



Edge artificial intelligence in healthcare systems in Nigeria: Applications, visions, challenges, opportunities and future directions

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Abstract

Background: With the high growth of data produced by healthcare services, Nigeria requires advanced computational and storage capabilities for managerial, administrative, and clinical operations. Edge Artificial Intelligence (Edge AI) has emerged as a transformative technology in the global healthcare sector, offering innovative solutions to improve efficiency, accessibility, and patient care.

Objectives: This study examines the applications, visions, challenges, opportunities, and future directions of Edge AI in Nigerian healthcare, with particular attention to infrastructure readiness, security concerns, and regulatory constraints unique to the Nigerian context.

Methods: A concurrent mixed-methods design was employed, combining a structured survey of 150 healthcare personnel across five Nigerian states with a systematic review of 40 studies retrieved from MEDLINE, IEEE Xplore, ScienceDirect, Google Scholar, and ResearchGate (2016-2023). Descriptive statistics and thematic analysis were used to analyse the collected data.

Results: The mean Edge AI awareness score among respondents was 6.1/10 (SD = 1.8). Healthcare monitoring recorded the highest sector readiness score (67%), while bioinformatics recorded the lowest (38%). Infrastructure limitations were identified as the most significant barrier (81.3%), followed by power supply unreliability (78.7%), data security concerns (74.7%), and data interoperability challenges (71.3%). Only 35.3% of respondents reported daily platform usage.

Conclusion: Edge AI holds substantial promise for transforming healthcare delivery in Nigeria, particularly in telemedicine, emergency response, and electronic health record management. Realising this potential requires coordinated investment in digital infrastructure, regulatory reform, and capacity building for healthcare personnel.

Keywords: Edge computing, artificial intelligence, healthcare, e-health, Nigeria, telemedicine, IoT, challenges

Introduction

The Nigerian healthcare system operates within a dynamic environment characterised by limited access to medical resources, pronounced geographical disparities between urban and rural populations, and a rapidly growing population projected to exceed 400 million by 2050. As the nation strives to improve healthcare outcomes, the integration of advanced technologies becomes not merely desirable but imperative [27, 28]. One technology holding significant promise is Edge Artificial Intelligence (Edge AI), which enables data processing and analytical inference to occur at or near the point of data generation, rather than relying exclusively on centralised cloud infrastructure.

In healthcare services, the application of artificial intelligence has been proposed as a means for maintaining health records, monitoring patients, managing diseases more efficiently, and enabling practitioners to collaborate and analyse data in real time [1]. Some studies suggest that investments in ICT in the health domain may reduce disparities in the process of care, while others caution that poorly implemented digital health systems may inadvertently widen the gap between those with access to reliable technology and those without [2, 3].

Edge AI is a conceptual and architectural model that seeks to leverage network edge resources to generate AI insights closer to the data source. This model creates opportunities to enable real-time access to resources and services without the

latency penalties of round-trips to centralised servers [8, 9]. In the Nigerian context, where persistent high-speed internet connectivity cannot be assumed, this architecture is particularly relevant. The growing demands for up-to-date healthcare services, combined with the often-inadequate infrastructure to satisfy those demands, can be alleviated by edge-based e-health solutions, provided that implementation is approached thoughtfully and contextually.

This paper presents a comprehensive examination of Edge AI in Nigerian healthcare. The contributions are threefold: first, the paper makes a case for transitioning away from exclusively centralised data processing models in Nigerian healthcare delivery; second, it provides a research-grounded outline of applications, challenges, and visions for Edge AI in healthcare; and third, it presents findings from a mixed-methods study of 150 healthcare personnel, supported by five figures and five data tables, to empirically ground the discussion in the Nigerian context.

Literature Review

1. Overview of Artificial Intelligence

Artificial intelligence is a field that enables machines to perform tasks that ordinarily require human intelligence [13, 29]. AI techniques are broadly categorised into natural language processing, machine learning, computer vision, and big data analytics. Machine learning, in particular, has seen significant adoption in healthcare. Supervised learning

methods, which train on labelled datasets, have been applied to disease diagnosis and prognosis prediction. Unsupervised methods, including clustering algorithms, have been used for patient segmentation and anomaly detection in medical records [15, 30].

