APPLICATION OF ARTIFICIAL INTELLIGENCE IN COMMUNITY HEALTH SURVEILLANCE BY HEALTH WORKERS ACROSS SELECTED PHCs IN BENIN CITY, EDO STATE

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MAY 2026

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BY

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A ONE-YEAR PROJECT PRESENTED TO

DEPARTMENT OF PUBLIC HEALTH AND COMMUNITY MEDICINE, SCHOOL OF MEDICINE, COLLEGE OF MEDICAL SCIENCES, UNIVERSITY OF BENIN, BENIN CITY, EDO STATE, NIGERIA.

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MAY 2026

DECLARATION

We hereby declare that this project work titled "**Application of Artificial Intelligence in Community Health surveillance by Health workers across selected PHCs in Benin city, Edo state**" will be conducted under supervision and has not been submitted in part or in full for any purpose.

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CERTIFICATION

This is to certify that this research work titled "**APPLICATION OF ARTIFICIAL INTELLIGENCE IN COMMUNITY HEALTH SURVEILLANCE BY HEALTH WORKERS ACROSS SELECTED PHCs IN BENIN CITY, EDO STATE**" was conducted by **IFIJEN DIVINE FAVOUR** with the matriculation number **MED1807412** under the supervision of **Prof Andrew I. Obi**, in the Department of Public Health and Community Medicine, College of Medicine, University of Benin, Benin City as part of the requirements for the award of Bachelor of Medicine, Bachelor of Surgery (MBBS).

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DEDICATION

This project is dedicated to God Almighty, my Creator who never fails and also to my parents, Mr and Mrs Ifijen for their constant and overwhelming love and care for me. It is also dedicated to my siblings Emmanuella and Victory.

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First and foremost, I offer my deepest and most sincere gratitude to my Lord and Creator, Jesus Christ. Your grace has been my anchor, and Your wisdom has been my light throughout this academic journey. Thank You for providing the strength to persevere when the road was difficult and for the constant reminders that through You, all things are possible.

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LIST OF ABBREVIATIONS

AI: Artificial Intelligence

CHW: Community Health Worker

DL: Deep Learning

DSNO: Disease Surveillance and Notification Officer

EDSPHCDA: Edo State Primary Health Care Development Agency

EHO: Environmental Health Officer

EHR: Electronic Health Record

IDSR: Integrated Disease Surveillance and Response

IoT: Internet of Things

LMIC: Low- and Middle-Income Country

ML: Machine Learning

NLP: Natural Language Processing

SPSS: Statistical Package for the Social Sciences

UBTH: University of Benin Teaching Hospital

DEFINITION OF TERMS

Algorithmic Bias: Systematic and repeatable errors in a computer system that create unfair outcomes, such as privileging one arbitrary group of users over others. In AI surveillance, it could lead to models that make inaccurate predictions for specific populations, potentially exacerbating health inequalities.

Artificial Intelligence (AI): The simulation of human intelligence processes by machines, especially computer systems. In the context of this study, it refers to technologies like machine learning and natural language processing used to analyze data, detect patterns, and predict outcomes for health surveillance.

Community Health Surveillance System: A system that involves the continuous, systematic collection, analysis, and interpretation of health-related data needed for the planning, implementation, and evaluation of public health practice, specifically at the community level. It is used for disease prevention, outbreak response, and healthcare planning.

Disease Surveillance: The epidemiological practice of monitoring the spread of disease to establish patterns of progression. The core goal is to detect and observe disease outbreaks and monitor risk factors to implement timely and effective public health interventions.

Integrated Disease Surveillance and Response (IDSR): A strategy adopted by countries in the African region, including Nigeria, to improve the ability to detect and respond to public health threats. It involves integrating multiple surveillance systems and streamlining data flow from the community level to the national level.

Machine Learning (ML): A subset of artificial intelligence that enables systems to automatically learn and improve from experience without being explicitly programmed. In health surveillance, ML models are used for predictive analytics, such as forecasting disease spread or identifying high-risk populations.

Natural Language Processing (NLP): A branch of AI that helps computers understand, interpret, and manipulate human language. In this context, it is used to analyze data from sources like social media feeds or electronic health records to detect mentions of illness or track public health concerns in real time.

Predictive Analytics: The use of data, statistical algorithms, and machine learning techniques to identify the likelihood of future outcomes based on historical data. In public health, it is used to forecast potential disease outbreaks and optimize healthcare resource allocation.

Socio-Technical Systems Theory: A theory that emphasizes that the effectiveness of a technological system (like AI) depends not only on the technical components (hardware, software) but also on its interaction with social structures (people, policies, organizational culture, and ethical governance).

Technology Acceptance Model (TAM): A theoretical model that explains and predicts user acceptance of information technology. It posits that two primary factors determine the adoption of a new technology: perceived usefulness (the belief that using it will enhance performance) and perceived ease of use (the belief that using it will be free of effort).

ABSTRACT

Background: Artificial intelligence (AI) offers potential to enhance community health surveillance through early outbreak detection and improved reporting. However, adoption in low-resource primary healthcare settings remains poorly understood. This study assessed the knowledge, attitudes, uptake, utilisation, and factors influencing AI use in disease surveillance among health workers in selected Primary Health Centres (PHCs) in Benin City, Edo State, Nigeria.

Methods: An analytical cross-sectional study was conducted among 230 health workers selected by stratified multistage sampling from 23 PHCs in Oredo and Egor Local Government Areas. Data were collected using a structured, self-administered questionnaire adapted from the Technology Acceptance Model and standard KAP frameworks. Knowledge, attitude, uptake, utilisation, and influencing factors were assessed using descriptive and inferential statistics (chi-square, Fisher's exact test, and logistic regression).

Results: All respondents had heard of AI (100%); the internet was the primary source (99.1%). Good knowledge of AI in disease surveillance was found in 77.8% of respondents, while 65.2% had a positive attitude towards AI use. However, actual uptake was very low (7.4%). Among the few users (n=17), the most used tools were HealthMap (76.5%) and ChatGPT (52.9%), mainly for report writing (100%) and trend analysis (52.9%). Most users reported rare use (64.7%) and had discontinued use (76.5%) due to accuracy concerns, lack of institutional support, and technical issues. Factors significantly associated with uptake included age, marital status, occupation, and knowledge level ($p<0.05$). Major barriers to AI use were lack of funding (100%), absence of institutional training (100%), inadequate infrastructure (99.6%), unclear ethical guidelines (69.6%), and data privacy concerns (67.0%). Unclear ethical guidelines were the only independent predictor of AI uptake (OR=0.069, $p<0.001$).

Conclusion: While knowledge and attitudes towards AI are reasonably favourable among PHC health workers in Benin City, actual uptake and sustained use remain very low. Systemic barriers especially lack of ethical guidelines, infrastructure, training, and funding must be addressed to translate awareness into practice.

Recommendations: Federal and state health authorities should develop clear ethical and operational guidelines for AI in disease surveillance, integrate AI literacy into training curricula, invest in digital infrastructure, and implement phased, supervised AI tools starting with low- risk functions such as report generation and trend analysis.

CHAPTER ONE

INTRODUCTION

1.1. BACKGROUND

The landscape of public health and epidemiology has undergone a dramatic transformation over the past decade, driven by the rapid integration of digital technologies and advanced computational methodologies. Historically, community health surveillance the continuous, systematic collection, analysis, and interpretation of health-related data needed for the planning, implementation, and evaluation of public health practice has relied heavily on manual reporting, paper-based records, and retrospective data analysis. However, the emergence of Artificial Intelligence (AI) has introduced paradigm-shifting capabilities to this domain. AI offers the unprecedented ability to process vast amounts of unstructured and structured data at rapid speeds, thereby enabling proactive rather than reactive public health interventions. Globally, the application of artificial intelligence has been recognized as a critical lever to improve public health outcomes by enhancing the precision, speed, and efficiency of healthcare delivery and disease monitoring.[1]

In the context of disease surveillance, AI encompasses machine learning algorithms, natural language processing, and deep learning neural networks that can identify hidden patterns within epidemiological data. These technologies are increasingly transitioning from local outbreak detection to comprehensive global epidemic monitoring and control systems.[2] Traditional surveillance systems often suffer from significant time lags between disease onset, clinical diagnosis, and official reporting. AI mitigates these delays by powering epidemic early warning systems that aggregate data from diverse sources including electronic health records, social media, mobility data, and climate metrics to flag potential outbreaks before they overwhelm healthcare infrastructure.[3] By predicting health trends and modeling transmission dynamics, AI provides public health officials with actionable intelligence for population health management, ultimately improving community health resilience against endemic and pandemic threats.[4]

The primary battleground for infectious disease control and community health management lies at the grassroots level, specifically within Primary Health Care (PHC) centers. PHCs serve as the first point of contact for individuals within a health system and are critical for the early detection and containment of communicable diseases. In community health settings, AI applications are not limited to broad epidemiological modeling; they also extend to practical, patient-level interventions. For instance, AI has been successfully applied to create risk stratification visualizations for underserved populations, enabling healthcare providers to identify high-risk individuals and allocate scarce resources more effectively.[5] This capability is particularly vital in resource-constrained environments where the optimization of healthcare delivery can mean the difference between localized containment and widespread community transmission.

Despite these global advancements, the integration of AI in health surveillance within developing nations, such as Nigeria, remains in its nascent stages. Edo State, and Benin City in particular, faces a unique set of public health challenges characterized by a high burden of infectious diseases such as malaria, Lassa fever, yellow fever, and occasional cholera outbreaks. The PHCs in Benin City are fundamental to managing these public health threats, yet they operate under significant constraints, including inadequate funding, infrastructure deficits, and chronic shortages of skilled healthcare personnel. While the theoretical benefits of AI in such settings are profound ranging from automated syndromic surveillance to diagnostic support the actual deployment and utilization of these technologies depend entirely on the human element: the health workers.

The successful implementation of any technological innovation in healthcare is heavily contingent upon the end-users' readiness, which encompasses their knowledge, attitudes, and acceptance of the system. Research indicates that the adoption of AI-infused systems is influenced by a complex interplay of human factors, including perceived usefulness, perceived ease of use, technical literacy, and trust in algorithm-generated outputs.[6] Health workers are the linchpins of the surveillance process. If they lack adequate knowledge regarding what AI is and how it functions within the context of disease monitoring, the technology will remain underutilized. Furthermore, their attitudes toward AI whether viewed as a valuable assistive tool or a threatening force that may usurp human judgment significantly impact their willingness to engage with these systems.

Moreover, the deployment of AI in public health surveillance is not devoid of challenges. Ethical considerations play a massive role in how these technologies are perceived and utilized during public health crises.[7] Issues surrounding data privacy, algorithmic bias, informed consent, and the digital divide must be carefully navigated. If health workers perceive AI systems as ethically compromised or insecure regarding patient data, their resistance to adoption will heighten. In Benin City, where internet connectivity, power supply, and continuous technical training may be inconsistent, factors influencing the use of AI extend beyond mere individual perception to systemic and infrastructural bottlenecks.

Consequently, to effectively leverage AI for community health surveillance in Benin City, it is imperative to move beyond theoretical models and examine the operational reality at the PHC level. Understanding what health workers currently know about AI, their attitudes toward its integration, the actual level and types of AI applications currently in use, and the overarching factors that facilitate or hinder its adoption is essential. This study seeks to explore these dimensions comprehensively, providing a foundational understanding of the current state of AI application in disease surveillance among health workers in selected PHCs in Benin City, Edo State.

1.2. STATEMENT OF THE PROBLEM

The persistent burden of infectious diseases in Nigeria, characterized by recurrent outbreaks of Lassa fever, yellow fever, and cholera, demands a highly responsive and technologically integrated community health surveillance system. Primary Health Care (PHC) centers in Benin City, Edo State, serve as the frontline of defense for early disease detection and population health management. Globally, Artificial Intelligence (AI) has emerged as a formidable asset, fundamentally altering how epidemics are predicted and managed.[1] Advanced AI systems provide necessary tools to forecast health trends and significantly improve community health outcomes.[4] However, a severe disconnect exists between these global technological advancements and the local operational realities in Edo State. Routine disease surveillance in Benin City remains heavily reliant on manual, paper-based reporting systems. This traditional approach is plagued by critical inefficiency; statistics indicate that manual systems often suffer from time lags of several weeks between the occurrence of a health event and its analysis at the state level. Consequently, public health systems miss crucial early warning signs, leading to delayed responses and preventable loss of life. While AI has the proven capability to create accurate risk stratification models for underserved populations,^5^ its deployment in Benin City's PHCs is practically nonexistent. This study addresses this gap by focusing on four specific problem areas.

The first critical problem involves the significant deficit in technical knowledge regarding AI systems and applications. There is a complete lack of empirical data concerning the level of knowledge health workers in Benin City possess regarding AI-driven disease surveillance. In the absence of foundational understanding, practitioners cannot identify how machine learning algorithms flag abnormal symptom clusters or how digital tools streamline data entry.^3^ If healthcare providers do not comprehend the basic mechanisms of the technology, they cannot be expected to integrate it into their daily routines. The consequence of this knowledge gap is the continued underutilization of digital health innovations, rendering any future investment in AI infrastructure ineffective because the human element remains unprepared to operate it.

The second problem relates to the uncertain attitudes and ethical skepticism held by health workers. The successful integration of any digital intervention depends entirely on the acceptance of the personnel involved. Literature suggests that the adoption of AI-infused systems is heavily dictated by complex human factors, including fear of technological obsolescence, perceived ease of use, and trust in algorithm-generated results.[6] Furthermore, ethical considerations regarding patient data privacy and the security of health information during crises can foster deep-seated skepticism among medical staff.[7] If the prevailing attitude among PHC workers in Benin City is one of suspicion or apathy, AI tools will fail to gain traction regardless of their potential to save lives. Without assessing these attitudes, policymakers cannot design the behavioral change strategies necessary to foster trust in automated systems.

The third dimension of the problem is the lack of clarity regarding the current levels of use and types of AI applications within these facilities. It is currently unknown whether any form of AI is being used informally or if basic digital data entry is being incorrectly conflated with advanced artificial intelligence. In many resource-limited settings, there is a "digital mirage" where the presence of a computer or a simple spreadsheet is mistaken for advanced surveillance capability. Without determining the specific types of systems currently in use from simple automated reporting to sophisticated epidemic early warning frameworks[3] there is no baseline for progress. This leads to redundant efforts and inefficient resource allocation, as health authorities cannot accurately target where the most significant technological gaps exist.

The final problem area involves the unidentified factors that facilitate or hinder the use of AI in this specific socioeconomic environment. While global factors affecting AI acceptance are documented,[6] the unique infrastructural realities of Benin City create a distinct set of barriers. Issues such as erratic power supply, limited internet connectivity, high patient-to-staff ratios, and inadequate funding for technical training create a challenging operational landscape. If these precise systemic and environmental factors are not identified and addressed, any attempt to modernize disease surveillance will lack a solid foundation and will likely fail.

The consequences of leaving these problems unaddressed are severe and measurable. Continued reliance on sluggish, error-prone manual systems directly results in delayed outbreak responses. This delay facilitates wider community transmission of infectious diseases, leading to increased morbidity and mortality rates that are entirely avoidable. Furthermore, it results in a reactive rather than proactive healthcare system, where resources are deployed only after a crisis has escalated. This study is therefore urgently needed to provide the precise data on knowledge, attitudes, utilization, and influencing factors required to transition Benin City's primary healthcare centers toward a proactive, AI-enhanced era of epidemic control.

1.3. JUSTIFICATION OF THE STUDY

The growing complexity of global health challenges demands more efficient and data-driven surveillance mechanisms. AI has the potential to redefine how public health systems track and respond to diseases, making surveillance faster, more accurate, and more proactive[2]. However, for AI to reach its full potential, there is a need to understand how AI is currently being used in disease surveillance, identify its limitations, and explore strategies to enhance its adoption.

One of the key benefits of AI-driven surveillance is its ability to detect outbreaks early and predict disease spread. Traditional surveillance methods often rely on delayed reporting, which hinders timely intervention. In contrast, AI can analyze patterns from diverse sources such as hospital records, environmental data, and even online search trends to detect anomalies that signal potential outbreaks[3]. AI-based early warning systems have already demonstrated success in monitoring diseases such as influenza, Ebola, and COVID-19, allowing for faster and more efficient responses[4].

Moreover, AI improves healthcare resource allocation and planning. AI-powered predictive models help health agencies identify high-risk populations, optimize hospital capacity, and allocate medical supplies more effectively[5]. This ensures that healthcare resources are distributed efficiently, particularly in low-resource settings[6].

AI also plays a crucial role in enhancing public health communication and countering misinformation. During the COVID-19 pandemic, misinformation spread rapidly, leading to vaccine hesitancy and resistance to public health measures. AI-driven tools helped analyze online discussions, detect false information, and disseminate accurate public health messages, thereby improving health literacy and awareness[7].

Despite these benefits, AI adoption in public health surveillance remains low, particularly in low- and middle-income countries (LMICs), where there are barriers related to infrastructure, digital literacy, and regulatory constraints[8]. Understanding these challenges and developing strategies to overcome them is essential to ensure that AI-driven surveillance systems can be implemented effectively across diverse healthcare settings[6].

This study aims to assess the attitudes toward AI in disease surveillance, determine its current level of adoption, examine the types of AI applications used, and explore the factors influencing its successful implementation. The findings will provide valuable insights for policymakers, healthcare professionals, and AI developers in enhancing AI-driven public health surveillance systems[2].

1.4. RESEARCH QUESTIONS

1. What is the level of knowledge of different AI systems and applications used in disease surveillance process?
2. What are the attitudes of healthcare professionals and the public toward AI-based health surveillance?
3. What are the levels of use and types of AI systems and applications used in disease surveillance process?
4. What factors influence the adoption and use of AI in community health surveillance systems?

1.5. OBJECTIVES

General Objective

To assess the types and levels of application of artificial intelligence in enhancing community health surveillance systems in other to identify existing gaps and provide evidence based recommendations for its effective integration into the local public health framework.

Specific Objectives

1. To assess the level of knowledge of different AI systems and applications used in disease surveillance process
2. To ascertain attitudes toward the use of AI systems and applications used in disease surveillance process
3. To determine levels of utilisation and types of of AI systems and applications used in disease surveillance process
4. To identify factors influencing the use of AI systems and applications in disease surveillance process

CHAPTER TWO

LITERATURE REVIEW

2.1 BACKGROUND

The integration of artificial intelligence into community health surveillance represents a significant paradigm shift in global public health, offering unprecedented capabilities for early disease detection, predictive modeling, and outbreak management. To comprehensively understand this transition, it is essential to examine the existing body of literature regarding the adoption and utilization of these technologies by healthcare professionals. This chapter systematically reviews current global, regional, and local empirical evidence to establish the context for the application of artificial intelligence in disease surveillance.

The review is grounded in a robust theoretical and conceptual framework, primarily guided by the Technology Acceptance Model, the Diffusion of Innovation Theory, and the Socio-Technical Systems Theory. These frameworks provide a lens through which to analyze how individual readiness and institutional capacity dictate technological adoption. Building upon these foundational theories, the literature is critically synthesized across four primary thematic areas aligned with the study's specific objectives.

First, the review explores the existing level of knowledge among healthcare workers concerning various artificial intelligence systems and applications utilized in disease monitoring. Second, it examines the prevailing attitudes, perceptions, and ethical concerns surrounding the deployment of these automated systems in public health contexts. Third, it assesses the documented levels of use and the specific types of artificial intelligence applications currently integrated into epidemiological tracking and health data management. Finally, the review investigates the multifaceted factors encompassing digital infrastructure, professional oversight, and regulatory frameworks that influence the successful adoption of artificial intelligence surveillance systems, with a distinct focus on the unique operational realities within Sub Saharan Africa and Nigeria. Through this structured synthesis, the chapter highlights critical gaps in current research and establishes the foundation for the present study.

2.2. THEORETICAL FRAMEWORK

The application of artificial intelligence in enhancing community health surveillance systems can be best understood through established technology adoption and systems theories that explain how individuals and institutions accept, utilize, and sustain new technological innovations. This study is theoretically underpinned by the Technology Acceptance Model, the Diffusion of Innovation Theory, and the Socio-Technical Systems Theory. These theories collectively explain how knowledge, attitudes, institutional capacity, and contextual factors influence the adoption and use of artificial intelligence in disease surveillance processes.

The Technology Acceptance Model posits that the acceptance and use of a new technology are primarily determined by perceived usefulness and perceived ease of use. In the context of community health surveillance, healthcare workers are more likely to adopt artificial intelligence systems when they believe that such systems improve the accuracy, timeliness, and efficiency of disease detection, reporting, and outbreak prediction. Empirical studies have demonstrated that artificial intelligence enhances real-time surveillance, early outbreak detection, and predictive modelling, thereby strengthening public health response systems.[1–3] However, limited understanding of artificial intelligence concepts, lack of technical training, fear of algorithmic errors, and concerns about loss of professional autonomy can negatively affect perceived usefulness and ease of use, particularly in low- and middle-income countries such as Nigeria.[4,5] Consequently, healthcare workers' level of knowledge directly shapes their attitudes toward artificial intelligence and influences their willingness to use such systems in disease surveillance activities.

