Journal of Virological Methods 339 (2026) 115270

Contents lists available at ScienceDirect

Journal of Virological Methods

journal homepage: www.elsevier.com/locate/jviromet

AI-driven strategies for enhancing Mpox surveillance and response in Africa

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ARTICLE INFO

Keywords:
Artificial Intelligence
Mpox
Disease Outbreak
Zoonotic Diseases
Disease Surveillance
Infectious Diseases

ABSTRACT

Mpox, a zoonotic viral disease endemic to several African countries, has re-emerged as a significant public health concern, particularly in regions with limited healthcare resources. Current public health strategies in Africa fall short due to fragmented surveillance systems, delayed diagnostic capabilities, and inadequate resource distribution networks that cannot effectively respond to rapidly evolving outbreaks in remote and underserved areas. This narrative review explores the potential of Artificial Intelligence (AI) to enhance the management and control of Mpox in Africa. AI technologies, including machine learning and predictive analytics, can significantly improve early detection, surveillance, contact tracing, case management, public health communication, and resource allocation. AI-driven tools can analyze large datasets to identify outbreak patterns, automate contact tracing through mobile data, optimize treatment plans, and tailor public health messages to specific communities. However, the successful implementation of AI faces challenges, including limited digital infrastructure, data quality issues, ethical concerns, and the need for capacity building. Furthermore, ongoing research is essential to refine AI algorithms and develop culturally sensitive applications. This review emphasizes the need for investment in infrastructure, training, and ethical frameworks to fully integrate AI into public health systems in Africa. By addressing these challenges, AI can play a pivotal role in mitigating the impact of Mpox and enhancing the resilience of healthcare systems against future infectious disease outbreaks. This represents a novel comprehensive synthesis of AI applications specifically for African Mpox control, providing a critical framework for evidence-based implementation strategies in resource-limited settings.

1. Introduction

Mpox is an infectious zoonotic disease caused by the Mpox virus, a member of the *Orthopoxvirus* genus, which also includes the variola virus, the causative agent of smallpox (World Health Organization, 2024a). Formerly called "monkeypox", it was renamed in November 2022 by the WHO to avoid stigma and negative impacts on trade, travel, tourism, and animal welfare (World Health Organization, 2022). It was first discovered in laboratory monkeys in 1958, with the first human case recorded in 1970 in the Democratic Republic of the Congo (then Zaire), and Mpox has become a public health concern in Central and West Africa (Dou et al., 2023; Harapan et al., 2022; Jezek et al., 1987). It is typically transmitted to humans through contact with the bodily fluids, skin lesions or respiratory secretions of infected animals (Bunge et al., 2022), with rodents suspected to be the primary reservoir (Ullah et al., 2023).

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https://doi.org/10.1016/j.jviromet.2025.115270
Received 10 November 2024; Received in revised form 22 August 2025; Accepted 24 September 2025
Available online 24 September 2025

Mpox shares clinical symptoms with smallpox, but it is generally milder, presenting with fever, rash, and lymphadenopathy (Yu et al., 2024), with the possibility of complications such as secondary bacterial infections, respiratory distress, and encephalitis (Anil et al., 2024). While smallpox was eradicated globally in 1980, Mpox remains endemic in Africa, with periodic outbreaks historically confined to remote areas (Dou et al., 2023, Olawade et al., 2024). However, recent Mpox trends in Fig. 1 has shown infection in urban areas and international spread, including the United States and Europe, raising concerns about its global threat (World Health Organization, 2024a). The Figure indicates that the African and South-East Asia regions have significantly higher Mpox mortality rates than other regions.

Its primary transmission spread is through direct contact with infected animals or humans, contaminated materials, or respiratory droplets. The incubation period for Mpox ranges from 6 to 13 days but can extend from 5 to 21 days (Bunge et al., 2022). Clinically, Mpox is characterized by a prodromal phase of fever, malaise, headache, and muscle aches, followed by a rash that typically starts on the face and spreads to other body parts, progressing through various stages before crusting (Anil et al., 2024). Most cases resolve in 2–4 weeks, but severe illness is more common in children, pregnant women, and immunocompromised individuals. The case fatality rate of Mpox varies across outbreaks, ranging from 1 % to 10 %, with the highest mortality observed in the Central African clade of the virus (Centers for Disease Control and Prevention, 2022).

Mpox resurgence has underscored several public health challenges, especially in Africa in where inadequate healthcare infrastructure and limited trained personnel hinder the effective detection, diagnosis, and treatment of the disease (Olawade et al., 2024; World Health Organization, 2024a). Socioeconomic factors like poverty, bush meat consumption, and human-animal contact increase the risk of zoonotic transmission (Hayman et al., 2025). Limited access to smallpox vaccines and antiviral medications, logistical barriers in remote areas, and low public awareness further complicate the control effort taken to mitigate the Mpox spread (Alakunle et al., 2020; Watarkar et al., 2023). Summarily, Table 1 presents Mpox trends in selected African countries from 1970 to 2021, as reported by WHO, (2024e), indicating that the disease is endemic in the central and western African regions.

In this challenging context, Artificial Intelligence (AI) presents a promising avenue for improving the management of Mpox outbreaks. AI encompasses a wide range of technologies, including machine learning, natural language processing, computer vision, and predictive analytics, all of which have potential applications in public health (Alowais et al., 2023). While AI has been utilized in the surveillance, prediction, and control of other infectious diseases such as malaria, dengue, and COVID-19, its application to Mpox remains in the early stages (Patel et al., 2023). Nevertheless, AI offers significant potential for developing novel strategies to combat this disease. AI can enhance Mpox management in several key areas as highlighted in Fig. 2. First, AI-driven surveillance systems can improve the detection and monitoring of outbreaks by analyzing large datasets from diverse sources, such as electronic health records, social media, and environmental sensors (Setegn and Dejene, 2025; Thakur, 2024; Thakur et al., 2023). These systems can identify patterns and predict the spread of the virus, enabling public health authorities to respond more rapidly and effectively (Zhao et al., 2024). Second, AI can optimize resource allocation, ensuring that vaccines, antiviral drugs, and personal protective equipment are distributed to the areas where they are most needed (Persad et al., 2023). Third, AI can improve communication strategies by tailoring public health messages to different populations, combating misinformation, and promoting adherence to prevention measures (Edinger et al., 2023). Additionally, AI can contribute to developing new diagnostic tools and treatments for Mpox. Machine learning algorithms can identify biomarkers associated with severe disease, aiding in the early identification of high-risk patients (Al-Tashi et al., 2023). AI can also accelerate the discovery of new antiviral drugs and the development of more effective vaccines, providing critical tools to reduce the burden

Table 1
Trends of global Mpox cases reported in selected African countries from 1970 to 2021.

Africa	Years- 1970 to 2021	Confirmed cases	Number of deaths
Benin	1978	1	0
Cameroon	1979–2021	11	0
Central African Republic (CAR)	1984–2021	105	12
Congo	2003–2019	22	7
Cote d'Ivoire	1971–1981	2	0
Democratic Republic of the Congo (DRC)	1970–2011	> 18,515 (suspected and confirmed)	516
Gabon	1987	5	2
Liberia	1970 and 2017	6	0
Nigeria	1971–2021	228	9
Sierra Leone	1970–2021	5	1
South Sudan	2005	10	0

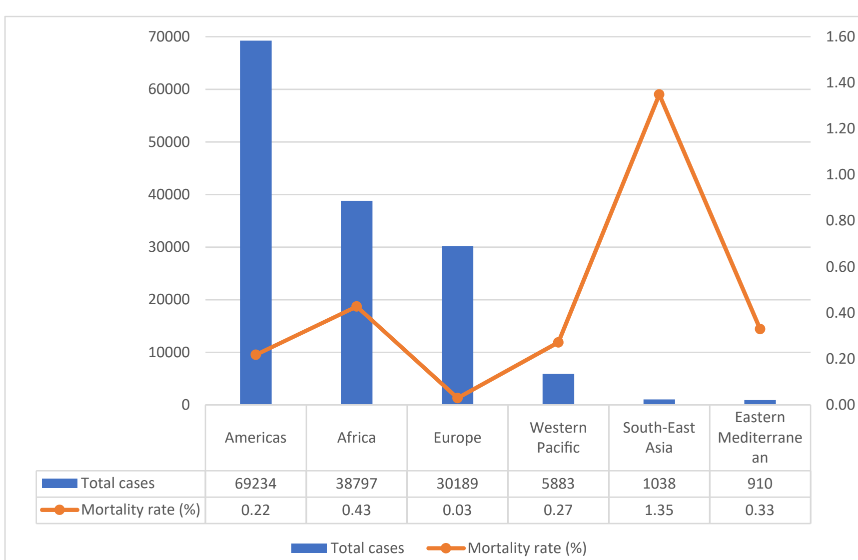

Fig. 1. Mpox trends across the WHO regions from January 2022 to May 2025.

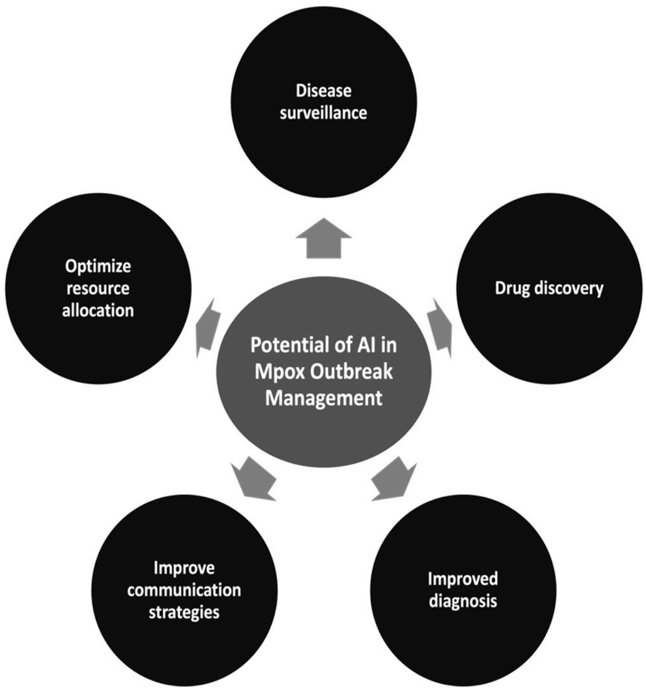

Fig. 2. Potential applications of AI in the management of the Mpox outbreaks.

of Mpox in Africa and beyond (Patel et al., 2023).