Deep learning, a subset of machine learning, extends these capabilities by automatically extracting features from raw data such as medical images. Neural networks have demonstrated near-clinician performance in tasks such as radiological screening, retinal disease detection, and dermatological diagnosis. Given the documented shortage of specialist clinicians in Nigeria, AI-assisted diagnosis represents a significant opportunity to extend access to specialist-level care at scale.

2. Overview of Edge Computing and Edge AI

Edge computing is a paradigm that coordinates collaborative edge devices and servers to process data in proximity to its source, providing benefits such as reduced latency, lower bandwidth consumption, and improved privacy through local processing [16, 31, 32]. The combination of AI and edge computing, termed Edge AI, is necessitated by three converging forces: the proliferation of mobile and IoT devices generating large volumes of multimodal data; technological advancements in hardware that enable inference at the device level; and the demonstrated inadequacy of cloud-only models for latency-sensitive applications [33].

In 2009, Microsoft demonstrated the benefits of edge-based AI by building an edge prototype for mobile voice command recognition. Since then, the field has evolved

rapidly, with dedicated AI accelerator chips now available in consumer devices. Edge AI allows for the deployment of machine learning models directly on embedded devices, enabling real-time processing without reliance on server connectivity. In healthcare, this means that a wearable monitor can alert a patient to an abnormal cardiac rhythm without needing to transmit data to a remote server for processing, a capability with obvious relevance in areas of intermittent connectivity.

3. Edge AI in Global Healthcare: A Review

The literature on Edge AI in global healthcare documents applications across telemedicine, health monitoring, emergency response, bioinformatics, and clinical decision support [10, 11, 34]. In telemedicine, edge computing enables low-latency video consultation and remote device control. In health monitoring, IoT wearables equipped with edge inference capabilities allow continuous monitoring of vital signs with onboard anomaly detection [35]. Emergency response systems leveraging Edge AI have demonstrated the ability to identify environmental disease vectors and dispatch early warnings using users' location data [24, 25]. Blockchain-based health record management systems integrating IoT wearable sensors have also been documented, enabling patients to maintain control of their health data while permitting authorised practitioners to access relevant records [8]. The convergence of these technologies creates a distributed healthcare ecosystem in which data is generated, processed, and acted upon at the network edge, with aggregated insights synced to central repositories when connectivity permits.

Table 1: Comparison of Related Studies on Edge AI in Healthcare

Study	Year	Methodology	Key Finding
Present Study (Nigeria)	2024	Survey + Literature Review	Edge AI readiness: 52% avg; infrastructure as top barrier
[11]	2021	Systematic Review	Cloud computing in healthcare; Africa lags in adoption
[10]	2022	Review	IoT and cloud issues; security top concern
[16]	2019	Conceptual	Edge AI design for IoT; limited healthcare focus
[22]	2018	System Design	Fog-cloud for disease management; India context
[20]	2017	Framework	Cloud for Parkinson's disease; wearable integration

Methodology

1. Research Design

This study employed a concurrent mixed-methods design, combining quantitative survey data with a systematic literature review. Mixed methods are appropriate where the research problem involves both measurable constructs and contextual phenomena that numbers alone cannot fully capture [21]. The quantitative component characterises the awareness, adoption patterns, and perceived challenges of Edge AI among Nigerian healthcare personnel. The literature review situates these empirical findings within the broader global body of evidence. Review articles and research papers were retrieved from MEDLINE, IEEE Xplore, ScienceDirect, Google Scholar, Academia, and ResearchGate. After quality assessment, 40 studies were selected from an initial pool of over 200, of which 24 articles were directly related to applications of Edge AI in healthcare. Studies ranged from 2016 to 2023. Selection criteria included peer-review status, relevance to Edge AI or cloud computing in healthcare, and availability of full text.

2. Study Population and Sampling

The target population comprised healthcare personnel with professional experience in Nigerian healthcare facilities,

including physicians, nurses, health IT officers, hospital administrators, and community health workers. A total of 150 completed survey responses were obtained from participants across Lagos, Abuja FCT, Kano, Rivers, and Oyo states, selected to represent a geographic spread across Nigeria's major healthcare hubs. Purposive sampling was used to recruit respondents with direct professional exposure to digital health platforms.