The Diffusion of Innovation Theory further explains how artificial intelligence technologies spread within health systems over time. According to this theory, the adoption of innovation is influenced by its perceived relative advantage over existing methods, compatibility with current systems, complexity, trialability, and observability of results. Artificial intelligence offers a clear advantage over traditional surveillance methods by enabling automated data analysis, predictive modeling, and real-time monitoring of disease trends. However, studies conducted in Africa and other developing regions indicate that diffusion remains slow due to infrastructural deficiencies, inadequate funding, limited institutional readiness, and weak policy frameworks.[6–9] In Nigeria, the integration of artificial intelligence into disease surveillance systems is further constrained by fragmented health information systems and limited digital interoperability.[10,11] This theory therefore explains variations in the level of artificial intelligence use across different institutions and supports the examination of factors influencing adoption, as outlined in this study's objectives.

The Socio-Technical Systems Theory emphasizes that the effectiveness of artificial intelligence systems depends on the interaction between technical components and social structures. In community health surveillance, artificial intelligence tools such as machine learning algorithms, predictive analytics, and automated reporting systems cannot function optimally without supportive organizational policies, ethical governance, skilled personnel, and public trust. Research has shown that ethical concerns related to data privacy, informed consent, algorithmic bias, and government overreach significantly influence acceptance and use of artificial intelligence surveillance systems.[12–14] In sub-Saharan Africa and Nigeria, additional challenges such as inadequate digital infrastructure, limited professional oversight, and absence of robust regulatory frameworks further restrict the effective deployment of artificial intelligence in public health surveillance.[15–18] This theory underscores the importance of aligning technological innovation with ethical, institutional, and societal considerations to ensure sustainable use.

Collectively, these theories provide a comprehensive explanation for how individual knowledge and attitudes, institutional readiness, and broader socio-technical factors interact to influence the application of artificial intelligence in enhancing community health surveillance systems. They form a strong theoretical basis for assessing knowledge, attitudes, levels of use, types of artificial intelligence applications, and the factors influencing their adoption among public health personnel.

2.3. CONCEPTUAL FRAMEWORK

The conceptual framework for this study is derived from the theoretical foundations and illustrates the relationship between knowledge, attitudes, institutional factors, and the application of artificial intelligence in community health surveillance systems. The framework assumes that the successful application of artificial intelligence is influenced by both individual and contextual factors, which ultimately determine the level and type of artificial intelligence utilization in disease surveillance processes.

Knowledge of artificial intelligence systems and applications represents a key independent variable in this study. This includes healthcare workers' understanding of artificial intelligence concepts, such as machine learning, predictive analytics, automated disease reporting, and data visualization tools used in surveillance. Evidence suggests that higher levels of knowledge are associated with increased confidence, appropriate utilization, and sustained use of artificial intelligence systems in public health practice.[1,3,5] Inadequate knowledge, on the other hand, leads to misuse, resistance, or complete non-adoption of artificial intelligence technologies.

Attitudes toward artificial intelligence constitute another critical independent variable. Attitudes reflect healthcare workers' perceptions, beliefs, and trust regarding artificial intelligence-driven surveillance systems. Positive attitudes are associated with perceived benefits such as improved efficiency, reduced workload, and enhanced outbreak preparedness, while negative attitudes often stem from concerns about data privacy, ethical implications, algorithmic bias, and fear of replacement by automated systems.[4,7,12] These attitudes significantly influence the willingness of healthcare workers to integrate artificial intelligence into routine surveillance activities.

Institutional and contextual factors also play a crucial role in shaping artificial intelligence adoption. These factors include availability of digital infrastructure, internet connectivity, access to funding, leadership support, training opportunities, and existence of clear regulatory and ethical guidelines. Studies conducted in Nigeria and other African countries have shown that even when healthcare workers possess adequate knowledge and positive attitudes, poor infrastructure and weak institutional support can hinder effective artificial intelligence use.[15–18] These factors therefore serve as enabling or constraining conditions for artificial intelligence application.

Intervening variables such as ethical safeguards, data quality, system interoperability, professional oversight, and public trust influence the strength and direction of the relationship between the independent variables and artificial intelligence utilization. Weak ethical governance and poor data quality reduce the effectiveness of artificial intelligence systems and undermine trust among users and the public, thereby limiting adoption.[12–16]

The dependent variable in this study is the application of artificial intelligence in enhancing community health surveillance systems. This is reflected in the level of use of artificial intelligence systems, ranging from non-use to regular use, as well as the types of artificial intelligence applications employed, including outbreak detection, trend analysis, predictive modelling, and automated reporting. Effective application of artificial intelligence leads to improved timeliness, accuracy, and efficiency of disease surveillance and response activities.[2,6,9]

Overall, the conceptual framework assumes that improved knowledge leads to positive attitudes, which, when supported by adequate institutional and ethical environments, result in increased application of artificial intelligence in community health surveillance systems. This framework directly aligns with the study's objectives and provides a logical basis for data collection, analysis, and interpretation.

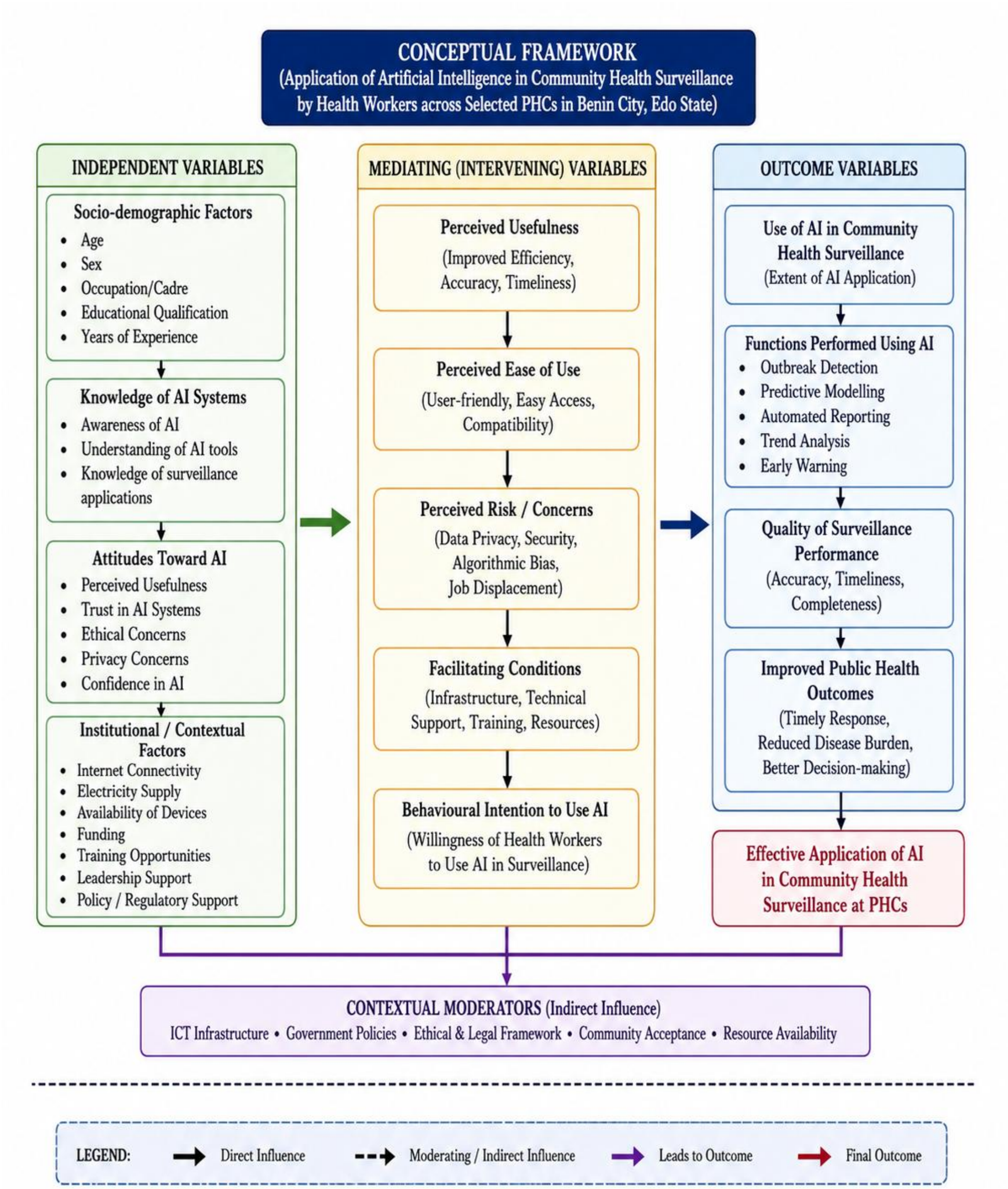

Figure 1: Conceptual Framework

2.4 POLICY FRAMEWORKS

Globally, the increasing integration of artificial intelligence into healthcare systems has led to the development of several policy frameworks aimed at regulating and guiding its ethical and effective use in disease surveillance and public health practice. One of the major international frameworks is the World Health Organization Global Strategy on Digital Health 2020–2025. This framework was developed to strengthen health systems through digital technologies and promote universal health coverage. The strategy encourages the adoption of digital innovations such as artificial intelligence, big data systems, and interoperable health information systems to improve disease surveillance, outbreak response, and healthcare delivery. The framework also emphasizes data protection, equity, ethical governance, and digital capacity building among healthcare workers.[53]

In addition, the World Health Organization Guidance on Ethics and Governance of Artificial Intelligence for Health provides ethical principles for the safe use of AI in healthcare systems. The framework highlights the importance of transparency, accountability, privacy protection, inclusiveness, and human oversight in AI implementation. It stresses that AI systems should complement rather than replace healthcare professionals in clinical and public health decision making. The policy further recommends proper regulation of AI technologies used in disease surveillance to prevent misuse, algorithmic bias, and breaches of confidentiality.[54]

Similarly, the Centers for Disease Control and Prevention Artificial Intelligence Strategy 2026–2030 was developed to improve the use of AI in disease prediction, outbreak preparedness, public health data analysis, and emergency response systems. The framework supports the development of secure AI infrastructure, workforce training, responsible AI governance, and improved surveillance systems capable of providing real time epidemiological information for effective public health interventions.[55]

At the African level, the Africa Centres for Disease Control and Prevention Digital Transformation Strategy provides a continental framework for strengthening digital health systems and epidemic intelligence across African countries. The strategy promotes the use of artificial intelligence, digital surveillance systems, electronic health records, and data analytics to improve disease monitoring and outbreak management. The framework also focuses on strengthening health information systems, internet connectivity, digital infrastructure, and workforce capacity across African healthcare systems.[56]

Furthermore, the African Union Continental Artificial Intelligence Strategy was established to guide responsible and inclusive AI development and adoption across Africa. The framework identifies healthcare and disease surveillance as major priority areas where AI technologies can improve early warning systems, predictive modelling, and public health decision making. The strategy also emphasizes ethical AI governance, innovation, local capacity building, and regional collaboration among African countries.[57]

Another important African framework is the emerging policy direction on Artificial Intelligence for Public Health Surveillance in Africa, which encourages the application of machine learning, predictive analytics, and automated reporting systems in disease surveillance activities. The framework recognizes that AI can improve timeliness, accuracy, and efficiency of outbreak detection and response despite existing infrastructural limitations within African healthcare systems.[58]

In Nigeria, the National Digital Health Strategy was developed by the Federal Ministry of Health to improve healthcare delivery through digital technologies and integrated health information systems. The strategy supports the use of digital innovations for disease surveillance, outbreak monitoring, health data management, and healthcare planning. The framework also encourages the strengthening of electronic reporting systems and digital health infrastructure across healthcare institutions in Nigeria.[59]

Nigeria has also developed the National Artificial Intelligence Strategy to promote the adoption of AI technologies across different sectors including healthcare. The framework encourages the use of AI for predictive analytics, disease surveillance, diagnostics, automated reporting, and healthcare decision support systems. It also emphasizes ethical governance, research and innovation, digital infrastructure development, and training of healthcare professionals on AI applications.[60]

In addition, Nigeria's Data Protection and Digital Health Governance policies provide legal and ethical guidelines for the safe use of digital technologies and health information systems. These frameworks focus on data privacy, confidentiality, cybersecurity, informed consent, and responsible management of patient information. Such policies are important in ensuring that AI based disease surveillance systems are implemented ethically and securely within Nigerian healthcare settings.[61]

2.5 LEVEL OF KNOWLEDGE OF DIFFERENT AI SYSTEMS AND APPLICATIONS USED IN DISEASE SURVEILLANCE PROCESS

A cross-sectional study conducted in 2020 assessed the level of knowledge of artificial intelligence (AI) in healthcare among medical doctors. The aim was to evaluate awareness and understanding of AI applications relevant to clinical practice and public health functions, including disease surveillance. The study was conducted in India among practicing doctors. The study population consisted of 100 medical doctors selected using convenience sampling. Data were collected using a structured self-administered questionnaire. The findings revealed that although a large proportion of respondents were aware of AI, the depth of knowledge regarding its specific applications, such as predictive analytics and surveillance systems, was only moderate, indicating gaps in detailed understanding of AI tools used in disease monitoring[19].

A 2023 cross-sectional study assessed knowledge and perception of AI among primary healthcare professionals. The aim was to evaluate understanding of AI as a healthcare tool, including its role in disease tracking and surveillance. The study was conducted in Central Catalonia, Spain, among primary care professionals. A sample size of 301 participants was selected using a non-probability sampling technique. Data were collected via an online questionnaire. Findings showed that while a majority (85.7%) understood the concept of AI, a significant proportion lacked formal training and detailed knowledge of its applications, particularly in real-time disease surveillance and data-driven outbreak prediction[20].

Both global studies demonstrate a consistent pattern of high awareness but limited in-depth knowledge of AI applications. However, the use of non-probability sampling techniques in both studies limits generalizability. In addition, neither study specifically focused on AI systems used in disease surveillance (e.g., HealthMap, BlueDot), indicating a gap in domain-specific knowledge assessment.

A 2024 cross-sectional study assessed awareness and knowledge of artificial intelligence among medical students. The aim was to evaluate their understanding of AI technologies and potential applications in healthcare, including disease surveillance. The study was conducted in Ghana among medical students. The study population included 302 participants selected through convenience sampling. Data were collected using structured questionnaires. The findings showed that about half of the respondents demonstrated moderate knowledge of AI, with limited understanding of its practical applications in disease surveillance systems[21].

A 2025 hospital-based cross-sectional study evaluated healthcare providers' knowledge of AI in healthcare delivery. The aim was to assess their understanding of AI applications, including surveillance and diagnostic support systems. The study was conducted in the Limbe and Buea Health Districts of Cameroon. The study population comprised 494 healthcare providers selected using multistage sampling. Data collection was carried out using structured questionnaires. The findings revealed that only 43.1% of respondents had good knowledge of AI, while a majority had poor exposure to AI training, reflecting limited understanding of AI systems used in disease surveillance and health data analysis[22].

The African studies highlight significant knowledge gaps compared to global settings, particularly in practical understanding and application of AI systems. The Cameroonian study is methodologically stronger due to its larger sample size and multistage sampling, improving representativeness. However, both studies focus broadly on AI in healthcare rather than specific surveillance technologies, suggesting that knowledge of AI in disease surveillance remains underexplored in Africa.

A nationwide cross-sectional study conducted in 2024 assessed knowledge, perception, and prospects of artificial intelligence and machine learning in healthcare. The aim was to evaluate the level of knowledge of AI among healthcare professionals, including its application in disease surveillance. The study was carried out across the six geopolitical zones of Nigeria among healthcare professionals. A large sample size was recruited using a multistage sampling technique. Data were collected using an online structured questionnaire. Findings indicated that although over half (57.2%) of respondents had good knowledge of AI and a high proportion had heard about AI applications, detailed knowledge of its use in disease surveillance systems remained limited[23].

Another 2024 cross-sectional study assessed knowledge and perception of AI among physicians in a Nigerian tertiary hospital. The aim was to evaluate awareness and practical understanding of AI applications in healthcare. The study population consisted of 110 physicians selected using convenience sampling. Data were collected using a structured questionnaire. The findings showed that while most respondents had heard of AI and were aware of its medical applications, only a small proportion had in-depth knowledge or practical experience with AI tools, including those used for disease surveillance and epidemiological monitoring[24].

The Nigerian studies reveal a pattern similar to global and African findings—high awareness but shallow knowledge. The nationwide study provides stronger external validity due to its sampling approach, while the hospital-based study offers context-specific insights but is limited by its small sample size and single-center design. Importantly, both studies fail to disaggregate knowledge by specific AI systems used in disease surveillance, leaving a critical gap in understanding system-level awareness.

2.6. ATTITUDES TOWARD THE USE OF AI MEASURES IN COMMUNITY HEALTH SURVEILLANCE

Artificial intelligence (AI) is increasingly being integrated into community health surveillance worldwide. However, attitudes toward its use vary significantly across different regions, influenced by factors such as trust in government institutions, concerns over data privacy, and perceived benefits.

A systematic review conducted in the United States assessed public perceptions of AI in healthcare, including its role in health surveillance.[9] The study analyzed 11 nationally representative surveys to understand how AI is perceived across various healthcare applications. Using a nonprobability sampling technique, the researchers collected data through secondary analysis of surveys from institutions such as the Pew Research Center and Monmouth University.[9] The findings revealed that while many Americans acknowledge the potential of AI in disease diagnosis and prediction, concerns remain regarding data privacy and algorithmic decision-making.[9] Public trust in AI varied based on the organization implementing it, with healthcare providers being more trusted than private technology companies.[1] The study highlighted the need for greater transparency in AI applications to build public confidence in AI-driven health surveillance.[9]

Across sub-Saharan Africa, attitudes toward AI-driven health surveillance are shaped by distinct socio-political and economic factors.[10] A scoping review explored knowledge, attitudes, perceptions, and preventative practices toward COVID-19 in the region, assessing how AI-driven surveillance was received.[10] The study reviewed 28 peer-reviewed and grey literature sources covering multiple African countries, including Nigeria, Ethiopia, Uganda, Rwanda, and Ghana.[10] It used a purposive sampling technique to select studies and systematically analyzed data using sources such as PubMed and the WHO library.[10] The review found that although AI-driven surveillance was recognized as a valuable tool in managing public health crises like COVID-19, attitudes toward its use varied significantly.[10] Many individuals expressed concerns about government overreach and excessive monitoring, fearing that AI technology could be misused beyond public health purposes.[10] The study concluded that public education on the benefits of AI in health surveillance, along with strong ethical guidelines, is necessary to improve trust and adoption of AI technologies.[10]

A systematic review conducted in 2023 assessed the challenges affecting implementation of Integrated Disease Surveillance and Response among health workers in Nigeria.[11] The study type was a systematic review. The study design involved systematic synthesis of studies related to disease surveillance implementation among health workers. The aim of the study was to evaluate factors affecting disease surveillance implementation in Nigeria including digital and AI based surveillance systems. The study location was Nigeria. The study population consisted of health workers and surveillance officers in Nigeria. Twenty three studies were included in the review. Purposive sampling of relevant literature from databases and grey literature was used. Data collection involved systematic literature search and thematic analysis.[11] The findings showed that many healthcare workers had positive attitudes toward digital and AI supported surveillance systems because they improved reporting speed disease monitoring and outbreak response. However negative attitudes were linked to poor training lack of technical support inadequate funding and fear of increased workload associated with digital surveillance technologies.[11]

Across international, African, and Nigerian contexts, attitudes toward AI in community health surveillance reflect varying levels of acceptance and skepticism. In developed countries like the United States, public trust in AI depends on the institutions deploying it, with greater acceptance of AI in medical diagnostics than in automated caregiving. In sub-Saharan Africa, skepticism toward AI-driven surveillance is influenced by concerns over government transparency and data misuse. In Nigeria, while AI-driven interventions hold promise for addressing public health challenges such as drug abuse, ethical considerations and privacy concerns remain significant barriers. To enhance public acceptance of AI in health surveillance, governments and health organizations must prioritize transparency, ethical regulations, and community engagement strategies.

2.7. LEVELS OF UTILIZATION AND TYPES OF AI SYSTEMS AND APPLICATIONS USED IN DISEASE SURVEILLANCE PROCESS

A comprehensive review explored the role of mathematical and computational modeling in informing outbreak response strategies, particularly regarding vaccination. This global study utilized a systematic synthesis of modeling experiences and peer-reviewed findings published in 2024. The study design focused on a systematic review and meta-synthesis of outbreak response models to determine how these tools guide contextual policy. The aim was to demonstrate how mathematical models inform various aspects of outbreak response, including surveillance, detection, and the prioritization of vaccine interventions. The study population encompassed global health systems and modeling groups involved in major infectious disease outbreaks. Data collection involved a systematic search of global infectious disease databases and collective modeling reports. The findings revealed that ML-driven mathematical models are critical for the "earliest stage" of outbreaks, providing insights into transmission dynamics and identifying reporting gaps in traditional surveillance systems[25].