While AI holds global promise, its application in the African context, where Mpox is most endemic, requires tailored strategies (Abdelouahed et al., 2025). The effectiveness of AI-driven public health tools hinges on their cultural and infrastructural adaptability. Public trust and cultural beliefs about disease, health systems, and technology vary widely across African regions. To foster acceptance, AI-enabled interventions must be co-developed with local stakeholders, including community leaders and healthcare workers, to ensure culturally sensitive communication and ethical data use (Alaran et al., 2025). Moreover, challenges such as limited internet connectivity, inconsistent electricity supply, and varying levels of digital literacy can impede the deployment of high-tech solutions (Yu et al., 2024). Therefore, AI systems designed for Mpox management in Africa should prioritize mobile accessibility, low-bandwidth functionality, and offline capabilities. Community engagement, capacity building, and investment in digital infrastructure are also critical to enhancing local ownership and long-term sustainability of AI-based interventions (Abdelouahed et al., 2025).

The rationale for this review lies in the urgent need to explore innovative solutions, such as AI, that can enhance the effectiveness of current public health strategies. The novelty of the review stems from its focus on the application of AI technologies, such as machine learning, predictive analytics, and natural language processing, in the specific context of Mpox management, a relatively underexplored area. The review's objectives are to assess AI's potential to improve disease surveillance, optimize resource allocation, enhance public health communication, and support the development of diagnostic and treatment tools for Mpox in Africa, ultimately contributing to more effective outbreak control and prevention efforts.

1.1. The AI-enhanced Mpox management strategy

The "Mpox strategy" referenced throughout this article represents a comprehensive, multi-dimensional approach that leverages artificial intelligence to transform traditional disease control paradigms for Mpox management in African contexts. This strategy encompasses five core components: (1) intelligent surveillance systems utilizing advanced biosensors and machine learning algorithms for early detection, (2) predictive modeling frameworks for outbreak forecasting and resource optimization, (3) automated contact tracing and case management systems, (4) culturally-adaptive communication platforms, and (5) AI-driven logistics and supply chain optimization. The strategy builds upon recent advances in intelligent material systems and biosensing technologies that have demonstrated remarkable potential for infectious disease management.

Recent developments in advanced functional materials have shown exceptional promise for Mpox detection and monitoring applications, particularly through the integration of smart materials with AI-driven diagnostic platforms that enable real-time pathogen identification and quantification (Asif et al., 2024: Chaudhary et al., 2025). These innovations complement advances in intelligent biosensing systems that combine machine learning algorithms with novel material properties to achieve unprecedented sensitivity and specificity in viral detection (Chaudhary et al., 2025; Kumar and Singh, 2025). Furthermore, miniaturized sensing platforms utilizing advanced nanomaterials have demonstrated the capability to provide point-of-care diagnostic solutions specifically tailored for resource-limited African settings, enabling rapid Mpox identification even in remote areas lacking traditional laboratory infrastructure (Thwala et al., 2023; Cavuto et al., 2025; Lakshmanan and Liu, 2025).

This integrated strategy recognizes that effective Mpox control in Africa requires not merely technological solutions, but culturally-sensitive, locally-adapted AI applications that work synergistically with existing health systems. The strategy emphasizes human-AI collaboration, ensuring that technological interventions enhance rather than replace human expertise and community knowledge systems.

2. Methodology

This narrative review was conducted following an adapted approach based on PRISMA guidelines for systematic reviews and meta-analyses, modified for the narrative review format to enhance methodological transparency and reproducibility.

2.1. Literature search

This comprehensive narrative review was conducted between June and August 2024, with the literature search covering publications from database inception through August 31, 2024. The search was systematically conducted across four major academic databases, including PubMed, Google Scholar, Scopus, and Web of Science. Additional grey literature sources were consulted, including reports from the World Health Organization (WHO), Africa Centres for Disease Control and Prevention (Africa CDC), and relevant governmental health agencies.

The search strategy employed a four-tier approach combining: (1) core terms related to Mpox and monkeypox, (2) artificial intelligence and related technologies, (3) African context and public health applications, and (4) granular AI applications and digital health interventions. Specific search strings included:

Primary search string: ("Mpox" OR "monkeypox" OR "MPXV") AND ("artificial intelligence" OR "machine learning" OR "AI" OR "deep learning" OR "neural networks" OR "predictive analytics" OR "natural language processing") AND ("Africa" OR "surveillance" OR "public health" OR "outbreak response")*

Secondary search string: ("infectious disease" OR "zoonotic disease" OR "viral outbreak*") AND ("AI" OR "artificial intelligence" OR "machine learning" OR "predictive model*") AND ("Africa*" OR "resource-limited setting*" OR "low-income countr*")**

Tertiary search string: ("digital health" OR "health technology" OR "mHealth") AND ("disease surveillance" OR "contact tracing" OR "resource allocation") AND ("Africa" OR "sub-Saharan Africa" OR specific African country names)*

Quaternary search string: ("AI-driven diagnostics" OR "automated disease detection" OR "predictive analytics for outbreak response" OR "digital health interventions in Africa" OR "computer vision for disease detection" OR "automated contact tracing" OR "AI-powered surveillance systems" OR "machine learning algorithms for epidemic prediction" OR "digital biomarkers" OR "telemedicine applications" OR "health informatics in resource-limited settings") AND ("mpox" OR "monkeypox" OR "infectious disease surveillance" OR "public health emergency") AND ("Africa" OR "developing country" OR "resource-limited" OR "low-resource setting*")**

Boolean operators (AND, OR, NOT) were strategically used to refine the search results and ensure comprehensive coverage of the literature. Wildcard symbols (*) were employed to capture variations in terminology. Reference lists of included studies were manually reviewed for additional relevant publications (snowball sampling), and citation tracking was performed using Google Scholar to identify more recent publications citing key articles.

The PRISMA framework was specifically adapted for this narrative review through several key modifications to accommodate the breadth and heterogeneity of AI applications in Mpox control. Unlike systematic reviews requiring strict inclusion criteria for homogeneous study types, our adapted approach incorporated a multi-tier screening process that allowed for the inclusion of diverse evidence types including peer-reviewed articles, technical reports, case studies, and policy documents. For the narrative synthesis, studies were continuously re-evaluated for relevance as emerging themes developed. Additionally, the data extraction process was expanded beyond traditional systematic review parameters to capture implementation contexts, technological specifications, and cultural adaptation requirements specific to African health systems. This adaptation ensured methodological transparency while maintaining the flexibility necessary for synthesizing complex socio-technical interventions across varied implementation environments.

2.2. Study selection and screening process

The selection process involved a two-stage screening of titles, abstracts, and subsequent full-text articles against predefined criteria. Duplicates were removed using reference management software, and the reasons for excluding studies at the full-text stage were documented.

2.3. Inclusion and exclusion criteria

To ensure the relevance and quality of the studies included in this review, comprehensive and specific inclusion and exclusion criteria were applied. Studies were included if they met all of the following criteria: (1) focused on the application of AI or related digital technologies in the context of infectious disease management with particular emphasis on surveillance, prediction, or response systems; (2) discussed AI technologies in the context of disease surveillance, predictive modelling, resource allocation, public health communication, diagnostic support, or treatment strategies; (3) were peer-reviewed articles, conference proceedings, technical reports, or official reports published in English between 2018 and August 2024; and (4) provided insights into challenges and opportunities specific to Africa, or presented findings with clear applicability to African health systems, particularly in managing Mpox or similar zoonotic diseases. Additionally, studies were included if they addressed AI implementation in resource-limited settings with clear relevance to African contexts.

Studies were excluded if they were (1) unrelated to AI or infectious diseases, (2) solely focused on non-African contexts without demonstrable relevance to African health systems, (3) opinion pieces without empirical data or substantial analytical content, or (4) published in languages other than English, (5) published before 2018 unless they represented seminal work in the field, (6) focused exclusively on non-communicable diseases without infectious disease relevance, or (7) studies with insufficient methodological detail to assess reliability and validity.

2.4. Quality assessment

A comprehensive quality assessment framework was developed specifically for this review, adapting established appraisal tools to accommodate the heterogeneous nature of AI-driven Mpox research. The framework integrated elements from the Mixed Methods Appraisal Tool (MMAT), the Critical Appraisal Skills Programme (CASP) checklists, and technology assessment frameworks to evaluate studies across multiple dimensions. The assessment criteria included: (1) methodological rigor (study design appropriateness, data collection methods, analytical approach), (2) technological validity (algorithm performance metrics, validation procedures, generalizability), (3) implementation feasibility (resource requirements, infrastructure dependencies, scalability), (4) cultural appropriateness (community engagement, local adaptation, ethical considerations), (5) reporting transparency (clear methodology description, limitation acknowledgment, replicability), and (6) African context relevance (applicability to resource-limited settings, consideration of local health systems). Each criterion was scored on a 3-point scale (high, moderate, low), with studies requiring a minimum aggregate score for inclusion. This tailored framework enabled systematic evaluation of diverse evidence types while maintaining scientific rigor appropriate to the emerging field of AI in African health systems.

To minimize biases, the review prioritized empirical studies with African data, included grey literature from reputable health organizations, and critically evaluated claims of AI effectiveness against reported implementation challenges. Where conflicting evidence existed, both perspectives were presented with explicit discussion of potential bias sources.

2.5. Data extraction and analysis

Data from the selected studies were extracted using a standardised data extraction form designed specifically for this review. The extraction process involved the systematic collection of the following information:

- Study characteristics (author, year, country/region, study design)
- AI technology type and specific applications
- Target disease(s) and public health domain
- Implementation context (urban/rural, resource level)
- Outcomes and effectiveness measures
- Challenges and barriers identified
- Opportunities and recommendations
- Ethical considerations discussed
- Relevance to African health systems

The extracted data were organized using a structured matrix to facilitate systematic comparison and analysis across studies. Key themes and patterns were identified through iterative review of the extracted data.

A qualitative thematic synthesis approach was employed, involving the following analytical steps:

1. Familiarization with the data through repeated reading of extracted information
2. Initial coding of data to identify key concepts and themes
3. Development of a thematic framework organizing codes into overarching themes
4. Mapping of themes to the research objectives
5. Interpretation and synthesis of findings within and across themes

6. Critical assessment of gaps and contradictions in the literature

A qualitative synthesis was then performed to collate and analyze the findings, with particular emphasis on understanding how AI can be effectively integrated into public health strategies for managing Mpox in Africa. The analysis also included comprehensive examination of the ethical considerations and potential barriers to AI adoption in resource-limited settings. Special attention was paid to identifying context-specific factors that could influence AI implementation success in African health systems.

