



Effects of artificial intelligence on healthcare delivery in selected cities in South-East Nigeria

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Abstract

Artificial intelligence (AI) is increasingly transforming healthcare delivery through applications in clinical diagnosis, electronic health records, virtual patient support, telemedicine, predictive analytics, and healthcare administration. This study examines the effects of AI on healthcare delivery in selected cities in South-East Nigeria, with particular attention to AI awareness and utilization, diagnostic AI, chatbot-assisted triage, AI-supported electronic health records, perceived usefulness, perceived ease of use, trust in AI, training, infrastructure readiness, and data privacy concerns. The study adopts a quantitative cross-sectional survey design and is anchored on the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), and the World Health Organization digital-health and responsible-AI perspective. The target population comprises healthcare workers, patients, and hospital administrators in Enugu, Owerri, Aba, Awka, and Abakaliki, with a planned sample of 800 respondents drawn from public, private, and teaching hospitals. Data are measured through structured scales covering AI awareness, frequency of AI use, perceived usefulness, perceived ease of use, trust in AI, privacy concerns, training, infrastructure readiness, service-delivery time, diagnostic accuracy, patient satisfaction, and a Healthcare Delivery Index. The analytical framework employs descriptive statistics, correlation, multiple regression, mediation, and moderation analysis. The supplied study parameters indicate that functional AI availability remains limited, higher AI use is associated with shorter service-delivery time, training improves perceived usefulness, and data privacy is a prominent barrier. The study concludes that AI can strengthen efficiency, diagnostic support, and patient experience, but its benefits depend on infrastructure, workforce competence, trustworthy systems, data governance, and human clinical oversight.

Keywords: Artificial intelligence, healthcare delivery, diagnostic AI, health records, AI chatbots, telemedicine, predictive analytics, patient satisfaction, digital health, South-East Nigeria

Introduction

Artificial intelligence (AI) has emerged as one of the most consequential technological developments shaping contemporary healthcare systems. Advances in machine learning, deep learning, natural language processing, computer vision, predictive modelling, and generative AI are changing how health information is generated, interpreted, communicated, and used for clinical and administrative decision-making. AI is increasingly embedded within diagnostic systems, electronic health records (EHRs), clinical decision-support tools, telemedicine platforms, patient-monitoring systems, automated chatbots, pharmaceutical research, and hospital administration. The World Health Organization (WHO, 2024) ^[19] recognizes AI as having substantial potential to address health-worker shortages, resource constraints, diagnosis, clinical care, surveillance, and health-system management, while emphasizing that its use must be safe, ethical, equitable, and appropriately governed.

The contemporary relevance of AI is particularly significant because health systems globally operate under increasing pressure from population growth, epidemiological transition, chronic disease, workforce shortages, rising costs, and growing patient expectations. AI offers possibilities for processing large volumes of clinical information more rapidly than would ordinarily be feasible through human effort alone. Algorithms can identify patterns in radiological images, pathology specimens, laboratory results, genomic information, electronic medical records, vital-sign data, and population datasets, thereby supporting disease detection, risk prediction, clinical

decision-making, resource planning, and patient management (Bajwa *et al.*, 2021; Rajkomar *et al.*, 2019) ^[11, 12].

One of the most important applications is diagnostic decision support. Deep-learning algorithms can assist in identifying abnormalities in X-rays, computed tomography scans, magnetic resonance imaging, mammography, retinal imaging, and pathology. The value of these technologies lies not simply in automating diagnosis but in helping professionals recognize patterns, prioritize urgent cases, and make more timely decisions. At the same time, external validation, risk of bias, clinical applicability, and workflow integration remain important limitations; therefore, AI systems require careful evaluation before widespread clinical implementation (Kelly *et al.*, 2019) ^[8].

AI is also transforming EHRs. Conventional electronic records primarily function as repositories of patient information, whereas AI-enhanced EHR systems can convert structured and unstructured data into actionable clinical information. Machine-learning algorithms may identify patients at increased risk of complications, predict readmission, detect medication-related risks, identify deterioration, and support personalized treatment decisions. Natural language processing can extract useful information from clinical notes, while predictive models can support risk stratification. These capabilities are especially relevant to facilities managing high patient volumes, but their reliability depends on data quality, interoperability, and appropriate governance.

Another rapidly growing area is the use of AI-powered conversational agents and healthcare chatbots. Chatbots can

provide basic health information, conduct preliminary symptom screening, support appointment scheduling, send medication reminders, provide health education, facilitate follow-up, and direct patients toward appropriate services. Generative AI has expanded these possibilities, but it also creates risks of inaccurate, incomplete, biased, or fabricated outputs. WHO (2024) therefore emphasizes transparency, accountability, privacy, safety, and meaningful human supervision in the use of advanced AI for health.

AI is increasingly converging with telemedicine. Telemedicine seeks to overcome geographical barriers by enabling consultation, monitoring, health education, and elements of diagnosis through digital communication technologies. AI can extend these capabilities through automated triage, remote risk assessment, decision support, speech and image analysis, documentation, and prediction of deterioration. This combination is particularly relevant in developing countries where shortages and unequal distribution of healthcare professionals create major differences in access to specialized services.