Another global investigation focused on the development and validation of an automated AI mapping tool for terminology standardization in healthcare data. This study employed a multi-institutional validation design, focusing on four major healthcare institutions. The primary aim was to evaluate an LLM-assisted tool for mapping clinical data to standardized medical terminologies like SNOMED CT, which is essential for semantic interoperability in disease surveillance. The study population consisted of clinical data sets and terminology records across these institutions. Data collection was performed via an automated mapping suite that compared AI-generated codes against manual human mapping. The findings showed that AI-assisted mapping reached a top-5 accuracy of 98.7% for diagnostic mapping and reduced the overall manual workload by up to 90%. This level of automation significantly improves the efficiency of high-quality data collection for surveillance systems[26].

In the broader African context, a study evaluated the efficacy of hybrid deep learning models for forecasting infectious disease trends across various sub-Saharan countries, including South Africa and Botswana. This study utilized a retrospective quantitative analysis and predictive modeling design. The aim was to compare the performance of hybrid

Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM) models against traditional statistical methods for predicting COVID-19 infection cases. The study population included national infection data from the health ministries of Nigeria, South Africa, and Botswana. Data collection was sourced from public health laboratory reporting systems and environmental data. The findings indicated that hybrid CNN-LSTM models achieved superior accuracy scores, reaching 97.60% in South Africa and 97.74% in Botswana, demonstrating the robust potential of AI to enhance predictive accuracy by 24–47% compared to traditional surveillance[27].

A 2023 review focused on the use of machine learning to address administrative and service delivery challenges within healthcare systems, which indirectly impacts the quality of surveillance data. This study employed a comprehensive review design, aiming to classify and investigate fraudulent practices in healthcare insurance that compromise data integrity. The study population included electronic health records and insurance claim databases across regional healthcare systems. Data collection was conducted through a review of machine learning-based investigation approaches. The study found that AI algorithms are highly effective in identifying "service frauds" and "billing frauds," such as false diagnoses or unbundling of services. By ensuring the accuracy of clinical records, these AI systems provide a more reliable foundation for disease surveillance and resource allocation within African public health sectors[28].

A Nigerian study assessed the integration of Nigerian Pidgin English (NPE) into the EPIWATCH® AI surveillance system to improve early detection of outbreaks. This research used a retrospective observational and technical validation design. The aim was to enhance the early warning capacity of the system by enabling it to analyze social media and news reports written in local vernacular. The study population consisted of social media posts and open-source intelligence (OSINT) from Nigerian users during the COVID-19 pandemic and

Lassa fever outbreaks. Data collection involved scanning millions of public posts using AI algorithms to identify trends in disease symptoms. The findings revealed that traditional surveillance was often delayed compared to AI-driven OSINT, which successfully detected early signals of the West African Ebola outbreak and monitored polio eradication efforts. The inclusion of NPE was found to be critical for identifying signals in a population where only 7% of outbreak news is captured in standard English[29].

Another investigation focused specifically on the use of ML for the early detection of Lassa fever outbreaks in Nigeria. This study utilized a predictive modeling design with integrated surveillance data. The aim was to evaluate the performance of Random Forest and Boosted Random Forest algorithms in predicting outbreaks using diverse data sources. The study population included clinical records from Lassa fever-endemic regions, environmental climate data, and genomic sequences. Data collection was performed by integrating electronic health records (EHRs) with laboratory reporting systems. The findings showed that Random Forest algorithms achieved a mean accuracy of 0.85, while a Boosted Random Forest approach achieved an accuracy of 94% in predicting patient health outcomes even with imbalanced datasets. These findings suggest that AI-ready data systems could significantly transition Nigeria's surveillance from reactive to proactive detection[30].

2.8. FACTORS INFLUENCING THE USE OF AI SURVEILLANCE SYSTEMS

A global scoping literature review conducted in 2024 examined the conceptualisation and implementation of integrated disease surveillance systems globally.[31] The study design was a scoping review aimed at evaluating how integrated disease surveillance systems were operationalised and the evidence supporting their effectiveness. The study was conducted globally using published literature from several countries. The study population consisted of published studies and surveillance reports related to integrated disease surveillance systems. A total of 13 eligible studies and reviews were included after screening. Purposive sampling of published literature from databases such as Medline Embase and Epistemonikos was used. Data collection was performed through systematic literature searches and narrative synthesis. Relevant findings showed that the use of AI driven surveillance systems was influenced by the availability of digital infrastructure interoperability of health information systems adequate funding availability of trained personnel and supportive legal frameworks for data sharing. The review also revealed that inadequate technological infrastructure and fragmented health information systems reduced the effectiveness of AI applications in disease surveillance.[31]

A systematic review conducted in 2024 evaluated the use of Artificial Intelligence and Internet of Things technologies in infectious disease health monitoring.[32] The study design was a systematic review aimed at assessing recent developments implementation and effectiveness of AI and IoT systems in infectious disease surveillance and outbreak prediction. The study was global in scope and included studies from different countries. The study population consisted of peer reviewed articles related to AI and IoT applications in infectious disease monitoring. Thirty five studies were included in the final review. Purposive sampling of relevant peer reviewed studies was used. Data collection involved systematic extraction of information from selected databases. The findings revealed that factors influencing the use of AI systems in disease surveillance included data quality internet connectivity accessibility of smart devices technical expertise and government investment in digital health systems. The study also found that poor internet infrastructure and limited technical capacity negatively affected adoption and implementation of AI surveillance technologies.[32]

A systematic review conducted in 2026 assessed the use of artificial intelligence based modelling techniques in One Health related infectious disease studies in Sub Saharan Africa.[33] The study design was a systematic review aimed at evaluating the extent and effectiveness of AI modelling techniques in infectious disease surveillance and prediction within the One Health framework. The study was conducted across Sub Saharan Africa. The study population consisted of peer reviewed articles focusing on AI applications in infectious disease surveillance and prediction. Sixty two studies were included in the review. Purposive sampling of eligible articles from databases including PubMed Scopus Web of Science and IEEE Xplore was used. Data collection involved systematic review and thematic analysis. The findings showed that the use of AI systems in disease surveillance was influenced by digital connectivity availability of computational infrastructure skilled manpower and government support. The review identified that countries with stronger digital infrastructure such as South Africa Kenya Ethiopia and Tanzania had greater adoption of AI surveillance systems. Inadequate data governance shortage of AI trained professionals and weak internet connectivity were major barriers limiting the use of AI applications in surveillance processes.[33]

A systematic review conducted in 2024 examined artificial intelligence for public health surveillance in Africa. The study design was a review article aimed at investigating the applications opportunities and challenges of AI in African public health surveillance systems.[34] The study location included several African countries. The study population consisted of published literature and case studies related to AI in public health surveillance. Twenty eight articles and reports were reviewed. Purposive sampling of articles from academic databases and grey literature sources was employed. Data collection was achieved through document review and thematic analysis. The findings revealed that the major factors influencing the use of AI systems in disease surveillance included poor health information systems inadequate funding low digital literacy and insufficient policy frameworks regulating AI implementation. The review also identified that inadequate electricity supply and limited internet access reduced the effectiveness of AI based disease surveillance systems in many African countries.[34]

A scoping literature review conducted in 2023 examined the uses applications challenges and future trends of artificial intelligence in epidemiology.[35] The study design was a scoping literature review aimed at reviewing AI applications in epidemiology including epidemic outbreak tracking and disease surveillance. The study was conducted in Nigeria using published epidemiological literature. The study population consisted of articles related to AI applications in epidemiology and surveillance. Fifty published articles were included in the review. Purposive sampling of relevant publications from online databases was adopted. Data collection involved literature search and thematic synthesis. The findings showed that the use of AI systems in disease surveillance in Nigeria was influenced by inadequate funding poor internet infrastructure lack of quality epidemiological data and limited availability of AI experts. The study also identified poor awareness and limited technical knowledge among healthcare workers as major barriers to effective adoption of AI systems in disease surveillance.[35]

A systematic review conducted in 2023 evaluated the challenges affecting the implementation of Integrated Disease Surveillance and Response among health workers in Nigeria.[36] The study design was a systematic review aimed at assessing barriers affecting effective disease surveillance implementation among Nigerian health workers. The study location was Nigeria. The study population consisted of health workers and published studies related to disease surveillance implementation. Twenty studies met the inclusion criteria for the review. Purposive sampling of studies from electronic databases was used. Data collection involved systematic extraction and analysis of relevant data from selected studies. The findings revealed that inadequate training lack of computer literacy poor funding shortage of skilled manpower and weak technological infrastructure negatively influenced the use of AI and digital disease surveillance systems in Nigeria. The review also identified poor supervision irregular electricity supply and inadequate government commitment as important barriers affecting the successful integration of AI applications into disease surveillance processes.[36]

CHAPTER THREE

METHODOLOGY

3.1 STUDY AREA

This study was carried out in Benin city, Edo State, Nigeria. Edo state is one of the 36 states in Nigeria. It is located in the southern region of Nigeria, the state is bounded by Kogi state to the northeast and east, Delta state to the southeast and south, and Ondo state to the west and northwest; the River Niger flows along the state's eastern boundary and demarcate it with Anambra state.[37]

The study was conducted within the Egor and Oredo Local Government Areas (LGAs) of Edo State, Nigeria. Edo State is situated in the South-South geopolitical zone, with Benin City serving as both the state capital and the primary metropolitan hub. Together with Ikpoba-Okha, Egor and Oredo LGAs constitute the core urban population and central service-delivery area of the state. Both LGAs are located within the Edo South Senatorial District and are characterized by high population densities and socially diverse urban communities, making them critical sites for primary healthcare assessment.[37]

Oredo LGA forms the central administrative and commercial core of Benin City. It contains major public institutions, traditional and administrative landmarks, markets, schools, transport routes and residential settlements. The official Oredo Government Council website lists health centres within the LGA, confirming the presence of PHC service points within the council area.[38] Egor LGA is also within Benin metropolis and includes communities such as Uselu and other urban settlements. A PHC facility assessment carried out in a local government area in Benin City showed that PHC delivery in this setting depends on the availability of personnel, infrastructure, equipment, drugs and basic services, confirming the relevance of PHC facilities as first-level service-delivery points in the metropolis. This makes both LGAs suitable for a study involving PHC-based health workers because their PHC facilities serve densely populated and socially diverse urban communities.[39]

Primary Health Care facilities in Egor and Oredo LGAs provide frontline health services to individuals, families and communities. These services include health education, immunisation, antenatal and postnatal care, family planning, child welfare services, treatment of minor ailments, disease surveillance and notification, environmental health activities, basic record keeping, referral of complicated cases and other preventive and promotive health services.[40]

In alignment with the National Primary Health Care Development Agency's (NPHCDA) minimum standards, these Local Government Areas (LGAs) utilize a ward-based health system to provide frontline services. According to the local government registries and state health assessments, Egor LGA features 15 healthcare facilities that range from comprehensive centers to localized health posts. The major Primary Health Centres (PHCs) in this area include Uwelu, which serves as a comprehensive center, alongside Uselu I, Ugbowo, Ogida, Evbuotubu, Egor, Adolor, Uteh, Oliha, Evbareke (Uselu II), and Useh. These are further complemented by support facilities, namely the Egor Health Post, Uwelu Market Clinic, and the Oviasuyi and Iguikpe Health Posts.[41]

In Oredo LGA, the study focused on 20 primary health service points, incorporating prominent facilities operating under the Basic Health Care Provision Fund (BHCPF). The core PHCs in this district consist of Arougba, Ekiosa, Ugbor, New Era, Oko, Iyaro, Ikpema, Ulemon, Emwinyomwanru, Ekae, and Utagban. Additionally, Oredo utilizes specialized units to deliver targeted care, including the LGA Secretariat Clinic, the NPI Unit for immunization, and the Epidemiology and Surveillance Unit.[41]

The workforce within these selected PHCs is composed of diverse professional cadres essential for routine service delivery. The professional distribution within the study area includes clinical and community staff, such as Nurses and Midwives, Community Health Officers (CHOs), Community Health Extension Workers (CHEWs), and Junior Community Health Extension Workers (JCHEWs). Additionally, the facilities are supported by specialized personnel, specifically Disease Surveillance and Notification Officers (DSNOs) and Environmental Health Officers, alongside essential administrative and support staff like Medical Records Officers and Health Assistants.[42]

These specific professionals were selected for the study because they are directly involved in critical tasks such as disease detection, community mobilization, and the overall implementation of public health programs. To be eligible for inclusion in the research, these health workers must have been actively employed and working in their respective facilities for at least six months prior to the study.

3.2 STUDY DESIGN

A analytical cross-sectional study design was adopted for this study.

3.3 STUDY DURATION

The study was conducted between December 2024 and May 2026.

3.4 STUDY POPULATION

The study population comprised public health personnel involved in disease surveillance and reporting within the selected institutions in Edo State. These include:

1. Community Health Workers (CHWs)
2. Disease Surveillance and Notification Officers (DSNOs)

3. Public Health Nurses
4. Health Information Officers
5. Medical Officers involved in disease surveillance activities

These cadres are directly engaged in disease detection, data collection, reporting, analysis, and response at community, facility, and state levels.

3.5 SELECTION CRITERIA

3.5.1 Inclusion Criteria

a. All health workers involved in disease surveillance activities at the selected PHCs

b. Respondents who provide informed consent

3.5.2 Exclusion Criteria

a. Personnel who decline consent

b. Personnel unavailable throughout the data collection period

3.6 SAMPLE SIZE ESTIMATION

The minimum sample size (n) was calculated using the Cochran's formula used for descriptive studies.[43]

$$n = \frac{Z^2 pq}{d^2}$$

Where,

n = minimum sample size

Z = standard normal deviate = 1.96 at 95% confidence interval

p = prevalence of the characteristic of interest

q = 1-p

d = degree of precision desired set at 0.05

For this study, p was set at 86.5% (0.865) based on a Nigerian cross-sectional study that reported 86.5% AI use among respondents.[44]

Thus:

- p = 0.865
- q = 1 − 0.865 = 0.135
- d = 0.05

$$n = \frac{(1.96)^2 \times (0.865) \times (0.135)}{(0.05)^2}$$

$$n \approx 179$$

To account for **10% non-response**:

$$n_f = \frac{n}{1 - 0.10} = \frac{179}{0.90} \approx 199$$

However, a final sample size of 230 was used for this study.

3.7 SAMPLING TECHNIQUE

A stratified multistage sampling technique was employed to select respondents from eligible health workers involved in disease surveillance and reporting activities in selected public Primary Health Care facilities in Egor and Oredo Local Government Areas of Edo State. This design ensured both adequate geographical spread across the two LGAs and sufficient representation of all professional cadres, including those with very small numbers in the workforce.

Stage 1: Selection of Primary Health Care facilities: A comprehensive list of all public PHCs in Oredo LGA (17 facilities) and Egor LGA (11 facilities) was obtained from the Edo State Primary Health Care Development Agency (EDSPHCDA). Using simple random sampling without replacement, 14 PHCs were selected from Oredo LGA and 9 PHCs from Egor LGA, giving a total of 23 PHCs. This large proportion of facilities was chosen to maximize coverage of the urban PHC network in Benin City while maintaining the logistical feasibility of data collection.

Stage 2: Stratified random sampling of health workers within selected PHCs: Within each of the 23 selected PHCs, the staff nominal register served as the sampling frame. All eligible health workers in a facility were first stratified into five mutually exclusive occupational cadres based on their primary role in disease surveillance:

- Community Health Extension Workers (CHEWs)
- Disease Surveillance and Notification Officers (DSNOs)
- Nurses/Midwives
- Health Information Officers (HIOs)
- Medical Officers/Doctors

Because DSNOs and Medical Officers typically form very small strata in PHC settings (often one or two individuals per facility), a census approach was adopted for these two cadres: all eligible DSNOs and Medical Officers in the 23 selected PHCs were invited to participate. This ensured that their perspectives would be captured in the analysis despite their small absolute numbers. For the larger cadres (CHEWs, Nurses, and HIOs), the required number of respondents per PHC was allocated approximately in proportion to the size of each stratum in that facility, and participants were subsequently drawn by simple random sampling within each stratum.

Where a selected respondent declined participation, did not provide informed consent, or was unavailable during the data collection period, a replacement was randomly selected from the same stratum within the same PHC. This process was continued until the overall target sample size of 230 respondents was attained across all cadres and facilities.

3.8 DATA MANAGEMENT

3.8.1 Tool for Data Collection

Data were collected using a structured, self-administered questionnaire adapted from the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and standard Knowledge, Attitude, and Practice (KAP) frameworks developed to assess the application of artificial intelligence in enhancing community health surveillance systems among disease surveillance personnel in Edo State. The questionnaire consisted mainly of closed-ended questions, incorporated specific variables from current literature on Epidemic Intelligence early warning systems, and was divided into five sections (A–E).[62, 63]

3.8.2 Sections of the Questionnaire

Data were collected using a structured, self-administered questionnaire developed to assess the application of artificial intelligence in enhancing community health surveillance systems among disease surveillance personnel in Edo State. The questionnaire consisted mainly of closed-ended questions and was divided into five sections (A–E).

Section A: Socio-demographic characteristics of respondents such as age, sex, religion, marital status, cadre, rank, years of experience, and educational qualification.

Section B: Knowledge of artificial intelligence in community health surveillance, including awareness, training, meaning, applications, benefits, risks, and examples of AI tools.

Section C: Attitude towards the use of artificial intelligence in community health surveillance, assessed using Likert-scale statements on perception, confidence, trust, privacy concerns, and willingness to use AI.

Section D: Uptake and level of utilisation of artificial intelligence, including ever-use, types of tools used, areas of use, frequency, duration, and reasons for discontinuation.

Section E: Factors influencing uptake and utilisation of artificial intelligence, including training, infrastructure, workload, ethical concerns, peer influence, privacy, and funding.

3.8.3 Method of Data Collection

Data collection was conducted over four weeks from march 5th to march 31st. Respondents were briefed on the study objectives, and informed consent was obtained before questionnaire administration. Confidentiality and anonymity were assured.

3.8.4 Research Assistants

No research assistants were employed for the study. The administration of the questionnaires, data collation, and data analysis were carried out by the researchers.

3.8.5 Pretesting

The questionnaire was pre-tested among 23 healthcare workers (10% of the minimum sample size) across a few PHCs in Ovia North East Local Government Area, Edo State, who were not part of the main study. The pilot study assessed the clarity of questions, appropriateness of response options, and time required for completion. The internal consistency of the instrument was assessed using Cronbach's alpha coefficient.

3.9 DATA ANALYSIS

Data collected were entered, cleaned, and analysed using IBM Statistical Package for the Social Sciences (SPSS) version 27. Data analysis involved:

1. **Descriptive statistics**, including frequencies, percentages, means, and standard deviations, to summarise socio-demographic characteristics and responses to questionnaire items.
2. **Inferential statistics**, including chi-square tests and logistic regression analysis, to examine associations between socio-demographic variables, knowledge, attitudes, uptake, and level of utilisation of artificial intelligence in clinical support.

SCORING SYSTEM

Knowledge of Artificial Intelligence in Clinical Assessment

A total of 17 questions assessed respondents' knowledge of artificial intelligence in clinical assessment. Each correct answer was scored as 1 point, while each incorrect answer was scored as 0 points.

The total knowledge score was calculated and converted into a percentage of the maximum obtainable score. Knowledge was interpreted as follows:

- **0%–49.9%:** Poor knowledge
- **50%–100%:** Good knowledge[45]

Attitude Towards the Use of Artificial Intelligence in Clinical Assessment

Respondents' attitudes toward the use of AI in clinical support were assessed using ten questions measured on a 5-point Likert scale: Strongly agree = 5, Agree = 4, Neutral = 3, Disagree = 2, and Strongly disagree = 0.

Negatively worded statements were reverse scored to ensure consistency in directionality. Each appropriate response was given a score of 1 and inappropriate response was given a score of 0. The total attitude score was summed and converted into a percentage of the maximum obtainable score.

Attitude was interpreted as follows:

I. **0%–49.9%:** Negative attitude toward AI use in community health surveillance

II. **50%–100%:** Positive attitude toward AI use in community health surveillance[46]

Uptake and Levels of utilisation of Artificial Intelligence

Uptake of artificial intelligence was assessed using respondents' self-reported ever use of any AI-based tool in clinical assessment. Respondents were categorised as having ever used AI or as never having used AI.

Scoring and Classification of AI Utilization

The uptake and utilization levels of Artificial Intelligence (AI) in community health surveillance were evaluated using three specific items (Questions 35, 36, and 38) from Section D of the study questionnaire. The scoring criteria were delineated as follows:

- **Areas of AI Application (Question 35):** Respondents were awarded one point for each selected area of AI use in disease surveillance, yielding a maximum possible score of five points.
- **Frequency of AI Use (Question 36):** Responses indicating infrequent use ("Never," "Rarely," and "Monthly") were scored as zero points. Conversely, indications of frequent use ("Weekly" and "Daily or Almost Daily") were awarded one point, establishing a maximum of one point for this item.