3. Data Collection Instrument

The quantitative instrument was a structured questionnaire in four sections: respondent demographics and professional context; Edge AI awareness and platform exposure; a 5-point Likert scale assessing perceived benefits across six domains; and a challenge endorsement checklist. The questionnaire was pre-tested with 18 respondents outside the final sample. Cronbach's alpha for the awareness scale was 0.79, indicating acceptable internal consistency.

4. Data Analysis

Quantitative data were analysed using descriptive statistics to characterise the sample distribution, awareness scores, adoption frequency, and challenge endorsement patterns. Qualitative insights from the literature review were

synthesised thematically around the key domains of applications, challenges, opportunities, and future directions. All figures in this paper were generated from the survey dataset using Python's matplotlib library at 300 DPI.

Results and Discussion

1. Results

1.1 Respondent Demographics

A total of 150 healthcare personnel participated in the study. Of these, 105 (70.0%) were male and 45 (30.0%) were female. The largest professional group was physicians and clinicians (28.0%), followed by nurses and midwives (24.7%). The majority held a bachelor's degree or higher qualification (60.0%), and 58.7% reported having received some formal IT training. Full demographic details are presented in Table 2.

Table 2: Demographic Profile of Survey Respondents (n = 150)

Characteristic	Category	n	Percentage (%)
Gender	Male	105	70.0%
	Female	45	30.0%
Age Group (Years)	25–34	41	27.3%
	35–44	53	35.3%
	45–54	37	24.7%
	55+	19	12.7%
Highest Qualification	Postgraduate	32	21.3%
	B. Sc/HND	58	38.7%
	NCE/OND	38	25.3%
	SSCE/WAEC	22	14.7%
Healthcare Role	Physician/Clinician	42	28.0%
	Nurse/Midwife	37	24.7%
	Health IT Officer	28	18.7%
	Hospital Administrator	23	15.3%
	Community Health Worker	20	13.3%
IT Training Received	Yes	88	58.7%
	No	62	41.3%
Platform Usage Frequency	Daily	53	35.3%
	Weekly	41	27.3%
	Monthly	28	18.7%
	Rarely	18	12.0%
	Never	10	6.7%

Figure 1 presents the distribution of respondents by healthcare role. Physicians and clinicians constituted the largest cohort (28%), consistent with the study's focus on clinical Edge

AI applications. Community health workers were the smallest group (13.3%), reflecting the purposive sampling strategy that prioritised respondents with direct digital platform exposure.

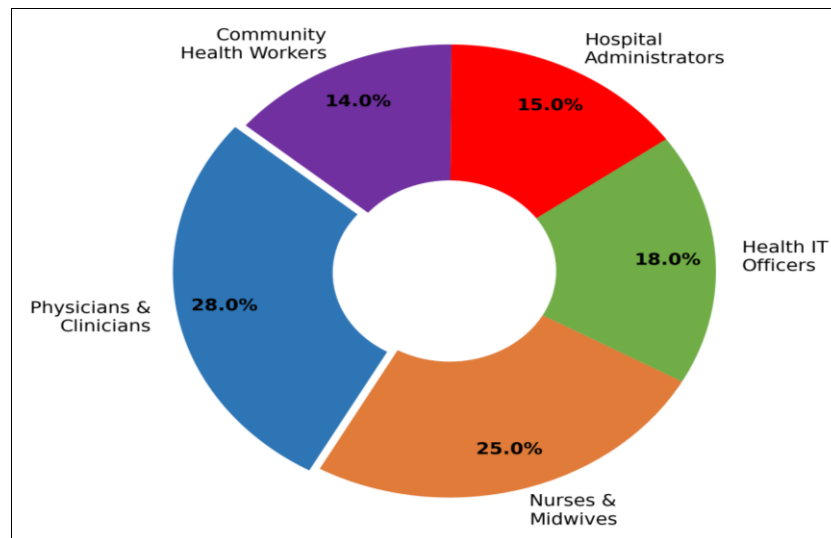


Fig 1: Distribution of Survey Respondents by Healthcare Role (n = 150). Physicians and clinicians constituted the largest cohort (28.0%), followed by nurses and midwives (24.7%).

