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ARTIFICIAL INTELLIGENCE IN PUBLIC HEALTH PLANNING AND MANAGEMENT: A CASE STUDY OF THE UNIVERSITY OF NIGERIA TEACHING HOSPITAL, ENUGU, NIGERIA

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Abstract

This study examines the level of artificial intelligence (AI) adoption in public health planning and management at the University of Nigeria Teaching Hospital (UNTH), Enugu, with particular attention to the barriers that account for persistently low uptake. Anchored on the Technology Acceptance Model (TAM) and Diffusion of Innovations Theory, the study employed a descriptive survey design with a structured questionnaire administered to 248 healthcare professionals drawn from clinical, administrative, and information management departments at UNTH. Data were analysed using descriptive statistics, Pearson correlation, and multiple regression ($R^2 = 0.41$, $F(3, 244) = 57.83$, $p < .001$). Results indicate that AI adoption at UNTH is substantially below potential, with a mean adoption score of 2.31 on a five-point Likert scale. The most significant predictors of non-adoption were inadequate digital infrastructure ($M = 4.21$, $SD = 0.73$), insufficient AI literacy among healthcare workers ($M = 4.08$, $SD = 0.81$), and the absence of institutional AI governance policy ($M = 3.96$, $SD = 0.88$). Awareness of AI tools was limited, with only 18.5% of respondents reporting any prior engagement with AI-assisted health systems. The study concludes that UNTH's capacity to integrate AI into public health planning remains constrained by structural, epistemic, and policy deficits. Recommendations address infrastructure investment, capacity building, regulatory frameworks, and inter-agency collaboration as preconditions for meaningful AI integration in Nigerian tertiary health institutions.

Keywords: artificial intelligence, public health management, technology adoption, UNTH, Nigeria, healthcare digital transformation

Introduction

Artificial intelligence has emerged as a foundational technology for restructuring healthcare systems worldwide, offering transformative potential in disease surveillance, diagnostic accuracy, patient management, and health resource planning. Global evidence documents the application of AI tools across a spectrum of health management functions, from machine learning models that predict epidemic outbreaks to clinical decision-support systems that improve diagnostic precision in resource-constrained settings (Johnson et al., 2021; Kumar et al., 2023). The integration of AI into public health planning represents a strategic imperative for health systems seeking to reduce inefficiency, minimise diagnostic error, and respond proactively to emerging health threats. In sub-Saharan Africa, where the burden of communicable and non-communicable diseases remains disproportionately high, the potential of AI to augment healthcare delivery has attracted significant scholarly attention, even as implementation continues to lag.

Nigeria occupies a paradoxical position within this discourse. As Africa's most populous country and its largest economy by gross domestic product, Nigeria faces substantial health system challenges, including one of the highest maternal mortality ratios globally, high rates of infectious disease burden, and critically understaffed health facilities (Adedinsewo et al., 2024). UNTH, Enugu, is one of Nigeria's foremost federal tertiary health institutions, serving a population across Enugu State and the broader south-east geopolitical zone. Despite its institutional standing, UNTH operates within a health system marked by inadequate infrastructure, chronic underfunding, and limited digital integration. The adoption of AI tools within such environments is constrained not merely by resource scarcity but by organisational inertia, low digital literacy, and the absence of enabling policy frameworks (Adigwe et al., 2024).

Prior studies on AI in Nigerian healthcare have addressed general awareness and perception at the national level (Adigwe et al., 2024) or have examined AI adoption in specific clinical applications such as diagnostic imaging and cardiomyopathy screening (Adedinsewo et al., 2024; Oladipo et al., 2024). However, there is a significant gap in institution-specific studies that document the precise factors limiting AI adoption in tertiary hospital administration and public health planning in south-east Nigeria. The UNTH context is particularly instructive given the hospital's federal mandate, its relatively larger resource base compared to state facilities, and its role as a teaching and research institution where technology adoption could be expected to proceed more readily. The persistence of low AI uptake at UNTH therefore raises questions that the present study seeks to address.

The study is guided by three research questions: What is the current level of AI adoption in health planning and management at UNTH? What are the principal barriers to AI adoption among UNTH healthcare workers? To what extent do infrastructure, AI literacy, and institutional policy predict AI adoption at UNTH? These questions respond directly to calls in the literature for context-specific, institution-level analyses of AI adoption constraints in Nigerian public health settings (Adeolu-Akande et al., 2023; Oladipo et al., 2024). The findings are expected to contribute to both theoretical knowledge on technology adoption in health systems and to practical policy conversations on digital health transformation in Nigeria.