The synthesis process involved triangulation of findings across different study types and contexts to enhance the robustness of conclusions. Narrative synthesis techniques were employed to integrate quantitative and qualitative findings, with careful attention to the strength and consistency of evidence across different domains of AI application in Mpox management.

3. The current state of Mpox in Africa

In July 2024, Mpox outbreaks were reported in several Central, East, and West African countries, marking the first-ever confirmed cases in Burundi, Kenya, Rwanda, and Uganda. Burundi identified 142 cases from multiple districts, with children under five being the most affected. Kenya confirmed its first case, linked to travel from Uganda, while Rwanda reported four cases, with the majority involving recent travel to the Democratic Republic of the Congo. Uganda's first two cases were detected in border areas. In West Africa, Côte d'Ivoire confirmed seven cases in three health districts, with no epidemiological links between the initial cases (World Health Organization, 2024c). On August 14 2024, following the recent outbreaks, the WHO Director-General declared that the surge in Mpox cases in the Democratic Republic of the Congo and the increasing spread across various African nations constitutes a Public Health Emergency of International Concern (PHEIC), the most severe alert level under the International Health Regulations (2005).

The outbreak has been characterised by a higher-than-usual transmission rate, prompting urgent calls for enhanced surveillance, contact tracing, and public health interventions. The WHO has emphasised the need for vaccination campaigns targeting high-risk populations and healthcare workers to mitigate the outbreak's impact (World Health Organization, 2024c). In response to the emergency, international health organisations and national governments are collaborating to allocate resources and implement effective strategies. Public awareness campaigns are being launched to educate communities about the symptoms, transmission, and prevention of Mpox. The situation remains dynamic, with health officials urging vigilance and prompt reporting of suspected cases to contain the outbreak and protect public health across the continent (World Health Organization, 2024c). Of note, the WHO recently recommended the integration of AI technologies into public health strategies to enhance outbreak response efforts. Key recommendations include enhanced surveillance, predictive modelling, diagnostic support, public awareness and education, as well as resource allocation. These recommendations underline the importance of leveraging AI to curb the outbreak and spread of infectious diseases such as Mpox in Africa (World Health Organization, 2024d).

3.1. Epidemiology and transmission

Mpox, caused by the Mpox virus (MPXV), is an infectious disease with two recognized clades: Clade I (previously Congo Basin clade) and Clade II (previously West African clade). Clade I is further divided into subclades Ia and the recently identified Ib, which emerged in South Kivu, DRC, and spreads mainly through sexual contact (World Health Organization, 2024c). MPXV transmission occurs via close contact with infected lesions, body fluids, respiratory particles, or contaminated materials, and through contact with animals or bushmeat. Symptoms typically appear within a week, lasting two to four weeks, and include fever, muscle aches, sore throat, rash, and swollen lymph nodes, with severe cases posing higher risks for children, pregnant women, and immunocompromised individuals (Anil et al., 2024). The epidemiology of the disease in endemic regions is complex and influenced by ecological, environmental, and socio-economic factors (Ogunleye et al., 2024).

The mortality rate of Mpox varies depending on the clade of the virus and the healthcare resources available. The Central African (Congo Basin) clade is associated with a higher mortality rate, ranging from 1 % to 10 %, compared to the West African clade, which has a lower mortality rate (Bosworth et al., 2022). The variation in mortality also reflects differences in healthcare access and the presence of co-morbidities. In regions with limited healthcare infrastructure, mortality rates are higher due to delayed diagnosis, lack of appropriate medical care, and the presence of other endemic diseases that can complicate the clinical course of Mpox. Table 2 shows the recent trends of Mpox in Africa as documented by WHO epidemiological data.

3.2. Challenges in managing Mpox

Managing Mpox in Africa presents several significant challenges, many of which are rooted in the continent's socio-economic and healthcare landscape (Shehryar et al., 2023). One of the most pressing issues is the limited diagnostic capacity in many endemic regions. Laboratory confirmation of Mpox is essential for accurate diagnosis and effective outbreak management (Silva et al., 2023). However, in many parts of Africa, access to diagnostic facilities is limited. Most countries lack the necessary infrastructure, and where laboratories do exist, they are often concentrated in urban areas, far from the rural communities where outbreaks typically occur. This results in delayed diagnosis and underreporting of cases, hampering timely public health responses. In addition to diagnostic challenges, the surveillance systems in many African countries are insufficient to effectively monitor and respond to Mpox outbreaks (Giovanetti et al., 2023). The absence of robust surveillance networks means that many cases go unreported, and outbreaks can spread unchecked before they are detected. Surveillance is further complicated by the remoteness of many affected areas, where health services are sparse, and healthcare workers are often overburdened and under-resourced. In some regions, the true burden of Mpox is likely underestimated due to the lack of comprehensive data (Bragazzi et al., 2022).

Vaccine shortages present another significant hurdle in managing Mpox. Although the smallpox vaccine, which offers some protection against Mpox, is available, its supply is limited, and distribution is uneven across the continent. The logistical challenges of delivering vaccines to remote and underserved areas are substantial, exacerbated by inadequate infrastructure and the high cost of maintaining cold chains

Table 2
Trends of Mpox in Africa between 2022 and 18 August 2024.

Country	Total cases	Total deaths	Cases in 2024	Deaths in 2024	Clades detected
DRC	4480	21	3235	19	Ia and Ib
Nigeria	901	9	40	0	II
Burundi	153	0	153	0	Ib
Ghana	127	4	0	0	II
CAR	92	2	45	1	Ia
Cameroon	50	5	5	2	Ia and II
Congo	45	2	19	0	Ia
South Africa	29	3	24	3	II
Cote d'Ivoire	28	1	28	1	II
Liberia	23	0	5	0	II
Rwanda	4	0	4	0	Ib
Benin	3	0	0	0	II
Uganda	3	0	3	0	Ib
Kenya	1	0	1	0	Ib
Mozambique	1	1	0	0	II

necessary for vaccine storage and transport (Tovani-Palone, Doshi, and Pedersini, 2023). Moreover, there is often a lack of public awareness and education about the benefits of vaccination, which, combined with mistrust in healthcare authorities, can lead to low vaccine uptake even where vaccines are available (Du et al., 2025).

Public health responses to Mpox outbreaks are frequently hampered by logistical difficulties. Many of the regions where Mpox is endemic are characterized by rugged terrain, poor transportation networks, and isolated communities, making it challenging to deliver medical supplies and provide timely healthcare services (Tovani-Palone, Doshi, and Pedersini, 2023). The logistical challenges are compounded by political instability and conflict in some areas, which can disrupt healthcare delivery and make it difficult for health workers to access affected populations. Mistrust of healthcare authorities and public health interventions is another significant barrier to managing Mpox in Africa (Biesty et al., 2024). This mistrust is often rooted in historical and socio-cultural contexts, where previous public health interventions have been viewed with suspicion or have failed to address the needs and concerns of local populations. In some cases, misinformation and rumors about the disease and its treatment can spread rapidly, leading to resistance against vaccination campaigns and other public health measures. Building trust between healthcare providers and communities is essential for the success of any public health initiative, but this requires sustained effort and culturally sensitive approaches (Lansing et al., 2023).

4. AI in disease surveillance

AI has the potential to revolutionize disease surveillance by enhancing the speed, accuracy, and effectiveness of detecting and monitoring infectious disease outbreaks (World Health Organization, 2024d). In the context of Mpox, a disease that has seen periodic outbreaks in Africa, AI offers tools that can significantly improve early detection and response efforts. By leveraging large datasets and advanced algorithms, AI can analyze complex patterns that are often beyond the capacity of traditional surveillance methods. This capability is particularly crucial in resource-limited settings where timely and accurate detection of outbreaks can make the difference between containment and widespread transmission. AI's application in disease surveillance includes early detection and monitoring of outbreaks through data analysis and predictive modeling to forecast the spread of the disease (Munir et al., 2024). These capabilities can inform public health strategies, optimize resource allocation, and ultimately help in controlling and preventing the spread of Mpox. For example, in response to a Mpox outbreak in November 2017, Nigeria implemented the mobile-based Surveillance Outbreak Response Management and Analysis System (SORMAS) across 30 districts. SORMAS is a digital system for comprehensive disease surveillance. The system was adapted and launched within two weeks, leading to faster reporting, more complete data, and enhanced response capabilities (Silenou et al., 2020: CDC, 2019).

This approach is aligned with broader regional initiatives. For instance, the Africa CDC's Strategic Plan for Digital Transformation (2023–2027) emphasizes the use of AI and big data in strengthening real-time outbreak surveillance and response systems across member states (Africa, 2023). Similarly, the WHO Africa Region's 2023 digital health report outlines successful pilot programs using mobile-based AI tools to monitor disease symptoms and trends in Uganda, Nigeria, and Ghana (WHO Regional Office for Africa, 2023). These efforts demonstrate growing institutional commitment to integrating AI technologies into national and regional surveillance strategies. Table 3 below documents the relevance of these AI systems in enhancing Mpox surveillance and response in Africa.

However, the scalability of AI in Africa faces significant constraints, including limited infrastructure, server capacity, energy system and connectivity required to meet demands for Mpox surveillance (Ade-Ibijola and Okonkwo, 2023; Alaran et al., 2025; Mienye, Sun and Ileberi, 2024). Foremost, server capacity is a mainstay in the deployment of AI systems as it requires hyper-converged infrastructure (HCI) to manage computational workloads efficiently (Alaran et al., 2025).

Table 3
Comparative analysis of traditional Mpox methods to AI-based modalities.