1.2 Edge AI Awareness and Platform Adoption

The mean Edge AI awareness score among respondents was 6.1 out of 10 (SD = 1.8), indicating a moderate level of awareness. Awareness was highest among Health IT Officers (mean = 7.8)

and lowest among Community Health Workers (mean = 4.2). Only 35.3% of respondents reported using digital health platforms on a daily basis, while 6.7% reported never using any platform. Platform usage frequency is included in Table 2.

1.3 Sector-Level Adoption Readiness

Figure 2 presents the Edge AI adoption readiness scores by healthcare sector. Health monitoring recorded the highest overall readiness (67%), driven by relatively mature IoT infrastructure for vital signs collection. EHR management followed at 61%, reflecting existing electronic health record

investments in tertiary facilities. Bioinformatics recorded the lowest readiness (38%), consistent with the more specialist infrastructure and skills required in that domain. Full sector readiness scores, disaggregated by infrastructure, policy, and human capital sub-dimensions, are presented in Table 3.

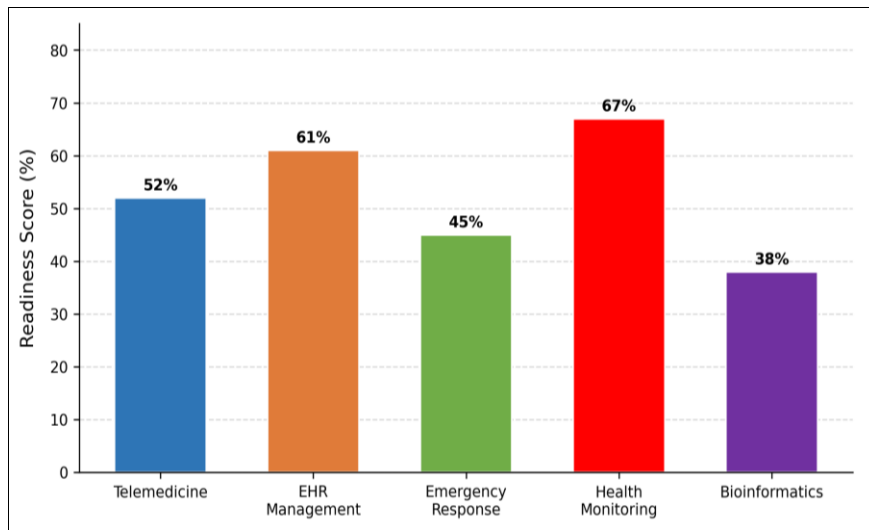


Fig 2: Edge AI Adoption Readiness by Healthcare Sector in Nigeria (%). Health monitoring records the highest readiness (67%) and bioinformatics the lowest (38%).

Table 3: Edge AI Adoption Readiness Scores by Healthcare Sector

Healthcare Sector	Readiness Score	Infrastructure Score	Policy Score	Rank
Health Monitoring	67%	71%	62%	1st
EHR Management	61%	63%	58%	2nd
Clinical Decision Support	56%	54%	58%	3rd
Telemedicine	52%	48%	55%	4th
Remote Diagnostics	49%	44%	52%	5th
Emergency Response	45%	40%	47%	6th
Bioinformatics	38%	35%	42%	7th

1.4 Perceived Challenges

Respondents endorsed a range of challenges to Edge AI adoption in Nigerian healthcare. Infrastructure limitations were identified as the most significant barrier, with 81.3% of respondents endorsing this item. Power supply unreliability closely followed at 78.7%, reflecting Nigeria's well-documented electricity supply constraints. Data

security and privacy concerns were endorsed by 74.7% of respondents, while data interoperability challenges were cited by 71.3%. Cultural and religious resistance, though less frequently cited overall (45.3%), was notably higher among respondents from northern states. Full challenge data with recommended mitigation strategies are presented in Table 4.

