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Artificial Intelligence for Health Equity and Health Security in Northern Nigeria: A Scoping Synthesis of Evidence, Health-System Readiness, and A Framework for Responsible Public Health Transformation

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Abstract

Artificial intelligence (AI) is moving from experimental applications toward practical use in healthcare, public health intelligence, health communication, diagnostics, workforce support and health-system management. Its potential is especially relevant to Northern Nigeria, where substantial public health needs coexist with socioeconomic deprivation, nutrition insecurity, infectious disease threats, maternal and child health inequalities, insecurity, population displacement and uneven health-system capacity. Yet AI readiness and evidence of real-world benefit remain uneven, and poorly governed deployment could reproduce or deepen existing inequities. To synthesise current evidence on the potential contribution of AI to health equity and health security in Northern Nigeria, examine the region's public health and health-system context, identify opportunities and implementation constraints, and propose an evidence-informed framework for responsible AI-enabled public health transformation. The paper uses a scoping synthesis and policy-framework approach. Peer-reviewed literature and authoritative institutional sources concerning AI, machine learning, digital health, health systems, public health surveillance, nutrition, maternal and child health, ethics and governance were examined, with emphasis on Nigeria, Africa and low- and middle-income countries. Updated contextual evidence was drawn from the 2024 Nigeria Demographic and Health Survey, the 2022 Nigeria Multidimensional Poverty Index, Nigeria's National Artificial Intelligence Strategy, the Federal Ministry of Health and Social Welfare's State of Health of the Nation reporting, WHO guidance and recent African evidence. Evidence was synthesised thematically rather than statistically pooled. The literature supports potential applications of AI in disease surveillance, epidemic intelligence, nutrition early warning, maternal and child health risk stratification, multilingual health communication, workforce decision support and resource optimisation. However, evidence from low-resource settings remains dominated by small-scale, research-oriented or externally funded projects, with limited national or state-level implementation evidence. Key constraints include fragmented and incomplete data, interoperability gaps, weak digital infrastructure, limited technical and AI literacy, insufficient local validation, algorithmic bias, cybersecurity and privacy risks, and variable institutional ability to act on AI-generated signals. Current Nigerian policy developments including the National AI Strategy and the Nigeria Data Protection Act provide an emerging governance foundation, but health-sector implementation requires stronger operational mechanisms. AI should be treated as a health-system capability rather than a stand-alone technology. Northern Nigeria would benefit from a problem-first, equity-centred and human-supervised approach that links high-priority public health needs to reliable data, local validation, workforce capability, accountable governance and response capacity. The paper proposes the AI–



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PUBLIC HEALTH–NIGERIA Framework, alongside a phased implementation roadmap, as a practical architecture for responsible adoption.

Keywords: artificial intelligence; health equity; health security; Northern Nigeria; digital health; machine learning; public health surveillance; nutrition; maternal and child health; health systems.

Introduction

Artificial intelligence (AI) has become an increasingly important component of the global digital transformation of health. Machine learning, deep learning, natural language processing, computer vision, predictive analytics and, more recently, generative and multimodal AI can process large and complex datasets, identify patterns, generate predictions and support human decision-making. In public health, the attraction of these technologies lies less in automation for its own sake than in the possibility of converting dispersed information into earlier warning, better targeting and more responsive action.

The public health relevance of AI is particularly pronounced in settings where needs are substantial but analytical and human resources are constrained. A systematic scoping review of AI applications in low- and middle-income countries (LMICs) found that real-world evidence was still limited and applications were heterogeneous, including decision support, triage and chatbots (Ciecierski-Holmes et al., 2022). More recent African literature similarly indicates expanding research activity but persistent challenges in infrastructure, data availability, workforce capability, governance and local validation (Alaran et al., 2025; Chipps et al., 2025).

Northern Nigeria represents a particularly important setting for this discussion. The region encompasses North-West, North-East and North-Central states and is characterised by substantial internal diversity. Public health vulnerability is shaped by poverty, food insecurity, malnutrition, rurality, population mobility, insecurity, displacement, environmental exposures and variable access to health services. These determinants interact rather than operate independently. A household facing food insecurity may simultaneously experience poor sanitation, limited healthcare access and recurrent childhood infection; an outbreak may be amplified by mobility, weak surveillance, delayed laboratory confirmation and barriers to care.

Nigeria's 2022 Multidimensional Poverty Index reported that 63% of the population about 133 million people were multidimensionally poor. The survey was designed to provide subnational estimates and demonstrated the scale of overlapping deprivation that must be considered when assessing health-system innovation (National Bureau of Statistics [NBS], 2022).

More recent evidence reinforces the importance of regional inequality. The 2024 Nigeria Demographic and Health Survey (NDHS) provides nationally representative information on maternal and child health, nutrition, fertility, health-seeking behaviour and other determinants, while the Federal Ministry of Health and Social Welfare's 2024 State of Health of the Nation reporting documents important variation in service capacity across geopolitical zones. For example, the report identified lower availability of several child-health and nutrition services in the North-West than in other zones, illustrating that technological readiness cannot be separated from underlying service capacity.

