopted for clinical practice. They were not substantially better than human diagnosticians, and they were poorly integrated with clinician workflows and medical record systems. (Davenport & Kalakota, 2019a).

IBM's Watson initially garnered significant media attention for its application in precision medicine, particularly in cancer diagnosis and treatment. The system integrates machine learning and natural language processing (NLP) capabilities. However, initial enthusiasm waned as challenges emerged in training Watson to address specific cancer types (Lee et al., 2018) and in integrating the technology into clinical workflows (Ross & Swetlitz, 2017). Rather than a single product, Watson comprises a suite of cognitive services accessible via application programming interfaces (APIs), including speech and language processing, computer vision, and machine learning-based data analysis. While Watson's APIs are widely regarded as technically competent, its ambitious goal of revolutionizing cancer treatment proved challenging. Additionally, proprietary systems like Watson have faced competition from open-source alternatives, such as Google's TensorFlow, which some vendors offer freely.

Implementation issues with AI bedevil many healthcare organisations. Although rule-based systems incorporated within EHR systems are widely used, including at the NHS, (Davenport & Kalakota, 2019) they lack the precision of more algorithmic systems based on machine learning. These rule-based clinical decision support systems are difficult to maintain as medical knowledge changes and are often not able to handle the explosion of data and knowledge based on genomic, proteomic, metabolic and other 'omic-based' approaches to care.

This situation is beginning to change, but it is mostly present in research labs and in tech firms, rather than in clinical practice. Scarcely a week goes by without a research lab claiming that it has developed an approach to using AI or big data to diagnose and treat a disease with equal or greater accuracy than human clinicians. Tech firms and startups are also working assiduously on the same issues. Google, for example, is collaborating with health delivery networks to build prediction models from big data to warn clinicians of high-risk conditions, such as sepsis and heart failure. (Aronson & Rehm, 2025). Google, Enlitic and a variety of other startups are developing AI-derived image interpretation algorithms. Jvion offers a 'clinical success machine' that identifies the patients most at risk as well as those most likely to respond to treatment protocols. Each of these could provide decision support to clinicians seeking to find the best diagnosis and treatment for patients.

Several companies specialize in providing diagnosis and treatment recommendations for specific cancers based on genetic profiling. Given the genetic basis of many cancers, clinicians face increasing challenges in understanding the vast array of genetic variants and their responses to emerging treatments and protocols. Companies such as Foundation Medicine and Flatiron Health—both now owned by Roche—focus on this precision medicine approach (Davenport & Kalakota, 2019a).

Additionally, both healthcare providers and payers are utilizing machine learning models for population health management. These models help predict individuals at risk for certain diseases (Rajkomar et al., 2018), accidents (Shimabukuro et al., 2017), or hospital readmission (Nait Aicha et al., 2018). While effective in risk prediction, these models sometimes lack crucial data—such as patients' socio-economic status—that could further enhance their predictive accuracy.

Whether rules-based or algorithmic, AI-driven diagnosis and treatment recommendations often face challenges in integrating with clinical workflows and electronic health record (EHR) systems. These integration hurdles have likely posed a more significant barrier to widespread adoption than concerns over accuracy or effectiveness. Many AI-based diagnostic and treatment tools from technology firms function as standalone solutions or focus on isolated aspects of care. While some EHR vendors have begun incorporating AI features beyond traditional rule-based clinical decision support (Low et al., 2015), these efforts remain in their early stages. As a result, healthcare providers must either undertake complex integration projects or wait for EHR vendors to expand their AI capabilities.

Patient engagement and adherence applications

Patient engagement and adherence have long been considered the "last mile" challenge in healthcare—the critical link between suboptimal and successful health outcomes. Active patient participation in their own care leads to better clinical results, improved healthcare utilization, cost efficiency, and enhanced patient experience. Increasingly, big data and AI are being leveraged to address these challenges.

Healthcare providers and hospitals rely on their clinical expertise to develop care plans that can significantly improve the health of patients with chronic or acute conditions. However, these efforts often fall short if patients fail to make necessary behavioral changes, such as losing weight, attending follow-up appointments, filling prescriptions, or adhering to treatment plans. Noncompliance—when patients do not follow prescribed treatments or medication regimens—remains a significant obstacle to effective care.