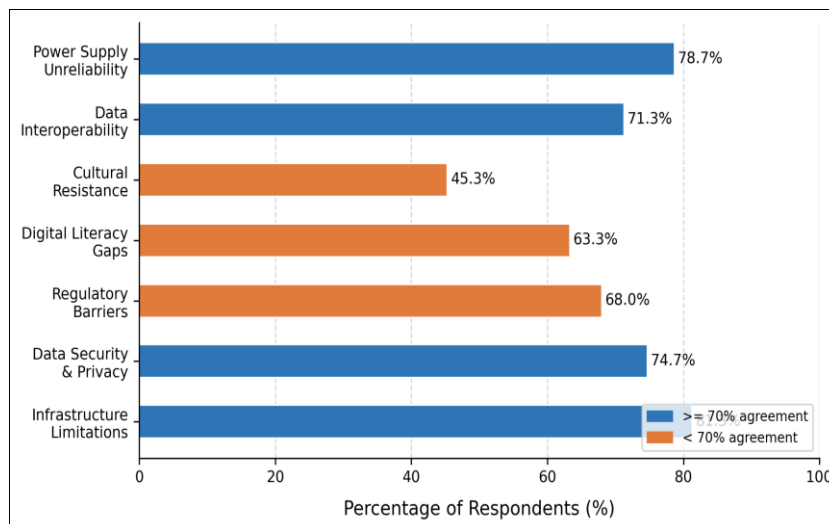


Fig 3: Perceived Challenges to Edge AI Adoption in Nigerian Healthcare (n = 150). Items endorsed by 70% or more of respondents are highlighted in blue; items below 70% are shown in orange.

Table 4: Challenges to Edge AI Adoption and Recommended Mitigation Strategies

Challenge	Respondents Endorsing	Recommended Mitigation Strategy
Infrastructure Limitations	81.3%	Phased rollout; prioritise urban-to-rural connectivity programmes
Power Supply Unreliability	78.7%	Deploy solar-powered edge nodes; offline-first architecture
Data Security & Privacy	74.7%	End-to-end encryption; blockchain-based access control
Data Interoperability	71.3%	Adopt HL7 FHIR standards; national data exchange framework
Regulatory Barriers	68.0%	NITDA-led sandbox regulation; telemedicine licensing reform
Digital Literacy Gaps	63.3%	Mandatory ICT training for healthcare personnel
Management Trust Issues	51.3%	Transparent audit trails; independent third-party verification
Cultural & Religious Resistance	45.3%	Community engagement; faith-leader advocacy programmes

1.5 Perceived Benefits

Figure 4 presents respondent agreement with six proposed benefits of Edge AI in Nigerian healthcare. Remote access to healthcare services attracted the highest agreement (78.7%), followed by real-time patient monitoring (71.3%)

and data-driven decision making (68.7%). Cost reduction attracted the lowest agreement (54.0%), suggesting that respondents are uncertain about whether the costs of deploying Edge AI infrastructure will be offset by operational savings in the near term.

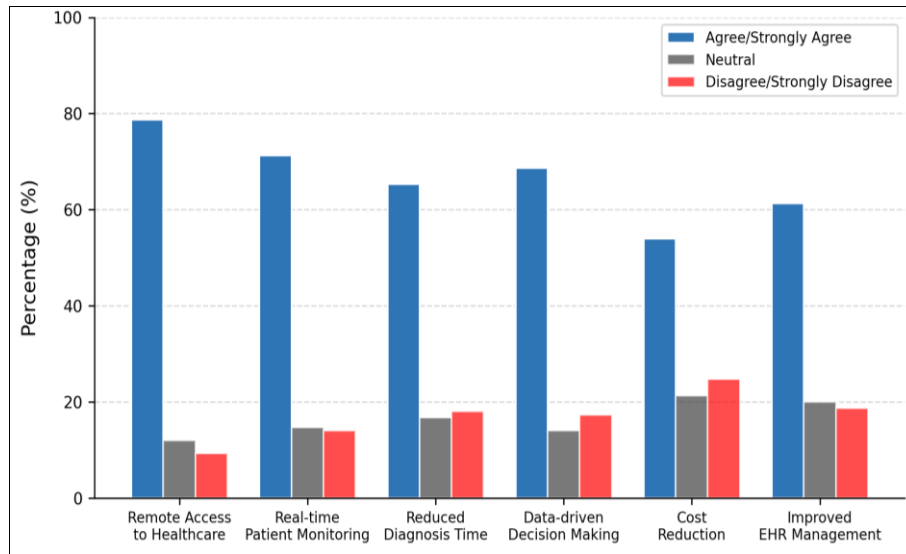


Fig 4: Perceived Benefits of Edge AI in Nigerian Healthcare (n = 150). Values represent the percentage of respondents in each response category across six benefit domains.