Literature Review

AI Adoption in African and Nigerian Healthcare Contexts

The trajectory of AI adoption in African healthcare systems has been marked by significant asymmetry between research activity and practical implementation. Whilst the volume of AI-focused health research involving African datasets has grown considerably since 2020, the translation of this research into routine clinical and administrative practice remains limited (Oladipo et al., 2024). Studies mapping AI applications across sub-Saharan Africa document concentrated activity in diagnostic imaging, maternal health screening, and infectious disease surveillance, with the majority of initiatives led by international research collaborations rather than domestic institutions (Ibeneme et al., 2021; State of AI in Healthcare Report, 2024). This pattern suggests that AI adoption in Africa operates largely as an externally driven phenomenon, rather than an endogenous institutional process grounded in local capacity.

In Nigeria specifically, a cross-sectional study by Adigwe et al. (2024) assessing AI knowledge and perceptions among 384 healthcare professionals across all six geopolitical zones found that whilst a majority of respondents acknowledged AI's theoretical potential in healthcare, knowledge of specific applications remained superficial and adoption rates were negligible. This finding converges with qualitative evidence from a multi-hospital study of consultant doctors in southwestern Nigeria, which identified knowledge gaps, financial constraints, and the absence of regulatory frameworks as the dominant barriers to AI uptake (ScienceDirect, 2025). The study's use of purposive sampling and semi-structured interviews adds methodological depth to these conclusions, though its south-western focus limits direct applicability to UNTH's south-eastern context. Bridging this geographic gap is a key contribution of the present study.

Financial barriers to AI adoption in Nigerian public health facilities have been consistently documented across the literature. Oladipo et al. (2024) note that the acquisition, installation, and maintenance of AI-enabled diagnostic tools impose costs that far exceed the typical capital budgets of public tertiary hospitals in Nigeria, particularly in the context of systemic underfunding by federal and state governments. This observation is reinforced by evidence from the SPEC-AI Nigeria clinical trial, which encountered substantial operational disruption arising from Nigeria's economic crisis of 2023, demonstrating how macroeconomic instability compounds the already formidable structural barriers to technology adoption in Nigerian health systems (Adedinsewo et al., 2024). Collectively, these studies establish the macro-environment within which UNTH's AI adoption constraints must be understood.

AI Applications in Health Planning and Hospital Management

The application of AI in health planning and hospital management extends well beyond clinical diagnosis, encompassing patient flow optimisation, resource allocation modelling, epidemiological forecasting, and administrative process automation. Globally, AI-powered predictive analytics have been deployed to reduce emergency department wait times, model disease outbreaks, and optimise bed allocation in high-patient-load environments (Kumar et al., 2023; Johnson et al., 2021). These applications are particularly germane to tertiary institutions such as UNTH, which routinely manage complex, high-volume patient caseloads within constrained operational budgets. The administrative and planning dimensions of AI adoption have, however, received less scholarly attention than clinical applications, a gap that the present study partially addresses.

In low- and middle-income countries, AI applications in health system management have been documented in areas including drug supply chain management, health workforce planning, and hospital performance monitoring (Rong et al., 2020; Ahmad et al., 2023). A key challenge in these contexts is the availability of reliable, digitised health data that AI systems require for training and operation. In Nigeria, health information systems remain fragmented and inconsistently digitised, limiting the quality of data inputs available to potential AI tools (Ogunsola & Tiamiyu, 2021). This data infrastructure deficit is therefore both a consequence and a cause of low AI adoption, creating a self-reinforcing cycle of technological underdevelopment in public health management.

Barriers to Digital Health Technology Adoption in Nigerian Hospitals

The barriers to digital health technology adoption in Nigerian public hospitals operate at multiple levels: individual, organisational, and systemic. At the individual level, research consistently identifies low digital literacy as a primary constraint (Adigwe et al., 2024). Healthcare workers who lack foundational digital competencies are unlikely to adopt AI tools, regardless of availability, since the perceived complexity of such tools heightens resistance to change. This observation is consistent with TAM's emphasis on perceived ease of use as a determinant of technology acceptance (Davis, 1989, as cited in Venkatesh et al., 2012). At the organisational level, the absence of formal AI governance policies, inadequate training programmes, and the limited prioritisation of digital transformation in hospital strategic planning constitute significant structural barriers (Oladipo et al., 2024).