The 2024 NDHS also creates an increasingly valuable evidence base for AI-enabled public health intelligence. However, having data is not equivalent to having an AI-ready health system. AI requires data that are sufficiently accurate, representative, timely and interoperable; people who



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can interpret and challenge algorithmic outputs; infrastructure capable of sustaining digital services; and institutions able to convert predictions into public health action.

Nigeria has begun to establish an enabling national policy environment. The National Artificial Intelligence Strategy 2024 identifies data quality, data access, interoperability, workforce development, research and responsible innovation as strategic priorities. The Nigeria Data Protection Act 2023 also provides a legal foundation for lawful, fair and accountable processing of personal data, including safeguards relevant to sensitive health information.

At the international level, WHO emphasises that AI for health should protect human autonomy, promote safety and the public interest, ensure transparency and explainability, establish responsibility and accountability, promote inclusiveness and equity, and remain responsive and sustainable. WHO further cautions that systems developed using predominantly high-income-country data may perform poorly in LMIC populations if not appropriately adapted and validated.

Against this background, the central question is not whether Northern Nigeria should 'adopt AI'. The more important question is where AI can solve clearly defined public health problems, under what conditions, for whom, with what evidence, and with what safeguards. This paper addresses that question by integrating the emerging literature with Nigeria's current policy and public health context.

Problem Statement

Northern Nigeria faces a combination of high public health need and uneven health-system capacity. Priority challenges include maternal, newborn and child health inequalities; acute and chronic malnutrition; infectious disease threats; non-communicable diseases; shortages and maldistribution of health workers; limited access to essential services; insecurity and displacement; and climate-sensitive risks. These challenges create demand for timely intelligence while simultaneously constraining the infrastructure required to generate and use it.

The conventional response has often been programme-specific. Surveillance, nutrition, maternal health, immunisation, supply chains and community engagement may use partially disconnected datasets and reporting processes. AI could potentially improve the integration and interpretation of these information streams. For example, a nutrition early-warning system could combine programme admissions, anthropometric data, food-security indicators, market prices, rainfall and disease patterns. An epidemic-intelligence platform could integrate routine surveillance, laboratory results, environmental indicators, mobility and facility utilisation.

The problem, however, is not simply analytical. Prediction without operational response may have little health value. A model may accurately identify a high-risk location while a health system remains unable to deploy staff, commodities, transport or community interventions. Likewise, a digital health communication tool may reach thousands of people while disseminating misinformation if its content is not clinically reviewed.

The implementation problem can therefore be expressed as a chain: data quality → analytical validity → human interpretation → institutional decision-making → operational response → population benefit. A weakness at any stage can reduce or reverse the expected value of AI.



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Aim

To examine the potential role of artificial intelligence in advancing health equity and health security in Northern Nigeria and to develop an evidence-informed framework for responsible, locally relevant and sustainable public health implementation.

Specific objectives

To characterise public health vulnerabilities relevant to AI-enabled interventions in Northern Nigeria.

To synthesise evidence on AI applications in Nigeria, Africa and LMICs.

To examine potential applications in disease surveillance and epidemic intelligence.

To assess opportunities for AI-supported maternal, newborn and child health.

To examine AI-enabled nutrition intelligence and early-warning applications.

To assess AI-supported health communication and workforce development.

To identify data, infrastructure, workforce and institutional requirements.

To examine ethical, legal, governance and equity risks.

To propose a state-sensitive AI readiness framework.

To develop a phased policy and implementation architecture for responsible AI-enabled public health transformation.

Literature Review

From technological promise to health-system value

The literature increasingly distinguishes between technical capability and real-world health impact. AI systems can perform classification, prediction, pattern recognition and language-related tasks at high speed, but technical accuracy is not equivalent to clinical effectiveness, implementation success or population-level benefit. Ciecierski-Holmes et al. (2022) found relatively few evaluated real-world AI applications in LMICs, suggesting that much of the literature remained at proof-of-concept or research stage. Saif-Ur-Rahman et al. (2023) similarly concluded that AI and digital health may strengthen primary healthcare delivery but identified barriers related to infrastructure, data, workforce and governance.

The implication for Northern Nigeria is important: the relevant unit of analysis should be the health system, not the algorithm. A model should be evaluated according to whether it improves a defined public health process—for example, earlier detection, more efficient referral, better targeting of outreach, improved stock management or faster response not merely whether it achieves a high performance metric in a retrospective dataset.

Evidence from Nigeria

Nigerian evidence shows growing awareness and professional interest in AI. Adigwe et al. (2024), in a national survey of healthcare professionals, reported that 57.2% of respondents described their AI and machine-learning knowledge as good, 66.7% viewed AI as augmenting human intelligence, and 77% believed machine learning could improve service efficiency. These findings suggest an emerging workforce base, while also indicating the need for structured AI literacy and governance education.

The Nigerian literature remains uneven across applications. Recent reviews have considered AI in general healthcare, infectious diseases and specific clinical fields, while African



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reviews have documented expanding use of AI and digital technologies for diagnostics, disease monitoring and decision support. However, implementation evidence remains much thinner than conceptual literature. This distinction is central to policy: a large number of publications does not necessarily mean that a technology has been validated, integrated into routine services or shown to improve health outcomes.