- **Utilization Metrics (Question 38):** A response of "No" was assigned one point, whereas responses of "Yes" or "Not Sure" received zero points, allowing for a maximum of one point.

The cumulative maximum obtainable score across these variables was seven points. To categorize the level of AI utilization, a predefined cut-off threshold of 70% (equivalent to 4.9 out of 7 points) was established. Based on this threshold, the respondents' utilization of AI-based tools in community health surveillance was classified into two distinct tiers:

- **Good Utilization:** Respondents achieving an aggregate score between 5 and 7 points.
- **Poor Utilization:** Respondents achieving an aggregate score between 0 and 4 points.[47]

Factors Influencing use of Artificial Intelligence

Factors influencing use of AI were assessed using 10 questions. These included training, infrastructure availability, institutional support, workload, data privacy concerns, ethical considerations, peer influence, cost, and community environment.

These variables were analysed for their association with uptake of AI using inferential statistical methods such as chi-square tests and logistic regression analysis. This approach enabled the identification of key predictors of AI uptake and utilisation among healthcare professionals.

3.10 Data Presentation

Findings from the study were presented using frequency distribution tables, contingency tables, charts, and narrative descriptions. These methods facilitated clear presentation of response distributions, relationships between variables, and key trends observed in the data.

3.11 Ethical Consideration

Ethical Clearance Number: ADM/E 22/A/VOL. VII/14865491272116. Informed consent was obtained from participants before administering the questionnaire. Participant confidentiality and anonymity were ensured. Institutional permission and ethical clearance was obtained from the Health Research Ethics Committee of the University of Benin Teaching Hospital (UBTH). Informed consent was also obtained from the health facilities and respondents before administering the questionnaires. The respondents were informed that they have the right to withdraw from the study at any time, and that doing so poses no loss or harm. This ensures participant autonomy, confidentiality, and trust, which increases response rates and data authenticity. By obtaining formal ethical clearance, informed consent, and guaranteeing the right to withdraw without penalty, the study protects vulnerable health workers from coercion or harm, while also enhancing the credibility and acceptability of the research findings for publication and policy use.

3.12 Study Limitation

The study relies on self-reported data, which may introduce recall and social desirability bias. Additionally, the evolving nature of AI applications may influence respondents' understanding and reporting of AI use.

CHAPTER FOUR

RESULTS

A total of 240 questionnaires were administered, and 230 questionnaires were completed and retrieved with a 95.8% response rate. The results are presented in the following sections in line with the specific objectives.

SECTION A: Socio-demographic characteristics of respondents.

SECTION B: Knowledge of artificial intelligence in disease surveillance

SECTION C: Attitude towards the use of artificial intelligence in disease surveillance

SECTION D: Uptake, levels of use and types of artificial intelligence in disease surveillance

SECTION E: Factors influencing the use of AI systems and applications in disease surveillance

SECTION A: SOCIO-DEMOGRAPHIC CHARACTERISTICS OF RESPONDENTS

Table 1: Socio-demographic characteristics of respondents

Variables	Frequency (n = 230)	Percent
Age (years)		
25–34	53	23.0
35–44	129	56.1
≥45	48	20.9
Mean ± SD	**39.14± 5.94**	
Sex		
Female	192	83.5
Male	38	16.5
Religion		
Christianity	222	96.5
Islam	8	3.5
Ethnic group		
Benin	141	61.3
Esan	43	18.7
Igbo	22	9.6
Etsako	11	4.8
Yoruba	9	3.9
Urhobo	3	1.3
Owan	1	0.4
Marital status		
Married	201	87.4
Single	23	10.0
Widowed	6	2.6
Occupation		
Community Health Extension Worker (CHEW)	115	50.0
Health Information Officer	53	23.0
Nurse	50	21.7
Medical Officer/Doctor	8	3.5
Disease Surveillance and Notification Officer (DSNO)	4	1.7
Facility		
Oredo PHC	132	57.4
Egor PHC	98	42.6
Years of Work Experience		
>5 years	124	53.9
≤5 years	106	46.1
Mean ± SD	**6.61± 4.62**	
Highest Educational Qualification		
Diploma	135	58.7
Bachelor's degree	81	35.2
Postgraduate diploma	10	4.3
Master's degree	4	1.7

A total of 230 respondents participated in the study. Regarding age distribution, more than half of the respondents were aged 35–44 years (56.1%), followed by those aged 25–34 years (23.0%), while respondents aged 45 years and above constituted 20.9%. The majority of respondents were female (83.5%), whereas males accounted for 16.5%. Nearly all respondents were Christians (96.5%), with only a small proportion practicing Islam (3.5%).

With respect to ethnic group, Benin constituted the largest proportion of respondents (61.3%), followed by Esan (18.7%) and Igbo (9.6%), while smaller proportions were Etsako (4.8%), Yoruba (3.9%), Urhobo (1.3%), and Owan (0.4%). Regarding marital status, the overwhelming majority of respondents were married (87.4%), while a smaller proportion were single (10.0%), and only a few were widowed (2.6%).

In terms of occupation, Community Health Extension Workers (CHEWs) formed half of the respondents (50.0%), followed by Health Information Officers (23.0%) and nurses (21.7%), while only a small proportion were Medical Officers/Doctors (3.5%) and Disease Surveillance and Notification Officers (1.7%). By facility, more than half of the respondents were from Oredo Primary Health Centre (57.4%), while the remaining were from Egor Primary Health Centre (42.6%). With respect to years of work experience, slightly more than half of the respondents had more than 5 years of experience (53.9%), while 46.1% had 5 years or less. In terms of educational qualification, the majority of respondents held a diploma (post-secondary) (58.7%), followed by those with a bachelor's degree (35.2%), while only a small proportion had a postgraduate diploma (4.3%) or a master's degree (1.7%).

SECTION B: KNOWLEDGE OF ARTIFICIAL INTELLIGENCE IN DISEASE SURVEILLANCE

Table 2: Awareness and source of information about AI in disease surveillance among health workers in selected PHCs

Variables	Frequency (n = 230)	Percent
Heard of Artificial Intelligence (AI)	230	100.0
Source of Information*		
Internet	228	99.1
Social media	142	61.7
Colleague	58	25.2
Television	24	10.4
Workplace training	1	0.4
Radio	1	0.4
Journal	1	0.4

*** = Multiple response question**

All respondents (100.0%) reported having heard of Artificial Intelligence (AI). Regarding sources of information, the vast majority of respondents identified the internet (99.1%) as their primary source, followed by social media (61.7%). A smaller proportion obtained information from colleagues (25.2%) and television (10.4%), while only a negligible proportion reported workplace training (0.4%), radio (0.4%), and journals (0.4%) as sources of information.

Table 3: Knowledge of AI in disease surveillance among health workers in selected PHCs

Variables	Frequency (n = 230)	Percent
Artificial intelligence refers to		
Computer systems that can perform tasks that normally require human intelligence	179	77.8
Automated machines that function independently without any human input or supervision	30	13.0
Machines that completely replace health workers	9	3.9
Internet communication systems	6	2.6
Use of computers only for record keeping	4	1.7
General equipment that uses electricity or digital displays	2	0.9
Artificial intelligence can be used in community health surveillance to*		
Support detection and monitoring of disease trends and outbreaks	148	64.3
Replace surveillance officers completely	55	23.9
Eliminate human judgement in surveillance decisions	25	10.9
Increase reporting errors	2	0.9
Which of the following are applications of AI in public health surveillance*		
Automated anomaly detection from routine surveillance data	171	74.3
Predictive outbreak risk modelling	98	42.6
Automated reporting summaries and dashboards	61	26.5
Natural language processing (NLP) for rumours/news event-based surveillance	16	7.0
Paper-based IDSR reporting only	8	3.5
Which of the following tools are you familiar with as examples of AI or AI-assisted systems for surveillance or health work?*		
HealthMap	36	15.7
WHO EIOS	13	5.7
BlueDot	7	3.0
Health Sentinel	7	3.0
GeoPole	7	3.0
EPIWATCH	6	2.6
BlueBox	4	1.7
What is a major benefit of AI in disease surveillance		
Earlier detection and faster response to outbreaks	193	83.9
Reduced need for data quality checks	20	8.7
Guaranteed accuracy without supervision	14	6.1
Removal of confidentiality requirements	3	1.3
A known risk of AI use in public health surveillance is		
Bias or errors in algorithms leading to wrong alerts	215	93.5
Improved workflow	6	2.6
Faster data processing	5	2.2
Better documentation	4	1.7
For AI to be used safely in public health surveillance, there must be		
Ethical, legal, and data protection guidelines	180	78.3
No data protection rules	25	10.9
No human supervision	17	7.4
Complete vendor control	8	3.5

*** = Multiple response question, α=0.720**

Regarding knowledge of Artificial Intelligence (AI), more than three-quarters of respondents correctly identified it as computer systems that can perform tasks that normally require human intelligence (77.8%), while notable proportions held misconceptions, including viewing it as automated systems functioning without human input (13.0%) or machines that completely replace health workers (3.9%). In relation to its role in community health surveillance, nearly two-thirds of respondents recognized its use in supporting detection and monitoring of disease trends and outbreaks (64.3%), although some incorrectly believed it could replace surveillance officers entirely (23.9%) or eliminate human judgement (10.9%).

In terms of applications, the most commonly identified was automated anomaly detection from routine surveillance data (74.3%), followed by predictive outbreak risk modelling (42.6%) and automated reporting summaries and dashboards (26.5%), whereas only a small proportion identified natural language processing for event-based surveillance (7.0%), and a few incorrectly selected paper-based IDSR reporting (3.5%). Awareness of specific AI tools was generally low, with only a small proportion of respondents familiar with HealthMap (15.7%), and even fewer aware of WHO EIOS (5.7%), BlueDot (3.0%), Health Sentinel (3.0%), GeoPole (3.0%), EPIWATCH (2.6%), and BlueBox (1.7%).

With respect to perceived benefits, the majority of respondents identified earlier detection and faster response to outbreaks (83.9%) as a key advantage of AI in disease surveillance, while smaller proportions selected reduced need for data quality checks (8.7%), guaranteed accuracy without supervision (6.1%), or removal of confidentiality requirements (1.3%). Concerning risks, almost all respondents correctly identified bias or errors in algorithms leading to wrong alerts (93.5%), whereas only a few selected improved workflow (2.6%), faster data processing (2.2%), and better documentation (1.7%) as risks. Finally, more than three-quarters of respondents correctly identified the need for ethical, legal, and data protection guidelines for the safe use of AI in public health surveillance (78.3%), although some still held incorrect views such as absence of data protection rules (10.9%), lack of human supervision (7.4%), or complete vendor control (3.5%).

Table 4: Correctness of Knowledge on AI in disease surveillance among health workers in selected PHCs

Variables	Knowledge of AI in disease surveillance Responses (n=230) Correct (%)	Incorrect (%)
Artificial intelligence refers to		
Computer systems that can perform tasks that normally require human intelligence	179 (77.8)	51 (22.2)
Artificial intelligence can be used in community health surveillance to		
Support detection and monitoring disease trends and outbreaks	148 (64.3)	82 (35.7)
Which of the following are applications of AI in public health surveillance*		
Predictive outbreak risk modelling	98 (42.6)	132 (57.4)
Automated anomaly detection from routine surveillance data	171 (74.3)	59 (25.7)
Natural language processing (NLP) for rumours/news event-based surveillance	16 (7.0)	214 (93.0)
Paper-based IDSR reporting only	222 (96.5)	8 (3.5)
Automated reporting summaries and dashboards	61 (26.5)	169 (73.5)
Which of the following tools are you familiar with as examples of AI for surveillance*		
HealthMap	36 (15.7)	194 (84.3)
BlueDot	7 (3.0)	223 (97.0)
WHO EIOS	13 (5.7)	217 (94.3)
EPIWATCH	6 (2.6)	224 (97.4)
Health Sentinel	223 (97.0)	7 (3.0)
BlueBox	226 (98.3)	4 (1.7)
GeoPole	223 (97.0)	7 (3.0)
What is a major benefit of AI in disease surveillance		
Earlier detection and faster response to outbreaks	193 (83.9)	37 (16.1)
A known risk of AI use in public health surveillance is		
Bias or errors in algorithms leading to wrong alerts	215 (93.5)	15 (6.5)
For AI to be used safely in public health surveillance, there must be		
Ethical, legal, and data protection guidelines	180 (78.3)	50 (21.7)

*** = Multiple response question, α= 0.720**

Regarding correctness of knowledge on Artificial Intelligence (AI) in disease surveillance, more than three-quarters of respondents correctly identified AI as computer systems that can perform tasks that normally require human intelligence (77.8%), while nearly two-thirds correctly recognized its role in supporting detection and monitoring of disease trends and outbreaks (64.3%).

In terms of applications, a high proportion correctly identified automated anomaly detection from routine surveillance data (74.3%) and predictive outbreak risk modelling (42.6%), whereas only a small proportion correctly identified natural language processing for event-based surveillance (7.0%) and automated reporting summaries and dashboards (26.5%). Notably, almost all respondents correctly rejected paper-based IDSR reporting as an application of AI (96.5%).

With respect to familiarity with AI tools, correct responses were generally low for most systems, including HealthMap (15.7%), WHO EIOS (5.7%), BlueDot (3.0%), and EPIWATCH (2.6%). However, very high proportions correctly identified some listed non-AI tools as incorrect, including BlueBox (98.3%), Health Sentinel (97.0%), and GeoPole (97.0%).

Regarding benefits and risks, the majority of respondents correctly identified earlier detection and faster response to outbreaks as a major benefit (83.9%) and bias or errors in algorithms as a key risk (93.5%). Similarly, more than three-quarters correctly recognized the need for ethical, legal, and data protection guidelines for safe AI use (78.3%).

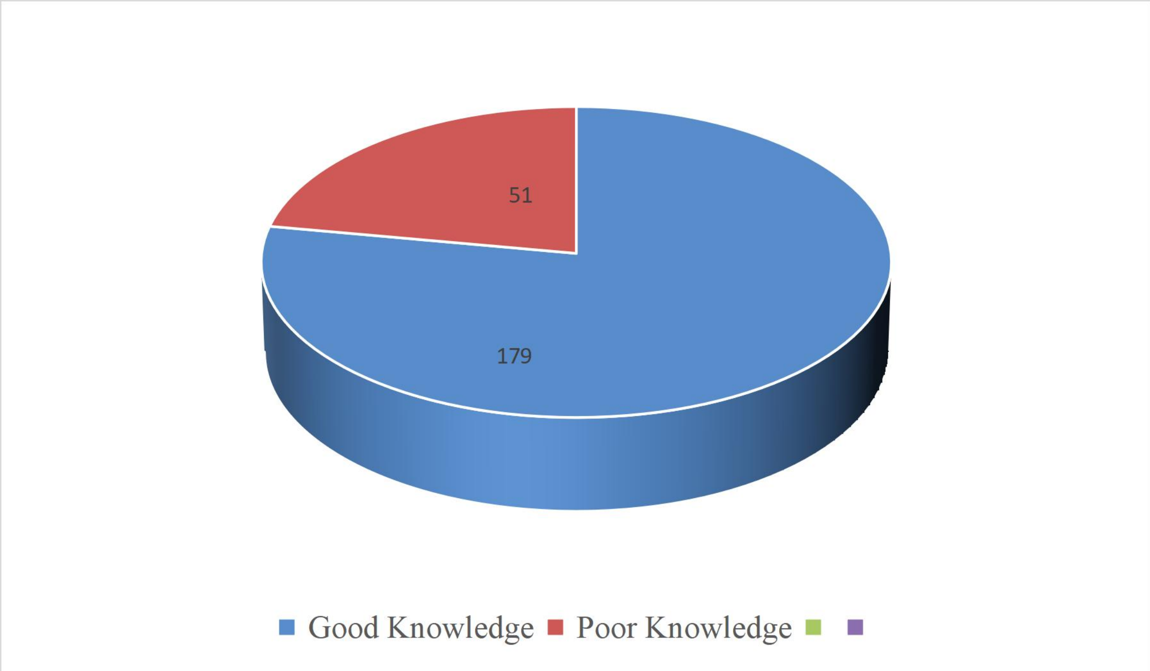

Figure 2: Level of Knowledge of AI in disease surveillance among health workers in selected PHCs

Almost four-fifth 179 (77.8%) of the respondents had good knowledge of AI in disease surveillance, while an estimated one-fifth 51 (22.2%) had poor knowledge.

Table 5: Factors associated with knowledge of AI in disease surveillance among health workers in selected PHCs

Variables	Knowledge		Test statistic	p-value
	Good (n=179) Freq(%)	poor (n=51) Freq(%)		
Age (years)				
25–34	48 (90.6)	5 (9.4)	6.523	**0.038**
35–44	96 (74.4)	33 (25.6)		
≥45	35 (72.9)	13 (27.1)		
Sex				
Male	32 (84.2)	6 (15.8)	1.075	0.300
Female	147 (76.6)	45 (23.4)		
Religion				
Christianity	175 (78.8)	47 (21.2)	3.719*	0.075
Islam	4 (50.0)	4 (50.0)		
Ethnicity				
Edo Indigene	148 (75.5)	48 (24.5)	4.121	**0.042**
Non-Edo Indigene	31 (91.2)	3 (8.8)		
Marital status				
Never married	23 (100.0)	0 (0.0)	7.281	**0.007**
Ever married	156 (75.4)	51 (24.6)		
Occupation				
CHEW	98 (85.2)	17 (14.8)	16.588*	**0.002**
DSNO	4 (100.0)	0 (0.0)		
Nurse	39 (78.0)	11 (22.0)		
Health Information Officer	35 (66.0)	18 (34.0)		
Medical Officer/Doctor	3 (37.5)	5 (62.5)		
Years of experience				
≤5 years	88 (83.0)	18 (17.0)	3.072	0.080
>5 years	91 (73.4)	33 (26.6)		
Educational qualification				
Diploma	110 (81.5)	25 (18.5)	5.848*	0.119
Bachelor's	61 (75.3)	20 (24.7)		
Postgraduate diploma	5 (50.0)	5 (50.0)		
Master's	3 (75.0)	1 (25.0)		

*Fisher's Exact Test.

With respect to age, respondents aged 25–34 years had the highest proportion with good knowledge, 48 (90.6%), compared to those aged ≥45 years, 35 (72.9%). Ethnicity was also significant, with non-Edo indigenes having a higher proportion with good knowledge, 31 (91.2%), compared to Edo indigenes, 148 (75.5%). Regarding marital status, never married respondents had a higher proportion with good knowledge, 23 (100.0%), compared to those ever married, 156 (75.4%). In terms of occupation, DSNOs and CHEWs had the highest proportions with good knowledge, 4 (100.0%) and 98 (85.2%) respectively, while the lowest was among medical officers/doctors, 3 (37.5%). These associations were statistically significant ($\chi^2 = 6.523$, $p = 0.038$; $\chi^2 = 4.121$, $p = 0.042$; $\chi^2 = 7.281$, $p = 0.007$; Fisher's exact test, $p = 0.002$). All other variables, including sex, religion, facility, years of experience, and educational qualification, were not statistically significantly associated with knowledge ($p > 0.05$).

Table 6: Predictors of Good knowledge of AI in disease surveillance among health workers in selected PHCs

Predictors	β	Odds ratio	95% CI for OR		p-value
			Lower	Upper	
Age (years)	-0.053	0.949	0.889	1.012	0.112
Sex					
Male*		1			
Female	-0.434	0.648	0.228	1.843	0.416
Religion					
Christianity*		1			
Islam	-1.976	0.139	0.026	0.751	**0.022**
Ethnicity					
Edo Indigene*		1			
Non-Edo Indigene	1.451	4.267	0.886	20.554	0.070
Marital status					
Never married*		1			
Ever married	-19.720	0.001	0.001	0.999	0.998
Occupation					
Surveillance staff*		1			
Clinical/Information staff	-0.439	0.645	0.267	1.555	0.329
Work experience					
≤5 years*		1			
>5 years	-0.449	0.638	0.319	1.278	0.205
Educational qualification					
Diploma*		1			
Bachelor's degree	-0.057	0.945	0.438	2.037	0.884
Postgraduate diploma	-0.681	0.506	0.120	2.131	0.353
Master's degree	0.016	1.016	0.083	12.420	0.990

CI = Confidence interval; **OR** = Odd ratio; *reference category; R^2 = 7.7–11.9%

Multivariate logistic regression analysis identified religion as the only independent predictor of knowledge of AI among healthcare professionals. Respondents who practiced Islam had significantly lower odds of having good knowledge of AI compared to Christians (OR = 0.139, 95% CI: 0.026–0.751, p = 0.022).

Other variables, including age, sex, ethnicity, occupation, facility, work experience, and educational qualification, were not significant predictors after adjustment.

