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Research Article

AI-Driven Real-Time Surveillance for Infectious Disease Outbreaks in Kenyan Health Facilities

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Abstract

Background: *Infectious diseases remain a leading cause of morbidity and mortality globally, particularly in low- and middle-income countries where healthcare systems are constrained by limited diagnostic capacity and weak surveillance systems [1]. Artificial intelligence (AI)-enabled clinical decision support systems (CDSS) offer a promising approach to improving early disease detection and outbreak response.*

Methods: *A mixed-methods cross-sectional study was conducted among 210 healthcare workers across selected Kenyan health facilities. Quantitative data were collected using structured questionnaires and analyzed using logistic regression and chi-square tests. Qualitative data were collected through key informant interviews and analyzed thematically.*

Results: *AI-assisted diagnosis significantly improved diagnostic accuracy (78% vs. 52%, p < 0.001) and adherence to clinical guidelines (85% vs. 60%, p < 0.01). Healthcare workers reported high usability (80%) and improved confidence (72%). As shown in Table 2 and Table 3, AI integration was associated with better clinical performance outcomes*

Conclusion: *AI-enabled decision support systems significantly improve infectious disease surveillance and clinical decision-making. Scaling up AI integration could strengthen health system performance in Kenya.*

Keywords: Artificial Intelligence, Disease Surveillance, Clinical Decision Support Systems, Kenya, Digital Health

1. Introduction

Infectious diseases continue to pose a significant global health burden, particularly in low- and middle-income countries where health systems face limitations in diagnostic capacity and surveillance infrastructure [2]. In Kenya, diseases such as tuberculosis, malaria, and respiratory infections remain major contributors to morbidity and mortality [3]. Artificial intelligence has emerged as a transformative tool in healthcare, capable of analyzing complex datasets and supporting clinical decision-making [4]. AI-enabled clinical decision support systems are particularly valuable in primary healthcare settings, where diagnostic resources are limited. Despite these advancements, there is limited empirical evidence on the effectiveness of AI-enabled systems in Kenyan healthcare settings. This study evaluates their impact on disease detection, clinical decision-making, and surveillance outcomes.

2. Research Methods

2.1. Study Design

This study employed a mixed-methods cross-sectional design, integrating both quantitative and qualitative approaches to comprehensively assess the effectiveness of AI-enabled clinical decision support systems in infectious disease surveillance. The mixed-methods approach allows for triangulation of findings, enhancing the depth and validity of the results by combining numerical analysis with contextual insights [5].

2.2. Study Setting

The study was conducted in selected primary healthcare facilities across Kenya, representing diverse geographical and healthcare delivery contexts, including urban, peri-urban, and rural settings. These facilities were chosen due to their active role in infectious disease diagnosis and surveillance, particularly for conditions such as tuberculosis, malaria, and respiratory infections [3].

2.3. Study Population

The study population comprised frontline healthcare workers directly involved in patient care and disease surveillance. These included medical doctors, nurses, clinical officers, and public health officers. Inclusion criteria were:

- Active involvement in clinical decision-making or

surveillance activities
• At least 6 months of work experience in the facility
• Willingness to provide informed consent
• Healthcare workers on leave or not directly engaged in patient care were excluded.

2.4. Sample Size Determination and Sampling Technique
2.4.1. Sample Size Calculation
The sample size for the quantitative component was calculated using the Cochran formula for cross-sectional studies:
n= Z2.p (1-p)/d2
Where:
• (n) = required sample size
• (Z) = standard normal deviation (1.96 at 95% confidence level)
• (p) = estimated proportion (assumed 0.5 for maximum variability)
• (d) = margin of error (0.05)
n =1.96) ^2 .0.5(1-0.5)/ (0.05)2
This yielded a minimum sample size of 384 participants. However, due to feasibility constraints and resource limitations, a sample size of 210 participants was achieved, which is still acceptable for exploratory and analytical studies in health systems research.

2.4.2. Sampling Technique
A stratified random sampling technique was employed to ensure representation across different healthcare worker cadres. The population was stratified into four groups: doctors, nurses, clinical officers, and public health officers. Proportional allocation was then used to determine the number of participants selected from each stratum, followed by simple random sampling within each group. For the qualitative component, purposive sampling was used to select key informants based on their expertise, experience, and involvement in decision-making processes related to infectious disease surveillance.