Nigeria's National AI Strategy 2024 provides a broader policy foundation. It identifies data quality and accessibility as major constraints and calls for an AI-ready workforce, research capacity and an enabling ecosystem. This policy direction aligns with the health-sector literature, which repeatedly identifies data and human capacity as prerequisites for responsible AI adoption.

Evidence from Africa

African evidence points to both opportunity and structural constraint. Alaran et al. (2025) describe potential applications in disease detection, resource allocation, continuity of care and health policy while emphasising privacy, infrastructure, integration and ethical-policy challenges. A 2025 review of AI and digital diagnostic tools in Africa identified applications in patient management, quality assurance, laboratory operations, decision-making, disease monitoring and prognosis, but the evidence base remained concentrated in selected countries and applications (Impact of artificial intelligence and digital technology-based diagnostic tools..., 2025).

The geographical distribution of AI research is also unequal. A recent review of One Health infectious-disease modelling in sub-Saharan Africa found increasing AI activity since 2019 but considerable concentration of research leadership and implementation capacity in a small number of countries. This matters for Northern Nigeria because imported models may not reflect local epidemiology, languages, health-seeking behaviour, environmental exposures or patterns of access.

Evidence from South Africa illustrates a similar pattern: a 2025 scoping review found increasing machine-learning research but challenges around access to large datasets, inclusive policy and AI literacy. The lesson is transferable but should not be assumed to be identical across settings. Northern Nigerian states require their own readiness assessments and local validation.

AI for disease surveillance and health security

Disease surveillance is one of the most plausible public-health applications for AI because surveillance generates repeated observations across time and geography. Machine-learning methods can support anomaly detection, classification, forecasting and prioritisation of investigation. AI may also integrate heterogeneous data sources that are difficult to interpret manually.

Recent African health-security scholarship argues that AI could strengthen preparedness and response, while stressing barriers around governance, implementation and African leadership. The appropriate architecture is therefore not 'AI declares an outbreak' but 'AI generates a signal that trained epidemiologists assess and validate'. This distinction protects against automation bias and false alarms.

For Northern Nigeria, surveillance applications should be designed around operational decision points: what signal triggers investigation, who reviews it, what threshold triggers field verification, which agency acts, and how feedback is returned to the model. Without these linkages, AI becomes another information product rather than a health-security capability.



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AI, maternal, newborn and child health

Maternal, newborn and child health (MNCH) is an important area for responsible AI because risk is often shaped by interacting clinical and social factors. Potential applications include identifying high-risk pregnancies, supporting referral prioritisation, forecasting service demand, identifying missed appointments and analysing community-level risk.

A 2025 scoping review of data science and AI for MNCH across Africa identified 52 relevant studies from 31 African countries. The review found that most were research projects or analyses of demographic surveys rather than operational government programmes, and highlighted infrastructure, data-quality, workforce and external-funding constraints.

This evidence suggests that Northern Nigeria should avoid deploying high-stakes maternal or newborn algorithms without prospective validation. An algorithm that predicts risk is only useful if women can access timely referral, skilled providers, medicines, blood, transport and emergency care. AI should therefore be positioned as a support layer around functioning MNCH systems rather than as a substitute for them.

AI and nutrition intelligence

Nutrition is another area where AI could contribute to earlier identification of risk. Northern Nigeria contains communities affected by poverty, food insecurity, infectious disease and displacement, all of which can influence child nutritional status. AI-enabled systems could potentially combine routine nutrition data with food-security, climate, market and population-movement indicators to identify emerging hotspots.

Current evidence from the 2024 NDHS illustrates why equity-sensitive nutrition intelligence is important. Recent analysis of the survey reported overall stunting of 39.1% among children under five, with substantially higher prevalence among children in poorer households and among children of mothers with no formal education. Stunting was also higher in rural than urban settings and remained concentrated in northern regions.

These figures should not be interpreted as evidence that AI itself is needed to solve malnutrition. Rather, they illustrate the scale and spatial distribution of a problem for which better targeting and earlier warning may be valuable. AI should complement, not replace, nutrition screening, clinical assessment, food-security programming and social protection.

AI for health communication and local-language services

Northern Nigeria's linguistic environment creates an important but underdeveloped opportunity for AI-supported health communication. Natural language processing can assist translation, summarisation, question answering, content adaptation and analysis of public feedback. The emergence of multilingual AI initiatives in Nigeria suggests that Hausa and other Nigerian languages can increasingly be incorporated into digital systems.

However, generative AI creates additional risks. WHO has warned that large language and multimodal models can produce convincing but false information and should therefore be governed through clear use cases, safety controls and evidence requirements. For public health communication, human review should be mandatory for content concerning vaccines, medicines, outbreaks, treatment and nutrition.

A locally appropriate model should also account for health literacy, cultural context, misinformation patterns and unequal digital access. AI-generated information should be treated as a draft or decision-support product unless it has been clinically and contextually verified.