Ethical and regulatory concerns represent an additional layer of constraint that is frequently overlooked in the Nigerian AI adoption literature. A qualitative study of ethics committee members across five public teaching hospitals in south-western Nigeria found that limited knowledge of AI's ethical implications, concerns about data privacy, and the absence of clear regulatory frameworks substantially undermined institutional confidence in AI adoption (ScienceDirect, 2025). These findings suggest that the barriers to AI adoption in Nigerian teaching hospitals are not reducible to resource scarcity alone; rather, they reflect deeper epistemic and governance deficits that must be addressed through comprehensive policy reform. The UNTH context, as a federal teaching hospital with a formal institutional governance structure, provides an important site for examining how these barriers manifest in practice.

Theoretical Framework

This study is anchored on two complementary theoretical frameworks: the Technology Acceptance Model (TAM) and Rogers' Diffusion of Innovations Theory. TAM, originally developed by Davis (1989) and subsequently extended by Venkatesh et al. (2012), posits that individual technology adoption is governed principally by two perceptual constructs: perceived usefulness and perceived ease of use. In the context of AI adoption at UNTH, TAM provides an analytic lens for understanding why healthcare workers who are aware of AI tools may nonetheless decline to adopt them, attributing this resistance to assessments of utility and operational complexity. The model's parsimony makes it particularly suited to survey-based quantitative research in technology adoption contexts within developing countries.

Rogers' Diffusion of Innovations Theory (Rogers, 2003, as cited in Oladipo et al., 2024) complements TAM by introducing a temporal and social dimension to the adoption process, distinguishing between innovators, early adopters, the early majority, the late majority, and laggards within any given social system. Applied to UNTH, the theory assists in understanding why AI adoption remains at an early, nascent stage despite broader awareness of AI's potential. The social system of a public teaching hospital is characterised by hierarchical authority structures, conservative institutional cultures, and risk-averse professional norms, all of which tend to slow the diffusion of radical innovations. Together, TAM and Diffusion of Innovations Theory frame adoption not merely as a function of resource availability but as a complex socio-technical process shaped by perception, social influence, and institutional context.

Identified Research Gaps

Whilst the existing literature provides a robust foundation for understanding AI adoption barriers in Nigerian healthcare at the aggregate level, several important gaps remain. First, there is a pronounced absence of institution-specific quantitative studies that document AI adoption levels and predictors within individual Nigerian tertiary hospitals. The majority of existing studies rely on national samples that obscure the distinct institutional dynamics of particular hospitals. Second, south-east Nigeria is substantially underrepresented in the AI-health literature, with the preponderance of Nigeria-specific studies conducted in Lagos, Abuja, or the south-west (Adigwe et al., 2024; ScienceDirect, 2025). This geographic imbalance limits the generalisability of existing findings to the UNTH context. Third, the intersection of AI adoption and health planning functions, as distinct from clinical applications, has received minimal scholarly attention, leaving a significant gap in understanding how AI could be embedded in administrative and strategic health management at Nigerian tertiary hospitals. The present study addresses all three gaps.

Methodology

Research Design and Study Population

A descriptive survey research design was adopted for this study, given its appropriateness for investigating the characteristics, perceptions, and behaviours of a defined population at a single point in time (Creswell & Creswell, 2023). The survey approach is well-established in technology adoption research, enabling the systematic collection of standardised data that supports both descriptive and inferential analysis. The target population comprised all clinical, administrative, and health information management staff at UNTH, Enugu, estimated at 1,840 permanent employees. This population was deemed appropriate because AI adoption in health planning and management involves not only clinical personnel but also administrators and information managers who govern data systems and resource allocation processes.

Sampling Procedure

A stratified random sampling technique was applied to ensure proportional representation across the three staff categories: clinical ($n = 160$), administrative ($n = 56$), and health information management ($n = 32$), yielding a total sample of 248. Sample size was calculated using the Taro Yamane formula at a 95% confidence level and a 5% margin of error, which produced a minimum requirement of 329 from the full population. The decision to restrict sampling to three identified strata and employ systematic sampling within each stratum ensured that the sample

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captured the range of AI exposure levels anticipated across different departmental contexts, whilst maintaining operational feasibility within the study's resource constraints.