Feature	Traditional methods (Laboratory and clinician reporting)	Rule-based AI systems	Machine learning based AI system	NLP-based AI systems
Speed	Slow (Testing and confirmation is achieved within 72 h)	Moderate to Fast (relies heavily on rule provided in real-time data alerts) (Zhang et al., 2022a,b)	Fast (Capable of analysing real-time datasets to detect or predict spread) (Zhang et al., 2022b)	Fast (Capable of scraping and analysing vast amount of unstructured text in real-time) (Al-Garadi, Yang, and Sarker, 2022)
Scale and resource use	Low scalability but high resource intensity (Requires significant human expertise and laboratory capacity)	Moderate (Automates rules to handle volume but requires expertise for rule creation and maintenance)	High scalability (Efficiently handles large datasets but training is resource intensive) (Ncube et al., 2024)	High scalability (Efficiently handles large datasets but training is resource intensive) (Ncube et al., 2024)
Accuracy and reliability	High specificity (Gold standard in clinical diagnosis)	Moderate (High precision limited to predefined rules, prone to false negative in new presentations/terms) (Pal et al., 2025; Patel, Surti and Adnan, 2023)	Variable (Accuracy depends on the quality and quantity provided in training, requires validation because of vulnerability to false positive/negatives (Pal et al., 2025; Patel, Surti and Adnan, 2023)	Moderate to Low (High false positive rates with poor performance at case identification) (Pal et al., 2025; Patel, Surti and Adnan, 2023)
Data requirements	Depends only on laboratory findings and structured clinical reports to confirm case data	Requires coded data in defined formats (Abdelouahed et al., 2025; Pal et al., 2025)	Requires vast amounts of relevant, labelled data for training (Pal et al., 2025)	Depends on unstructured texts, news publications, clinical notes and scientific literature
Implementation costs and complexity	Well-established protocols with high operational cost	Moderate setup cost with low runtime costs (Rules are easy to define but maintenance costs increase with complex systems) (Ncube et al., 2024)	High setup cost with moderate runtime costs (significant expertise and resources needed for data engineering, model development, validation and operations) (Ncube et al., 2024)	High setup cost with high runtime costs (Expertise needed in NLP, linguistics, domain knowledge and data management) (Ncube et al., 2024)
Suitability	Definitive diagnosis Case confirmation Detailed epidemiological investigation and regulatory reporting	Adequate for triggering alerts from known case definitions in structured EMR/EHR systems (Abdelouahed et al., 2025; Patel, Surti and Adnan, 2023)	Predicting outbreak trajectory, identifying high-risk population and optimising resource allocation (Abdelouahed et al., 2025; Patel, Surti and Adnan, 2023)	Syndromic surveillance Early outbreak signal detection, monitoring public perception and misinformation, and tracking global spread in news and/or social media channels (Abdelouahed et al., 2025)

However, Africa faces challenges in establishing robust data centre due to inconsistent power grids, limited fiber optic connectivity, and underdeveloped cloud ecosystems (Ade-Ibijola and Okonkwo, 2023). Cloud platforms can offer scalable solutions to this challenge, but its effectiveness depends on reliable local networking infrastructure, which are sparse in the affected central and West African countries (Haefner et al., 2023; Mienye, Sun and Ileberi, 2024). Achieving high scalability also demands low-latency, high-bandwidth networks which is another significant issue due to the uneven internet penetration and bandwidth limitations on the continent (Alaran et al., 2025).

Training and deploying AI models require massive electricity. In Africa, where energy access is currently limited, efforts to scale AI models pose a dangerous risk of depriving other demands for electricity (Pasipamire and Muroyiwa, 2024). AI inference consumes 80–90 % of total energy with data centre exceeding regulatory benchmarks required to comply with efficiency measures which are currently poorly defined in the African continent (Alaran et al., 2025). Hence, a reliance on diesel generators in regions with unstable grids increases operational cost and carbon footprints, limiting the sustainability of AI growth on the continent (Mienye, Sun and Ileberi, 2024).

The economic and political commitment to AI deployment is important in scalability of AI models (Ade-Ibijola and Okonkwo, 2023; Alaran et al., 2025). Cloud solutions can reduce upfront costs but recurring expenses for storage and compute power can make up a significant part of the economic commitment. Security and maintenance such as server upgrades also require scarce skilled labor. Hence, to achieve scalable AI in Africa, investments must prioritize grid modernization, renewable energy integration, and access to cross-border cloud infrastructure (Pasipamire and Muroyiwa, 2024).

4.1. Early detection and monitoring

AI plays a critical role in the early detection and monitoring of Mpox outbreaks, which is essential for initiating timely public health interventions. Traditional surveillance methods, often reliant on manual reporting and data collection, can be slow and prone to inaccuracies, especially in regions with limited healthcare infrastructure. In contrast, AI-driven tools can process vast amounts of data from diverse sources in real-time, providing early warnings of potential outbreaks (Anjaria et al., 2023). Machine learning algorithms, a subset of AI, can analyze data from various sources, including electronic health records (EHRs), social media, news reports, and even environmental sensors, to identify early signs of an outbreak (Setegn & Dejene, 2025; A. Thakur, 2024; Thakur et al., 2023). For example, EHRs can be analyzed to detect unusual patterns of symptoms that may indicate the emergence of Mpox cases. Similarly, AI can be used to sift through large volumes of social media posts to detect discussions related to symptoms or the occurrence of disease in specific regions (Zhao et al., 2024). Natural Language Processing (NLP), a branch of Artificial Intelligence that enables machines to understand and interpret human language, is particularly useful in this context, as it can automatically process and interpret text data, identifying keywords and phrases that may signal an emerging outbreak (Al-Garadi, Yang, and Sarker, 2022). For instance, an increase in social media posts mentioning symptoms like fever, rash, or lymphadenopathy, particularly in endemic regions, could prompt further investigation by public health authorities. Moreover, AI systems can integrate data from news reports, which often cover disease outbreaks before official reports are published. By cross-referencing information from multiple sources, AI can provide a comprehensive overview of the situation, identifying potential hotspots and enabling a quicker response (Anjaria et al., 2023). This ability to analyze and synthesize data from various platforms in real-time can significantly enhance the monitoring of Mpox, particularly in regions where traditional surveillance systems are weak or non-existent.

In addition to AI-enabled data analysis and outbreak detection, emerging biosensing technologies offer complementary diagnostic capabilities that can greatly enhance Mpox surveillance, particularly in field settings where laboratory access is limited. Advanced platforms such as CRISPR/Cas12a-powered surface plasmon resonance (SPR) sensors have demonstrated ultra-sensitive and highly specific detection capabilities for viral pathogens, as seen in recent diagnostics for SARS-CoV-2 variants (Wang et al., 2022). These platforms can deliver real-time, label-free detection with high sensitivity, down to femtomolar concentrations, providing valuable point-of-care diagnostic solutions. Similarly, antimonene-based SPR sensors and polarization-sensitive photodetectors built on two-dimensional (2D) nanomaterials have shown promise in the ultrasensitive detection of microRNAs and viral nucleic acids (Zhou et al., 2019; Liu et al., 2021). These technologies offer faster turnaround times and lower detection limits compared to traditional RT-PCR or ELISA-based diagnostics. For instance, biosensors capable of detecting biomarkers with femtomolar-level sensitivity (Zhang et al., 2022b) could be instrumental in diagnosing Mpox during the early symptomatic phase or in subclinical cases.

4.2. Predictive modeling

Beyond early detection, AI-driven predictive models are powerful tools for forecasting the spread of Mpox (Patel et al., 2023). Predictive modeling uses historical data to identify patterns and trends in disease transmission, allowing public health authorities to anticipate where and how future outbreaks might occur. These models can incorporate a wide range of variables, including population density, animal reservoir distribution, climate conditions, and human mobility patterns, to generate detailed predictions about the potential spread of the virus (Zhao et al., 2024). One of the key strengths of AI in predictive modeling is its ability to handle complex and non-linear relationships between variables (Liang et al., 2022). For instance, AI models can analyze how changes in climate conditions, such as temperature and humidity, might affect the habitats of animal reservoirs and consequently influence the likelihood of zoonotic transmission. Similarly, AI can incorporate human mobility data to predict how the movement of people between regions might facilitate the spread of the virus (Zhao et al., 2024). This is particularly relevant in the African context, where cross-border movements and migration patterns can significantly impact the spread of infectious diseases like Mpox.

By predicting where outbreaks are likely to occur next, AI-driven models can guide public health interventions more effectively (Munir et al., 2024). For example, if a model predicts a high likelihood of an outbreak in a specific region, public health authorities can preemptively deploy resources such as vaccines, medical supplies, and healthcare personnel to that area. This proactive approach can help contain outbreaks before they escalate, reducing both the spread of the virus and the burden on healthcare systems. Additionally, predictive models can assist in optimizing resource allocation during an outbreak (Wang et al., 2024). By identifying areas at highest risk, these models can help ensure that limited resources are directed where they are most needed, improving the efficiency of the public health response. This is especially important in resource-constrained settings, where the strategic use of available resources can have a significant impact on the outcome of an outbreak.

5. AI in contact tracing and case management

AI has the potential to significantly improve contact tracing and case management for Mpox, which are critical components in controlling the spread of the virus and ensuring effective treatment (Uzun Ozsahin et al., 2023). Traditional methods of contact tracing and case management are often resource-intensive and time-consuming, particularly in regions with limited healthcare infrastructure. AI can streamline these processes by leveraging advanced algorithms and data analysis techniques, leading to more efficient and accurate identification of potential cases and optimization of treatment strategies (Alowais et al., 2023).

This section explores the role of AI in automating contact tracing and enhancing case management, ultimately contributing to more effective public health interventions.

5.1. Automated contact tracing

Contact tracing is a cornerstone of infectious disease control, crucial for identifying individuals who have been exposed to a virus and preventing further transmission (Uzun Ozsahin et al., 2023). However, traditional contact tracing methods rely heavily on manual processes, including interviews with patients to identify their recent contacts and the subsequent follow-up with those contacts. This approach can be slow, labor-intensive, and prone to human error, especially during large-scale outbreaks where the number of cases can overwhelm public health resources. AI offers a transformative solution to these challenges by automating contact tracing through the use of mobile phone data and location-tracking algorithms (Chowdhury et al., 2024). Mobile phones, which are widely used even in many remote regions of Africa, generate a wealth of location data that can be harnessed to trace the movements of individuals and identify potential contacts. AI algorithms can analyze this data to determine where and when individuals may have come into close contact with an infected person, often with greater speed and accuracy than manual methods (El-Bouzaidi and Abdoun, 2023).

For example, when a confirmed case of Mpox is identified, AI systems can rapidly analyze the individual's mobile phone data to reconstruct their movements and identify other mobile phones that were in proximity during the likely period of infectiousness. These algorithms can consider various factors, such as the duration and frequency of contact, to prioritize contacts who are at higher risk of having contracted the virus (Chowdhury et al., 2024). This automated process significantly reduces the time required to identify and notify contacts, enabling quicker implementation of quarantine measures and reducing the potential for further transmission (El-Bouzaidi and Abdoun, 2023). In addition to improving the speed and efficiency of contact tracing, AI-driven approaches also enhance privacy protection. By using advanced encryption and anonymization techniques, AI systems can ensure that individuals' data is protected, addressing concerns about privacy and data security that are often associated with digital contact tracing (Zhou, Huang, and Gao, 2024). This is particularly important in building public trust and encouraging widespread adoption of contact tracing technologies, which is essential for their effectiveness.