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AI and the health workforce

AI is sometimes framed as a response to health-worker shortages, but substitution is a weak policy premise in settings where workforce gaps are already severe. The more appropriate model is augmentation: AI supports health workers by reducing administrative burden, improving access to evidence, identifying patterns and assisting data analysis.

Adigwe et al. (2024) found substantial interest among Nigerian health professionals in AI-enabled efficiency and human augmentation. Nevertheless, implementation requires competency in digital literacy, data quality, interpretation of model outputs, bias recognition, cybersecurity, privacy and evidence verification. Training should extend beyond clinicians to epidemiologists, programme managers, laboratory professionals, health-information officers and policymakers.

Health equity and the digital divide

The relationship between AI and health equity is bidirectional. AI can potentially reduce inequities by directing scarce resources toward high-need communities, but it can also amplify inequities when models are trained on unrepresentative data or when digitally excluded populations are poorly represented.

This risk is particularly relevant to Northern Nigeria because the populations with the greatest health needs may have the weakest digital connectivity, electricity reliability and access to digital services. Equity must therefore be incorporated at every stage: selection of use cases, dataset construction, model development, validation, procurement, deployment and post-deployment monitoring.

WHO's six principles—autonomy; well-being and safety; transparency and explainability; accountability; inclusiveness and equity; and responsiveness and sustainability—provide a useful normative foundation.

Data governance, privacy and cybersecurity

Health AI depends on personal and often sensitive data. Nigeria's Data Protection Act 2023 provides a legal foundation for privacy and responsible data processing, while the Nigeria Data Protection Commission has emphasised privacy-by-design and protection of sensitive health data.

AI governance should therefore address data minimisation, lawful processing, purpose limitation, access control, secure storage, retention, breach response, auditability and appropriate human oversight. These requirements become even more important where data are combined across programmes or jurisdictions. Data interoperability should not be interpreted as unrestricted data sharing.

The governance challenge also includes automated decision-making. High-stakes decisions affecting access to health services should not be delegated blindly to opaque systems. Patients and communities require mechanisms for explanation, contestation and redress.

Research gap

Four major gaps emerge from the literature. First, there is limited evidence from Northern Nigeria specifically. Second, much of the African evidence concerns model development or retrospective datasets rather than routine implementation. Third, local validation and subgroup performance are often underreported. Fourth, there is insufficient evidence on cost-effectiveness, sustainability and institutional ownership.



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The research gap is therefore not simply a shortage of AI studies. It is a shortage of implementation evidence connecting AI performance to measurable improvements in public health processes and outcomes in resource-constrained Nigerian settings.

Conceptual and Theoretical Framework

The study integrates three complementary perspectives: the health-systems perspective, the social determinants of health perspective and responsible innovation. Together, they support a central proposition: AI produces public health value only when technological capability interacts with adequate data, human expertise, institutional readiness, equity and response capacity.

The framework can be represented as: Public health impact = $f(\text{AI capability} \times \text{data quality} \times \text{human capacity} \times \text{institutional readiness} \times \text{equity} \times \text{response capacity})$. The multiplicative expression is conceptual rather than statistical. It emphasises that a failure in a critical component can substantially reduce the value of the whole system.

The pathway is: Population health need → data generation → data quality and integration → AI analysis → human interpretation → institutional decision → public health action → health equity and health security.

Public Health Vulnerability–AI Readiness Matrix

States should be assessed simultaneously on public health vulnerability and AI readiness. Vulnerability can include disease burden, nutrition, poverty, insecurity and displacement. Readiness can include data quality, interoperability, connectivity, electricity, workforce, governance and institutional response capacity. The purpose is not to rank states, but to identify the type of investment required.

Readiness / Vulnerability	High public-health vulnerability	Lower public-health vulnerability
High AI readiness	Equity-focused innovation and rapid evaluation	Innovation leadership and controlled scale-up
Low AI readiness	Foundational investment before high-stakes AI; simple, offline-capable tools	Gradual capability development and targeted pilots

Methodology

Study design

This paper uses a scoping synthesis and policy-framework design. The approach is appropriate because the evidence spans multiple technologies, public health functions, populations and implementation environments, and because the principal objective is to map the evidence and identify a practical policy architecture rather than calculate a pooled effect estimate.

The manuscript follows the logic of scoping-review reporting, including explicit research questions, eligibility concepts, thematic synthesis and transparent acknowledgement of evidence limitations. It should not be interpreted as a formal systematic review or meta-analysis because no quantitative pooling was undertaken and the underlying search and screening process was not prospectively registered.



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Evidence sources

The evidence base comprised peer-reviewed literature indexed in PubMed and related scholarly databases, authoritative reports and guidance from WHO and other international agencies, Nigerian government and regulatory sources, and major population-health datasets. Search concepts combined terms related to artificial intelligence, machine learning, predictive analytics, digital health and public health with Nigeria, Africa, LMICs, surveillance, outbreak response, nutrition, maternal health and health systems.