In a survey of more than 300 clinical leaders and healthcare executives, more than 70% of the respondents reported having less than 50% of their patients highly engaged and 42% of respondents said less than 25% of their patients were highly engaged. (Davenport et al., 2018).

If increased patient engagement leads to improved health outcomes, can AI-driven solutions enhance care by personalizing and contextualizing interventions? There is a growing focus on leveraging machine learning and business rules engines to deliver tailored interventions throughout the care continuum (Manoj Kumar Singh, 2018). Research in this area highlights the potential of targeted messaging, real-time alerts, and context-aware content to prompt meaningful patient actions at critical moments.

Another emerging priority in healthcare is the strategic design of 'choice architecture' to proactively influence patient behavior using real-world evidence. By leveraging data from electronic health records (EHRs), biosensors, smartwatches, smartphones, conversational interfaces, and other digital tools, software can generate personalized recommendations. These recommendations are informed by comparisons with effective treatment pathways for similar patient cohorts and can be delivered to providers, patients, nurses, call-center agents, or care coordinators to enhance decision-making and patient engagement.

Bridging infrastructure gaps

A major opportunity for artificial intelligence in Africa is its potential to solve the infrastructure deficiencies that impede efficient healthcare delivery. Numerous areas on the continent experience restricted access to healthcare services, diagnostic equipment, and medical resources. AI can play a crucial role in overcoming these challenges by implementing innovative solutions like telemedicine, mobile health applications, and automated diagnostic systems.

Integrating telemedicine with artificial intelligence (AI) offers a transformative approach to improving healthcare access and quality in rural areas, where medical resource shortages and geographical barriers limit care delivery. Innocent et al., (2024) in his study examines the combined potential of telemedicine and AI in addressing healthcare disparities by enabling remote consultations, diagnosis, and treatment. AI enhances telemedicine through advanced diagnostic tools, predictive analytics, and personalized treatment recommendations, mitigating challenges such as provider shortages and delays in care. AI-driven systems analyze medical data, including imaging, electronic health records, and real-time patient monitoring, to assist healthcare providers in making accurate and timely decisions. Machine learning algorithms can detect disease patterns, predict progression, and optimize treatment plans, thereby improving patient outcomes. Additionally, AI-integrated telemedicine platforms support continuous patient monitoring via wearable devices and mobile health applications, facilitating early intervention for chronic diseases like diabetes, cardiovascular conditions, and cancer. This study underscores the potential of AI and telemedicine to revolutionize rural healthcare delivery by enhancing diagnostic accuracy, patient management, and overall healthcare efficiency.

Artificial intelligence presents a significant opportunity to address infrastructure gaps that hinder efficient healthcare delivery in Africa. Many regions across the continent face limited access to medical services, diagnostic tools, and essential healthcare resources. AI can help bridge these gaps by enabling innovative solutions such as telemedicine, mobile health applications, and automated diagnostic systems, enhancing healthcare accessibility and efficiency.

Leveraging large language models

Large Language Models (LLMs) offer a significant opportunity to advance healthcare in Africa by overcoming language barriers, enhancing communication, and providing tailored health information and support (Wang & Zhang, 2024).

Mohammad et al., (2024) examines the integration of Natural Language Processing (NLP) techniques and Large Language Models (LLMs) in healthcare, emphasizing their growing role in widely studied languages such as English and Chinese. While NLP applications are well-researched, the use of LLMs in healthcare remains an emerging field requiring expert oversight to ensure accuracy and reliability. This is an opportunity to leverage for better healthcare service delivery.

Meng et al., (2024) systematic review analyzed 550 studies on the application of Large Language Models (LLMs) in medicine, highlighting their transformative role in diagnostics, medical writing, education, and healthcare project management. LLMs, such as ChatGPT, have been leveraged for drafting medical documents, creating training simulations, and streamlining research workflows. They have also shown promise in assisted diagnosis and enhancing doctor-patient communication.

Integration of AI in nursing

Wei et al., (2025) review critically examines the integration of artificial intelligence (AI) in nursing, highlighting its applications in clinical decision support, patient monitoring, and nursing education. It explores AI's potential to enhance personalized care and robotics in nursing. The review underscores the importance of aligning AI advancements with nursing needs to maximize benefits while mitigating risks, ultimately improving patient outcomes.