SECTION C: ATTITUDE TOWARDS THE USE OF ARTIFICIAL INTELLIGENCE IN DISEASE SURVEILLANCE

Table 7: Attitude of health workers in selected PHCs towards the use of AI in disease surveillance

Variables		Attitudinal	responses		
	SA (n=230) Freq (%)	A (n=230) Freq (%)	N(n=230) Freq (%)	D (n=230) Freq (%)	SD (n=230) Freq (%)
Artificial intelligence can improve the quality of community health surveillance.	24 (10.4)	97 (42.2)	67 (29.1)	32 (13.9)	10 (4.3)
AI can enhance efficiency in my daily work.	25 (10.9)	98 (42.6)	63 (27.4)	32 (13.9)	12 (5.2)
I feel confident using AI tools for surveillance activities.	35 (15.2)	84 (36.5)	59 (25.7)	42 (18.3)	10 (4.3)
I trust AI systems for outbreak detection.	33 (14.3)	94 (40.9)	64 (27.8)	31 (13.5)	8 (3.5)
AI should be routinely integrated into surveillance systems.	29 (12.6)	83 (36.1)	62 (27.0)	39 (17.0)	17 (7.4)
AI may negatively affect data privacy/confidentiality.	9 (3.9)	55 (23.9)	54 (23.5)	76 (33.0)	36 (15.7)
AI threatens professional autonomy of surveillance personnel.	11 (4.8)	44 (19.1)	62 (27.0)	80 (34.8)	33 (14.3)
Training would increase willingness to use AI.	33 (14.3)	89 (38.7)	60 (26.1)	35 (15.2)	13 (5.7)
AI should support judgement of surveillance personnel.	30 (13.0)	93 (40.4)	58 (25.2)	33 (14.3)	16 (7.0)
AI should replace judgement of surveillance personnel.	16 (7.0)	44 (19.1)	49 (21.3)	83 (36.1)	38 (16.5)

***SA=Strongly Agree, A = Agree, N = Neutral, D = Disagree, SD = Strongly Disagree; α=0.745**

Regarding respondents' attitude towards the use of Artificial Intelligence (AI) in disease surveillance, more than half of respondents expressed positive perceptions of its benefits. Slightly more than half agreed that AI can improve the quality of community health surveillance (52.6%) and enhance efficiency in daily work (53.5%). Similarly, more than half expressed trust in AI systems for outbreak detection (55.2%) and agreed that AI should support the judgement of surveillance personnel (53.4%). About half of respondents also indicated that training would increase their willingness to use AI (53.0%), while slightly less than half supported routine integration of AI into surveillance systems (48.7%).

In terms of confidence, just over half of respondents reported feeling confident using AI tools for surveillance activities (51.7%), although a notable proportion remained neutral (25.7%) or expressed lack of confidence (22.6%). Concerning perceived risks, more than two-fifths of respondents disagreed that AI negatively affects data privacy and confidentiality (48.7%) and that it threatens professional autonomy (49.1%), although a considerable proportion remained neutral or expressed concern.

Furthermore, more than half of respondents rejected the notion that AI should replace the judgement of surveillance personnel, with over half disagreeing or strongly disagreeing (52.6%), while only about one-quarter expressed agreement (26.1%). Overall, these findings suggest a generally positive attitude towards AI use in disease surveillance, with respondents recognizing its supportive role while maintaining the importance of human oversight.

Table 8: Appropriateness of responses to attitudinal questions on AI use in disease surveillance among health workers in selected PHCs

Variables	Attitudinal responses Responses (n=230)	
	Appropriate (%)	Inappropriate (%)
Artificial intelligence can improve the quality of community health surveillance.	121 (52.6)	109 (47.4)
The use of AI in clinical assessment can enhance efficiency in my daily work.	123 (53.5)	107 (46.5)
I feel confident using AI-based tools to support disease surveillance activities.	119 (51.7)	111 (48.3)
I trust AI-assisted systems to support outbreak detection and trend monitoring.	127 (55.2)	103 (44.8)
AI should be routinely integrated into disease surveillance systems in Edo State.	112 (48.7)	118 (51.3)
AI may negatively affect data privacy and confidentiality.	112 (48.7)	118 (51.3)
AI use in surveillance threatens professional autonomy of surveillance personnel.	113 (49.1)	117 (50.9)
Adequate training would increase my willingness to use AI in disease surveillance.	122 (53.0)	108 (47.0)
AI should support the judgement of surveillance personnel when making public health decisions.	123 (53.5)	107 (46.5)
AI should replace the judgement of surveillance personnel when making public health decisions.	121 (52.6)	109 (47.4)

α= 0.745

Regarding the appropriateness of responses to attitudinal questions on AI use in disease surveillance, responses were relatively balanced, with a slight predominance of appropriate attitudes across most items. Slightly more than half of respondents demonstrated appropriate attitudes towards the role of AI in improving the quality of community health surveillance (52.6%), enhancing efficiency in daily work (53.5%), confidence in using AI-based tools (51.7%), and trust in AI-assisted systems for outbreak detection (55.2%). Similarly, more than half showed appropriate responses regarding the need for training to improve willingness to use AI (53.0%) and the role of AI in supporting professional judgement (53.5%).

However, appropriate responses were slightly lower for some domains, including routine integration of AI into surveillance systems (48.7%), concerns about data privacy and confidentiality (48.7%), and perceived threats to professional autonomy (49.1%), where inappropriate responses marginally predominated. Notably, just over half of respondents also gave appropriate responses rejecting the replacement of human judgement by AI (52.6%).

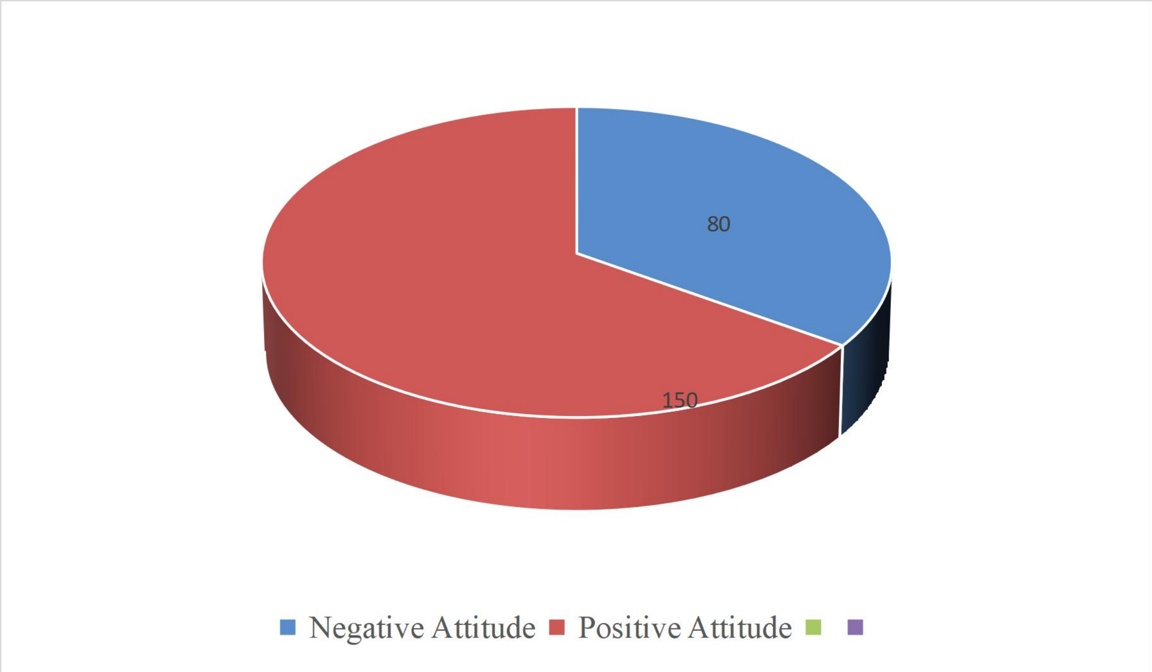

Figure 3: Attitude towards AI use in disease surveillance among health workers in selected PHCs

A little less than two-third, 150 (65.2%) of the respondents had a positive attitude towards AI use in disease surveillance, while slightly more than one-third, 80 (34.8%), had a Negative attitude.

Table 9: Factors associated with attitude towards AI use in disease surveillance among health workers in selected PHCs

Variables	Attitude towards AI use in disease surveillance		Test statistic	p-value
	Positive (n=150) Freq(%)	Negative (n=80) Freq(%)		
Age (years)				
25–34	37 (69.8)	16 (30.2)	2.060	0.357
35–44	79 (61.2)	50 (38.8)		
≥45	34 (70.8)	14 (29.2)		
Sex				
Male	29 (76.3)	9 (23.7)	2.472	0.116
Female	121 (63.0)	71 (37.0)		
Religion				
Christianity	142 (64.0)	80 (36.0)	4.420*	0.053
Islam	8 (100.0)	0 (0.0)		
Ethnicity				
Edo Indigene	128 (65.3)	68 (34.7)	0.005	0.946
Non-Edo Indigene	22 (64.7)	12 (35.3)		
Marital status				
Never married	17 (73.9)	6 (26.1)	0.852	0.356
Ever married	133 (64.3)	74 (35.7)		
Occupation				
CHEW	76 (66.1)	39 (33.9)	0.521*	0.971
DSNO	2 (50.0)	2 (50.0)		
Nurse	32 (64.0)	18 (36.0)		
Health Information Officer	35 (66.0)	18 (34.0)		
Medical Officer/Doctor	5 (62.5)	3 (37.5)		
Years of experience				
≤5 years	70 (66.0)	36 (34.0)	0.058	0.809
>5 years	80 (64.5)	44 (35.5)		
Educational qualification				
Diploma	95 (70.4)	40 (29.6)	5.589*	0.133
Bachelor's	49 (60.5)	32 (39.5)		
Postgraduate diploma	4 (40.0)	6 (60.0)		
Master's	2 (50.0)	2 (50.0)		
Knowledge level				
Poor knowledge	30 (58.8)	21 (41.2)	1.181	0.277
Good knowledge	120 (67.0)	59 (33.0)		

*Fisher's Exact Test.

All variables assessed, including age, sex, religion (Fisher's exact test), ethnicity, marital status, occupation (Fisher's exact test), facility, years of experience, educational qualification (Fisher's exact test), and knowledge level, were not statistically significantly associated with attitude towards AI use in disease surveillance ($p > 0.05$).

Table 10: Predictors of positive attitude towards AI use in disease surveillance among health workers in selected PHCs

Predictors	β	Odds ratio	95% CI for OR		p-value
			Lower	Upper	
Age (years)	0.019	1.019	0.960	1.082	0.536
Sex					
Male*		1			
Female	-0.767	0.464	0.192	1.121	0.088
Ethnicity					
Edo Indigene*		1			
Non-Edo Indigene	-0.167	0.846	0.371	1.931	0.691
Marital status					
Never Married*		1			
Ever Married	-0.434	0.648	0.221	1.896	0.428
Occupation					
Surveillance staff*		1			
Clinical/Information staff	0.285	1.330	0.622	2.847	0.462
Years of Work Experience					
≤5 years*		1			
>5 years	-0.041	0.960	0.534	1.728	0.892
Education					
Diploma*		1			
Bachelor's degree	-0.668	0.513	0.264	0.997	**0.049**
Postgraduate diploma	-1.463	0.232	0.056	0.962	**0.044**
Master's degree	-1.141	0.320	0.040	2.583	0.285
Knowledge level					
Poor knowledge*		1			
Good knowledge	0.322	1.380	0.700	2.721	0.352

CI = Confidence interval; **OR** = Odd ratio; *reference category R^2 = 25.3–38.6%

Educational level was the only statistically significant predictor of positive attitude towards AI use in disease surveillance among health workers in selected PHCs. Respondents with a bachelor's degree had significantly lower odds of a positive attitude compared to those with a diploma (OR = 0.513, 95% CI = 0.264–0.997, p = 0.049). Similarly, respondents with a postgraduate diploma had significantly lower odds of a positive attitude compared to diploma holders (OR = 0.232, 95% CI = 0.056–0.962, p = 0.044).

Although not statistically significant, females had lower odds of a positive attitude compared to males (OR = 0.464, 95% CI = 0.192–1.121, p = 0.088). Ever married respondents also had lower odds compared to those never married (OR = 0.648, 95% CI = 0.221–1.896, p = 0.428), while non-Edo indigenes had slightly lower odds compared to Edo indigenes (OR = 0.846, 95% CI = 0.371–1.931, p = 0.691).

Clinical/information staff had higher odds of a positive attitude compared to surveillance staff (OR = 1.330, 95% CI = 0.622–2.847, p = 0.462), while respondents with more than 5 years of work experience had slightly lower odds compared to those with ≤5 years of experience (OR = 0.960, 95% CI = 0.534–1.728, p = 0.892). Respondents with a master's degree also had lower odds compared to diploma holders (OR = 0.320, 95% CI = 0.040–2.583, p = 0.285). In addition, respondents with good knowledge had higher odds of a positive attitude compared to those with poor knowledge (OR = 1.380, 95% CI = 0.700–2.721, p = 0.352), although this was not statistically significant.

SECTION D: UPTAKE, LEVELS OF UTILIZATION OF ARTIFICIAL INTELLIGENCE IN DISEASE SUREVEILLANCE

Table 11: Uptake, Level of utilisation AI systems in disease surveillance among health workers in selected PHCs

Variables	Frequency (n = 230)	Percent
Ever used any AI-based tool in surveillance		
Yes	17	7.4
No	213	92.6
AI-based tools used* (n = 17)		
HealthMap	13	76.5
ChatGPT	9	52.9
WHO EIOS	4	23.5
Areas where AI has been used in disease surveillance* (n = 17)		
Report writing and situation reports	17	100.0
Trend analysis and forecasting	9	52.9
Early outbreak detection/alerts	4	23.5
Data cleaning and validation support	4	23.5
Community event-based surveillance	1	5.9
Frequency of AI use (n = 17)		
Rarely	11	64.7
Monthly	3	17.6
Weekly	2	11.8
Daily/Almost daily	1	5.9
Duration of AI use (n = 17)		
3–11 months	12	70.6
≥12 months	5	29.4
AI improves surveillance efficiency (n = 17)		
Yes	7	41.2
Not sure	10	58.8
Stopped using AI (n = 17)		
Yes	13	76.5
No	4	23.5
Reasons for discontinuing AI use* (n = 13)		
Accuracy/false alert concerns	10	76.9
Lack of institutional support	10	76.9
Technical issues	8	61.5
Poor workflow integration	8	61.5

*= Multiple response question

Regarding uptake of Artificial Intelligence (AI) in disease surveillance, only a small proportion of respondents had ever used any AI-based tool (7.4%), while the vast majority had never used such tools (92.6%). Among users (n = 17), the most commonly used tools were HealthMap (76.5%), ChatGPT (52.9%), and WHO EIOS (23.5%), with all users applying AI for report writing and situation reports (100.0%), and about half for trend analysis and forecasting (52.9%), while fewer used it for outbreak detection (23.5%), data validation (23.5%), and community event-based surveillance (5.9%).

Use was largely infrequent, with most respondents reporting rare use (64.7%), and the majority having used AI for only 3–11 months (70.6%). Less than half perceived AI as improving surveillance efficiency (41.2%), while most were uncertain (58.8%). Notably, a large proportion had discontinued use (76.5%), mainly due to concerns about accuracy or false alerts (76.9%), lack of institutional support (76.9%), technical issues (61.5%), and poor workflow integration (61.5%), indicating low uptake and limited sustained use driven by systemic and trust-related barriers.

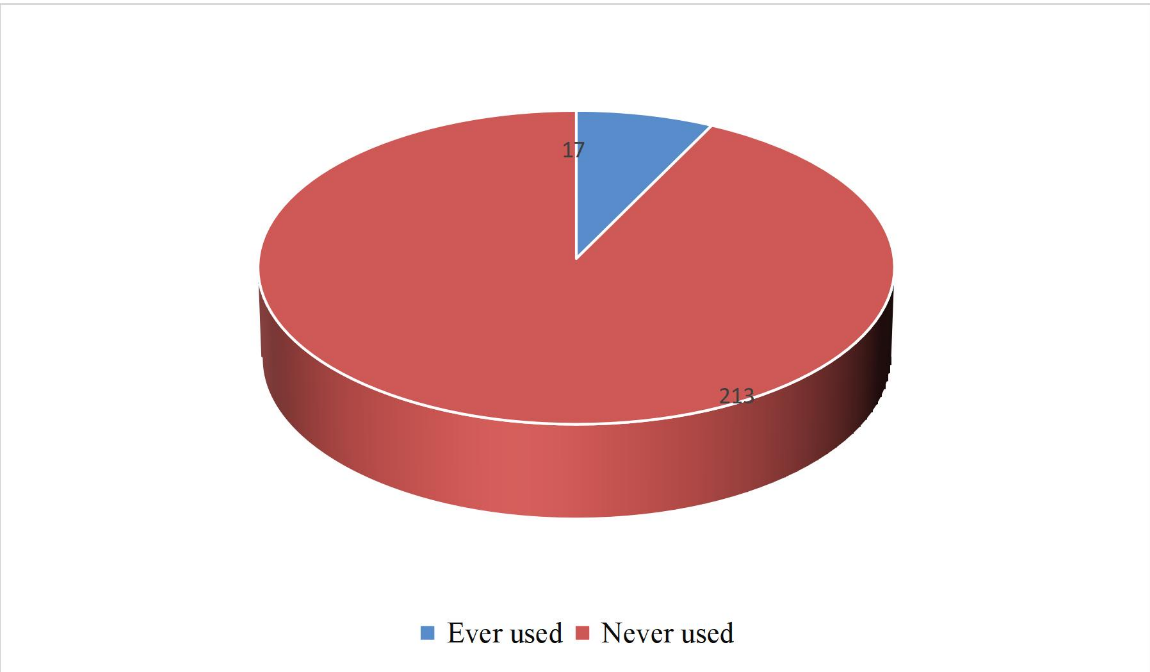

Figure 4: Uptake of AI in disease surveillance among health workers in selected PHCs

More than nine-tenth 213 (92.6%) of the respondents have never used AI in disease surveillance, while less than one-tenth, 17 (7.4%), had used AI.

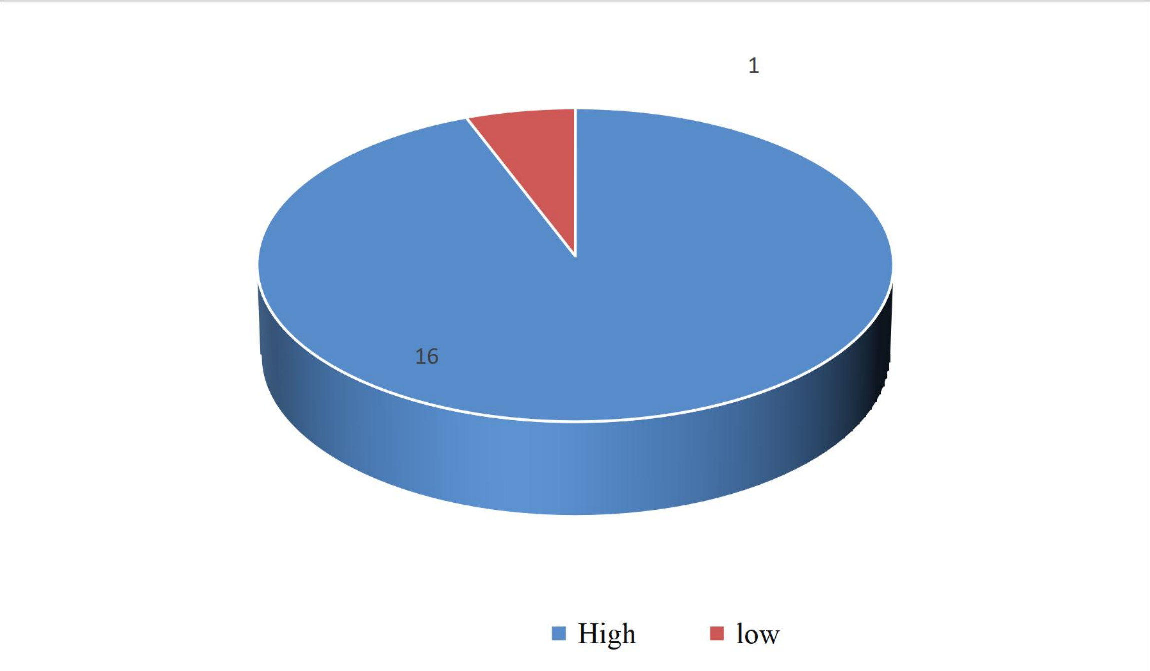

Figure 5: Level of utilisation of AI in disease surveillance among health workers in selected PHCs

Among the 17 respondents who had ever used AI in disease surveillance, more than nine-tenth, 16 (94.1%), had high utilisation, while less than one-tenth 1 (5.9%) had low utilisation.