Eligibility

Priority was given to peer-reviewed empirical studies, systematic or scoping reviews, policy documents and authoritative institutional sources addressing AI or machine learning in health, with emphasis on Nigeria, Africa and LMICs. Sources were excluded when they lacked a substantive health or AI component, were duplicative, or provided insufficient information for interpretation.

Contextual data

The contextual analysis incorporated the 2024 NDHS, the 2022 Nigeria MPI, Nigeria's National AI Strategy 2024, the Nigeria Data Protection Commission's current regulatory information, WHO AI-governance guidance, and recent Nigerian health-sector reporting. The 2024 NDHS is a nationally representative source covering maternal and child health, nutrition and other population-health indicators.

Synthesis

Evidence was organised into six analytical domains: public health need; AI applications; data and digital infrastructure; workforce and institutional readiness; ethics and governance; and health equity. Claims were classified conceptually as evidence of current use, evidence of potential use, or policy recommendation. This distinction is important because many AI applications in the literature remain at prototype or research stage.

Findings and Synthesis

Priority application areas

Public-health function	Potential contribution AI	Critical prerequisite	Primary risk
Disease surveillance	Anomaly detection, forecasting, geographic signals risk	Timely and interoperable surveillance data	False alarms, missed signals, automation bias
Epidemic intelligence	Multisource risk modelling and prioritisation	Epidemiological validation and response protocols	Overconfidence in predictions
Nutrition	Hotspot detection, demand forecasting, early warning	Reliable nutrition, food-security and contextual data	Geographic and socioeconomic bias



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MNCH	Risk stratification, referral support, missed-care identification	Functional referral and emergency systems	Unsafe risk classification
Health communication	Translation, content adaptation, feedback analysis	Expert verification and local-language validation	Misinformation and hallucination
Workforce	Training, documentation, analytics and decision support	AI literacy and supervision	Deskilling and automation bias
Resource management	Demand forecasting and allocation support	Reliable service and supply-chain data	Perpetuation of historical inequities

Public health vulnerability and AI readiness

Domain	Illustrative indicators
Health vulnerability	Maternal/newborn/child burden; infectious disease; NCDs
Nutrition	Stunting, wasting, food insecurity, admissions
Social vulnerability	Poverty, deprivation, displacement, education
Access	Facility density, travel barriers, service coverage
Data readiness	Completeness, timeliness, representativeness, interoperability
Digital infrastructure	Electricity, connectivity, devices, computing
Workforce	Health informatics, epidemiology, data science and AI literacy
Governance	Privacy, cybersecurity, ethics, accountability
Response capacity	Ability to investigate signals and implement interventions

The AI–PUBLIC HEALTH–NIGERIA Framework

This study proposes the AI–PUBLIC HEALTH–NIGERIA Framework as an implementation architecture rather than a technology product. It translates the evidence into twelve linked principles:

Element	Operational meaning
A — Access	Strengthen electricity, connectivity, device access and digital inclusion.
I — Intelligence	Improve data quality, interoperability, analytics and information-to-action pathways.
P — People	Develop health workers, epidemiologists, informaticians, data scientists and policymakers.



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U — Usefulness	Select AI applications according to clearly defined, measurable public health problems.
B — Building trust	Embed transparency, community engagement, documentation and safeguards.
L — Localisation	Use Nigerian data, languages, epidemiology and service realities; validate locally.
I — Integration	Embed AI within existing health-information, surveillance and service-delivery systems.
C — Collaboration	Link government, universities, health institutions, communities, civil society and technology actors.
H — Human oversight	Keep qualified professionals responsible for high-stakes interpretation and decisions.
E — Equity	Monitor access and performance across geography, sex, age, socioeconomic position and vulnerability.
A — Accountability	Define responsibility, auditability, procurement standards, redress and post-deployment monitoring.
L — Learning and transformation	Evaluate continuously and scale only interventions that demonstrate safety, usefulness, equity and sustainability.

The implementation logic

The framework follows a problem-first sequence: public health problem → measurable decision point → data requirement → AI use case → local validation → human-supervised implementation → outcome and equity evaluation → controlled scale-up. This sequence prevents technology from becoming the starting point of policy.

For example, rather than asking whether a state should deploy a chatbot, policymakers should ask whether there is a defined information gap, whether the population can access a digital channel, whether the content can be clinically verified, whether local-language performance is adequate, and whether the intervention improves knowledge or care-seeking compared with existing approaches.

Phased Implementation Roadmap

Phase I: Foundation (0–12 months)

Conduct state-level AI readiness assessments.

Map priority public health decisions where better intelligence could improve outcomes.

Establish data-governance and privacy-by-design procedures.

Assess interoperability of existing health-information systems.

Develop baseline AI and data-literacy competencies for health workers and managers.

Create a multidisciplinary governance mechanism linking health, technology, data-protection and public-health institutions.



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Phase II: Pilot (12–24 months)

Pilot low- to moderate-risk applications such as surveillance analytics, nutrition early warning, routine reporting support and verified health communication.

Use prospective evaluation designs where feasible.

Predefine safety, equity, accuracy, acceptability and implementation outcomes.