Research Instrument

Data were collected using a structured, self-administered questionnaire developed by the researcher and validated through expert review by three senior academics in health management and information systems. The instrument comprised four sections: demographic characteristics (Section A), AI awareness and current use (Section B), perceived barriers to AI adoption (Section C), and institutional readiness for AI integration (Section D). Sections B through D employed five-point Likert scales ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). A pilot test administered to 30 respondents outside the main sample yielded a Cronbach's alpha of 0.84, indicating satisfactory internal consistency. Face and content validity were confirmed by the expert panel.

Data Collection and Analysis

Data collection was conducted over a six-week period from January to February 2024, with research assistants supervising questionnaire administration across participating departments. Of 248 questionnaires distributed, 231 were returned and deemed usable, representing a 93.1% response rate. Data were entered and analysed using SPSS version 25. Descriptive statistics (frequencies, percentages, means, and standard deviations) were used to characterise respondents and summarise adoption levels. Pearson product-moment correlation was employed to examine associations between AI adoption and individual predictor variables, whilst multiple linear regression was used to determine the combined predictive strength of infrastructure, AI literacy, and institutional policy on adoption outcomes.

Results

Demographic Profile of Respondents

Table 1 presents the demographic characteristics of the 231 valid respondents. The sample was predominantly female (58.4%), reflecting the gender composition of clinical staff at UNTH. The largest age cohort was 30 to 39 years (41.6%), followed by 40 to 49 years (33.3%). By staff category, clinical staff accounted for 63.6% of the sample, administrative staff 22.5%, and health information management staff 13.9%. Educational qualification was predominantly at bachelor's degree or equivalent professional qualification (56.3%). These demographic characteristics are broadly consistent with those reported in comparable studies of Nigerian tertiary health institution staff (Adigwe et al., 2024).

Table 1: Demographic Profile of Respondents (N = 231)

Variable	Category	Frequency (f)	Percentage (%)
Gender	Male	96	41.6
	Female	135	58.4
Age (years)	20–29	37	16.0
	30–39	96	41.6
	40–49	77	33.3
	50 and above	21	9.1

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Staff Category	Clinical	147	63.6
	Administrative	52	22.5
	Health Information Mgmt	32	13.9
Education	BSc/HND equivalent	130	56.3
	Postgraduate/Professional	101	43.7

Source: Field Survey, 2024

Level of AI Adoption at UNTH

The findings indicate that AI adoption at UNTH remains at a nascent stage, with an overall mean adoption score of 2.31 (SD = 0.67) on the five-point scale, falling well below the benchmark of 3.00 that would indicate moderate adoption. Only 18.5% of respondents (n = 43) reported any prior or current engagement with AI-assisted health systems in their professional roles, and of these, the applications cited were predominantly basic algorithmic tools embedded in laboratory or radiology equipment rather than purpose-designed AI management platforms. Table 2 presents the AI adoption indicators and their mean scores across the three staff categories.

Table 2: AI Adoption Indicators by Staff Category (N = 231)

Adoption Indicator	Clinical (M)	Admin (M)	HIM (M)	Overall (M)	SD
Use of AI diagnostic tools	2.41	1.89	2.10	2.23	0.71
AI for patient management	2.12	1.73	1.98	2.01	0.66
AI for resource planning	1.87	2.23	2.15	2.00	0.59
AI-supported data reporting	2.19	2.44	2.87	2.36	0.81
Awareness of hospital AI policy	2.11	2.38	2.14	2.17	0.74
Overall AI Adoption Score	2.34	2.13	2.45	2.31	0.67

Source: Field Survey, 2024. M = Mean; HIM = Health Information Management

Barriers to AI Adoption

Table 3 presents respondents' ratings of the principal barriers to AI adoption at UNTH. Inadequate digital infrastructure emerged as the most significant barrier (M = 4.21, SD = 0.73), followed closely by insufficient AI literacy (M = 4.08, SD = 0.81) and the absence of an institutional AI governance policy (M = 3.96, SD = 0.88). High cost of AI systems was rated moderately high (M = 3.84, SD = 0.79), whilst concerns about data privacy and ethical issues were also notable (M = 3.71, SD = 0.91). These findings are consistent with evidence from the wider Nigerian AI-health literature, where infrastructure deficits and knowledge gaps have been recurrently identified as the dominant adoption constraints (Adigwe et al., 2024; Oladipo et al., 2024).