Table 12: Factors associated with uptake of AI in disease surveillance among health workers in selected PHCs

Variables	Uptake of AI		Test statistic	p-value
	Ever used (n=17) Freq(%)	Never used (n=213) Freq(%)		
Age (years)			24.167*	**<0.001**
25–34	12 (22.6)	41 (77.4)		
35–44	5 (3.9)	124 (96.1)		
≥45	0 (0.0)	48 (100.0)		
Sex			0.301*	0.745
Male	2 (5.3)	36 (94.7)		
Female	15 (7.8)	177 (92.2)		
Religion			0.662*	>0.999
Christianity	17 (7.7)	205 (92.3)		
Islam	0 (0.0)	8 (100.0)		
Ethnicity			0.120*	0.723
Edo Indigene	14 (7.1)	182 (92.9)		
Non-Edo Indigene	3 (8.8)	31 (91.2)		
Marital status			37.610*	**<0.001**
Never married	9 (39.1)	14 (60.9)		
Ever married	8 (3.9)	199 (96.1)		
Occupation			16.261*	**0.003**
CHEW	10 (8.7)	105 (91.3)		
DSNO	2 (50.0)	2 (50.0)		
Nurse	5 (10.0)	45 (90.0)		
Health Information Officer	0 (0.0)	53 (100.0)		
Medical Officer/Doctor	0 (0.0)	8 (100.0)		
Years of experience			1.198	0.274
≤5 years	10 (9.4)	96 (90.6)		
>5 years	7 (5.6)	117 (94.4)		
Educational qualification			1.303*	0.729
Diploma	10 (7.4)	125 (92.6)		
Bachelor's degree	7 (8.6)	74 (91.4)		
Postgraduate diploma	0 (0.0)	10 (100.0)		
Master's degree	0 (0.0)	4 (100.0)		
Knowledge level			5.230*	**0.016**
Poor knowledge	0 (0.0)	51 (100.0)		
Good knowledge	17 (9.5)	162 (90.5)		
Attitude level			1.025	0.311
Negative	4 (5.0)	76 (95.0)		
Positive	13 (8.7)	137 (91.3)		

*Fisher's Exact Test.

With respect to age, respondents aged 25–34 years had the highest uptake of AI, 12 (22.6%), while no uptake was observed among those ≥45 years. Marital status was also significant, with never married respondents having a higher uptake, 9 (39.1%), compared to ever married, 8 (3.9%). In terms of occupation, DSNOs had the highest uptake, 2 (50.0%), while no uptake was observed among health information officers and medical officers/doctors. Regarding knowledge level, uptake was observed only among those with good knowledge, 17 (9.5%), with none among those with poor knowledge. These associations were statistically significant (Fisher's exact test, $p < 0.001$; $p < 0.001$; $p = 0.003$; $p = 0.016$).

All other variables, including sex, religion, ethnicity, facility, years of experience, educational qualification, and attitude level, were not statistically significantly associated with AI uptake ($p > 0.05$).

Table 13: Predictors of uptake of AI in disease surveillance among health workers in selected PHCs

Predictors	β	Odds ratio	95% CI for OR Lower	Upper	p-value
Age (years)	-0.232	0.793	0.669	0.940	**0.008**
Sex					
Male*		1			
Female	0.978	2.659	0.387	18.267	0.320
Religion					
Christianity*		1			
Islam	-16.976	0.000	0.000	.	0.999
Ethnicity					
Edo Indigene*		1			
Non-Edo Indigene	-0.217	0.805	0.150	4.315	0.800
Marital status					
Never married*		1			
Ever married	-1.718	0.179	0.046	0.696	**0.013**
Occupation					
Surveillance staff*		1			
Clinical/Information staff	0.257	1.293	0.229	7.311	0.771
Staff rank					
Junior staff*		1			
Senior staff	-0.640	0.527	0.154	1.809	0.309
Level of education					
Diploma*		1			
Bachelor's degree	1.116	3.052	0.635	14.670	0.164
Postgraduate diploma	-15.127		0.000		
Master's degree	-55.169		0.000		
Knowledge level					
Poor knowledge*		1			
Good knowledge	17.830	553.629	0.000	.	0.997
Attitude level					
Negative attitude*		1			
Positive attitude	0.664	1.942	0.491	7.678	0.344

CI = Confidence interval; **OR** = Odd ratio; *reference category R^2 = 5.4–7.8%

Age and marital status were statistically significant predictors of uptake of AI in disease surveillance among health workers in selected PHCs. For each additional year of age, respondents had significantly **lower odds** of AI uptake (OR = 0.793, 95% CI = 0.669–0.940, p = 0.008). Similarly, ever married respondents had significantly **lower odds** of uptake compared to those never married (OR = 0.179, 95% CI = 0.046–0.696, p = 0.013). All other variables, including sex, religion, ethnicity, occupation, staff rank, level of education, knowledge level, and attitude level, were not statistically significant predictors (p > 0.05).

Table 14: Factors associated with level of utilisation of AI in disease surveillance among health workers in selected PHCs

Variables	Level of Utilisation of AI		Test statistic	P-value
	High(n=16) Freq(%)	Low(n=214) Freq(%)		
Age (years)				
25–34	11 (20.8)	42 (79.2)	21.070*	**<0.001**
35–44	5 (3.9)	124 (96.1)		
≥45	0 (0.0)	48 (100.0)		
Sex				
Male	2 (5.3)	36 (94.7)	0.001*	>0.999
Female	14 (7.3)	178 (92.7)		
Religion				
Christianity	16 (7.2)	206 (92.8)	0.587*	>0.999
Islam	0 (0.0)	8 (100.0)		
Ethnicity				
Edo Indigene	13 (6.6)	183 (93.4)	0.136*	0.713
Non-Edo Indigene	3 (8.8)	31 (91.2)		
Marital status				
Never married	8 (34.8)	15 (65.2)	37.041*	**<0.001**
Ever married	8 (3.9)	199 (96.1)		
Occupation				
CHEW	9 (7.8)	106 (92.2)	16.860*	**0.002**
DSNO	2 (50.0)	2 (50.0)		
Nurse	5 (10.0)	45 (90.0)		
Health Information Officer	0 (0.0)	53 (100.0)		
Medical Officer/Doctor	0 (0.0)	8 (100.0)		
Years of experience				
≤5 years	9 (8.5)	97 (91.5)	0.343	0.558
>5 years	7 (5.6)	117 (94.4)		
Educational qualification				
Diploma	9 (6.7)	126 (93.3)	1.420*	0.701
Bachelor's degree	7 (8.6)	74 (91.4)		
Postgraduate diploma	0 (0.0)	10 (100.0)		
Master's degree	0 (0.0)	4 (100.0)		
Knowledge level				
Poor knowledge	0 (0.0)	51 (100.0)	5.001*	**0.026**
Good knowledge	16 (8.9)	163 (91.1)		
Attitude level				
Negative	4 (5.0)	76 (95.0)	0.336	0.562
Positive	12 (8.0)	138 (92.0)		

*Fisher's Exact Test.

With respect to age, respondents aged 25–34 years had the highest proportion with high utilisation of AI, 11 (20.8%), while no high utilisation was recorded among those aged 45 years and above. Marital status was also significantly associated, with never married respondents having a substantially higher proportion of high utilisation, 8 (34.8%), compared to ever married respondents, 8 (3.9%). In terms of occupation, DSNOs had the highest proportion of high utilisation, 2 (50.0%), while no high utilisation was observed among health information officers or medical officers/doctors. Regarding knowledge level, high utilisation was recorded only among respondents with good knowledge, 16 (8.9%), with none among those with poor knowledge. These associations were statistically significant (χ^2 = 21.070, $p < 0.001$; Fisher's Exact Test, $p < 0.001$; Fisher's Exact Test, $p = 0.002$; Fisher's Exact Test, $p = 0.026$). All other variables, including sex, religion, ethnicity, facility, years of experience, educational qualification, and attitude level, were not statistically significantly associated with level of AI utilisation ($p > 0.05$).

Table 15: Predictors of high level of utilisation of AI in disease surveillance among health workers in selected PHCs

Predictors	β	Odds ratio	95% CI for OR Lower	Upper	p-value
Age (years)	-0.229	0.795	0.661	0.957	**0.015**
Sex					
Male*		1			
Female	0.931	2.537	0.363	17.742	0.341
Religion					
Christianity*		1			
Islam	-16.842	0.000	0.000	.	0.999
Ethnicity					
Edo Indigene*		1			
Non-Edo Indigene	-0.189	0.828	0.152	4.506	0.826
Marital status					
Never married*		1			
Ever married	-1.827	0.161	0.041	0.630	**0.009**
Occupation					
Surveillance staff*		1			
Clinical/Information staff	0.194	1.214	0.281	5.240	0.795
Years of Work Experience					
≤5 years*		1			
>5 years	-0.587	0.556	0.152	2.032	0.375
Level of education					
Diploma*		1			
Bachelor's degree	0.569	1.767	0.290	10.767	0.537
Postgraduate diploma	-2.501	0.082	0.000		
Master's degree	-33.087		0.000		
Knowledge level					
Poor knowledge*		1			
Good knowledge	17.511	402	0.000	.	0.998
Attitude level					
Negative attitude*		1			
Positive attitude	0.591	1.806	0.448	7.278	0.408

CI = Confidence interval; OR = Odd ratio; *reference category; R^2 = 20.1–36.4%

Age and marital status were statistically significant predictors of high level of utilisation of AI in disease surveillance among health workers in selected PHCs. For each additional year of age, respondents had significantly lower odds of high AI utilisation (OR = 0.795, 95% CI = 0.661–0.957, p = 0.015). Similarly, ever married respondents had significantly lower odds of high utilisation compared to those never married (OR = 0.161, 95% CI = 0.041–0.630, p =

0.009). All other variables, including sex, religion, ethnicity, occupation, years of work experience, level of education, knowledge level, and attitude level, were not statistically significant predictors ($p > 0.05$).

SECTION E: ADDITIONAL FACTORS INFLUENCING THE USE AI IN DISEASE SURVEILLANCE

Table 16: Factors influencing the use of AI in disease surveillance

Variables	Frequency (n = 230)	Percent
Unclear ethical guidelines limit AI use		
Yes	160	69.6
No	70	30.4
AI tools would enhance efficiency in surveillance reporting		
Yes	214	93.0
No	16	7.0
AI tools are easy to learn and use		
Yes	101	43.9
No	129	56.1
AI tools integrate smoothly into surveillance systems		
Yes	81	35.2
No	149	64.8
Community trust influences willingness to use AI		
Yes	121	52.6
No	109	47.4
Colleagues' use influences adoption		
Yes	213	92.6
No	17	7.4
Adequate infrastructure is available for AI use		
Yes	1	0.4
No	229	99.6
High workload limits AI use		
Yes	118	51.3
No	112	48.7
Institutional training is available for AI use		
Yes	0	0.0
No	230	100.0
Data privacy concerns limit AI use		
Yes	154	67.0
No	76	33.0
Cost or lack of funding limits AI use		
Yes	230	100.0
No	0	0.0

Regarding factors influencing the use of Artificial Intelligence (AI) in disease surveillance, the majority of respondents identified several key barriers and facilitators. Most respondents agreed that AI tools would enhance efficiency in surveillance reporting (93.0%) and that colleagues' use influences adoption (92.6%), while just over half indicated that community trust (52.6%) and high workload (51.3%) also affect AI use.

However, significant barriers were identified, including cost or lack of funding (100.0%), absence of institutional training (100.0%), and lack of adequate infrastructure (99.6%). Additionally, more than two-thirds reported that unclear ethical guidelines (69.6%) and data privacy concerns (67.0%) limit AI use. Furthermore, over half of respondents indicated that AI tools are not easy to learn (56.1%) and do not integrate smoothly into existing surveillance systems (64.8%). Overall, these findings highlight that despite strong perceived benefits, AI adoption is largely constrained by systemic, technical, and organizational challenges.

Table 17: Association between Factors influencing and uptake of AI in disease surveillance among health workers in selected PHCs

Variables	Uptake of AI		Test statistic	p-value
	Ever used (n=17) Freq(%)	Never used (n=213) Freq(%)		
Unclear ethical guidelines limit AI use				
No	9 (12.9)	61 (87.1)	4.392	**0.036**
Yes	8 (5.0)	152 (95.0)		
AI enhances efficiency				
No	0 (0.0)	16 (100.0)	1.372*	0.241
Yes	17 (7.9)	197 (92.1)		
AI tools are easy to learn and use				
No	0 (0.0)	129 (100.0)	23.446	**<0.001**
Yes	17 (16.8)	84 (83.2)		
AI integrates smoothly into surveillance systems				
No	0 (0.0)	149 (100.0)	33.767	**<0.001**
Yes	17 (21.0)	64 (79.0)		
Community trust influences AI use				
No	9 (8.3)	100 (91.7)	0.227	0.634
Yes	8 (6.6)	113 (93.4)		
Colleague use influences adoption				
No	2 (11.8)	15 (88.2)	0.513*	0.474
Yes	15 (7.0)	198 (93.0)		
Adequate infrastructure available				
No	16 (7.0)	213 (93.0)	12.584*	**<0.001**
Yes	1 (100.0)	0 (0.0)		
High workload limits AI use				
No	13 (11.0)	105 (89.0)	4.654	**0.031**
Yes	4 (3.6)	108 (96.4)		
Data privacy concerns limit AI use				
No	2 (2.6)	74 (97.4)	3.757	0.053
Yes	15 (9.7)	139 (90.3)		

*Fisher's Exact Test.

The proportion of respondents with uptake of AI was higher among those who reported that unclear ethical guidelines did not limit use (12.9%) compared to those who reported that it did (5.0%), and this association was statistically significant ($\chi^2 = 4.392$, $p = 0.036$). Uptake was also significantly higher among those who reported that AI tools were easy to learn and use (16.8%) compared to those who did not (0.0%) ($\chi^2 = 23.446$, $p < 0.001$), and among those who reported smooth integration of AI into surveillance systems (21.0%) compared to those who did not (0.0%) ($\chi^2 = 33.767$, $p < 0.001$). Similarly, respondents who reported availability of adequate infrastructure had markedly higher uptake (100.0%) compared to those without (7.0%) (Fisher's Exact Test, $p < 0.001$). Uptake was also lower among those who reported that high workload limits AI use (3.6%) compared to those who did not (11%), and this was statistically significant ($\chi^2 = 4.654$, $p = 0.031$).

All other factors, including perceived efficiency of AI (Fisher's Exact Test, $p = 0.241$), community trust ($p = 0.634$), colleague influence (Fisher's Exact Test, $p = 0.474$), and data privacy concerns ($p = 0.053$), were not statistically significantly associated with uptake ($p > 0.05$).

Table 18: Predictors of uptake among factors influencing use of AI in disease surveillance among health workers in selected PHCs

Predictors	β	Odds ratio	95% CI for OR Lower	Upper	p-value
Unclear ethical guidelines limit AI use					
No*		1			
Yes	-1.799	0.165	0.044	0.623	**0.008**
AI enhances efficiency					
No*		1			
Yes	-2.944	0.053	0.000	3207.1	0.600
AI tools are easy to learn and use					
No*		1			
Yes	1.924	6.852	0.260	180.3	0.249
AI integrates smoothly into surveillance systems					
No		1			
Yes	4.504	90.400	4.530	1803.9	**0.003**
Community trust influences AI use					
No*		1			
Yes	-1.416	0.243	0.065	0.906	**0.035**
Colleague use influences adoption					
No*		1			
Yes	-1.988	0.137	0.009	2.089	0.153
Adequate infrastructure available					
No*		1			
Yes	3.363	28.882	0.275	3027.8	0.157
High workload limits AI use					
No*		1			
Yes	0.123	1.131	0.343	3.728	0.840
Data privacy concerns limit AI use					
No*		1			
Yes	0.870	2.387	0.557	10.238	0.241

CI = Confidence interval; **OR** = Odd ratio; *reference category R^2 = 22.2%–54.1%

Unclear ethical guidelines, smooth integration of AI into surveillance systems, and community trust were statistically significant predictors of uptake of AI in disease surveillance among health workers in selected PHCs. Respondents who reported that unclear ethical guidelines limit AI use had significantly **lower odds** of uptake compared to those who did not (OR = 0.165, 95% CI = 0.044–0.623, p = 0.008). Similarly, respondents who reported that community trust influences AI use had significantly **lower odds** of uptake (OR = 0.243, 95% CI = 0.065–0.906, p = 0.035). In contrast, respondents who stated that AI integrates smoothly into surveillance systems had significantly **higher odds** of uptake compared to those who did not (OR = 90.400, 95% CI = 4.530–1803.900, p = 0.003).

Although not statistically significant, respondents who perceived AI tools as easy to learn and use had higher odds of uptake (OR = 6.852, 95% CI = 0.260–180.300, p = 0.249), while those who reported adequate infrastructure availability also had higher odds (OR = 28.882, 95% CI = 0.275–3027.800, p = 0.157). Respondents who reported that colleague use influences adoption had lower odds of uptake (OR = 0.137, 95% CI = 0.009–2.089, p = 0.153), although this was not statistically significant.

High workload limiting AI use (OR = 1.131, 95% CI = 0.343–3.728, p = 0.840), data privacy concerns (OR = 2.387, 95% CI = 0.557–10.238, p = 0.241), and perception that AI enhances efficiency (OR = 0.053, 95% CI = 0.000–3207.100, p = 0.600) were also not statistically significant predictors. Overall, all variables apart from unclear ethical guidelines, smooth integration into surveillance systems, and community trust were not statistically significant predictors ($p > 0.05$).

Table 19: Association between Factors influencing and level of utilisation of AI in disease surveillance among healthcare workers in selected PHC

Variables	Level of utilisation of AI		Test statistic	p-value
	High (n=16) Freq(%)	Low (n=217) Freq(%)		
Unclear ethical guidelines limit AI use				
No	8 (11.4)	62 (88.6)	4.392	0.093
Yes	8 (5.0)	152 (95.0)		
AI tools would enhance efficiency				
No	0 (0.0)	16 (100.0)	1.237*	0.610
Yes	16 (7.5)	198 (92.5)		
AI tools are easy to learn and use				
No	0 (0.0)	129 (100.0)	21.964	**<0.001**
Yes	16 (15.8)	85 (84.2)		
AI tools integrate smoothly into surveillance systems				
No	0 (0.0)	149 (100.0)	31.633	**<0.001**
Yes	16 (19.8)	65 (80.2)		
Community trust influences AI use				
No	8 (7.3)	101 (92.7)	0.047	0.828
Yes	8 (6.6)	113 (93.4)		
Colleagues' use influences adoption				
No	2 (11.8)	15 (88.2)	0.520*	0.335
Yes	14 (6.6)	199 (93.4)		
Adequate infrastructure available				
No	15 (6.6)	214 (93.4)	14.073*	0.070
Yes	1 (100.0)	0 (0.0)		
High workload limits AI use				
No	3 (2.7)	109 (97.3)	6.172	**0.013**
Yes	13 (11.0)	105 (89.0)		
Data privacy concerns limit AI use				
No	1 (1.3)	75 (98.7)	5.580	**0.018**
Yes	15 (9.7)	139 (90.3)		

*Fishers exact test

The proportion of respondents with high level of utilisation of AI was significantly higher among those who reported that AI tools are easy to learn and use (15.8%) compared to those who did not (0.0%) ($\chi^2 = 21.964$, $p < 0.001$), and among those who reported smooth integration of AI into surveillance systems (19.8%) compared to those who did not (0.0%) ($\chi^2 = 31.633$, $p < 0.001$). Similarly, high utilisation was significantly more frequent among those who reported that high workload limits AI use (11.0%) compared to those who did not (2.7%) ($\chi^2 = 6.172$, $p = 0.013$), and among those who reported data privacy concerns (9.7%) compared to those who did not (1.3%) ($\chi^2 = 5.580$, $p = 0.018$). All other factors, including unclear ethical guidelines ($p = 0.093$), perceived efficiency of AI (Fisher's Exact Test, $p = 0.610$), community trust ($p = 0.828$), colleague influence (Fisher's Exact Test, $p = 0.335$), and adequate infrastructure (Fisher's Exact Test, $p = 0.070$), were not statistically significantly associated with level of AI utilisation ($p > 0.05$).

Table 20: Predictors of level of utilisation among factors influencing use of AI in disease surveillance

Predictors	β	Odds ratio	95% CI for OR Lower	Upper	p-value
Unclear ethical guidelines limit AI use					
No*		1			
Yes	-1.509	0.221	0.061	0.807	**0.022**
AI enhances efficiency					
No*		1			
Yes	-2.577	0.076	0.000	644.9	0.577
AI tools are easy to learn and use					
No*		1			
Yes	1.605	4.979	0.182	136.5	0.342
AI integrates smoothly into surveillance systems					
No		1			
Yes	4.249	70.005	3.522	1391.6	**0.005**
Community trust influences AI use					
No*		1			
Yes	-1.017	0.362	0.101	1.291	0.117
Colleague use influences adoption					
No*		1			
Yes	-1.950	0.142	0.009	2.181	0.161
Adequate infrastructure available					
No*		1			
Yes	2.615	13.674	0.200	936.5	0.225
High workload limits AI use					
No*		1			
Yes	-0.187	0.829	0.255	2.699	0.756
Data privacy concerns limit AI use					
No*		1			
Yes	1.362	3.905	0.824	18.500	0.086

CI = Confidence interval; **OR** = Odd ratio; *reference category R^2 = 20.3–51.1%

Unclear ethical guidelines and smooth integration of AI into surveillance systems were statistically significant predictors of level of utilisation of AI in disease surveillance. Respondents who reported that unclear ethical guidelines limit AI use had significantly lower odds of high utilisation compared to those who did not (OR = 0.221, 95% CI = 0.061–0.807, p = 0.022). In contrast, respondents who reported that AI integrates smoothly into surveillance systems had significantly higher odds of high utilisation compared to those who did not (OR = 70.005, 95% CI = 3.522–1391.600, $p = 0.005$).