Include rural, low-connectivity and underserved populations in validation.

Phase III: Evaluation (18–30 months)

Assess technical performance and calibration.

Assess implementation outcomes such as adoption, fidelity and usability.

Assess equity across relevant population groups.

Estimate cost and resource requirements.

Conduct privacy, cybersecurity and algorithmic-impact assessments.

Document unintended consequences and establish corrective mechanisms.

Phase IV: Scale (24–48 months)

Scale only interventions demonstrating measurable benefit and acceptable risk.

Integrate successful tools into routine budgets, supervision and workforce development.

Establish continuous monitoring and periodic revalidation.

Develop procurement standards that prevent dependence on opaque or non-interoperable systems.

Ethical, Legal and Governance Considerations

Ethics should be treated as an operational requirement rather than a final compliance step. WHO's guidance identifies six core principles for AI in health, while its more recent guidance on large multimodal models expands the governance agenda to include data protection, risk management, external validation, transparency, post-deployment auditing and human rights.

Risk	Potential public-health consequence	Mitigation
Biased training data	Unequal performance and exclusion	Local validation, subgroup analysis, equity audits
Poor data quality	Incorrect predictions and decisions	Data-quality standards and monitoring
Privacy breach	Loss of trust and potential harm	Privacy-by-design, access control, secure storage
Automation bias	Uncritical acceptance of model outputs	Mandatory human oversight and escalation
Opaque models	Limited accountability and contestability	Documentation, explainability and audit trails
Digital exclusion	Widening inequity	Offline and low-tech alternatives; equity-by-design
Cybersecurity threats	Service disruption or data compromise	Security controls, incident response and testing
Generative AI misinformation	Incorrect public-health advice	Verified content pipelines and expert review



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Vendor lock-in	Unsustainable costs and weak interoperability	Open standards and contractual safeguards
Model drift	Declining accuracy over time	Continuous monitoring and revalidation

Discussion

The central finding of this synthesis is that AI's public health value in Northern Nigeria will depend less on technological sophistication than on health-system readiness. This conclusion is consistent with the LMIC literature, which shows substantial interest in AI but comparatively limited evidence of sustained, real-world implementation (Ciecierski-Holmes et al., 2022; Saif-Ur-Rahman et al., 2023).

Three implications follow. First, AI investments should be problem-led. The appropriate question is not 'Where can AI be used?' but 'Which public health decision is currently too slow, fragmented or difficult to make, and can better intelligence improve it?' This orientation reduces technology-driven procurement and encourages measurable outcomes.

Second, implementation must be equity-centred. Northern Nigeria contains communities with very different levels of deprivation, connectivity and access to care. A system that performs well in an urban tertiary facility may not perform similarly in a rural primary-care setting. The 2024 NDHS and other national evidence demonstrate that socioeconomic and geographic differences remain substantial. AI systems that do not represent these differences may reproduce them.

Third, AI must be linked to response capacity. The chain from signal to action should be explicit. For surveillance, this means an AI-generated anomaly must lead to epidemiological review and field verification. For nutrition, a hotspot signal should connect to screening, treatment and food-security response. For MNCH, a high-risk classification should connect to referral, transport and clinical capacity.

The literature also supports caution regarding imported technologies. WHO has emphasised that models trained predominantly on high-income-country populations may not transfer reliably to LMIC contexts. Local validation is therefore not simply a technical preference; it is an equity and safety requirement.

Nigeria's policy environment is increasingly supportive of responsible AI. The National AI Strategy highlights data quality and workforce development, while the Data Protection Act establishes legal protections around personal data. The next challenge is translating national policy into operational standards for health-sector procurement, validation, auditing and accountability.

A final consideration is sustainability. AI systems often require continuing investment in computing, data pipelines, cybersecurity, technical staff, model maintenance and user support. Pilot projects that depend entirely on external funding may fail when grants end. Sustainability should therefore be assessed from the outset, including recurrent cost, institutional ownership, workforce retention and interoperability.

Policy and Practice Recommendations

Recommendation	Priority action
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Establish a Northern Nigeria AI for Public Health Consortium	Create a multidisciplinary platform involving federal and state health institutions, universities, teaching hospitals, public-health agencies, technology experts, data-protection actors and civil society.
Conduct state-level AI readiness assessments	Assess data, infrastructure, workforce, governance, financing and response capacity before deploying high-stakes systems.
Prioritise high-impact public health problems	Initial applications should focus on surveillance, nutrition intelligence, MNCH support, supply-chain intelligence and verified health communication where a measurable decision gap exists.
Adopt a problem-first procurement standard	Every AI investment should specify the public health problem, baseline process, intended user, measurable outcome, risks and exit criteria.
Require local validation	Models should be evaluated using data representing the populations and service environments in which they will be used.
Institutionalise algorithmic equity audits	Performance should be assessed across geography, sex, age, socioeconomic status, disability where relevant, rurality and other meaningful vulnerability groups.
Build AI and data literacy	Training should extend beyond technical specialists to health professionals, epidemiologists, programme managers, health-information officers and policymakers.
Strengthen governance and privacy	Embed the Nigeria Data Protection Act, privacy-by-design, cybersecurity, accountability and human oversight into procurement and deployment.
Design for low-resource environments	Where appropriate, use offline-capable workflows, low-bandwidth interfaces and non-digital alternatives so that AI does not become a new access barrier.
Evaluate before scale	Use implementation, safety, equity and economic evidence to determine whether a pilot should be adapted, expanded or discontinued.