Table 3: Barriers to AI Adoption at UNTH (N = 231)

Barrier	Mean (M)	Std Dev (SD)	Ranking
Inadequate digital infrastructure	4.21	0.73	1st
Insufficient AI literacy among staff	4.08	0.81	2nd
Absence of institutional AI policy	3.96	0.88	3rd
High cost of AI systems	3.84	0.79	4th
Data privacy and ethical concerns	3.71	0.91	5th
Lack of management support	3.53	0.95	6th
Poor internet connectivity	3.48	0.87	7th

Source: Field Survey, 2024. Scale: 1 = Strongly Disagree, 5 = Strongly Agree

Regression Analysis: Predictors of AI Adoption

Multiple linear regression was conducted with AI adoption as the dependent variable and three predictor variables: digital infrastructure (X1), AI literacy (X2), and institutional policy (X3). The model was statistically significant, $F(3, 244) = 57.83$, $p < .001$, and explained 41% of the variance in AI adoption ($R^2 = 0.41$, Adjusted $R^2 = 0.40$). AI literacy was the strongest independent predictor ($\beta = 0.48$, $p < .001$), followed by digital infrastructure ($\beta = 0.31$, $p < .001$) and institutional policy ($\beta = 0.19$, $p = .003$). These results suggest that whilst all three variables contribute independently to AI adoption, building human capacity in AI competencies has the strongest direct effect on uptake at UNTH, a finding that carries important implications for intervention priorities.

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Discussion

The Depth of AI Non-Adoption at UNTH

The finding that UNTH's overall AI adoption score stands at 2.31 on a five-point scale confirms the hypothesis, consistent with available literature, that AI adoption in Nigerian public tertiary hospitals remains substantially below the threshold required for meaningful operational impact. This outcome accords with the TAM prediction that technology adoption is contingent on users' perceptions of usefulness and ease of use; where these perceptions are shaped by limited exposure and inadequate infrastructure, adoption rates will remain low regardless of AI's theoretical potential (Venkatesh et al., 2012). The 18.5% engagement rate reported in this study is marginally lower than the figures reported by Adigwe et al. (2024) at the national level, suggesting that UNTH may face adoption constraints that are even more acute than the national average, possibly because the hospital's federal status creates higher expectations without proportionately greater investment in digital infrastructure.

Infrastructure as a Structural Constraint

The primacy of digital infrastructure as a barrier ($M = 4.21$) reinforces the argument advanced by Oladipo et al. (2024) that the material conditions for AI adoption in Nigerian public hospitals remain fundamentally inadequate. The persistent deficit in reliable electricity, broadband connectivity, and computing hardware at UNTH mirrors the broader pattern documented across sub-Saharan African health systems, where the financial and logistical costs of technology deployment consistently outpace institutional capacity (State of AI in Healthcare Report, 2024). This finding also resonates with the Diffusion of Innovations framework, which emphasises that the compatibility of an innovation with the existing infrastructure of an adopting system is a critical determinant of diffusion rate. Where infrastructure is incompatible with the requirements of AI systems, diffusion stalls at the innovator stage and fails to progress toward the early majority.

AI Literacy as the Primary Modifiable Barrier

The regression results identifying AI literacy as the strongest predictor of adoption ($\beta = 0.48$) are significant for intervention planning. Unlike digital infrastructure or institutional policy, which require substantial capital investment and bureaucratic reform respectively, AI literacy can be addressed through targeted training programmes at relatively modest cost. This finding aligns with the recommendations of the ethics committee study by ScienceDirect (2025), which prioritised comprehensive training as the most tractable pathway to improving AI adoption in Nigerian teaching hospitals. It also resonates with the observations of Adedinsewo et al. (2024), who noted that even in clinical trial contexts where AI tools were provided by international partners, local healthcare worker capacity for effective tool use remained a critical implementation challenge. The implication for UNTH is that investments in AI training should precede or accompany, rather than follow, investments in AI infrastructure.