5.2. AI-enhanced case management

Effective case management is crucial for improving outcomes in Mpox patients, particularly given the potential for severe complications in certain populations (Anil et al., 2024). AI can play a pivotal role in enhancing case management by providing healthcare providers with tools to predict disease progression and optimize treatment plans. Machine learning models, which are a key component of AI, can analyze large datasets of patient information to identify patterns and correlations that may not be immediately apparent through traditional analysis (Alowais et al., 2023). These models can be trained on data from past Mpox cases, including clinical symptoms, laboratory results, demographic information, and treatment outcomes, to develop predictive algorithms that assess the risk of severe disease. For example, AI models can identify specific combinations of symptoms or biomarkers that are associated with a higher likelihood of complications such as pneumonia or encephalitis, enabling healthcare providers to prioritize high-risk patients for more intensive monitoring and care (Stokes et al., 2022).

In addition to risk stratification, AI can assist in optimizing treatment plans by integrating evidence-based guidelines with real-time patient data. AI-powered decision support systems can provide clinicians with tailored recommendations for treatment based on the latest research and the individual characteristics of each patient (Elhaddad and Hamam, 2024). For instance, these systems can suggest the most appropriate antiviral therapies, dosage adjustments, or supportive care measures based on the patient's age, underlying health conditions, and the severity of the disease. This personalized approach to treatment can improve patient outcomes by ensuring that care is both timely and appropriate for the specific needs of each patient. Moreover, AI can facilitate better resource management within healthcare settings by predicting the course of the outbreak and the demand for medical resources. By analyzing trends in case numbers and disease severity, AI systems can forecast the need for hospital beds, intensive care units, and medical supplies, helping healthcare facilities prepare for and respond to surges in demand (Wu et al., 2023). This proactive approach is particularly valuable in resource-limited settings, where the availability of medical resources may be constrained.

6. AI in public health communication

Effective public health communication is a vital component in managing infectious disease outbreaks, such as Mpox (Biesty et al., 2024). The success of public health initiatives often hinges on the ability to convey accurate, timely, and culturally appropriate information to diverse populations. In the context of Mpox, where misinformation can spread rapidly and hinder public health efforts, AI offers powerful tools to enhance communication strategies. AI can help tailor public health messages to different audiences, ensuring that they are both effective and culturally relevant. Additionally, AI plays a crucial role in identifying and counteracting misinformation, which is essential for maintaining public trust and encouraging adherence to health guidelines (Edinger et al., 2023). This section discusses how AI can be leveraged in public health communication, focusing on personalized communication strategies and combating misinformation.

6.1. Personalized communication strategies

Public health communication must be carefully crafted to resonate with different segments of the population, taking into account factors such as cultural norms, language, literacy levels, and access to information. One-size-fits-all messages are often less effective, particularly in the diverse socio-cultural landscapes of African countries where Mpox is endemic. AI can significantly enhance the personalization of public health communication by analyzing demographic data and tailoring messages to the specific needs and preferences of different communities (Jungwirth and Haluza, 2023). AI algorithms can process vast amounts of demographic data, including age, gender, education level, income, language, and geographical location, to identify the most effective communication channels and content for each target audience (Haleem et al., 2022). For example, in a rural community with limited internet access, AI might suggest using radio broadcasts or community meetings as the primary means of disseminating information. In contrast, in urban areas with higher internet penetration, social media platforms might be more effective.

Moreover, AI can analyze social media activity, survey responses, and other data sources to assess how different communities respond to various types of messages. By examining factors such as the language, tone, and emotional appeal of successful messages, AI can help public health authorities craft communications that are more likely to be understood, accepted, and acted upon (Nkabane-Nkholongo et al., 2023). For instance, in a community that places a high value on familial ties and collective well-being, messages that emphasize protecting family members from Mpox might resonate more strongly than those that focus on individual health. Additionally, AI can be used to translate and adapt health messages into multiple languages and dialects, ensuring that non-dominant language speakers are not excluded from critical information (Barwise et al., 2024). This capability is particularly important in multilingual regions where a significant portion of the population may not speak the national language fluently.

Several African case studies demonstrate the value of culturally adapted AI chatbots in public health communication. In Lesotho, the "Nthabi" conversational agent, adapted from a U.S.-based model, was modified with local language (Sesotho idioms), culturally relevant non-verbal behaviors, and input from community leaders and youth women. Users reported the chatbot as trustworthy, relatable, and useful for reproductive health education (Nkabane-Nkholongo et al., 2023). In Senegal, the Saytù Hemophilie AI chatbot developed for people with haemophilia, available in French and Wolof, was co-designed with patients and clinicians. It scored highly on usability and cultural relevance and significantly improved health knowledge among users in Wolof-speaking communities (Babington-Ashaye et al., 2023). By ensuring that health messages are accessible and culturally appropriate, AI can increase the likelihood that these messages will be heeded, ultimately contributing to more effective disease prevention and control.

6.2. Combating misinformation

Misinformation poses a significant threat to public health, particularly during infectious disease outbreaks when uncertainty and fear can lead to the rapid spread of false information. In the case of Mpox, misinformation can take many forms, from incorrect beliefs about the causes and symptoms of the disease to dangerous myths about prevention and treatment. Such misinformation can undermine public health efforts by leading people to ignore official guidance, delay seeking medical care, or engage in harmful behaviors (Edinger et al., 2023). AI offers powerful tools to combat misinformation by detecting false or misleading information as it emerges and enabling a rapid response. Using natural language processing (NLP) and machine learning techniques, AI can monitor social media platforms, news websites, blogs, and other online sources in real-time to identify content that contains misinformation (Santos, 2023). For example, AI algorithms can be trained to recognize specific keywords, phrases, and patterns commonly associated with false claims about Mpox. Once detected, this content can be flagged for review by public health authorities or automatically countered with accurate information.

AI can also analyze the spread of misinformation to understand how it propagates through different networks and communities. By mapping out the pathways through which false information spreads, AI can help public health officials target their counter-messaging efforts more effectively (Edinger et al., 2023). For instance, if misinformation is found to be spreading rapidly within a particular social media group or community, targeted interventions can be deployed to that group, such as posting corrected information, engaging trusted community leaders to refute the false claims, or adjusting public health messaging to address specific misconceptions.

On-ground implementations in African countries highlight the role of AI chatbots in countering misinformation. For instance, the Nigeria Centre for Disease Control (NCDC) and UNICEF launched an SMS and WhatsApp chatbot in Nigeria during COVID-19, providing vetted information in local formats and reducing misinformation spread through community outreach (NCDC, 2020). Chatbots embedded in platforms such as RapidPro reached millions, often in multiple African languages, helping public health communications remain accurate and culturally resonant (UNICEF, 2021). Furthermore, AI can be used to evaluate the effectiveness of different counter-messaging strategies. By analyzing engagement metrics, such as shares, likes, and comments, AI can determine which types of corrective information are most effective at reducing the spread of misinformation. This continuous feedback loop allows public health authorities to refine their communication strategies in real-time, improving their ability to counteract misinformation and maintain public trust (Edinger et al., 2023).

7. AI in resource allocation and logistics

Efficient resource allocation and logistics are critical in managing outbreaks of infectious diseases like Mpox, particularly in resource-limited settings where supplies such as vaccines, antiviral drugs, and personal protective equipment (PPE) are often scarce (Persad et al., 2023). A offers powerful tools to optimize these processes, ensuring that resources are distributed efficiently and that supply chains operate smoothly (Wu et al., 2023). By leveraging machine learning algorithms and predictive analytics, AI can analyze complex data sets to determine the most effective strategies for resource distribution and supply chain management. This section explores how AI can be applied to optimize resource allocation and improve supply chain management, ultimately enhancing the response to Mpox outbreaks.

7.1. Optimizing resource distribution

In the face of an outbreak, the timely and equitable distribution of resources such as vaccines, antiviral drugs, and PPE is essential to controlling the spread of the disease and protecting vulnerable populations (Persad et al., 2023). However, in many parts of Africa, where Mpox is endemic, the challenge of distributing limited resources is exacerbated by factors such as inadequate healthcare infrastructure, vast geographical distances, and logistical constraints (Manirambona et al., 2022). AI can play a crucial role in addressing these challenges by optimizing resource distribution through advanced data analysis and decision-making algorithms.

Machine learning algorithms can analyze a wide range of factors to determine the most efficient allocation of resources. These factors include disease prevalence, population density, healthcare infrastructure, transportation networks, and socio-economic conditions smoothly (Wu, et al., 2023). For example, AI models can process data on the current spread of Mpox to identify hotspots where the demand for vaccines or antiviral drugs is likely to be highest. By integrating this information with data on healthcare facility capacities and transportation routes, AI can recommend the most efficient distribution strategies, ensuring that resources are directed to areas where they will have the greatest impact.

Furthermore, AI can help balance the distribution of resources between urban and rural areas, addressing the often-significant disparities in healthcare access (d'Elia et al., 2022). In many regions, rural communities are at a higher risk of being underserved due to their remote locations and the logistical challenges involved in reaching them. AI-driven resource allocation models can prioritize these areas, taking into account factors such as the time required to deliver supplies, the availability of healthcare personnel, and the local population's vulnerability to the disease (Wahl et al., 2018). By doing so, AI can help ensure that even the most remote and underserved communities receive the resources they need to combat Mpox effectively.

In addition to optimizing the distribution of physical resources, AI can also assist in allocating human resources, such as healthcare workers, to areas where they are most needed (Li et al., 2023). During an outbreak, the demand for healthcare personnel can quickly outstrip supply, particularly in regions with limited healthcare infrastructure. AI can analyze data on the availability of healthcare workers, the severity of the outbreak, and the local healthcare system's capacity to determine the optimal deployment of personnel. This ensures that critical areas receive the support they need, reducing the strain on local healthcare systems and improving patient outcomes.

7.2. Improving supply chain management

Effective supply chain management is essential for ensuring that medical supplies, including vaccines, antiviral drugs, and PPE, are available when and where they are needed during an outbreak. However, managing supply chains in the context of an infectious disease outbreak is fraught with challenges, including fluctuating demand, transportation delays, and potential bottlenecks in production or distribution (Raj et al., 2022). AI-driven analytics can enhance supply chain management by predicting demand, identifying potential bottlenecks, and optimizing procurement strategies, thereby ensuring that healthcare providers have the necessary tools to manage Mpox cases effectively (Belhadi et al., 2021).