In nursing, these technologies hold the potential to support various aspects of practice, including patient assessment, care planning, education, and administrative activities (Pepito & Locsin, 2019). Nursing-specific AI tools are designed to address the unique aspects of nursing practice, focusing on functionalities such as patient education, care coordination, and holistic assessments. Unlike general AI applications, these tools are tailored to enhance nursing workflows and improve patient outcomes. As healthcare systems face increasing challenges, such as growing patient demands, complex care needs, and resource constraints, AI offers promising solutions to improve efficiency, accuracy, and patient outcomes (Reddy et al., 2020). The COVID-19 pandemic has further accelerated the adoption of digital health technologies, highlighting both the opportunities presented by AI and the need for nursing professionals to actively engage with these innovations (Ye, 2020).

Challenges

The adoption of AI in African healthcare faces several challenges, including data scarcity, infrastructure limitations, workforce shortages, ethical concerns, and policy gaps. The lack of high-quality, representative datasets and fragmented health records hinder AI model effectiveness. Infrastructure deficits, such as poor internet connectivity, unreliable electricity, and inadequate computational resources, further limit AI deployment. Additionally, a shortage of AI-trained professionals necessitates investment in capacity-building initiatives. Ethical concerns, including data privacy, algorithmic bias, and transparency, require regulatory frameworks to ensure responsible AI implementation. High costs and existing healthcare system challenges, such as workforce shortages and limited access to care, also pose significant barriers. Addressing these issues through strategic investment, policy development, and international collaboration is crucial for AI-driven healthcare advancements in Africa (Elijah Kolawole Oladipo et al., 2024)

Meng et al., (2024) However, challenges remain, including contextual limitations and the risk of over-reliance on AI-generated outputs. The increasing body of research emphasizes medical writing, diagnostics, and communication while underscoring the need for validation, ethical considerations, and integration with traditional medical practice. Future research should focus on multimodal LLMs, refining algorithmic understanding, and ensuring their responsible and effective use in healthcare.

AI has the potential to enhance healthcare in Africa by improving diagnosis, disease surveillance, resource allocation, and policy development through data-driven decision-making. However, challenges related to data privacy, equity, infrastructure integration, and ethical considerations must be addressed to maximize its benefits. AI applications, including telehealth and remote monitoring, may improve accessibility and

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affordability, but concerns over security and patient autonomy necessitate strict regulatory frameworks (Alaran et al., 2025a).

AI applications, such as mobile-based diagnostics and precision medicine, offer solutions to accessibility and resource constraints. However, challenges including infrastructure limitations, data privacy concerns, and gaps in healthcare professionals' training remain significant barriers. (Oladipo et al., 2024).

Ethical, regulatory and privacy concerns

The adoption of AI in healthcare presents critical ethical, regulatory, and privacy challenges, especially in relation to the collection, storage, and analysis of extensive datasets such as electronic health records and social media data. This underscores the need for thorough evaluation and the implementation of strong protective measures.

Mondal & Mondal, (2024) explores the ethical considerations surrounding the integration of artificial intelligence (AI) in healthcare, with a focus on microbiology and clinical decision-making. It highlights key concerns such as data security, informed consent, and the potential risks of AI-driven decision-making without human oversight. Particular emphasis is placed on the ethical challenges faced in developing countries, where informed consent protocols are often overlooked. The study also discusses biases in AI algorithms and strategies for ensuring equitable healthcare access. Additionally, five case studies and a real-world example illustrate the ethical implications of AI in healthcare, providing insights into responsible AI development and implementation.

According to Wei et al., (2025) several barriers to successful implementation are identified, including technical constraints, ethical dilemmas, and the need for workforce adaptation. Significant gaps in the literature are also evident, such as the limited development of nursing-specific AI tools, insufficient long-term impact assessments, and the absence of comprehensive ethical frameworks tailored to nursing contexts.

Health data sharing is subject to regulatory frameworks that vary across jurisdictions. In Africa, numerous factors complicate the regulation of health data sharing, including technological, motivational, economic, and political barriers, as well as ethical and legal challenges. (Nienaber et al., 2024). Although the sharing of health data is a critical resource for enhancing the quality and efficiency of healthcare systems, it raises concerns about privacy, confidentiality, and data protection. These concerns are evident in an African context where the legal and regulatory frameworks governing data sharing are less well known and are considered less accessible than better-known frameworks such as the European General Data Protection Regulation (GDPR). (The European Parliament And The Council Of The European Union, 2016).