The potential importance of these technologies is pronounced in Africa, where many health systems operate under constraints involving limited financial resources, inadequate infrastructure, uneven distribution of health workers, growing populations, and substantial urban-rural disparities. AI may improve diagnosis, healthcare productivity, disease surveillance, clinical decision-making, resource allocation, remote care, and continuity of care. At the same time, insufficient locally representative datasets, algorithmic bias, inadequate regulation, data privacy concerns, infrastructure limitations, and unequal access remain significant challenges. AI adoption in Africa therefore requires locally responsive implementation rather than simple replication of models developed in high-income settings.

Nigeria combines a very large population and substantial disease burden with persistent challenges in healthcare financing, workforce availability, infrastructure, access, and quality. Digital-health interventions have increasingly been proposed as mechanisms for improving healthcare delivery. Egwudo *et al.* (2025)^[6], in a scoping review of digital health technologies in Nigeria, found opportunities for improved healthcare utilization, treatment adherence, community engagement, and health-data quality, but also identified network coverage, logistical, operational, technological, cultural, and training barriers. These constraints are highly relevant to AI because sophisticated algorithms are useful only when the technological ecosystem required to operate them is functional.

Infrastructure readiness is therefore not merely a background condition but a potential moderator of the relationship between AI adoption and healthcare outcomes. AI systems frequently rely on stable electricity, computers or mobile devices, network connectivity, reliable databases, secure servers or cloud infrastructure, digital records, technical maintenance, and trained personnel. Where electricity is unstable or hospitals operate predominantly paper-based systems, even highly accurate algorithms may have limited operational value.

The importance of perceived usefulness and perceived ease of use can be understood through the Technology Acceptance Model (TAM). Davis (1989)^[5] proposed that users are more likely to accept a technological system when they believe that it improves performance and is relatively

easy to use. Applied to healthcare AI, perceived usefulness concerns whether doctors, nurses, administrators, and patients believe that AI improves diagnosis, efficiency, documentation, patient management, or other aspects of care, while perceived ease of use concerns whether the technology can be used without excessive effort.

The Unified Theory of Acceptance and Use of Technology (UTAUT) provides a complementary framework by emphasizing performance expectancy, effort expectancy, social influence, and facilitating conditions as determinants of technology acceptance and use (Venkatesh *et al.*, 2003)^[15]. Facilitating conditions are particularly relevant because healthcare AI depends on institutional resources, infrastructure, training, technical assistance, compatible information systems, and management support. The present study therefore incorporates infrastructure readiness, training availability, perceived usefulness, perceived ease of use, and trust as explanatory factors.

Trust in AI is especially important in clinical environments because incorrect decisions can have serious consequences. Healthcare workers may hesitate to rely on systems whose reasoning is difficult to interpret, whose training data are unclear, or whose accuracy is uncertain in the local population. Ayorinde *et al.* (2024)^[1] found that healthcare professionals' experiences with AI were shaped by understanding, trust and confidence, perceived added value, data limitations, time pressures, governance concerns, and collaboration. Trust must therefore be calibrated: insufficient trust can impede useful adoption, while excessive trust can produce automation bias.

Health-data privacy and security constitute another central concern. AI applications may process medical histories, diagnoses, prescriptions, laboratory results, imaging, personal identifiers, and other sensitive information. Inadequate governance can expose patients to unauthorized disclosure, cyberattacks, misuse, discrimination, or loss of control over personal information. WHO (2021, 2023, 2024) consequently stresses autonomy, transparency, accountability, privacy, inclusiveness, safety, and equity in the governance of AI for health.

The effects of AI on healthcare delivery should be assessed using outcomes reflecting both efficiency and quality. Reduced service-delivery time is one such outcome because AI-assisted scheduling, triage, documentation, diagnosis, and decision support can potentially reduce delays. Diagnostic accuracy is another critical outcome, while patient satisfaction captures the user's experience of timeliness, responsiveness, confidence, communication, accessibility, and quality. A composite Healthcare Delivery Index can therefore provide a broader assessment of AI-related service performance.

Within South-East Nigeria, Enugu, Owerri, Aba, Awka, and Abakaliki are important urban healthcare centres serving the five states of the geopolitical zone. They contain combinations of teaching hospitals, specialist facilities, public hospitals, and private institutions. Yet differences in resources, digitization, infrastructure, staff capacity, patient characteristics, and technology availability may produce substantial variation in AI adoption and outcomes.

A major empirical gap remains. Awareness of AI does not establish that AI improves healthcare delivery, and favourable attitudes do not demonstrate reductions in waiting time, improvements in diagnostic accuracy, or increases in patient satisfaction. There is a need for context-

specific evidence examining whether stakeholders actually use diagnostic AI, AI-supported EHR systems, chatbots, telemedicine AI, and predictive analytics; whether perceived usefulness and ease of use encourage adoption; whether trust mediates the effects of AI use; whether training and infrastructure strengthen its benefits; and whether privacy concerns inhibit implementation.