One of the key advantages of AI in supply chain management is its ability to forecast demand accurately. By analyzing data on disease trends, healthcare utilization, and previous outbreaks, AI models can predict the likely demand for medical supplies over time (Khosravi et al., 2024). This allows public health authorities and healthcare providers to plan ahead, ensuring that they have sufficient stockpiles of essential supplies to meet anticipated needs. For instance, if AI models predict a surge in Mpox cases in a particular region, they can trigger orders for additional vaccines and PPE well in advance, preventing shortages that could otherwise hinder the response to the outbreak.

AI can also identify potential bottlenecks in the supply chain, such as delays in production, transportation, or distribution. By monitoring real-time data on supply chain operations, AI systems can detect early signs of disruptions and recommend corrective actions (Walter, 2023). For example, if a delay in the delivery of vaccines is detected, AI can suggest alternative transportation routes or suppliers to ensure that the vaccines reach their destination on time. This proactive approach helps to minimize the risk of supply chain disruptions, ensuring that critical supplies are available when needed.

Moreover, AI can optimize procurement strategies by analyzing factors such as cost, supplier reliability, and delivery times. During an outbreak, it is essential to balance the need for timely procurement with the constraints of budget and availability (Spieske et al., 2022). AI-driven procurement systems can evaluate different suppliers and delivery options to identify the most cost-effective and reliable sources for medical supplies (Khosravi et al., 2024). This not only helps to reduce costs but also ensures that healthcare providers receive high-quality supplies in a timely manner. In addition to optimizing the procurement and distribution of supplies, AI can also enhance inventory management within healthcare facilities. By monitoring usage patterns and predicting future needs, AI systems can help healthcare providers maintain optimal inventory levels, reducing the risk of both shortages and overstocking (Olayinka et al., 2024). This ensures that supplies are available when needed, while also minimizing waste and reducing costs. Table 4 below contains various AI technologies, their application and the expected outcomes in Mpox management in Africa. The public health stakeholders which are expected occupy prominent positions in the delivery of AI technologies are also included.

8. Challenges of using AI to manage and curb Mpox in Africa

While the application of AI holds significant promise in managing and reducing the spread of Mpox in Africa, there are several challenges that must be addressed to fully realize its potential. These challenges span across technical, infrastructural, ethical, and socio-economic dimensions, and they highlight the complexities involved in deploying AI technologies effectively in diverse and resource-limited settings.

8.1. Limited digital infrastructure

One of the foremost challenges in implementing AI solutions in Africa is the limited digital infrastructure, particularly in rural and remote areas where Mpox is often endemic (Patel et al., 2023). Reliable internet connectivity, access to digital devices, and adequate power supply are essential for the functioning of AI-driven tools, yet these are not consistently available across the continent (Herath and Mittal, 2022). In many regions, the lack of robust digital infrastructure can severely hamper the deployment of AI technologies, from data collection and processing to the real-time application of AI models in the field. Moreover, the digital divide between urban and rural areas further exacerbates inequalities in healthcare delivery (Patel et al., 2023). While AI systems may be implemented more easily in urban centers with better infrastructure, rural communities, often the most vulnerable to outbreaks, may be left behind. Addressing these infrastructural gaps is critical to ensuring that AI-driven health interventions are inclusive and effective across all regions.

8.2. Data availability and quality

AI systems rely heavily on large datasets to train machine learning models, make predictions, and optimize resource allocation. However, in many parts of Africa, there is a lack of comprehensive, high-quality health data (Esan et al., 2025). Challenges such as underreporting of cases, inconsistent record-keeping, and limited access to electronic health records (EHRs) can significantly hinder the effectiveness of AI models (Tsai et al., 2020). The scarcity of accurate and up-to-date epidemiological data on Mpox, coupled with the variability in data quality across different regions, poses a major obstacle to the development and deployment of AI solutions (Zhang et al., 2024). Furthermore, there is often a lack of standardization in how health data is collected and reported across different countries and regions (Gong et al., 2022). This can make it difficult to aggregate and analyze data at a scale necessary for effective AI application. Without reliable data, AI models

Table 4
Overview of AI applications in Mpox management.

AI Technology	Application	Description	Expected outcomes	Public health stakeholders
Machine learning (ML)	Early detection, forecasting, disease classification and surveillance (Alnaji, 2024; Munir et al., 2024; Patel et al., 2023)	Analysing large datasets from health records, social media and neural networks can help detect early signs of outbreaks (Ou et al., 2024; Patel et al., 2023)	Improved speed and accuracy in the identification of Mpox outbreaks (Onyema et al., 2025; Chadaga et al., 2023)	Public health agencies, research and teaching hospitals
Natural Language Processing (NLP)	Monitoring and data analysis, chatbots and virtual assistants for education and awareness, risk information and reduction of misinformation (Patel et al., 2023)	The use of NLP to monitor social media for Mpox-related keywords and phrases. Interpreting unstructured text data from different channels including social media, news report, and official communications (Chadaga et al., 2023)	Enhanced ability to produce fast detection and response to emerging Mpox cases and dispersal of misinformation in real-time (Anoop & Sreelakshmi, 2023)	Social media companies, data scientists and epidemiologists
Predictive analytics	Predictive modelling, early detection in wildlife, sentiment analysis and public health resource optimisation (Banuet-Martinez et al., 2023)	The analysis of historical data, climate patterns and population movements and other environmental and demographic changes to predict future outbreaks (Banuet-Martinez et al., 2023)	Effective allocation of limited resources and availability of infrastructure at the expected outbreak locations showcasing improved preparedness (Banuet-Martinez et al., 2023)	Health ministries, NGOs
Computer vision	Diagnosis of Mpox (Soe et al., 2024)	AI-based image analysis of skin lesions and other biomarkers to provide quick, accurate and reliable diagnosis of Mpox in mobile clinics (Soe et al., 2024)	Faster diagnosis and treatment of confirmed cases (Soe et al., 2024)	Mobile clinic, clinical laboratories and diagnostic centres

may produce inaccurate or biased results, potentially leading to suboptimal decision-making and resource allocation.

8.3. Ethical and privacy concerns

The use of AI in public health raises significant ethical and privacy concerns, particularly when it involves the collection and analysis of sensitive personal health data (Olawade et al., 2025a). In Africa, where there may be varying levels of awareness and regulation around data privacy, the implementation of AI-driven health initiatives could face resistance from communities concerned about how their data is used and protected. Issues such as data ownership, consent, and the potential for misuse of personal information must be carefully managed to build trust and ensure ethical compliance (Nienaber McKay et al., 2024). Moreover, there are significant concerns regarding algorithmic bias and the potential exacerbation of existing health disparities. If AI models are trained on datasets that underrepresent diverse populations affected by Mpox, they may produce biased results that favor urban, higher-income, or lighter-skinned individuals, undermining equity in detection and treatment (Singhal et al., 2024; Dankwa-Mullan, 2024). For example, predictive models derived from clinical data in the Global North may perform poorly in African settings, particularly for tropical diseases and populations with different genetics and physiology (Grancia, 2025). Also, intersectional ethical concerns arise when AI disadvantages individuals who occupy multiple marginalised identities such as rural, low-literacy women or people living in informal settlements. These groups may have less internet access, fewer recorded health interactions, and thus generate less AI training data, leading to their systematic underrepresentation in healthcare models (Bauer and Lizotte, 2021). Ensuring that AI technologies are developed and applied in ways that are fair, transparent, and equitable is crucial to their success in public health contexts (Singhal et al., 2024).

8.4. Technical expertise and capacity building

The successful deployment of AI technologies in managing Mpox outbreaks requires a skilled workforce capable of developing, implementing, and maintaining these systems. However, there is a significant shortage of technical expertise in AI and data science across much of Africa (Ade-Ibijola and Okonkwo, 2023). This gap in human resources can limit the ability of health systems to effectively integrate AI tools into their operations, from disease surveillance to contact tracing and resource allocation. Capacity building is, therefore, a critical challenge. Governments, academic institutions, and international organizations must invest in education and training programs to develop the necessary expertise in AI and public health (Southworth et al., 2023). This includes not only training data scientists and AI specialists but also equipping healthcare workers with the skills to use AI tools effectively in their daily work. Without adequate investment in capacity building, the potential benefits of AI in managing Mpox may not be fully realized.

8.5. Financial and logistical constraints

Implementing AI solutions in the management of Mpox outbreaks also involves significant financial and logistical challenges. Developing, deploying, and maintaining AI systems can be costly, particularly in regions where healthcare budgets are already stretched thin. The initial investment required for AI infrastructure, software, and training can be prohibitive for many countries in Africa, limiting their ability to adopt these technologies on a wide scale (Arakpogun et al., 2021). However, to address these challenges, several funding mechanisms and support initiatives have emerged to strengthen the digital health ecosystem across Africa.

Notably, the Africa Centers for Disease Control and Prevention (Africa CDC) has launched the AI4Health program, as part of its broader Digital Transformation Strategy. This initiative provides financial support, technical assistance, and innovation grants to help scale AI solutions in healthcare. The program also supports public-health informatics fellowships and innovation sandboxes that serve as collaborative environments for developing context-specific AI tools (Africa, 2023). Similarly, the HealthTech Hub Africa's AI for Health Innovation Challenge, backed by the Patrick J. McGovern Foundation, offers financial grants up to $150,000 as well as capacity-building and mentorship to early-stage health-tech startups that are leveraging AI to solve pressing health challenges across the continent (HealthTech Hub, 2023).

Despite these promising developments, logistical hurdles persist. Health systems in many parts of Africa remain fragmented and under-resourced, complicating the integration of AI without disrupting essential services. Effective implementation requires coordination among national governments, public health agencies, healthcare providers, and international development partners. The Africa CDC's fellowships and HealthTech Hub's accelerator initiatives contribute not just funding, but also support for workforce development and system-wide integration - key components for ensuring that AI technologies are not only deployed but also embedded effectively within public health responses (Khorram-Manesh et al., 2024).