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Create public engagement mechanisms	Communities should be informed about how health data are used and should have meaningful avenues to raise concerns and challenge harmful outcomes.
Develop a national learning agenda	Document what works, where it works, for whom and at what cost, and share evidence across Nigerian states.

Strengths and Limitations

A major strength of this paper is its integration of AI literature with current Nigerian public-health, poverty, health-system and governance evidence. It also distinguishes potential applications from demonstrated real-world effectiveness and places health equity at the centre of implementation.

The paper has several limitations. First, peer-reviewed evidence specifically focused on Northern Nigeria remains limited. Second, the AI evidence base is heterogeneous across technologies, diseases, datasets and outcome measures. Third, many African studies remain research-oriented rather than embedded in routine government programmes. Fourth, contextual population surveys such as the NDHS are not real-time operational surveillance datasets and should not be treated as such. Fifth, this paper is a scoping synthesis rather than a formal systematic review or meta-analysis; no pooled effect estimates are presented. Finally, the AI-PUBLIC HEALTH-NIGERIA Framework is conceptual and requires prospective testing through implementation research.

Future Research Agenda

State-level AI readiness and digital maturity assessments.

Prospective evaluation of AI-assisted disease surveillance in Nigerian public-health systems.

Nutrition hotspot prediction using integrated nutrition, food-security, climate and service data.

AI-supported maternal and child health risk stratification with explicit equity evaluation.

Hausa and other Nigerian-language health communication models with clinical and cultural validation.

AI literacy and readiness among Nigerian health workers and managers.

Algorithmic bias and performance across rural, urban, conflict-affected and underserved populations.

Public trust, consent and community attitudes toward health-data use and automated decision support.

Cost-effectiveness and sustainability of AI-enabled public-health interventions.

Implementation research using established frameworks to assess adoption, fidelity, acceptability, feasibility and sustainability.

Conclusion

Artificial intelligence offers a potentially important new capability for public health in Northern Nigeria, particularly in surveillance, epidemic intelligence, nutrition, maternal and child health, communication, workforce support and resource optimisation. However, the current

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evidence does not justify treating AI as a universal solution. The strongest lesson from the literature is that technology produces value only when it is embedded within capable institutions, reliable information systems, skilled workforces, ethical governance and functioning services.

Northern Nigeria should therefore pursue a problem-first and equity-first approach. The objective should be to improve specific public health decisions and outcomes, not simply to increase the number of AI projects. Local validation, human oversight, privacy protection, community engagement and continuous evaluation should be non-negotiable for high-stakes applications.

The proposed AI–PUBLIC HEALTH–NIGERIA Framework provides a practical architecture linking access, intelligence, people, usefulness, trust, localisation, integration, collaboration, human oversight, equity, accountability and learning. Its underlying principle is straightforward: data should generate intelligence; intelligence should support action; action should improve health equity and health security. AI should serve public health—not the other way around.

Declarations

Ethics approval and consent to participate

Not applicable. This paper is a scoping synthesis and policy analysis based on published literature and publicly available secondary sources; no primary human-participant data were collected.

Consent for publication

Not applicable.

Data availability

The evidence base consists of published literature and publicly accessible institutional sources cited in the manuscript.

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Competing interests

The authors declare no competing interests.

Author contributions

All three authors contributed to the conception and development of the manuscript, interpretation of the evidence, framework development and critical revision. The final manuscript was approved by all three authors.

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References

Adigwe, O. P., Onavbavba, G. O., & Sanyaolu, S. E. (2024). Exploring the matrix: Knowledge, perceptions and prospects of artificial intelligence and machine learning in Nigerian healthcare. *Frontiers in Artificial Intelligence*, 6, 1293297. <https://doi.org/10.3389/frai.2023.1293297>



Artificial Intelligence... (Abdullahi, M. S & Gwarzo, A. A 2026) DOI: <https://doi.org/10.59479/jiaheri.v3i1.161>

Alaran, M. A., Lawal, S. K., Jiya, M. H., Egya, S. A., Ahmed, M. M., Abdulsalam, A., Haruna, U. A., Musa, M. K., & Lucero-Prisno, D. E. (2025). Challenges and opportunities of artificial intelligence in African health space. *Digital Health*, 11, 20552076241305915. <https://doi.org/10.1177/20552076241305915>

Akuze, J., Otieno, G. P., Amare, S. Y., Ngatia, B., Wanduru, P., Kirakoya-Samadoulougou, F., Kananura, R. M., Amouzou, A., Estifanos, A. S., & Ohuma, E. O. (2025). Data science and artificial intelligence for maternal, newborn and child health: Scoping review and thematic analysis. *BMC Public Health*, 26, 314. <https://doi.org/10.1186/s12889-025-25430-0>