South Africa, Ghana, Kenya, Nigeria, and Uganda, have enacted and enforceable data protection laws. Ghana imposed formal legislative data protection from October 2012, whereas Uganda (February 2019), Nigeria (June 2023), Kenya (November 2019), and South Africa (July 2020) enacted similar legislation only recently. However, a significant obstacle in health data sharing is the lack of consistency in defining what is encompassed by the term 'health data' in the different countries' legislation. This circumstance is an additional hurdle in cases of sharing health data across borders. Researchers and research sponsors must have certainty about which of their activities falls under the ambit of legislation that governs health data sharing for them to comply with legislation. It is urgent that an attempt is made in each regulatory process to define exactly what is understood by the term 'health data'. A second obstacle is that some countries' legislation does not specifically provide for cross-border transfer of personal data. This circumstance creates an obstacle to the international sharing of data. Ghana has not enacted a provision that governs the transfer of personal health data outside its national borders. An absence of regulation, necessarily, complicates any form of data exchange with Ghana, as additional protections to supplement legislative protection in the form of DTAs will be required. (Nienaber et al., 2024a).

According to Alaran et al., (2025a). *data Privacy and Security* - AI systems rely heavily on the collection and analysis of vast amounts of personal health data. In many African countries, the regulatory frameworks for data protection are still developing. This raises significant concerns about the potential misuse of personal health information, including unauthorized access, data breaches, and the violation of individuals' privacy rights. Robust encryption, access controls, and regular audits are indispensable for maintaining the integrity and confidentiality of medical data and preventing unauthorized access or breaches.

Electricity limitations

Beyond these challenges, the unreliable and inconsistent electricity supply in many low-resource areas presents a major obstacle to the successful deployment of AI technologies (Streatfeild, 2018; Lee et al., 2022). Frequent power disruptions and limited access to a stable electrical grid can interfere with AI system operations, affecting continuous data processing and real-time monitoring. Since AI models depend on a steady power supply for training and real-time functionality, these limitations significantly hinder their effectiveness (Desislavov et al., 2023).

Capacity Development

The effective implementation of AI technologies for disease detection and prediction in Africa relies heavily on strengthening local expertise and training. Many healthcare systems across the continent struggle with challenges such as limited technological access, inadequate infrastructure, and a shortage of professionals skilled in AI and data analytics (Nsoesie et al., 2021). Bridging these gaps requires significant investment in education and training programs to empower healthcare workers with the skills needed to utilize AI effectively. Also, capacity-building efforts should prioritize developing local expertise in AI and machine learning, enhancing innovation, and creating tailored solutions. Partnerships between governments, academic institutions, and international organizations can support knowledge exchange and resource-sharing, further advancing AI adoption in healthcare (Kutcher et al., 2019).

Infrastructure Gaps

One of the most significant barriers to AI adoption in healthcare is inadequate infrastructure. Many healthcare facilities, particularly in rural areas, still lack the digital infrastructure for deploying AI-powered solutions. Without reliable internet access, electricity, or digital tools, the potential for AI to transform healthcare remains limited. Governments and private organizations must invest in building the digital infrastructure needed to support AI technologies' ethical and equitable rollout (Elijah Kolawole Oladipo et al., 2024).

RECOMMENDATIONS TO OVERCOME THESE CHALLENGES

The implementation of AI in sub-Saharan Africa is hindered by a variety of obstacles, including limited access to data, the absence of regulatory frameworks, inadequate infrastructure and networking connectivity, as well as a scarcity of talent and expertise in advanced AI16. To overcome these challenges, (Owoyemi et al., 2020) suggested a need to accelerate ongoing improvements in African infrastructure, particularly in electricity and internet accessibility, which could help in the generation and analysis of data required for advanced mechanization of processes that have to do with patient care. (López et al., 2022) stressed the need for AI models to be trained and organized under a robust legal and regulatory framework to meet the public health system requirements of low and middle-income countries (LMICs). Luo et al., (2016) further highlighted the secondary use of data health to overcome barriers to data availability, which could help the researcher uncover novel insights and advancement in medical science. Finally, Ibeneme et al., (2021) urged the government and all stakeholders to convene to facilitate the necessary focus on artificial intelligence and digital health in the advancement of the healthcare sector in Africa.