Although not statistically significant, respondents who reported that data privacy concerns limit AI use had higher odds of high utilisation (OR = 3.905, 95% CI = 0.824–18.500, $p = 0.086$), while those who stated that community trust influences AI use had lower odds (OR = 0.362, 95% CI = 0.101–1.291, $p = 0.117$). Similarly, respondents who reported that colleague use influences adoption had lower odds of high utilisation (OR = 0.142, 95% CI = 0.009–2.181, $p = 0.161$), while those who stated that adequate infrastructure was available had higher odds (OR = 13.674, 95% CI = 0.200–936.500, $p = 0.225$), although these associations were not statistically significant.

Respondents who perceived AI tools as easy to learn and use had higher odds of high utilisation (OR = 4.979, 95% CI = 0.182–136.500, $p = 0.342$), whereas those who reported that high workload limits AI use had lower odds (OR = 0.829, 95% CI = 0.255–2.699, $p = 0.756$). AI enhancing efficiency was also not a statistically significant predictor (OR = 0.076, 95% CI = 0.000–644.900, $p = 0.577$). Overall, all variables apart from unclear ethical guidelines and smooth integration into surveillance systems were not statistically significant predictors ($p > 0.05$).

CHAPTER FIVE

5.1 DISCUSSION, RECOMMENDATION, CONCLUSION

This study assessed the application of artificial intelligence in community health surveillance among health workers in selected Primary Health Centres in Benin City, Edo State. The discussion is presented in line with the specific objectives of the study.

The socio-demographic characteristics of the respondents provide an important background for interpreting the findings. The study population was largely made up of mature frontline health workers, with most respondents being female, married, diploma-trained, and having several years of work experience. Community Health Extension Workers formed the largest occupational group, followed by Health Information Officers and nurses, while doctors and Disease Surveillance and Notification Officers were few. This pattern reflects the structure of PHC service delivery in Nigeria, where routine disease notification, health education, immunization activities, and community-level data reporting are mainly carried out by mid-level health workers rather than specialist physicians. The implication is that any AI-based surveillance intervention introduced at PHC level must be designed primarily around the cadres who already perform routine surveillance functions. Training programmes that focus only on doctors or senior officers would miss the main workforce responsible for generating and transmitting surveillance data. This finding is similar to a Nigerian digital-health adoption study conducted among healthcare workers, where adoption of digital health tools was strongly shaped by cadre, training background, and enabling work conditions.[49] It is also similar to a Nigerian qualitative study conducted among consultant doctors across five tertiary hospitals, which showed that institutional role and exposure to innovation strongly influenced AI adoption behaviour.[48]

This study found that more than three-quarters of respondents had good knowledge of AI in disease surveillance. This is an encouraging finding because knowledge is a necessary foundation for the acceptance and safe use of AI tools in surveillance. The high level of knowledge may be explained by the fact that all respondents had heard of AI, with the internet and social media serving as the dominant sources of information. It may also be related to the increasing visibility of AI in health, education, communication, and public discourse. However, the knowledge observed in this study appeared stronger at the general level than at the practical surveillance-specific level. Respondents understood the broad meaning of AI, its role in early detection, its usefulness in outbreak monitoring, and the need for ethical safeguards, but familiarity with specific AI surveillance tools such as HealthMap, WHO EIOS, BlueDot, and EPIWATCH remained poor. This suggests that awareness of AI has not yet translated into operational competence in disease surveillance. The implication is that PHC workers may be able to describe AI in general terms but may not yet be prepared to apply AI tools confidently in routine surveillance work. This finding is similar to a 2024 nationwide Nigerian study conducted among healthcare professionals, where general knowledge of AI was fairly good but detailed understanding of its practical application in surveillance remained limited.[23] It is also similar to a 2025 study conducted in Cameroon among healthcare providers, where knowledge of AI in healthcare was still limited despite increasing awareness.[22] In contrast, a 2023 study conducted in Spain among primary healthcare professionals reported higher conceptual understanding of AI, although formal training and practical surveillance-specific competence were still limited.[20]

The pattern of knowledge in this study shows that the major gap is not complete ignorance of AI, but shallow and uneven understanding of its application in surveillance. This is important because disease surveillance requires more than casual knowledge of digital tools. Health workers need to understand how AI detects abnormal trends, supports early warning signals, improves reporting, assists forecasting, and still requires human verification. If this deeper knowledge is lacking, AI may either be underused or used inappropriately. This finding is similar to a 2024 African study conducted among medical students in Ghana, where respondents demonstrated moderate knowledge of AI but limited understanding of its practical health applications.[21] It is also similar to a Nigerian tertiary hospital study conducted among physicians, where most respondents had heard of AI but only a small proportion had practical experience with AI tools.[24] The implication is that future training should move beyond general sensitization and focus on practical, tool-specific AI literacy for disease surveillance.

Age, ethnicity, marital status, and occupation were significantly associated with knowledge of AI in disease surveillance. Younger respondents, never-married respondents, non-Edo indigenes, CHEWs, and DSNOs demonstrated better knowledge. A probable explanation is that younger workers may have greater exposure to digital platforms and may be more willing to learn from online sources. The better knowledge among CHEWs and DSNOs may be because these cadres are closer to routine surveillance reporting and may more readily appreciate tools that support disease monitoring. However, the weak knowledge among doctors should be interpreted carefully because doctors formed only a small proportion of the sample. The finding may therefore reflect their limited representation in PHC surveillance activities rather than poor knowledge among doctors generally. The implication is that AI readiness is not evenly distributed across cadres, and training should be targeted according to occupational role and existing exposure. This finding is similar to a Nigerian qualitative study conducted across tertiary hospitals, where AI familiarity was shaped by professional role and day-to-day relevance of AI to the worker’s duties.[48]

On further analysis, religion was the only independent predictor of good knowledge. Respondents who practiced Islam were less likely to have good knowledge compared with

Christians. This finding should be interpreted with caution because the number of Muslim respondents was very small. It is unlikely that religion itself directly determines AI knowledge. More likely, this result reflects sample imbalance or differences in access to information, social exposure, or training opportunities within the study population. The implication is that AI education should be inclusive and should not assume equal exposure among all groups of health workers. This finding is partly similar to a Nigerian digital-health adoption study, where contextual and enabling factors were more important than individual demographic characteristics alone in determining readiness for digital health use.[49]

This study found that about two-thirds of respondents had a positive attitude towards AI use in disease surveillance. This suggests that most health workers were receptive to AI as a supportive tool in community health surveillance. Respondents generally believed that AI could improve surveillance quality, enhance efficiency, support outbreak detection, and strengthen professional judgement. This positive attitude may be due to the perceived usefulness of AI in reducing delays, improving reporting, and supporting decision-making. However, the attitude was not uniformly strong. Some respondents remained uncertain about routine integration, data privacy, professional autonomy, and their own confidence in using AI tools. This shows that although respondents were generally open to AI, they still had reasonable concerns about how it would be used in practice. The implication is that positive attitude alone will not guarantee adoption unless concerns about safety, confidentiality, training, and human oversight are addressed. This finding is similar to a Nigerian study conducted among consultant doctors across tertiary hospitals, where respondents acknowledged the benefits of AI but expressed concerns about privacy, regulation, errors, and over-reliance on technology.[48] It is also similar to an African review on AI in infectious disease surveillance, where AI was viewed as promising but limited by ethical, technical, and governance concerns.[33]

The finding that more than half of respondents rejected the idea that AI should replace the judgement of surveillance personnel is particularly important. It shows that health workers were more comfortable with AI as a support system than as a replacement for human decision-making. This is appropriate in public health surveillance because AI-generated alerts require human interpretation, field verification, ethical judgement, and contextual understanding. The implication is that AI implementation in PHCs should be presented as a decision-support tool, not as a system that removes the role of trained health workers. This finding is similar to international evidence showing that healthcare workers are more willing to accept AI when it supports professional judgement rather than replacing human responsibility. It is also consistent with the Technology Acceptance Model used in this study, where perceived usefulness and trust influence acceptance.

None of the socio-demographic variables was significantly associated with attitude at the bivariate level. This suggests that positive or negative attitude towards AI was not strongly determined by age, sex, occupation, marital status, or knowledge level when considered separately. However, level of education emerged as an independent predictor, with respondents who had bachelor’s degree and master’s degree showing lower likelihood of positive attitude compared with diploma-trained respondents. This may appear surprising, but it is understandable. More highly educated respondents may be more aware of the ethical, technical, legal, and governance risks associated with AI. They may therefore be more cautious and less likely to accept AI uncritically. This does not necessarily mean that they are resistant to innovation; rather, their attitude may reflect a more critical understanding of the requirements for safe implementation. This finding is similar to a Nigerian tertiary hospital study where more professionally exposed respondents recognized both the opportunities and risks of AI in healthcare.[38] The implication is that AI advocacy should not be limited to promoting benefits. It should also provide evidence, guidelines, demonstrations, and safeguards that address the concerns of more critical health workers.

This study found that uptake of AI in disease surveillance was very low, as less than one-tenth of respondents had ever used any AI-based tool for surveillance-related work. This is one of the most important findings of the study because it shows a clear gap between knowledge, attitude, and actual practice. Although many respondents knew about AI and many had a positive attitude, very few had used it in surveillance. A probable reason is that AI has not been formally integrated into routine PHC surveillance systems in the study area. Use appeared to be driven mainly by individual exposure and self-initiated experimentation rather than institutional deployment. This finding has serious public health implications. If AI remains at the level of awareness without actual uptake, its expected benefits for early outbreak detection, faster reporting, trend analysis, and improved response will not be realized at community level. This finding is similar to a 2024 review conducted across sub-Saharan Africa, which reported that AI-based bio surveillance remains limited by weak infrastructure, poor data systems, and low implementation capacity.[50] It is also similar to a Nigerian digital-health adoption study, where actual adoption was influenced by perceived usefulness, ease of use, infrastructure, and institutional support.[49]

Among the few respondents who had ever used AI tools, HealthMap, ChatGPT, and WHO EIOS were the main tools reported. These tools were used mostly for report writing, situation reports, trend analysis, and forecasting, while use for early outbreak detection, data cleaning, and community event-based surveillance was limited. This suggests that respondents were more comfortable using AI for low-risk supportive tasks than for direct outbreak detection or surveillance decision-making. A probable reason is that report writing and trend analysis are less risky and easier to experiment with, while outbreak detection requires stronger technical competence, reliable data, institutional approval, and trust in system accuracy. The implication is that AI use in these PHCs is still at an early and informal stage. This finding is similar to a 2023 African scoping review on natural language processing technologies for public health, which found that AI tools in African public health settings remain fragmented and are often not fully integrated into formal health systems.[51] In contrast, global studies from better-resourced settings have reported wider use of AI for automated disease monitoring, terminology mapping, outbreak modelling, and decision support.[25],[26] The difference may be explained by stronger infrastructure, better funding, clearer governance systems, and more established digital health ecosystems in those settings.

Age, marital status, occupation, and knowledge level were significantly associated with uptake of AI. Younger respondents, never-married respondents, DSNOs, and respondents with good knowledge were more likely to have used AI. This pattern suggests that AI uptake depends on a combination of digital confidence, role relevance, and basic knowledge. Younger workers may be more willing to experiment with new digital tools, while DSNOs are more directly involved in surveillance and may therefore see AI as more relevant to their work. The absence of uptake among respondents with poor knowledge is also expected, as health workers are unlikely to use tools they do not understand. The public health implication is that AI uptake will remain low if knowledge-building is not combined with practical opportunity and role-specific exposure. This finding is similar to a Nigerian digital-health adoption study where perceived usefulness and enabling conditions influenced whether healthcare workers moved from awareness to actual use.[49]

Age and marital status were the independent predictors of uptake. Younger and never-married respondents were more likely to have used AI tools. This may reflect greater digital flexibility, more frequent online engagement, and more willingness to experiment with new technologies. Ever-married respondents may have had less time for self-directed digital exploration because of work and household responsibilities. However, this should not be interpreted as a biological or fixed difference. Rather, it shows that when AI adoption depends on personal effort instead of institutional training, uptake will naturally concentrate among workers with greater time, confidence, and digital exposure. The implication is that PHC surveillance programmes should not depend on spontaneous individual adoption. AI onboarding should be structured, supervised, and accessible to all cadres and age groups. This finding is similar to a Nigerian implementation study where contextual realities strongly influenced who could adopt AI in low-resource settings.[52]

With respect to level of utilisation, most of the few respondents who had ever used AI had high utilisation. This finding is important but must be interpreted cautiously because the number of AI users was small. It suggests that once health workers begin to use AI tools, they may apply them across several surveillance-related tasks. However, this high utilisation does not mean that AI use was widespread or sustained in the PHCs. The evidence of occasional use, short duration of use, and frequent discontinuation shows that utilisation was still fragile. In practical terms, the finding indicates that AI has potential for deeper engagement among users, but the system does not yet support long-term, routine use. The implication is that increasing uptake alone is not enough. The real goal should be sustained utilisation within routine surveillance workflows. This finding is similar to a 2024 sub-Saharan African biosurveillance review, where AI showed potential but sustained use was limited by weak infrastructure, poor integration, and inadequate implementation capacity.[50] It is also similar to a 2023 African public health technology review, where digital tools often remained at pilot or fragmented stages rather than becoming routine practice.[51]

The high level of utilisation among the few users also suggests that early adopters can become important champions for AI use in PHC surveillance. Younger and never-married respondents were more likely to have high utilisation, which mirrors the pattern observed for uptake. A probable reason is that the same characteristics that encourage first-time use may also encourage more frequent or broader use once the tools are accessed. However, relying only on younger or self-motivated users would create unequal adoption across the workforce. The implication is that early adopters should be used strategically as peer mentors, but responsibility for AI implementation should remain institutional. Facility managers and surveillance coordinators should identify workers who already use AI tools and involve them in peer learning, demonstrations, and supervised pilot activities. This finding is similar to digital adoption literature showing that peer influence and visible use by colleagues can support uptake when institutional conditions are favourable.[49]

This study also found that discontinuation of AI use was common among those who had ever used AI. Reported reasons included concerns about accuracy or false alerts, lack of institutional support, technical difficulties, poor workflow integration, and confidentiality concerns. This finding shows that initial interest in AI does not guarantee sustained utilisation. Health workers may try AI tools but abandon them when the tools are unreliable, difficult to use, unsupported, or poorly integrated into daily reporting systems. The public health implication is that unsustained AI use cannot improve surveillance outcomes. For AI to strengthen community health surveillance, it must be embedded into existing reporting systems, supported by supervision, and guided by clear protocols. This finding is similar to a 2024 African review which reported that AI implementation in infectious disease surveillance is constrained by technical capacity, governance gaps, and weak organisational support.[33] It is also similar to a sub-Saharan African bio surveillance review where fragmented systems and weak infrastructure limited sustainable use.[50]

This study found that the factors influencing the use of artificial intelligence in disease surveillance were predominantly systemic, organizational, and infrastructural rather than purely individual factors. Although the overwhelming majority of respondents believed that AI could enhance efficiency in surveillance reporting and acknowledged that colleagues' use could influence adoption, actual uptake and utilisation remained poor because the enabling conditions necessary for implementation were largely absent. The most frequently identified barriers were lack of institutional training, inadequate infrastructure, cost and funding limitations, unclear ethical guidelines, poor integration into existing surveillance systems, and data privacy concerns. These findings suggest that respondents were not resistant to AI because they doubted its usefulness, but because the operational environment required for safe and practical implementation was weak. The implication is that willingness alone cannot drive AI adoption in PHC surveillance settings if structural readiness is lacking.

The finding that almost all respondents identified lack of infrastructure and absence of institutional training as barriers highlights the major implementation gap facing AI-supported surveillance within PHCs. AI systems depend heavily on stable internet connectivity, digital reporting systems, electricity supply, technical support, and trained personnel. In settings where these basic requirements are absent, uptake is likely to remain limited regardless of how useful the technology appears. The absence of institutional training is particularly important because it suggests that most respondents had acquired their AI knowledge informally through the internet and social media rather than through structured professional education. This may partly explain why awareness of AI was high while practical familiarity with surveillance-specific AI tools remained poor. The implication for public health practice is that AI integration into disease surveillance cannot be sustained through self-learning alone. Structured institutional capacity-building and investment in digital infrastructure will be necessary before AI can become part of routine surveillance practice. This finding is similar to a 2024 review conducted across sub-Saharan Africa on AI-based biosurveillance, which identified weak digital infrastructure, fragmented health information systems, and inadequate workforce capacity as major barriers to implementation.[50] It is also similar to a Nigerian digital-health adoption study conducted among healthcare workers, where institutional readiness and enabling conditions strongly influenced uptake of digital innovations.[49]

More than two-thirds of respondents reported that unclear ethical guidelines and data privacy concerns limited AI use in disease surveillance. This finding is important because surveillance systems involve sensitive health information, outbreak alerts, population-level data, and decisions that can affect entire communities. In the absence of clear rules regarding confidentiality, accountability, human oversight, and responsible use of AI-generated outputs, health workers may be reluctant to adopt such tools even when they perceive them as useful. A probable explanation is that respondents were uncertain about the legal and ethical implications of AI use in surveillance activities, particularly in a setting where formal guidance on AI governance is limited. The implication is that ethical governance is central to AI adoption and not merely an additional consideration. If health workers do not trust that AI systems are safe, regulated, and professionally defensible, uptake is likely to remain poor. This finding is similar to a Nigerian study conducted among consultant doctors in tertiary hospitals, where concerns regarding data privacy, regulation, and ethical accountability strongly shaped attitudes toward AI in healthcare.[48] It is also similar to an African review on AI use in infectious disease surveillance, which emphasized that governance and ethical safeguards are critical determinants of adoption across low-resource settings.[33]

This study also found that more than half of respondents believed that AI tools were difficult to learn and did not integrate smoothly into existing surveillance systems. This suggests that respondents perceived AI systems as potentially disruptive to routine workflow rather than as tools that naturally fit into existing reporting structures. A probable reason may be the continued reliance on paper-based or semi-digital reporting systems within PHCs, where advanced digital integration is still limited. Health workers may therefore view AI as technically complex, unfamiliar, or difficult to combine with current surveillance procedures.

The implication is that AI implementation strategies should prioritize simplicity, compatibility, and gradual integration into routine workflow. AI systems that increase complexity or disrupt reporting patterns are less likely to be accepted by frontline surveillance personnel. This finding is similar to a 2023 study conducted in Nigeria among healthcare workers, where perceived ease of use and compatibility with existing systems influenced acceptance of digital health technologies.[49] It is also consistent with the Technology Acceptance Model, which proposes that perceived ease of use significantly affects technology adoption behaviour.

At bivariate level, uptake of AI was significantly associated with unclear ethical guidelines, ease of learning, smooth integration into surveillance systems, availability of infrastructure, and workload. Respondents who perceived AI tools as easy to learn and well integrated into surveillance systems were more likely to have used them. This finding is understandable because health workers are more likely to experiment with tools that appear accessible, practical, and relevant to their daily duties. Similarly, the strong association between infrastructure availability and uptake reflects the reality that digital technologies cannot function effectively without the required technical environment. The finding that uptake was lower among respondents who perceived workload as a limiting factor suggests that heavy routine responsibilities may discourage workers from experimenting with unfamiliar technologies. The implication is that AI uptake is shaped not only by perceived usefulness but also by practical feasibility within routine work settings. This finding is similar to a Nigerian digital-health adoption study where ease of use, enabling infrastructure, and workload significantly influenced actual adoption of digital technologies among healthcare workers.[49]

On multivariate analysis, unclear ethical guidelines, smooth integration into surveillance systems, and community trust emerged as independent predictors of uptake. Respondents who perceived unclear ethical guidelines as a limitation had significantly lower odds of AI uptake, while those who believed AI integrated smoothly into surveillance systems had markedly higher odds of uptake. This reinforces the idea that health workers are unlikely to adopt technologies that appear ethically uncertain or operationally disruptive. The finding regarding community trust is also important because disease surveillance activities occur within community settings where trust influences cooperation, information sharing, and acceptance of public health interventions. Health workers may therefore hesitate to use AI tools if they believe communities may distrust automated systems or fear misuse of health information. The implication is that successful AI implementation in surveillance will require both institutional trust among health workers and public trust within communities. This finding is similar to an African review conducted on AI-supported surveillance during infectious disease outbreaks, where public trust and governance were identified as key determinants of adoption.[33]

With respect to level of utilisation, respondents who perceived AI tools as easy to learn and well integrated into surveillance systems were significantly more likely to demonstrate high utilisation. This suggests that sustained use of AI depends heavily on usability and compatibility with existing workflow. Once health workers become comfortable with AI tools and perceive them as fitting naturally into their duties, they are more likely to engage with them repeatedly across multiple surveillance-related tasks. The implication is that long-term utilisation requires more than initial exposure; it requires systems that are practical, accessible, and capable of supporting routine surveillance work without creating additional complexity. This finding is similar to digital adoption evidence from low-resource settings where sustained technology use was strongly influenced by simplicity and workflow integration.[49]

Interestingly, respondents who reported that workload and data privacy concerns limited AI use were more likely to demonstrate high utilisation at bivariate level. This finding may appear contradictory initially, but it likely reflects the fact that individuals who had actually used AI tools were more aware of the operational challenges and privacy implications associated with them. In contrast, respondents who had never used AI may have lacked sufficient practical exposure to recognize these concerns. The implication is that actual users of AI may develop more realistic and critical perceptions of both the benefits and limitations of these technologies. This finding highlights the importance of providing practical implementation support rather than relying solely on theoretical sensitization.