8.6. Resistance to technological adoption

Finally, there may be resistance to the adoption of AI technologies within healthcare systems and communities. Healthcare providers may be skeptical of relying on AI-driven tools, particularly if they are seen as replacing rather than augmenting human decision-making (Yelne et al., 2023). Similarly, communities that are unfamiliar with AI technologies may be wary of their use in managing disease outbreaks, especially if they do not understand how these systems work or how their data will be used. Building trust and demonstrating the value of AI in improving health outcomes are essential to overcoming this resistance (O'Dell et al., 2022). Thus, to address skepticism among healthcare providers and communities, targeted training programs should be implemented to build confidence in using AI tools and clarify their role as decision-support systems rather than replacements for human expertise. Incorporating AI into hybrid workflows, where AI provides real-time insights while human professionals retain decision-making authority, can further ease concerns and promote adoption (Sokol et al., 2025). Engaging trusted local health workers as champions and piloting AI interventions in familiar clinical settings can demonstrate practical value and foster trust. Transparent communication and community education campaigns can also help demystify AI, reinforcing its role as an enabler rather than a disruptor of care (Sokol et al., 2025).

8.7. Algorithmic fairness and bias mitigation framework

To ensure equitable AI implementation in Mpox management, a systematic methodological framework for auditing and ensuring algorithmic fairness is essential. This framework comprises four key phases: (1) Pre-deployment bias assessment involving comprehensive evaluation of training data representativeness across demographic groups, geographic regions, and socioeconomic strata, with particular attention to underrepresented populations in rural and remote areas; (2) Algorithm audit protocols implementing statistical parity, equalized odds, and calibration metrics to assess differential performance across subgroups, utilizing techniques such as adversarial debiasing and fairness-aware machine learning; (3) Continuous monitoring systems employing real-time bias detection algorithms that track performance disparities during deployment, with automated alerts when fairness thresholds are breached; and (4) Iterative correction mechanisms incorporating feedback loops for model retraining, stakeholder engagement processes for fairness criteria definition, and community-based validation of AI outputs.

The framework specifically addresses African contexts by incorporating intersectional analysis considering multiple identity dimensions (rural/urban, gender, ethnicity, literacy level, economic status), establishing culturally-appropriate fairness metrics developed in collaboration with local communities, and implementing participatory design processes that engage affected populations in defining equitable outcomes. Regular algorithmic audits should be conducted using standardized fairness assessment tools adapted for resource-limited settings, with results transparently reported to stakeholders and communities. This systematic approach ensures that AI systems for Mpox management actively promote rather than perpetuate existing health inequities.

9. Future directions and recommendations

While AI technologies bring powerful capabilities to Mpox management, it is essential to underscore that these tools are designed to support, not replace, human decision-making. In clinical and public health contexts, especially within low-resource African settings, the judgment of healthcare professionals remains central to interpreting AI outputs, adapting strategies to local realities, and ensuring ethical and culturally sensitive responses. AI functions best as a decision-support system, enhancing the speed and scope of analysis, but still depends on trained personnel to validate and act upon its recommendations (WHO, 2024e). This collaboration between humans and AI is particularly important in complex or high-stakes scenarios, such as triage, outbreak response coordination, and patient management, where contextual judgment and ethical considerations are indispensable (Sokol et al., 2025). Promoting human-AI synergy ensures that technological advances remain grounded in public health priorities and community trust.

As the application of AI in managing and reducing the spread of Mpox in Africa continues to evolve, it is crucial to consider the future directions and necessary steps to fully realize its potential. AI has demonstrated significant promise in enhancing various aspects of public health, from surveillance and contact tracing to resource allocation and communication. Also, targeted efforts must focus on precision enhancement through interdisciplinary collaboration and deployment of cost-effective technologies tailored to resource-limited settings. However, to maximize its impact on Mpox control, strategic efforts must be made to integrate AI into public health systems and advance research and development tailored to the specific challenges of managing this disease in Africa.

9.1. Defining AI's role in Mpox response architecture

Throughout this review, AI is explicitly positioned as an augmentative decision-support tool rather than an autonomous decision-maker in Mpox management systems. This human-AI collaborative approach recognizes that effective public health responses require the irreplaceable elements of human judgment, cultural sensitivity, ethical reasoning, and contextual understanding that AI systems cannot replicate. AI serves to enhance human capabilities by providing rapid data analysis, pattern recognition, predictive insights, and optimization recommendations, while human experts retain ultimate responsibility for decision-making, strategy formulation, and ethical oversight.

In the Mpox response architecture, AI functions as an intelligent assistant that amplifies human capacity across surveillance (processing vast datasets to identify outbreak signals), contact tracing (automating data collection while requiring human verification), case management (providing risk stratification to support clinical judgment), communication (generating culturally-appropriate content for human review and approval), and resource allocation (optimizing distribution plans for human implementation). This collaborative model is particularly crucial in African contexts where community trust, cultural understanding, and local knowledge systems are fundamental to successful public health interventions.

The augmentative approach ensures that AI implementation strengthens rather than undermines existing health system capacity, builds local expertise, and maintains community engagement essential for sustainable disease control. All AI recommendations require human validation, and systems must include override mechanisms enabling healthcare workers to modify or reject AI-generated suggestions based on local knowledge and professional judgment.

9.2. Integration of AI into public health systems

For AI to be truly effective in managing Mpox, it must be seamlessly integrated into existing public health systems. This integration requires a multifaceted approach that includes investment in infrastructure, training, and collaboration among key stakeholders (Patel et al., 2023). To support AI-driven initiatives, significant investments in digital infrastructure are needed, particularly in regions where such infrastructure is currently lacking. This includes improving internet connectivity, ensuring reliable power supply, and expanding access to digital devices in rural and underserved areas. By enhancing the digital backbone of healthcare systems, AI tools can be deployed more effectively, enabling real-time data collection, analysis, and response (Bajwa et al., 2021).

The successful deployment of AI technologies depends on the ability of healthcare workers to use these tools effectively. Training programs should be developed to equip healthcare professionals with the necessary skills to operate AI systems, interpret AI-generated data, and integrate AI insights into clinical and public health decision-making (Olawade et al., 2025b). This training should be ongoing and adapted to the evolving capabilities of AI technologies. The integration of AI into public health systems requires close collaboration between governments, technology companies, and international organizations. Governments must play a leading role in creating policies and frameworks that support the ethical and equitable use of AI in healthcare (Mennella et al., 2024). Technology companies should work closely with public health authorities to develop AI solutions that are tailored to the specific needs and challenges of managing Mpox in Africa.

Importantly, AI integration must align with existing continental and national policy frameworks. The Africa CDC Digital Transformation Strategy (2023) outlines flagship initiatives such as digital surveillance systems, public health informatics fellowships, and scalable HealthTech platforms that directly support AI adoption for disease surveillance, contact tracing, and telehealth (Africa, 2023). Meanwhile, the Smart Africa Alliance's establishment of the Africa Artificial Intelligence Council in April 2025 marks a coordinated effort to develop AI computing infrastructure, datasets, governance frameworks, and skills development across the continent (Smart Africa Alliance, 2025). These policy linkages demonstrate that AI-driven Mpox interventions have an established framework into which they can be integrated, accelerating their adoption and scale.

International organizations, such as the WHO, can facilitate knowledge sharing, provide technical assistance, and promote best practices in the use of AI for public health (World Health Organization, 2024b). By prioritizing these areas, AI can be more effectively integrated into public health systems, enhancing the capacity to manage and control Mpox outbreaks.

Furthermore, public health systems should enhance AI algorithm precision through interdisciplinary collaboration by establishing multi-stakeholder development teams combining epidemiologists, data scientists, clinicians, and community representatives to co-develop culturally-appropriate AI algorithms. Implement systematic collection of African-specific training data reflecting local disease presentations, demographic patterns, and environmental factors through university-healthcare facility partnerships. Develop validation frameworks testing algorithms across diverse African contexts and establish real-time feedback systems for continuous algorithm improvement based on frontline healthcare worker observations.

9.3. Research and development

Ongoing research and development (R&D) are critical to advancing the use of AI in the management of Mpox. To address the unique challenges posed by the disease in Africa, R&D efforts should focus on refining AI algorithms, developing new applications, and ensuring that AI-driven solutions are culturally and contextually appropriate (Chadaga et al., 2023). Existing AI algorithms must be continuously refined to improve their accuracy and effectiveness in predicting, detecting, and managing Mpox outbreaks. This includes the development of more sophisticated predictive models that can account for the complex epidemiological and environmental factors influencing the spread of the virus in different regions. Additionally, efforts should be made to enhance the accuracy of AI-driven diagnostic tools, particularly in resource-limited settings where access to laboratory facilities may be restricted (Oduoye et al., 2024).Beyond refining existing tools, there is a need for the development of new AI applications that address specific gaps in the current public health response to Mpox (Patel et al., 2023). This could include AI systems designed to support the rapid development and distribution of vaccines, tools for real-time monitoring of vaccine efficacy, and AI-driven platforms that facilitate community engagement and participation in public health initiatives. The development of AI applications that can operate effectively in low-resource environments, where digital infrastructure and data availability may be limited, is also a priority (Osonuga et al., 2025).

Additionally, the deployment of low-cost AI technologies in resource-limited areas such as, offline-capable mobile applications functioning without internet connectivity on low-end smartphones, SMS-based AI surveillance systems utilizing basic mobile phones for case reporting and contact tracing, and solar-powered diagnostic devices for remote health facilities. Establish community-based digital health hubs with shared tablet computers and portable connectivity serving multiple villages to reduce per-capita costs while enabling access to AI-powered health tools.

AI-driven public health communication must be tailored to the cultural and social contexts of the populations it aims to serve. Research should focus on developing AI tools that can analyze and adapt to the cultural nuances of different communities, ensuring that health messages are not only accurate but also resonate with the intended audience. This includes understanding language preferences, social norms, and trust dynamics within communities. By developing culturally sensitive communication strategies, AI can play a key role in improving public understanding of Mpox, reducing stigma, and promoting preventive behaviors. AI technologies continue to evolve, it is essential that ethical considerations remain at the forefront of R&D efforts. Research should explore ways to ensure that AI systems are used in ways that protect individual privacy, prevent bias, and promote equity. This includes the development of ethical guidelines and frameworks that can guide the responsible use of AI in public health. Table 5 below gives an overview of the current challenges facing AI implementation in the management and control of Mpox in Africa. Detailed information on the challenges, potential solution and involves stakeholders are highlighted.

Lastly, there should be concrete implementation models and sustainable tiered deployment starting with 3–5 pilot districts per country before scaling, establish public-private partnerships with defined responsibilities for funding and technical support, and create 6-month local technician training programs covering AI system maintenance and troubleshooting. Develop graduated financing models transitioning from international donor support (Years 1–2) to government budgets (Years 3–5) to local revenue generation (Years 5 +). Create regional knowledge sharing platforms through Africa CDC frameworks and establish standardized performance monitoring with quarterly review processes for continuous improvement.