DISCUSSION

Africa faces numerous health challenges, straining the continent's limited health services. Emerging threats, such as Ebola, mpox, and frequent cholera outbreaks highlight the need for a proactive, coordinated, and unified approach to infectious disease surveillance, detection, prevention, and control. (Nkengasong & Tessema, 2020). Climate change further exacerbates the situation, highlighting the urgent need to deploy innovative strategies, including artificial intelligence (AI) to enhance surveillance, detection, prediction, and response capabilities in Africa. (Brownstein et al., 2023).

AI can revolutionize African public health with enhanced analyses of diverse data streams to predict disease outbreaks and model the effects of climate change. (Brownstein et al., 2023; Brownstein et al., 2023a). AI can also enhance health-care accessibility with diagnostics and telemedicine, and address workforce shortages in crucial areas such as data science.

The integration of artificial intelligence and ma chine learning (ML) in disease detection and pre diction is proving to be a transformative approach in public health, especially in resource-limited set tings like sub-Saharan Africa. The ability of AI to analyze large and complex datasets from various sources, including electronic health records (Tshim ula et al., 2023), social media, and environmental sensors, has improved the speed and accuracy of detecting disease outbreaks. This capability is crucial for timely interventions, which are vital for preventing widespread epidemics and managing existing health conditions more effectively (Ebulue et al., 2024a; Xu et al., 2022b).

To bring AI to African public health institutions, AI-driven machine learning can be deployed to identify patterns in epidemiological, genomic, human mobility, and environmental data to detect emerging diseases and enable timely public health responses. Here we outline four areas where AI can complement and modernize infectious disease detection and surveillance in Africa.

First, AI can be used for outbreak detection and characterization. Africa reports more than 160 disease outbreaks annually. The Africa Centres for Disease Control and Prevention (CDC) with the Africa Pathogen Genomic Initiative is enhancing the capacity for countries to detect outbreaks in a timely manner. The use of AI can improve the speed, scale, and accuracy and can provide real-time information to detect and respond to outbreaks. AI can also extract insights from epidemiological, genomic, and other data types, crucial for identifying genetic variations and designing intervention strategies, such as diagnostics and vaccines. (Tanui et al., 2024).

Second, AI can be used for data analytics, integration, and prediction. AI has been successfully deployed to integrate diagnostic, genomic, and environmental data to model disease outbreaks and assess the effects of climate change. African public health institutions can use AI to identify hotspots, disease patterns, seasonal changes, and facilitate the deployment of proactive public health measures. (Agrebi & Larbi, 2020)

Third, AI can be used to augment the public health workforce. AI automates tasks, such as contact tracing during emergencies (eg, COVID-19), enhancing efficiency, and reduces the time to identify a contact. AI can also predict, identify, and address skill gaps; leveraged to create personalised, adaptive, and continuous learning platforms; respond to user inquiries (eg, AI-powered chatbots); and promote ongoing skill development for public health workforce in Africa. Challenges include job displacement and ethical concerns about technology's role in public health. Last, AI can be used for data translation for decision making. AI can analyse vast datasets to improve public health strategies with pattern recognition and real-time monitoring. The limited data science capacity in Africa can be augmented by AI, if the biases and transparency in algorithmic decision making are addressed for public health purposes. (Tanui et al., 2024).

Adopting AI in African public health faces challenges, including inadequate infrastructure, restricted internet access, power interruption, outdated hardware, and a lack of skilled professionals. To overcome these challenges, it is crucial to invest in technological infrastructure, expand internet access, ensure stable power supply, enhance skill development for the ethical use of AI, and foster multisectoral partnerships and policy initiatives that incentivise and promote AI adoption. These changes will drive innovation and sustainable health development across the continent. AI is transforming public health across the world; it is time to act and not leave Africa behind.