On multivariate analysis, unclear ethical guidelines and smooth integration into surveillance systems remained the only independent predictors of high utilisation. Respondents who believed that AI systems integrated smoothly into surveillance activities had significantly higher odds of high utilisation, while those who perceived unclear ethical guidance had lower odds. These findings reinforce the central importance of governance and operational compatibility in sustaining AI use. The implication is that even when health workers initially adopt AI, long-term utilisation is unlikely to persist if systems remain poorly regulated, ethically uncertain, or difficult to integrate into routine reporting structures. This finding is similar to a 2024 sub-Saharan African review on AI-based biosurveillance, which concluded that sustainable utilisation depends heavily on governance structures, technical integration, and institutional support systems.[50]

Overall, the findings from this study demonstrate that the major barriers to AI uptake and utilisation in disease surveillance are not lack of perceived usefulness or outright rejection by health workers, but deficiencies in infrastructure, governance, training, workflow integration, and institutional readiness. Health workers in selected PHCs in Benin City generally recognize the potential benefits of AI in surveillance, but the health system has not yet created the conditions necessary for routine adoption and sustained utilisation. The findings therefore suggest that strengthening ethical governance, improving infrastructure, ensuring smooth integration into existing surveillance systems, and providing institutional training should be prioritized before large-scale implementation of AI-supported surveillance can be successfully achieved within PHC settings in Edo State.

5.2 CONCLUSION

With respect to knowledge of artificial intelligence in disease surveillance, more than three-quarters of the respondents had good knowledge, while less than one-quarter had poor knowledge. Age, ethnicity, marital status, and occupation were significantly associated with knowledge level, while religion was the only independent predictor on multivariate analysis, with respondents who practiced Islam having lower odds of good knowledge compared to Christians.

With respect to attitude towards artificial intelligence in disease surveillance, about two-thirds of the respondents had a positive attitude, while about one-third had a negative attitude. No variable showed a statistically significant association with attitude at the bivariate level. However, educational level was the only independent predictor on multivariate analysis, with respondents who had degree-level education or above showing lower odds of a positive attitude compared to those with diploma-level education.

With respect to uptake of artificial intelligence in disease surveillance, less than one-tenth of the respondents had ever used any artificial intelligence tool, while more than nine-tenths had never used such tools. Uptake was significantly associated with age, marital status, occupation, and knowledge level. Age and marital status were the independent predictors on multivariate analysis, with younger and never-married respondents being more likely to have used artificial intelligence.

With respect to level of utilisation, among the few respondents who had ever used artificial intelligence tools, the majority (94.1%) had high utilisation based on the composite scoring of areas of use, frequency of use, and discontinuation. However, use was mostly occasional and short-lived overall. Most had used such tools for less than one year, and discontinuation of use was common. Age and marital status were the independent predictors of high utilisation on multivariate analysis, with younger and never-married respondents being more likely to have high utilisation.

With respect to factors influencing uptake and utilisation, infrastructural deficits, lack of institutional training, unclear ethical guidelines, funding constraints, poor workflow integration, and data privacy concerns were identified as the main barriers to AI use. Ethical concerns were the only independent predictor on multivariate analysis, with respondents who reported unclear ethical guidelines having significantly lower odds of having used artificial intelligence.

Overall, the study shows that while knowledge and attitude towards artificial intelligence in disease surveillance are reasonably favourable among health workers in primary healthcare settings, actual uptake and sustained use remain very low, driven largely by strong system-level barriers that must be addressed if AI is to contribute meaningfully to disease surveillance in this context.

5.3 RECOMMENDATION

Recommendations to the Federal Ministry of Health and National Regulatory Bodies

1. The Federal Ministry of Health should develop clear national ethical and operational guidelines on the use of artificial intelligence in disease surveillance, including standards on data privacy, confidentiality, accountability, and human oversight.
2. The Federal Ministry of Health should incorporate AI-supported surveillance strategies into the Integrated Disease Surveillance and Response (IDSR) framework and other national digital health policies.
3. National health training institutions and regulatory bodies should incorporate AI literacy, digital surveillance, and AI governance into the training curriculum of public health workers, nurses, CHEWs, and surveillance personnel.

Recommendations to Edo State Ministry of Health and Local Health Authorities

1. The Edo State Ministry of Health and Edo State Primary Health Care Development Agency should organize regular practical workshops on AI applications in disease surveillance, focusing on outbreak detection tools, predictive modelling, dashboards, and event-based surveillance systems.
2. State and local health authorities should begin phased implementation of simple AI-supported surveillance tools within PHCs, starting with low-risk functions such as report generation, trend analysis, and surveillance dashboards.
3. State and local governments should improve internet connectivity, electricity supply, and availability of digital devices required for AI-supported surveillance activities within PHCs.

Recommendations to Health Facilities and Surveillance Coordinators

1. PHC managers and surveillance coordinators should integrate supervised AI use into routine surveillance activities rather than relying on individual experimentation.
2. Health facilities should establish continuous technical support, supportive supervision, and peer-learning systems to encourage sustained use of AI tools in surveillance work.
3. Health facility managers should ensure that AI tools introduced into surveillance activities align with existing reporting systems and daily workflow to minimize disruption and improve acceptance.

Recommendations to Health Workers

1. Health workers should actively participate in AI-related training programmes and seek opportunities to improve their competence in digital surveillance tools.
2. Health workers should use AI as a supportive decision-making tool while maintaining professional judgement, ethical responsibility, and human verification during surveillance activities.

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APPENDIX I
QUESTIONNIARE
DEPARTMENT OF PUBLIC HEALTH AND COMMUNITY MEDICINE
UNIVERSITY OF BENIN, BENIN CITY

APPLICATION OF ARTIFICIAL INTELLIGENCE IN ENHANCING COMMUNITY HEALTH SURVEILLANCE SYSTEMS AMONG DISEASE SURVEILLANCE PERSONNEL IN EDO STATE

Dear Respondent,

I am a student of the University of Benin conducting a research project to assess the knowledge, attitude, and utilisation of artificial intelligence (AI) in community health surveillance systems among personnel involved in disease surveillance activities in Edo State. Kindly complete this questionnaire. All responses will be treated with strict confidentiality and used solely for academic purposes.

Thank you for your cooperation.

1. Age (in years): _____________
2. Sex: Male ( ) Female ( )
3. Religion: Christianity ( ) Islam ( ) African Traditional Religion ( ) Others (Specify) ________
4. Ethnic group: Benin ( ) Esan ( ) Etsako ( ) Igbo ( ) Yoruba ( ) Urhobo ( ) Others (specify)_____________
5. Marital Status: Single ( ) Married ( ) Widowed ( ) Cohabiting ( ) Divorced ( ) Separated ( )
6. Occupation/Professional Cadre:
   Community Health Extension Worker (CHEW) ( )
   Disease Surveillance and Notification Officer (DSNO) ( )
   Environmental Health Officer (EHO) ( )
   Community Health Officer ( )
   Health Information Officer ( )
   Medical Officer/Doctor ( )
   Others (Specify) ______________________
7. Designation (in current employment): ______________
8. Facility/Organisation (tick one):
   Primary Health Care Centre (Oredo LGA) ( )
   University of Benin Teaching Hospital (UBTH) ( )
   Central Hospital, Benin City ( )
   Edo State Ministry of Health (ESMOH) ( )
   Edo State Primary Health Care Development Agency (EDSPHCDA) ( )
   Others (Specify) ______________________
9. Staff Rank: Junior staff ( ) Senior staff ( )
10. Years of Work Experience (in current employment): __________
11. Highest Educational Qualification:
    Diploma (Post-secondary) ( ) Bachelor’s degree ( )
    Postgraduate diploma ( ) Master’s degree ( ) Fellowship ( ) Doctorate (PhD) ( ) Others (specify)_____________

SECTION B: KNOWLEDGE OF ARTIFICIAL INTELLIGENCE (AI) IN COMMUNITY HEALTH SURVEILLANCE

12. Have you heard of the term Artificial Intelligence (AI) before? (a) Yes ( ) (b) No ( )

If No, skip to Section C (Question 23)

13. If Yes, what is your source of information? (Select all that apply)
    (a) Television ( ) (b) Social media ( ) (c) Colleagues ( ) (d) Internet ( )
    (e) Workplace training/seminars ( ) (f) Radio ( ) (g) Journal ( ) (h) Others (Specify) ______
14. Have you received any formal training on artificial intelligence or digital health tools relevant to surveillance?
    Yes ( ) No ( )
15. If Yes, When ____________________
16. Artificial intelligence refers to (Single response question):
    (a) Computer systems that can perform tasks that normally require human intelligence ( )
    (b) Machines that completely replace health workers ( )
    (c) Use of computers only for record keeping ( )
    (d) Internet communication systems ( )
    (e) Automated machines that function independently without any human input or supervision ( )
    (f) General equipment that uses electricity or digital displays ( )
17. Artificial intelligence can be used in community health surveillance to (Single response question):
    (a) Support detection and monitoring of disease trends and outbreaks ( )
    (b) Replace surveillance officers completely ( )
    (c) Eliminate human judgement in surveillance decisions ( )
    (d) Increase reporting errors ( )
18. Which of the following are applications of AI in public health surveillance? (Select all that apply)
    (a) Predictive outbreak risk modelling ( )
    (b) Automated anomaly detection from routine surveillance data ( )
    (c) Natural language processing (NLP) for rumours/news event-based surveillance ( )
    (d) Paper-based IDSR reporting only ( )
    (e) Automated reporting summaries and dashboards ( )
19. Which of the following tools are you familiar with as examples of AI or AI-assisted systems for surveillance or health work? (Select all that apply)
    (a) HealthMap ( )
    (b) BlueDot ( )
    (c) WHO EIOS ( )
    (d) EPIWATCH ( )
    (e) Health Sentiel ( )
    (f) BlueBox ( )
    (g) GeoPole ( )
20. What is a major benefit of AI in disease surveillance? (Single response question):
    (a) Earlier detection and faster response to outbreaks ( )
    (b) Reduced need for data quality checks ( )

(c) Removal of confidentiality requirements ( )
(d) Guaranteed accuracy without supervision ( )

21. A known risk of AI use in public health surveillance is (Single response question):
    (a) Bias or errors in algorithms leading to wrong alerts ( )
    (b) Faster data processing ( )
    (c) Improved workflow ( )
    (d) Better documentation ( )
22. For AI to be used safely in public health surveillance, there must be (Single response question):
    (a) Ethical, legal, and data protection guidelines ( )
    (b) No human supervision ( )
    (c) No data protection rules ( )
    (d) Complete vendor control ( )

SECTION C: ATTITUDE TOWARDS THE USE OF ARTIFICIAL INTELLIGENCE IN COMMUNITY HEALTH SURVEILLANCE

Please pick one answer per row, where SA = strongly agree, A = agree, N = Neutral, D = disagree, SD = strongly disagree

S/N	STATEMENT	SD	D	N	A	SA
23	Artificial intelligence can improve the quality of community health surveillance.					
24	The use of AI in clinical assessment can enhance efficiency in my daily work.					
25	I feel confident using AI-based tools to support disease surveillance activities.					
26	I trust AI-assisted systems to support outbreak detection and trend monitoring.					
27	AI should be routinely integrated into disease surveillance systems in Edo State.					
28	I am concerned that AI use may negatively affect data privacy and confidentiality.					
29	AI use in surveillance threatens professional autonomy of surveillance personnel.					
30	Adequate training would increase my willingness to use AI in disease surveillance..					
31	AI should support the judgement of surveillance personnel when making public health decisions.					
32	AI should replace the judgement of surveillance personnel when making public health decisions.					

SECTION D: UPTAKE AND LEVEL OF UTILISATION OF ARTIFICIAL INTELLIGENCE IN COMMUNITY HEALTH SURVEILLANCE

Instruction: Please tick the option that best applies to you.

33. Have you ever used any artificial intelligence (AI)–based tool to support your disease surveillance duties (e.g., reporting, analysis, outbreak monitoring, data summarisation)?
    Yes ( )   No ( )
    If No, skip to Section E (Question 41)
34. Which of the following AI-based tools have you used to support disease surveillance work? (Select all that apply)
    (a) HealthMap ( )
    (b) BlueDot ( )
    (c) WHO EIOS ( )
    (d) EPIWATCH ( )
    (e) EWORS analytics ( )
    (f) Epitweetr ( )
    (g) VetWiz 2.0 ( )
    (h) Others (specify)____________
35. In which areas of disease surveillance have you used AI-based tools? (Select all that apply)
    (a) Early outbreak detection/alerts ( )
    (b) Trend analysis and forecasting ( )
    (c) Data cleaning and validation support ( )
    (d) Report writing and situation reports ( )
    (e) Community event-based surveillance ( )
36. How often do you use AI-based tools in your surveillance work?
    (a) Never ( ) (b) Rarely ( ) (c) Monthly ( ) (d) Weekly ( ) (e) Daily/Almost daily ( )
37. For how long have you been using AI-based tools in your surveillance work?
    _________ (Months)
38. Has the use of AI-based tools improved your efficiency or quality of surveillance work?
    Yes ( )   No ( )   Not sure ( )
39. Have you ever stopped using an AI-based tool after initial use?
    Yes ( )   No ( )
    If No, skip to Question .
40. If Yes, what were the reasons for discontinuing AI use? (Select all that apply)
    (a) Lack of training ( )
    (b) Technical/system issues ( )
    (c) Poor integration into routine workflow ( )
    (d) Concerns about accuracy or false alerts ( )
    (e) Lack of institutional support ( )
    (f) Concerns about confidentiality/data privacy ( )
    (g) Others (Specify) ______________________

SECTION E: FACTORS INFLUENCING UPTAKE AND UTILISATION OF AI IN COMMUNITY HEALTH SURVEILLANCE

Instruction: Please tick the either option YES or NO

S/N	STATEMENT	YES	NO
41	Unclear ethical guidelines limit willingness to use AI in disease surveillance.		
42	AI tools would enhance efficiency in disease reporting and surveillance activities.		
43	AI tools are easy to learn and use for disease surveillance		
44	AI tools would integrate smoothly into routine disease surveillance reporting systems.		
45	Community trust influences willingness to use AI in health surveillance.		
46	The use of AI tools by colleagues influences willingness to adopt AI in surveillance work.		
47	Adequate infrastructure (reliable electricity and internet access) is available to support the use of AI tools.		
48	High workload and time constraints limit the use of AI tools in surveillance work..		
49	Adequate institutional training is available for the use of AI Surveillance tools.		
50	Concerns about health data privacy limit the use of AI tools in disease surveillance.		
51	Cost or lack of funding limits the use of AI tools in my workplace.		

APPENDIX II

INFORMED CONSENT FORM

HEALTH RESEARCH ETHICS COMMITTEE (HREC)

UNIVERSITY OF BENIN TEACHING HOSPITAL

P.M.B. 1111 BENIN CITY NIGERIA Telephone: 052-600418 Website: ubth.org

CHIEF MEDICAL DIRECTOR
Prof. (Mrs) I.N Ize-Iyamu

DIRECTOR OF ADMINISTRATION
Jim Uwadie, Esq

CHAIRMAN
Prof. (Mrs.) Antoinette N. Ofili

HREC OFFICE:
Committee email: ubthresearchethics@gmail.com
Registration Number:
NHREC-UBTH-HREC/24/12/2022B

PROTOCOL NUMBER: ADM/E 22/A/VOL. VII/14865491272116

PROPOSAL TITLE: "APPLICATION OF ARTIFICIAL INTELLIGENCE IN ENHANCING COMMUNITY HEALTH SURVEILLANCE SYSTEMS"

PRINCIPAL INVESTIGATOR(S): IFIJEN DIVINE FAVOUR

DEPARTMENT/INSTITUTION: DEPARTMENT OF PUBLIC HEALTH AND COMMUNITY MEDICINE, SCHOOL OF MEDICINE, UNIVERSITY OF BENIN, BENIN CITY, EDO STATE, NIGERIA

DATE CONSIDERED: MARCH 18TH, 2026

DECISION OF THE COMMITTEE: APPROVED

THIS APPROVAL DATES 18/03/2026 TO 17/03/2027. IF THERE IS DELAY IN STARTING THE RESEARCH, PLEASE INFORM THE HREC SO THAT THE DATES OF APPROVAL CAN BE ADJUSTED ACCORDINGLY

REMARK:

CHAIRMAN: PROF (MRS) A.N. OFILI SIGNATURE & DATE: 18/3/2026

SUPERVISOR (S): PROF. A.J. OBI

DECLARATION BY INVESTIGATOR(S):

PROTOCOL NUMBER (please quote in all enquiries)

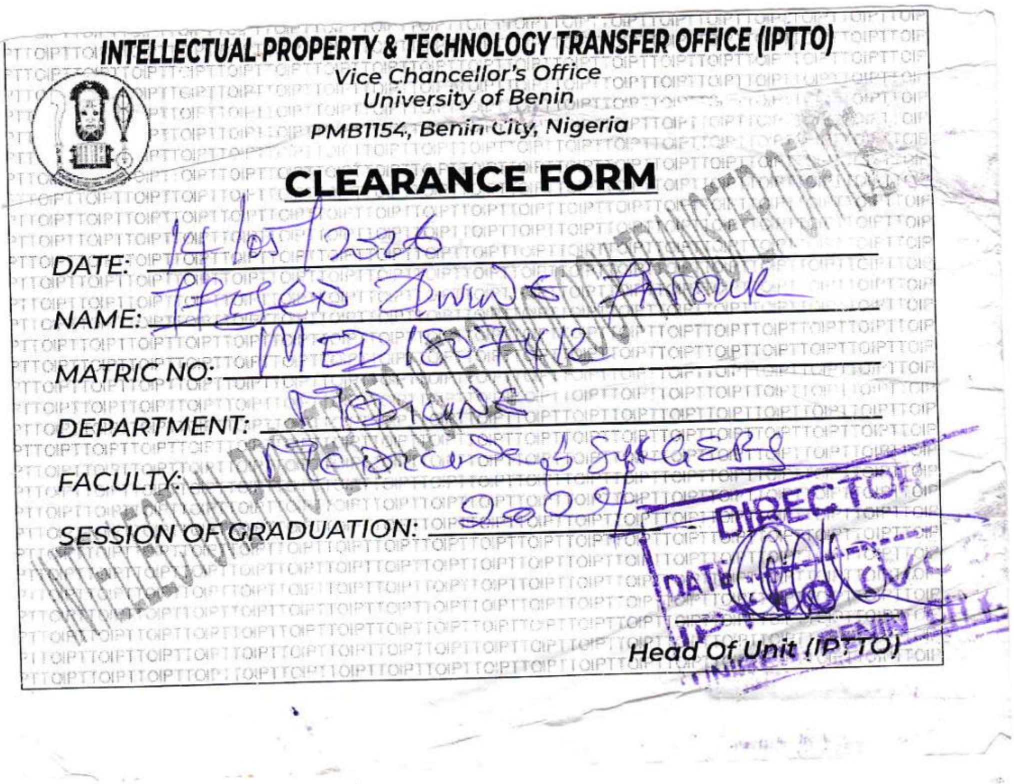
Note that no participant accrual or activity related to this research may be conducted outside of these dates and **you are to furnish the committee with the research activities at the completion of the study.** All informed consent forms used in this study must carry the HREC assigned number and duration of HREC approval of the study. In multiyear research, endeavor to submit your annual report to the HREC early in order to obtain renewal of your approval and avoid disruption of your research. No changes are permitted in the research without prior approval by the HREC except in circumstances outlined in the Code. The HREC reserves the right to conduct compliance visit your research site without previous notification.

Signature & Date..............................

ubthresearchethics@gmail.com Registration Number: NHREC/24/01/2020

APPENDIX III

ETHICAL CLEARANCE



INTELLECTUAL PROPERTY & TECHNOLOGY TRANSFER OFFICE (IPTTO)

Vice Chancellor's Office

University of Benin

PMB1154, Benin City, Nigeria

CLEARANCE FORM

DATE: 14/05/2026

NAME: [illegible] FAVOUR

MATRIC NO: MED1807412

DEPARTMENT: MEDICINE

FACULTY: Medicine & Surgery

SESSION OF GRADUATION: 2009

DIRECTOR

DATE

Head Of Unit (IPTTO)