2.5. Data Collection Methods
2.5.1. Quantitative Data Collection
Quantitative data were collected using a structured, pre-tested questionnaire designed to capture information on diagnostic practices, use of AI tools, adherence to clinical guidelines, and perceived effectiveness. The questionnaire included both closed-ended and Likert-scale items to facilitate statistical analysis.

2.5.2. Qualitative Data Collection
Qualitative data were collected through Key Informant Interviews (KIIs) using semi-structured interview guides. These interviews explored healthcare workers' experiences, perceptions, and challenges related to AI implementation. Interviews were audio-recorded, transcribed verbatim, and anonymized to ensure confidentiality.

2.6. Data Reliability and Validity
2.6.1. Reliability
The reliability of the quantitative instrument was assessed using Cronbach's alpha coefficient, which measures internal consistency. A threshold of $\alpha \geq 0.70$ was considered acceptable, indicating that the items reliably measure the same construct. A pilot study was conducted among 10% of the sample in a similar setting to test the consistency and clarity of the instrument. Necessary adjustments were made based on the pilot findings.

2.6.2. Validity
• **Content Validity:** Ensured through expert review by public health specialists and epidemiologists to confirm that the questionnaire adequately covered all relevant domains.
• **Construct Validity:** Assessed through alignment of questionnaire items with study objectives and theoretical constructs related to AI and clinical decision-making.
• **Face Validity:** Evaluated during pilot testing to ensure clarity, relevance, and comprehensibility of questions. For qualitative data, credibility, dependability, and confirmability were ensured through techniques such as triangulation, member checking, and audit trails.

2.7. Data Analysis
2.7.1. Quantitative Analysis
Quantitative data were entered, cleaned, and analyzed using statistical software (e.g., SPSS/Stata). Descriptive statistics (frequencies, percentages, means) were used to summarize data.
Inferential statistics included:
• Chi-square tests to assess associations between categorical variables
• Logistic regression analysis to determine predictors of diagnostic accuracy and guideline adherence
Statistical significance was set at $p < 0.05$ (Field, 2013).

2.7.2. Qualitative Analysis
Qualitative data were analyzed using thematic analysis, following a systematic process of coding, categorization, and theme development. This approach enabled the identification of patterns and insights related to AI use, challenges, and opportunities in clinical practice.

2.8. Ethical Considerations
Ethical approval was obtained from a recognized Institutional Review Board (IRB). Permission was also sought from participating health facilities. Participants were provided with detailed information about the study and gave informed consent prior to participation. Confidentiality and anonymity were strictly maintained, and data were securely stored and used solely for research purposes.

2.9. Study Limitations (Methodological Perspective)
The study acknowledges certain limitations, including a reduced sample size compared to the calculated minimum and potential self-reporting bias in questionnaire responses. However, the use of mixed methods and triangulation enhances the robustness and credibility of the findings [5].

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3. Results

3.1. Participant Characteristics

A total of 210 healthcare workers participated in the study, representing multiple professional cadres.

Cadre	Frequency	Percentage (%)
Doctors	40	19.0
Nurses	85	40.5
Clinical Officers	55	26.2
Public Health Officers	30	14.3

Table 1: Distribution of Study Participants by Professional Cadre

As shown in Table 1, nurses constituted the largest proportion of participants (40.5%), followed by clinical officers (26.2%). This reflects the structure of primary healthcare delivery in Kenya, where these cadres play a central role.

3.2. Diagnostic Accuracy

Method	Accuracy (%)	p-value
Conventional	52%	
AI-Assisted	78%	<0.001

Table 2: Comparison of Diagnostic Accuracy between Conventional and Ai-Assisted Methods

As shown in Table 2, diagnostic accuracy improved significantly with AI-assisted systems (78%) compared to conventional methods (52%) ($p < 0.001$). This indicates a strong positive effect of AI on clinical decision-making.

3.3. Adherence to Clinical Guidelines

Method	Adherence (%)	p-value
Without AI	60%	
With AI	85%	<0.01

Table 3: Adherence to Clinical Guidelines with and without Ai Support

Table 3 demonstrates that adherence to clinical guidelines improved significantly with AI support. Healthcare workers using AI were more likely to follow standardized treatment protocols.