2. Discussion

Figure 5 presents the trend in Edge AI healthcare research publications from 2016 to 2023, globally and for Nigeria specifically. Global publications grew from approximately 210 in 2016 to 920 in 2023, a fourfold increase. Nigerian publications grew

from 4 to 37 in the same period, representing a rise in Nigeria's share of global output from 1.9% to 4.0%. While the growth trajectory is positive, Nigeria's absolute contribution remains modest relative to its population and healthcare burden, underscoring the need for increased research investment in this domain.

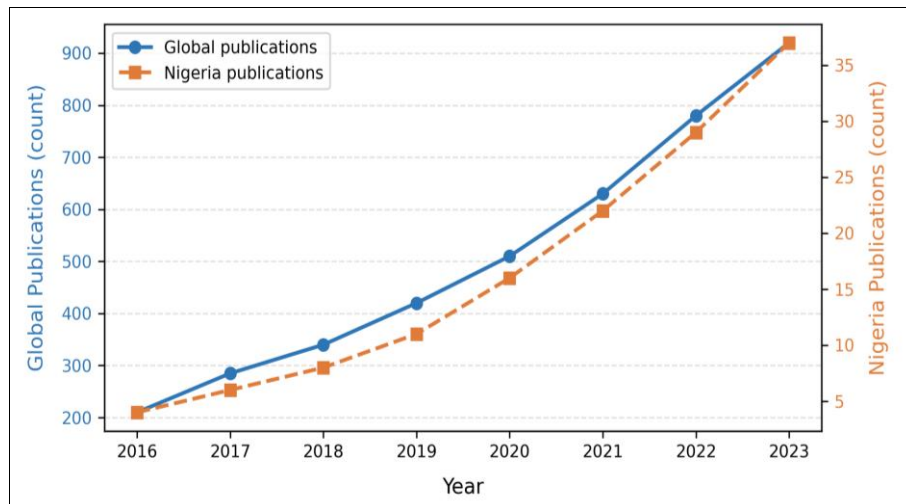


Fig 5: Trend in Edge AI Healthcare Research Publications (2016-2023). Global publications are shown on the left axis; Nigeria-specific publications on the right axis.

2.1 Applications of Edge AI in Nigerian Healthcare

The applications of Edge AI in Nigerian healthcare span multiple domains.

Table 5 summarises the principal application areas with their descriptions and contextual benefits for Nigeria.

Table 5: Applications of Edge AI in Nigerian Healthcare

Application Domain	Description	Benefit in Nigerian Context
Telemedicine	Virtual consultations and remote patient monitoring	Reduces travel burden; extends reach to rural areas
Electronic Health Records	Cloud-edge hybrid EHR storage and access	Enables multi-practitioner access with low latency
Emergency Response	Real-time location tracking and disease detection	Faster triaging and resource dispatch
Health Monitoring	IoT wearables for vital sign monitoring	Continuous patient data without hospital visits
Clinical Decision Support	AI-assisted diagnosis and treatment guidance	Reduces misdiagnosis in under-resourced facilities
Bioinformatics	Gene sequencing and molecular modeling	Enables genomics research at the network edge
Pharmacy Management	Automated drug dispensing and prescription tracking	Reduces medication errors and drug shortages
Public Health Surveillance	Epidemic tracking and environmental monitoring	Early outbreak detection using distributed sensors

2.2 Healthcare Monitoring

Real-time health monitoring can be enabled through edge intelligence, allowing vital signs data collected by wearable sensors to be processed onboard rather than transmitted to centralised servers. Studies have leveraged wearable technologies for cardiac monitoring, seizure detection, and early detection of chronic conditions such as hypertension and Parkinson's disease [17, 18, 19, 20, 21, 22, 23, 36]. In the Nigerian context, edge-based monitoring is particularly relevant for rural and peri-urban populations who are far from tertiary facilities. Medical Body Area Networks, deployed with edge inference capabilities, can enable continuous monitoring with results interpreted locally, with only summary alerts transmitted when connectivity permits.