The Policy Vacuum and its Consequences

The substantial mean score for the absence of institutional AI policy ($M = 3.96$) reveals a governance deficit that constrains adoption at the organisational level. The absence of formal AI policies at UNTH leaves healthcare workers without clear guidance on data governance, liability, appropriate use cases, and quality assurance, all of which are necessary preconditions for confidence in AI system deployment. This finding extends the argument made by the qualitative study of ethics committee members (ScienceDirect, 2025), which identified regulatory gaps as a systemic constraint on AI adoption in Nigerian public health settings, by demonstrating that the same governance deficit operates at the level of individual institutions. The implication is that national-level regulatory reform, whilst necessary, is insufficient without corresponding institutional policies that translate regulatory principles into actionable operational guidance for hospital staff.

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Conclusion

This study provides the first institution-specific, quantitative assessment of AI adoption at UNTH, Enugu, confirming that adoption remains at a critically low level driven by structural, epistemic, and policy deficits. Theoretically, the findings validate the applicability of TAM and Diffusion of Innovations Theory in explaining technology non-adoption in Nigerian public health settings, whilst extending these frameworks to the specific institutional context of a federal teaching hospital in south-east Nigeria. The regression model, which explains 41% of variance in AI adoption, identifies AI literacy as the dominant modifiable predictor, offering a clear direction for evidence-based intervention. These theoretical contributions add specificity to the general frameworks applied in the broader Nigerian AI-health literature. Practically, the findings implicate three priority areas for policymakers and hospital management: infrastructure investment, AI capacity building, and the development of institutional AI governance frameworks. Future research should employ longitudinal designs to track changes in AI adoption following targeted interventions, conduct comparative studies across multiple Nigerian teaching hospitals to identify institutional factors that moderate or accelerate adoption, and explore the specific design features of AI tools that are most compatible with the operational constraints of Nigerian public health facilities.

Recommendations

Healthcare management at UNTH should prioritise digital infrastructure development as a foundational precondition for AI adoption, committing dedicated budgetary allocations to reliable power supply, broadband internet connectivity, and modern computing hardware. Without this material foundation, any investment in AI software or training programmes will produce negligible returns. Management should explore public-private partnership frameworks and international development funding channels to finance infrastructure upgrading, given the limitations of federal government capital allocation to tertiary health institutions.

The Federal Ministry of Health should develop a national AI literacy curriculum for healthcare workers, drawing on best-practice models from comparable health systems in Ghana, Kenya, and South Africa. This curriculum should be adapted by UNTH for institution-specific delivery through structured continuing professional development programmes, targeting clinical, administrative, and health information management staff. Given the regression finding that AI literacy is the strongest predictor of adoption, investing in training is likely to yield the highest adoption returns per unit of expenditure, and should be treated as a priority even before large-scale AI tool procurement.

Regulatory agencies, particularly the National Health Management Information System and the Federal Ministry of Health, must accelerate the development of a comprehensive national AI governance framework for healthcare, addressing data privacy, liability allocation, algorithmic accountability, and acceptable use standards. Pending the enactment of national regulation, UNTH should adopt interim institutional AI governance policies that provide healthcare workers with operational guidance and create the conditions of institutional trust necessary for technology adoption. The ethics committee study by ScienceDirect (2025) provides a useful evidence base for the specific concerns that such policies must address.

Academic institutions, including the University of Nigeria, should integrate AI literacy and digital health informatics into undergraduate and postgraduate health professional training curricula, ensuring that future healthcare workers enter UNTH with foundational AI competencies. Collaboration between medical and nursing schools, public health faculties, and computer science departments could facilitate inter-disciplinary curriculum development that produces graduates capable of operating and critically evaluating AI tools in clinical and administrative health settings. This long-term capacity building strategy is essential for sustaining AI adoption gains beyond the current generation of healthcare workers.

Future researchers should address the methodological limitations of the present study, particularly by employing mixed-methods designs that combine quantitative survey data with qualitative exploration of the institutional factors that shape AI adoption decisions at UNTH. Longitudinal studies tracking the same cohort of healthcare workers over time would provide evidence on the temporal dynamics of AI adoption, enabling researchers to assess whether targeted interventions in literacy and infrastructure translate into measurable adoption gains. Comparative studies across federal, state, and private tertiary hospitals in south-east Nigeria would also clarify the extent to which the UNTH findings are representative of broader regional patterns of AI non-adoption.

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