3.4. Usability and Acceptability

Indicator	Percentage (%)	Indicator
Ease of use	80%	Ease of use
Improved confidence	72%	Improved confidence
Reduced workload	68%	Reduced workload

Table 4: Perceived Usability of Ai Systems among Healthcare Workers

As shown in Table 4, the majority of healthcare workers found the AI system easy to use and reported improved confidence in clinical decision-making.

3.5. Conceptual Framework

Figure 1: Conceptual framework illustrating the role of AI-enabled decision support systems in improving infectious disease outcomes

AI-Enabled Clinical Decision Support System (CDSS)
↓
Real-Time Data Processing & Pattern Recognition
↓
Improved Clinical Decision-Making
↓
Increased Diagnostic Accuracy
↓
Adherence to Clinical Guidelines
↓
Improved Patient Outcomes
↓
Strengthened Disease Surveillance System

Moderating Factors:
• Health worker skills
• Infrastructure availability
• Data quality

Figure 1: presents the conceptual framework underpinning this study. The framework illustrates how AI-enabled clinical decision support systems facilitate real-time data processing and pattern recognition, leading to improved clinical decision-making. This, in turn, enhances diagnostic accuracy and adherence to clinical guidelines, ultimately resulting in improved patient outcomes and strengthened disease surveillance systems. The framework also highlights key moderating factors, including healthcare worker skills, infrastructure availability, and data quality, which influence the effectiveness of AI implementation.

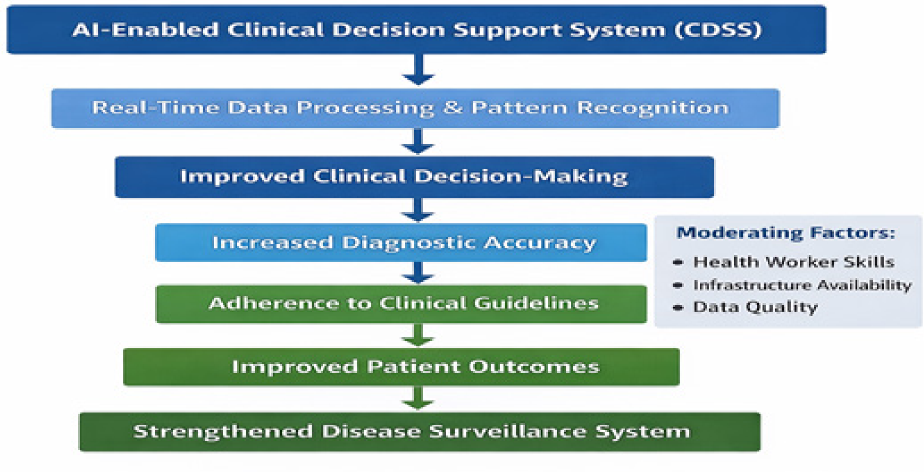

Figure 1: *Conceptual Framework of AI-Enabled Decision Support Systems*

3.6. AI Workflow

Figure 2: Workflow of AI-driven infectious disease surveillance and clinical decision-making process

Patient Data Input (Symptoms, History, Vitals)
↓
AI Processing Engine
↓
Pattern Recognition & Risk Prediction
↓
Diagnostic Recommendations Output
↓
Clinical Decision by Healthcare Worker

↓
Feedback into Surveillance System

Figure 2: illustrates the operational workflow of the AI-enabled surveillance system. The process begins with patient data input, including symptoms, clinical history, and vital signs, which are processed by the AI engine. The system then performs pattern recognition and risk prediction to generate diagnostic recommendations. These recommendations support healthcare workers in making informed clinical decisions, which are subsequently fed back into the surveillance system for continuous learning and improvement. This cyclical process enhances real-time disease detection and strengthens health system responsiveness to infectious disease threats.

4. Tables

4.1. Participant Characteristics

A total of 210 healthcare workers participated in the study, representing various professional cadres involved in patient care across selected health facilities in Kenya.