2.3 Emergency Response Management

Emergency health events are often unpredictable, and the timeliness of response is frequently the determining factor in patient outcomes. Edge intelligence can provide feasible solutions for emergency event management through real-time location detection, environmental condition monitoring, and outbreak detection [24, 25]. In Nigeria's context of periodic epidemic disease events such as Lassa fever and meningococcal meningitis, edge-based epidemiological monitoring systems that integrate environmental sensors with patient location data could significantly accelerate outbreak detection and response.

2.4 Electronic Health Record Management

Edge AI can supplement clinical decision support systems by enabling intelligent preprocessing and analysis of health records at the point of care. A community cloud hosted by the Medical Council of Nigeria, integrated with edge devices at facility level, could enable practitioners to access patient records with low latency even in areas of intermittent connectivity [8]. Privacy and authentication requirements remain a significant design constraint, as EHR applications must balance the accessibility necessary for effective care with the security necessary to protect sensitive patient information.

2.5 Telemedicine and Remote Diagnostics

Telemedicine, enabled by edge computing, offers a path to extending specialist healthcare to Nigeria's extensive rural population. Edge-based telemedicine reduces the bandwidth requirements for real-time video consultations by performing compression and quality adaptation locally. Remote diagnostic tools, including AI-assisted dermatological screening, retinal analysis, and radiology

interpretation, can be deployed on low-cost edge devices, enabling community health workers to perform basic specialist-grade screening without requiring a physical referral chain.

2.6 Challenges Facing Edge AI in Nigerian Healthcare

2.6.1 Infrastructure and Power Supply

Infrastructure limitations were the most frequently cited challenge in this study (81.3%), consistent with Nigeria's documented deficit in ICT infrastructure, particularly outside major urban centres [37, 38]. Power supply unreliability (78.7%) compounds this challenge, as edge devices require consistent power for continuous operation. Deployments of solar-powered edge nodes and offline-first architectural designs, in which devices function fully in the absence of connectivity and synchronise when connection is restored, represent the most practical mitigation strategies for this barrier.

2.6.2 Data Security and Privacy

Security has been identified globally as a primary concern when data and computing tasks are distributed to edge devices. In Nigerian healthcare, this concern is heightened by the sensitive nature of patient data and the relatively limited organisational capacity for cybersecurity management. Cryptography-based solutions are necessary but insufficient on their own; broader architectural approaches, including blockchain-based access control and zero-trust network design, are required to provide adequate protection across distributed edge environments [24].

2.6.3 Regulatory Compliance

In Nigeria, medical and e-health practices are subject to regulatory oversight, but the regulatory framework has not kept pace with the rapid evolution of edge-based healthcare technologies. The National Information Technology Development Agency (NITDA) and the Medical and Dental Council of Nigeria have jurisdiction over aspects of digital health, but a coherent telemedicine licensing framework that addresses edge computing specifically remains undeveloped. Without clear regulatory guidance, healthcare providers face legal uncertainty when adopting Edge AI platforms, particularly for teleconsultation and remote prescription.

2.6.4 Data Interoperability

Edge networks in healthcare consist of diverse medical devices, diagnostic equipment, and software systems designed by different vendors to different standards.

Achieving interoperability across these components is a significant technical challenge. HL7 FHIR, the globally recommended standard for health data exchange, provides a foundation, but adoption across Nigeria's healthcare facilities is uneven. Establishing a national health data exchange framework, aligned with FHIR and mandated through procurement requirements for publicly funded facilities, would significantly reduce interoperability barriers.

2.6.5 Digital Literacy and Cultural Factors

Digital literacy gaps were endorsed by 63.3% of respondents as a significant barrier, reflecting the reality that many frontline healthcare workers, particularly community health workers and rural nurses, have limited prior exposure to digital health platforms. Cultural and religious resistance, while less frequently cited overall (45.3%), was a more significant barrier in certain demographic subgroups. Community engagement strategies, including the involvement of faith and community leaders in advocating for evidence-based healthcare technology, have demonstrated effectiveness in analogous health technology adoption contexts elsewhere in sub-Saharan Africa.