One of the standout areas where AI has made significant strides is in the detection and prediction of HIV. The use of advanced algorithms such as XGBoost, Random Forest, and Artificial Neural Networks has shown high accuracy in identifying HIV-positive individuals and predicting drug resistance mutations (Powers et al., 2018; Ebulue et al., 2024b). These technologies not only improve the precision of diagnoses but also facilitate targeted screening interventions and personalized treatment plans. This is particularly beneficial in sub-Saharan Africa, where the burden of HIV is substantial, and healthcare resources are often limited. AI-driven models improve healthcare outcomes and support public health authorities in making informed decisions by allowing more efficient allocation of resources and better management of treatment programs (Roche et al., 2024)

Xu et al., (2022a) developed a machine learning-based risk-prediction tool to estimate an individual's likelihood of acquiring HIV or other sexually transmitted infections (STIs) within 12 months. Using data from over 65,000 consultations at Melbourne’s largest public sexual health center between 2015 and 2019, the model demonstrated acceptable predictive performance for HIV (AUC = 0.72), syphilis (AUC = 0.75), gonorrhea (AUC = 0.73), and chlamydia (AUC = 0.67). Delivered via a web application, this tool could be integrated into digital health platforms to support targeted interventions, enhance testing, and reduce future HIV/STI risk.

AI has been instrumental in monitoring and predicting the spread of vector-borne diseases such as Zika virus and malaria. Machine learning models have been developed to map epi demic outbreaks, identify high-risk areas, and forecast disease prevalence based on climatic factors (Jiang et al., 2018a; Akhtar et al., 2019).

In nursing, these technologies hold the potential to support various aspects of practice, including patient assessment, care planning, education, and administrative activities (Pepito & Locsin, 2019; Reddy et al., 2020).

In malaria prediction, Mariki et al. (2022) demonstrated the effectiveness of machine learning in accurately predicting malaria using clinical symptoms and demographic data, particularly in regions with limited access to parasitological tests. Similarly, Nkiruka et al. (2021) proposed a machine learning-based model for classifying malaria incidence by leveraging climate variability data across six Sub-Saharan African countries over a 28-year period, highlighting the potential of AI-driven approaches in malaria surveillance and prediction.

In Ebola outbreak prediction, Leo et al. (2019) demonstrated a strong correlation between seasonal weather changes and cholera outbreaks, achieving high prediction accuracy using a machine learning model that integrated data from the Tanzania Meteorological Agency, Ministry of Health, and Dar es Salaam Water and Sewerage Authority. Similarly, Siettos et al. (2015) developed an agent-based model to examine the epidemic dynamics of Ebola virus disease (EVD) in Liberia and Sierra Leone. These studies highlight the effectiveness of data-driven models in predicting and analyzing infectious disease outbreaks.

The integration of AI and ML in disease detection, prediction, and surveillance has shown substantial benefits in public health, particularly in African countries. More accurate and timely predictions from AI-driven models support public health authorities in efficiently allocating resources and implementing targeted interventions (Mayemba et al., 2024).

Limitation

This scoping review faced several limitations that may impact the generalizability and comprehensiveness of its findings. First, despite a broad search strategy, the review may have missed relevant studies published in non-indexed or regional journals, particularly those not available in English, which could limit the representation of Africa as a whole in non-English-speaking African countries.

CONCLUSION

Artificial intelligence presents a transformative opportunity for health surveillance in Africa, particularly in diagnostics and disease prediction. AI-powered tools, such as mobile diagnostic applications and predictive models, enhance healthcare accessibility in resource-limited settings by analyzing vast datasets for early disease detection. Successful implementations, including AI-driven malaria mapping and tuberculosis detection through chest X-ray analysis, HIV, cholera, Ebola, measles, Zika virus, and malaria, enabling targeted screening interventions, personalized treatment plans, and efficient resource allocation, demonstrate AI’s potential to improve public health outcomes. Despite challenges such as infrastructure limitations and data privacy concerns, AI continues to revolutionize disease monitoring and response. By leveraging machine learning for targeted interventions and efficient resource allocation, AI holds promise for a future of more proactive and effective healthcare across the continent.

Necessary Declarations

1. **Funding Declaration**: there was no funding for this scoping review
2. **Clinical Trial Number**: Clinical trial number: not applicable
3. **Consent to Publish declaration missing**: Consent to Publish declaration: not applicable
4. **Consent to Participate declaration missing**: Consent to Participate declaration: not applicable
5. **Ethical Declaration**: Since this scoping review involves secondary data analysis of publicly available research, no formal ethical approval is required. However, all studies are handled according to standard ethical guidelines for conducting literature reviews, ensuring that data is reported accurately and objectively.

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