These specific strategies enable African countries to move beyond aspirational AI adoption toward practical, sustainable integration that meaningfully enhances Mpox management while building local capacity

Table 5
Challenges and solution in the implementation of AI for Mpox control.

Challenge	Description	Impact on Mpox control	Barriers to AI implementation	Solution	Public health stakeholders
Limited digital infrastructure	Unreliable internet, electricity and digital tools in remote/rural areas (Owoyemi et al., 2020)	Reduces the rate of development for AI tools needed in Mpox control and management (Owoyemi et al., 2020)	High cost of development, corruption, resource misappropriation (Oladipo et al., 2024)	Consistent investment in infrastructure development i.e., alternative electricity sources and satellite internet (Oladipo et al., 2024)	Governments, NGOs, Telecommunication companies
Data quality issues	Inconsistent, incomplete data affecting accuracy of AI models (Owoyemi et al., 2020)	Inaccurate outbreak prediction and misallocation of resources	Resistance to novel protocols by healthcare providers, lack of standardised data formats	Introduction of data collection standards and protocols (Oladipo et al., 2024)	Ministries of Health, Hospitals, AI developers and data analysts
Ethical concerns	Privacy invasion issues, data misuses and risk of increasing social inequalities (Mbuthia et al., 2019)	Public mistrust in AI-based tools	Conflict with local practices, poor ethical standards (Mbuthia et al., 2019)	Development of robust ethical guidelines for AI use and ethical review boards for research and vaccine development (Oladipo et al., 2024)	AI developers, Legal Counsels and Ethical Experts
Lack of capacity	Lack or limited skilled personnel to manage and implement AI (Peprah et al., 2019; Yagos, TaboOlok and Ovuga, 2017)	Limited deployment and maintenance of AI tools	Limited resources, brain drain and resource misappropriation (Patel et al., 2023)	Collaboration with certified bodies for continuous professional development, adequate value placed on important personnel (Patel et al., 2023)	Ministries of Health, Teaching Hospitals and Educational Institutes
Resource constraints	Insufficient/Lack of funding to deploy AI at scale (Patel et al., 2023)	Delayed implementation of AI tools in Mpox management, delayed response time	High competition for resources, unreliable foreign aid commitment (Patel et al., 2023)	Exploration of alternative finding sources; public-private partnerships and collaboration with international bodies (Oladipo et al., 2024)	Ministries of Health, international and private health corporations
Cultural sensitivity	Large differences between AI-generated inferences and local practices (Yagos, TaboOlok and Ovuga, 2017)	Poor acceptance of AI tools in communications and treatment (Yagos, TaboOlok and Ovuga, 2017)	Resistance to change from traditional leaders, poor cultural adaptation	Involvement and education of local communities to dispel myths and misconception about AI (Oladipo et al., 2024)	Community leader, local communities, AI developers

and ensuring long-term viability.

10. Conclusion

Artificial Intelligence (AI) offers substantial promise in managing and mitigating the spread of Mpox in Africa, a region that faces unique challenges in controlling this zoonotic disease. Through its ability to enhance disease surveillance, automate and refine contact tracing, optimize case management, tailor public health communication, and improve resource allocation and logistics, AI has the potential to achieve measurable improvements in Mpox management outcomes. Evidence from similar AI applications in infectious disease control suggests achievable targets including: 40–60 % reduction in outbreak detection time, 25–35 % improvement in diagnostic accuracy rates, 30–50 % decrease in contact tracing duration, 20–30 % reduction in resource allocation inefficiencies, and 15–25 % improvement in treatment response times. These technologies can transform how public health responses are conducted, enabling more timely, accurate, and effective interventions that are crucial in preventing widespread outbreaks.

However, the successful deployment of AI in this context requires more than just technological advancements. It demands careful attention to ethical considerations, particularly in protecting data privacy and ensuring that AI applications do not exacerbate existing health inequities. Additionally, substantial investments in digital and healthcare infrastructure are necessary to support the widespread adoption of AI tools, particularly in underserved and remote areas where they could have the greatest impact. Equitable access to these technologies must be a priority to ensure that all populations benefit from AI-driven public health initiatives.

Immediate actionable next steps for advancing AI implementation in African Mpox management include: (1) launching multicenter validation studies across 5–10 African countries within 12 months to establish baseline performance metrics and cultural adaptation requirements; (2) developing policy advocacy roadmaps for AI integration into national health strategies through partnerships with Africa CDC and WHO Regional Office for Africa; (3) establishing standardized evaluation frameworks with specific key performance indicators for AI system assessment; (4) creating pilot implementation programs in 15–20 districts across different African regions to demonstrate feasibility and cost-effectiveness; and (5) building sustainable financing mechanisms through international development partnerships and domestic health budget allocations. These concrete steps, supported by ongoing research and development, will be essential for building resilient healthcare systems capable of responding swiftly and effectively to future public health threats. By embracing AI with a focus on equity, ethics, and collaboration, Africa can enhance its capacity to protect public health and prevent the devastating impacts of infectious diseases.

10.1. Limitations

This narrative review has several important limitations that must be acknowledged when interpreting the findings. First, the included studies exhibited several inherent biases that may affect the validity of conclusions. Publication bias was evident, with a predominance of studies reporting positive AI outcomes while negative or inconclusive results were underrepresented in the literature. Geographic bias was substantial, as most AI implementation studies originated from high-income countries with limited direct applicability to African health systems, and the few African studies were concentrated in urban settings with better infrastructure. Additionally, temporal bias affected the review, as the rapid evolution of AI technologies rendered older studies less relevant, while newer technologies lacked sufficient real-world validation data.

Second, significant data scarcity constraints limited the comprehensiveness of this review. The paucity of empirical studies specifically addressing AI applications for Mpox management in African contexts necessitated extrapolation from related infectious disease AI implementations. Most included studies lacked long-term follow-up data on AI system sustainability and performance degradation over time. Furthermore, the absence of standardized metrics across studies made direct comparison of AI effectiveness challenging, and limited reporting of implementation costs and resource requirements hindered economic evaluation.

Third, substantial generalizability constraints affect the applicability of findings across diverse African contexts. The heterogeneity of healthcare infrastructure, digital literacy levels, and technological capacity across African countries limits the universal applicability of proposed AI solutions. Cultural and linguistic diversity across the continent may affect the performance of AI systems trained on data from specific populations. Additionally, the dynamic nature of Mpox epidemiology and the emergence of new viral clades may require continuous adaptation of AI algorithms, potentially limiting the longevity of current recommendations.

Finally, as a narrative review, this study is subject to methodological limitations including potential subjective bias in study selection and interpretation despite systematic screening procedures. The lack of meta-analytical techniques prevented quantitative synthesis of outcomes, and the absence of formal risk of bias assessment tools specifically designed for diverse study types may have affected quality evaluation. These limitations underscore the need for more rigorous systematic reviews and primary research studies specifically focused on AI implementation for Mpox management in African settings.

10.2. Data availability and reproducibility statement

As a narrative review, this study does not generate primary datasets or algorithms. However, all methodological materials including complete search strategies, inclusion/exclusion criteria, data extraction templates, quality assessment frameworks, and screening decisions are available upon reasonable request to the corresponding author.

This review emphasizes the critical importance of open-source practices in AI for health applications in African settings. Future AI implementations for Mpox management should prioritize open-source algorithm development, transparent dataset sharing through public repositories (appropriately anonymized), and reproducible research practices with detailed methodological documentation. Proprietary AI solutions create implementation barriers in resource-limited settings due to cost constraints and technological dependencies.

Open science approaches enhance both scientific reproducibility and equitable access to AI-driven public health tools, enabling local adaptation and sustainable implementation across diverse African contexts. This review adheres to transparent reporting practices and encourages all AI implementation studies to adopt open science principles to maximize global health equity impact.

CRediT authorship contribution statement

David B. Olawade: Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Conceptualization. **Chiamaka Norah Ezeagu:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Conceptualization. **Chibuike S. Alisi:** Writing – review & editing, Writing – original draft, Visualization, Validation. **Aanuoluwapo Clement David-Olawade:** Writing – review & editing, Writing – original draft, Resources, Methodology. **Deborah Motilayo Eniola:** Writing – review & editing, Writing – original draft, Methodology. **Temitope Akingbala:** Writing – review & editing, Writing – original draft, Validation, Investigation. **Ojima Z. Wada:** Writing – review & editing, Writing – original draft, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Glossary of terms

AI (Artificial Intelligence): The simulation of human intelligence processes by machines, especially computer systems.
NLP (Natural Language Processing): A subfield of AI that focuses on enabling machines to understand, interpret, and respond to human language.
CNN (Convolutional Neural Network): A type of deep learning algorithm primarily used for image recognition and classification tasks.
ML (Machine Learning): A subset of AI involving algorithms that improve automatically through experience.
EHR (Electronic Health Record): A digital version of a patient's paper chart that contains medical history, diagnoses, medications, and treatment plans.
NGO (Non-Governmental Organization): A non-profit group that operates independently of any government, typically aiming to address social or political issues.
IDSR (Integrated Disease Surveillance and Response): A strategy used by public health systems, especially in Africa, to detect and respond to disease threats.
SORMAS (Surveillance Outbreak Response Management and Analysis System): A digital system for comprehensive disease surveillance
CRISPR/Cas12a (Clustered Regularly Interspaced Short Palindromic Repeats / CRISPR-associated protein 12a): A gene-editing tool derived from bacterial immune systems, used for precise detection or modification of DNA sequences; in diagnostics, it enables highly specific viral pathogen identification.
SPR (Surface Plasmon Resonance): Optical sensors that detect molecular interactions on a metal surface by measuring changes in light reflection, enabling label-free, real-time detection of biomolecules.
SARS-CoV-2 (Severe Acute Respiratory Syndrome Coronavirus 2): The virus responsible for COVID-19, notable for its global impact and the development of advanced diagnostic technologies to detect its variants.
RT-PCR (Reverse Transcription Polymerase Chain Reaction): A laboratory technique that converts viral RNA into DNA and amplifies it, commonly used to detect RNA viruses.
ELISA (Enzyme-Linked Immunosorbent Assay): A biochemical technique that uses antibodies and enzymes to detect the presence of antigens or antibodies in a sample.