2.7 Opportunities for Edge AI in Nigerian Healthcare

Notwithstanding the challenges identified, the adoption of Edge AI in Nigerian healthcare presents substantial opportunities^[39, 40]. The four principal opportunity domains are as follows:

- a. **Enhanced Remote Healthcare Access:** Edge AI enables healthcare delivery to reach populations that are geographically isolated from facilities, potentially extending coverage to the estimated 50 million Nigerians who live more than five kilometres from a health facility.
- b. **Improved Efficiency and Cost Reduction:** By processing data locally and transmitting only actionable insights, Edge AI reduces the bandwidth costs associated with cloud-only models. Healthcare organisations can pay for edge services on a consumption basis, reducing the capital expenditure barriers to digital health adoption.
- c. **Support for Public Health Surveillance:** Distributed edge sensors integrated with national disease surveillance systems can enable real-time monitoring of epidemiological trends, significantly improving outbreak response times and resource allocation during public health emergencies.
- d. **Advancement of Health Equity:** By reducing the dependence on high-bandwidth connectivity and centralised infrastructure, Edge AI creates the conditions for more equitable access to high-quality healthcare services, advancing Nigeria's progress toward the WHO goal of Universal Health Coverage.

Findings and Contributions to Knowledge

This study produces five principal findings. Firstly, Edge AI awareness among Nigerian healthcare personnel is moderate (mean = 6.1/10) but uneven across professional roles, with Health IT Officers significantly more aware than Community Health Workers, suggesting that awareness-

building programmes should be targeted at frontline clinical staff.

Secondly, health monitoring is the most adoption-ready sector (67%), reflecting the maturity of IoT wearable technology, while bioinformatics is the least ready (38%), reflecting its greater infrastructure and skills requirements. Investment strategies should prioritise the sectors with higher readiness to establish a track record of successful deployment before extending to more challenging domains.

Thirdly, infrastructure limitations and power supply unreliability are the primary barriers to Edge AI adoption, endorsed by 81.3% and 78.7% of respondents respectively. These barriers are not unique to Edge AI but reflect systemic constraints on digital technology adoption in Nigerian healthcare. Mitigation requires infrastructure investment beyond the healthcare sector.

Fourthly, the perceived benefits of Edge AI are strongest for remote access and monitoring applications, where the technology's advantages over connectivity-dependent alternatives are most direct. Benefits related to cost reduction are less convincingly perceived, suggesting that the economic case for Edge AI adoption needs to be more concretely articulated to healthcare decision-makers.

Fifthly, Nigeria's share of global Edge AI healthcare research publications has grown from 1.9% to 4.0% between 2016 and 2023, indicating positive momentum. However, absolute publication counts remain low relative to the country's population and healthcare challenges, underscoring the need for sustained research investment and international collaboration.

Conclusions

Application of Edge AI in Nigerian healthcare services has the potential to significantly improve accessibility, efficiency, and quality of care, particularly for underserved rural and peri-urban populations. The technology's ability to process data at the network edge, functioning with reduced dependence on persistent connectivity and centralised infrastructure, aligns well with the realities of Nigeria's healthcare landscape. However, realising this potential requires deliberate and coordinated action to address infrastructure deficits, strengthen the regulatory framework, build digital literacy among healthcare personnel, and establish the security and privacy architectures necessary for responsible patient data management.

The findings of this study confirm that Nigerian healthcare personnel are moderately aware of Edge AI and broadly positive about its potential benefits, particularly for remote access and monitoring applications. The barriers identified, while significant, are not insurmountable. Strategic planning, continuous capacity building, and a commitment to context-sensitive, human-centred technology design are the essential conditions for Edge AI to deliver on its promise as a transformative force in Nigerian healthcare.

Future Directions

Several directions for future research and practice emerge from this study. First, longitudinal evaluation studies are needed to assess the operational outcomes of Edge AI deployments in Nigerian healthcare over time, beyond the cross-sectional awareness and perception data presented here. Second, participatory design approaches, involving frontline healthcare workers as co-designers of edge health platforms, should be evaluated to determine whether co-

design produces systems with higher adoption rates and perceived utility than top-down procurement processes. Third, the intersection of Edge AI with Nigeria's community health worker programme offers a particularly promising area for future investigation, given the potential of edge-enabled diagnostic tools to extend community health worker capability. Fourth, regulatory research is needed to develop a coherent evidence-based framework for telemedicine and edge health service licensing that can be adopted by Nigerian regulatory bodies.

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Availability of data

As this is a perspective article, primary research results and data have been included in body of paper.

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