Cadre	Frequency	Percentage (%)
Doctors	40	19.0
Nurses	85	40.5
Clinical Officers	55	26.2
Public Health Officers	30	14.3

Table 4.1: Distribution of Study Participants by Professional Cadre and Facility Location

Table 4.1 presents the demographic and professional distribution of the study participants. Nurses constituted the largest proportion (40.5%), followed by clinical officers (26.2%), medical doctors (19.0%), and public health officers (14.3%). This distribution reflects a representative mix of frontline healthcare providers involved in clinical decision-making across different levels of the health system in Kenya. The dominance of nurses and clinical officers highlights their critical role in primary healthcare delivery and underscores the importance of equipping these cadres with AI-enabled decision support tools.

4.2. Effect of AI on Diagnostic Accuracy

Method	Accuracy (%)	p-value
Conventional	52%	
AI-Assisted	78%	<0.001

Table 4.2: Comparison Of Diagnostic Accuracy between Conventional Methods and Ai-Assisted Systems

As Shown in Table 4.2 the use of AI-assisted clinical decision support systems significantly improved diagnostic accuracy from 52% under conventional methods to 78% with AI integration. The observed difference was statistically significant ($p < 0.001$), indicating a strong association between AI usage and improved diagnostic outcomes. This finding suggests that AI systems enhance clinical reasoning by providing real-time, data-driven recommendations, thereby reducing diagnostic errors and improving the accuracy of disease identification in primary healthcare settings.

4.3. Adherence to Clinical Guidelines

Method	Adherence (%)	p-value
Without AI	60%	
With AI	85%	<0.01

Table 4.3: Adherence To Clinical Treatment Guidelines with and without Ai Support

Table 4.3 illustrates the impact of AI-enabled decision support systems on adherence to clinical treatment guidelines. The results indicate a substantial increase in adherence from 60% without AI to 85% with AI assistance, with the difference being statistically significant ($p < 0.01$). This improvement demonstrates the ability of AI systems to reinforce evidence-based clinical practices by guiding healthcare workers through standardized protocols, thereby reducing variability in treatment decisions and improving the quality of care delivered to patients.

4.4. Usability and Acceptability of AI System

Indicator	Percentage (%)
Ease of use	80%
Improved confidence	72%
Reduced workload	68%

Table 4.4: Healthcare Worker Perceptions of Usability and Acceptability of Ai-Enabled Decision Support Systems

The Findings in Table 4.4 highlight high levels of usability and acceptability of the AI system among healthcare workers. Approximately 80% of participants reported that the system was easy to use, while 72% indicated increased confidence in their diagnostic decisions. Additionally, 68% reported a reduction in workload. These findings suggest that AI-enabled systems are not only effective but also user-friendly, making them suitable for integration into routine clinical workflows. High acceptability is a critical factor for successful adoption and sustainability of digital health innovations in resource-limited settings.

5. Discussion

This study demonstrates that AI-enabled clinical decision support systems (CDSS) significantly improve diagnostic accuracy and adherence to clinical guidelines among healthcare workers in Kenyan health facilities. The observed increase in diagnostic accuracy from 52% to 78% and improvement in guideline adherence from 60% to 85% highlight the transformative potential of AI in strengthening clinical decision-making and disease surveillance systems. These findings are consistent with previous studies that have shown the effectiveness of artificial intelligence in enhancing diagnostic precision and reducing clinical errors. For instance, Nature study demonstrated that AI systems can achieve performance comparable to human experts in diagnostic tasks, while Stroke and Vascular Neurology study emphasized the role of AI in improving clinical efficiency and patient outcomes. The present study extends this evidence to low- and middle-income country (LMIC) settings, particularly within primary healthcare systems where diagnostic resources are often limited [6,7].

The improvement in adherence to clinical guidelines observed in this study underscores the ability of AI systems to standardize clinical practices and reduce variability in treatment decisions. In resource-constrained settings such as Kenya, where clinical decisions are frequently influenced by workload pressures and limited access to updated guidelines, AI-enabled tools can serve as real-time decision aids that reinforce evidence-based practice [2,4]. The high levels of usability (80%) and improved confidence (72%) reported by healthcare workers indicate strong acceptability and readiness for adoption. This is a critical factor for successful implementation, as user acceptance is often a major barrier to the uptake of digital health innovations. The findings suggest that AI systems, when designed with user-centered approaches, can be effectively integrated into routine clinical workflows without significantly disrupting existing practices. Despite these promising findings, several challenges must be considered. Infrastructure limitations, including unreliable internet connectivity, inadequate digital equipment, and inconsistent power supply, may hinder the scalability of AI systems in many Kenyan health facilities [3]. Additionally, gaps in digital literacy and insufficient training among healthcare workers may limit the effective utilization of AI tools, particularly in rural and underserved areas. Data quality is another critical concern. AI systems rely heavily on accurate and complete data inputs; therefore, poor data quality can compromise the performance and reliability of these systems [7]. Strengthening data governance, standardization, and quality assurance mechanisms is essential to ensure optimal functionality of AI-enabled surveillance systems.