Bracken, A., Reilly, C., Feeley, A., Sheehan, E., Merghani, K., & Feeley, I. (2025). Artificial intelligence-powered documentation systems in healthcare: A systematic review. *Journal of Medical Systems*, 49, 28. <https://doi.org/10.1007/s10916-025-02157-4>

Chipps, J., Sibindi, T., Cromhout, A., & Bagula, A. (2025). Use of artificial intelligence in healthcare in South Africa: A scoping review. *Health SA Gesondheid*, 30, 2977. <https://doi.org/10.4102/hsag.v30i0.2977>

Ciecierski-Holmes, T., Singh, R., Axt, M., Brenner, S., & Barteit, S. (2022). Artificial intelligence for strengthening healthcare systems in low- and middle-income countries: A systematic scoping review. *npj Digital Medicine*, 5, 162. <https://doi.org/10.1038/s41746-022-00700-y>

Federal Ministry of Health and Social Welfare. (2025). State of health of the nation report 2024. Government of Nigeria.

National Bureau of Statistics. (2022). Nigeria multidimensional poverty index survey 2022. Federal Republic of Nigeria.

National Centre for Artificial Intelligence and Robotics/NITDA. (2024). National artificial intelligence strategy 2024. Government of Nigeria.

National Data Protection Commission. (2023). Nigeria Data Protection Act, 2023. Government of Nigeria.

National Population Commission (NPC) [Nigeria] & ICF. (2025). Nigeria demographic and health survey 2024. NPC and ICF.

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McGuinness, L. A., & Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ*, 372, n71. <https://doi.org/10.1136/bmj.n71>

Saif-Ur-Rahman, K. M., Islam, M. S., Alaboson, J., Ola, O., Hasan, I., Islam, N., Mainali, S., Martina, T., Silenga, E., Muyangana, M., & Joarder, T. (2023). Artificial intelligence and digital health in improving primary health care service delivery in low- and middle-income countries: A systematic review. *Journal of Evidence-Based Medicine*, 16(3), 303–320. <https://doi.org/10.1111/jebm.12547>

Standley, C. J., Breugelmans, J. G., Chaudhari, A., Cherian, N., Chwalek, S., Deol, A., Dietrich, J., du Moulin, L., Otim, G., James, W., Kloth, S., Masmoudi, S., Ndembu, N., Ndlovu, N., Scarponi, D., Schnetzinger, F., & Shapiro, M. (2025). Artificial intelligence for health security in Africa: Benefits, risks and opportunities. *Epidemics*, 53, 100870. <https://doi.org/10.1016/j.epidem.2025.100870>

World Health Organization. (2021). Ethics and governance of artificial intelligence for health: WHO guidance. World Health Organization.



Artificial Intelligence... (Abdullahi, M. S & Gwarzo, A. A 2026) DOI: <https://doi.org/10.59479/jiaheri.v3i1.161>

World Health Organization. (2023). Regulatory considerations on artificial intelligence for health. World Health Organization.

World Health Organization. (2024). Ethics and governance of artificial intelligence for health: Guidance on large multi-modal models. World Health Organization. <https://doi.org/10.2471/9789240084759>

World Health Organization. (2025). Harnessing artificial intelligence for health. World Health Organization.

Younis, H. A., Eisa, T. A. E. E., Nasser, M., Sahib, T. M., Noor, A. A., Alyasiri, O. M., Salisu, S., Hayder, I. M., & Younis, H. A. K. (2024). A systematic review and meta-analysis of artificial intelligence tools in medicine and healthcare: Applications, considerations, limitations, motivation and challenges. *Diagnostics*, 14(1), 109. <https://doi.org/10.3390/diagnostics14010109>

Wubneh, B. Z., Deriba, F. G., & Woldeyohannis, M. M. (2024). Exploring the opportunities and challenges of implementing artificial intelligence in healthcare: A systematic literature review. *Urologic Oncology: Seminars and Original Investigations*, 42(3), 48–56. <https://doi.org/10.1016/j.urolonc.2023.11.019>

Impact of artificial intelligence and digital technology-based diagnostic tools for communicable and non-communicable diseases in Africa. (2025). Review article indexed in PubMed.

Arama, U. O., Ayo-Farai, O., Oshingbesan, M., Murtaza, B., Rasheed, S., Akhtar, Z., Isiko, I., Adegoke, A. A., Olayinka, B. S., Abdulkarim, A. S., & Oduoye, M. O. (2025). Exploring the role of artificial intelligence toward management of HIV and TB co-infection in Nigeria: A comprehensive narrative review. *Therapeutic Advances in Infectious Disease*, 12, 20499361251395916. <https://doi.org/10.1177/20499361251395916>

Owoyele, V., Ogungbangbe, O. O., Oluwasami, J., Abolarin, P. O., & Ayinla, M. T. (2025). The role of artificial intelligence in health care. *Nigerian Journal of Physiological Sciences*, 39(1), 1–8. <https://doi.org/10.54548/njps.v39i1.1>