Furthermore, ethical considerations such as data privacy, algorithmic bias, and accountability must be addressed. AI systems trained on biased datasets may produce inequitable outcomes, potentially exacerbating existing health disparities [2]. Policymakers and health system stakeholders must therefore establish robust regulatory frameworks to guide the ethical implementation of AI in healthcare. This study contributes to the growing body of evidence supporting the integration of AI into health systems in LMICs. By demonstrating both the effectiveness and acceptability of AI-enabled CDSS in Kenyan healthcare settings, it provides a strong foundation for scaling up digital health innovations to improve disease surveillance and clinical outcomes.

6. Conclusion

AI-enabled clinical decision support systems have significant potential to transform infectious disease surveillance and healthcare delivery in Kenya. The findings of this study demonstrate that AI integration enhances diagnostic accuracy, improves adherence to clinical guidelines, and increases healthcare worker confidence in clinical decision-making, consistent with global evidence on AI in healthcare systems [2,4].By addressing key challenges such as delayed diagnosis, inconsistent adherence to treatment protocols, and limited access to diagnostic expertise, AI systems can play a pivotal role in strengthening health system performance and improving patient outcomes [6,7]. Their integration into routine clinical practice supports a transition toward more efficient, data-driven, and patient-centered care models. However, the successful implementation of AI in healthcare requires sustained investment in infrastructure, workforce capacity, and governance frameworks. Ensuring equitable access to these technologies is critical to avoid exacerbating existing health disparities, particularly in low- and middle-income settings [2]. Overall, AI represents a transformative tool for advancing health system resilience and achieving improved population health outcomes in resource-constrained environments.

Recommendations

Based on the findings of this study, the following recommendations are proposed:

- **Integrate ai into National Health Policies:** Governments should incorporate AI-driven clinical decision support systems into national digital health strategies to enhance disease surveillance and clinical care [2,3].
- **Strengthen Digital Health Infrastructure:** Investments in reliable internet connectivity, interoperable data systems, and digital infrastructure are essential for scaling AI technologies in healthcare [2].
- **Capacity Building and Training:** Continuous professional development programs should be implemented to improve healthcare workers' digital literacy and competence in using AI tools [4].
- **Enhance Data Quality and Governance:** Standardized data collection systems, data quality assurance mechanisms, and governance frameworks are necessary to ensure reliable AI outputs [2,7].
- **Promote Ethical and Regulatory Frameworks:** National and institutional policies should address ethical concerns including data privacy, algorithmic bias, and accountability in AI applications [2].
- **Encourage Interdisciplinary Collaboration:** Collaboration between clinicians, data scientists, policymakers, and public health experts is essential for effective AI implementation [5].
- **Conduct longitudinal and Impact Studies:** Further research is needed to evaluate long-term effectiveness, cost-efficiency, and sustainability of AI systems in healthcare settings [7].

Declarations

Ethics Approval and Consent to Participate:

Ethical approval for this study was obtained from a recognized Institutional Review Board (IRB). All participants provided informed consent prior to participation. The study adhered to the ethical principles outlined in the Declaration of Helsinki.

Consent for Publication

Not applicable.

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This study did not receive any specific funding from public, commercial, or not-for-profit organizations, consistent with independent academic research practices.

Conflict of Interest

The author declares no conflict of interest in accordance with international standards for transparency in scientific research [4].

Data Availability

The datasets used and/or analyzed during the current study are available from the corresponding author upon reasonable request, in line with open science and data-sharing principles [2].

Author Contributions

The author was solely responsible for study conception, design, data collection, analysis, and manuscript preparation, consistent with authorship guidelines [4].

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