Accordingly, this study investigates the effects of artificial intelligence on healthcare delivery in selected cities in South-East Nigeria. It draws evidence from doctors, nurses, patients, and hospital administrators across public, private, and teaching-hospital settings. The study examines AI awareness, AI usage frequency, diagnostic AI, chatbot-assisted triage, AI-enabled EHRs, perceived usefulness, perceived ease of use, trust, data-privacy concerns, training, and infrastructure readiness, while healthcare delivery is assessed through service-delivery time, diagnostic accuracy, patient satisfaction, and a composite Healthcare Delivery Index.

Review of Related Literature

Concept of Artificial Intelligence in Healthcare

Artificial intelligence broadly describes computational systems capable of performing functions associated with human intelligence, including learning from data, recognizing patterns, interpreting language, predicting outcomes, and supporting decision-making. Within healthcare, AI encompasses machine learning, deep learning, natural language processing, computer vision, predictive analytics, expert systems, robotic technologies, and generative AI. Its growing importance is associated with the increasing volume and complexity of health information generated through EHRs, laboratory tests, medical imaging, prescriptions, monitoring equipment, and administrative systems (Bohr & Memarzadeh, 2020; Davenport & Kalakota, 2019) [3, 4].

AI should primarily be understood as an augmentative rather than substitutive technology. Its central value lies in enhancing professionals' capacity to interpret information, prioritize cases, predict risks, and manage routine activities. This distinction is critical because clinical decisions involve contextual judgement, ethical responsibility, interpersonal communication, and professional accountability.

Artificial Intelligence and Healthcare Delivery

Healthcare delivery comprises the processes through which preventive, diagnostic, therapeutic, rehabilitative, and supportive services are made available to individuals and populations. Effective delivery is characterized by accessibility, timeliness, safety, effectiveness, efficiency, responsiveness, equity, continuity, and patient-centredness. AI can influence these dimensions through automated clinical decision support, predictive analytics, intelligent scheduling, triage, documentation, and remote care.

The relevant question is therefore not merely whether AI technologies are present in a facility, but whether their use produces meaningful improvements in measurable outcomes. The present study focuses on service-delivery time, diagnostic accuracy, patient satisfaction, and a composite Healthcare Delivery Index.

Diagnostic Artificial Intelligence

Diagnostic AI uses algorithms to examine patient information and identify patterns associated with diseases,

abnormalities, or clinical risks. Applications are prominent in radiology, pathology, ophthalmology, dermatology, cardiology, oncology, and laboratory medicine. Deep-learning systems can analyse X-rays, CT scans, MRI, mammograms, retinal images, and pathological slides, potentially supporting prioritization and interpretation (Esteva *et al.*, 2019) [7].

Real-world effectiveness depends on more than algorithmic accuracy. Ayorinde *et al.* (2024) [19] showed that healthcare professionals vary in their assessment of AI's added value and may have concerns about reliability, interpretability, and governance. Clinical integration and professional verification therefore remain essential.

Artificial Intelligence and Electronic Health Records

AI-enhanced EHR systems can analyse stored clinical data to predict readmission, deterioration, medication complications, disease progression, and other outcomes. Natural language processing can extract information from unstructured notes, while predictive alerts can identify high-risk patients. However, poor-quality records can generate unreliable predictions because algorithmic outputs are fundamentally influenced by the quality and representativeness of the data supplied to the model.

AI Chatbots, Triage, and Telemedicine

AI chatbots can support symptom screening, health education, appointment scheduling, medication reminders, chronic-disease management, follow-up care, and preliminary triage. Their availability may be useful in overstretched systems, but incorrect interpretation of symptoms can result in inappropriate recommendations or delayed care. Human escalation pathways are therefore essential.

AI-supported telemedicine may strengthen remote consultation through automated triage, monitoring, decision support, image analysis, and predictive modelling. In South-East Nigeria, this could extend elements of specialist care beyond major urban hospitals, but the model depends on electricity, connectivity, secure platforms, devices, and digital literacy. Egwudo *et al.* (2025) [6] show that Nigerian digital-health implementation continues to face network, operational, logistical, technological, and training barriers.

Predictive Analytics in Healthcare

Predictive analytics uses historical and real-time data to estimate the probability of future events. In healthcare, AI-driven models can identify patients at risk of deterioration, complications, readmission, disease progression, or adverse medication events. Administrators can also use predictive tools for patient demand, bed occupancy, staffing, supplies, and emergency-department congestion. In resource-constrained environments, these capabilities may improve allocation, although local validation is necessary.

AI Awareness, Perceived Usefulness, and Ease of Use

Awareness is an important precursor to adoption but does not necessarily translate into utilization. Healthcare professionals may know about AI through education, conferences, media, or consumer applications without having access to functioning clinical systems. The distinction between awareness and usage frequency is therefore analytically important.

Perceived usefulness describes the extent to which users believe that technology improves performance. In healthcare, this can involve diagnostic support, reduced workload, faster service, better documentation, and improved patient management. Perceived ease of use concerns whether a system can be operated without excessive effort. These constructs are central to TAM (Davis, 1989)^[5] and remain highly relevant in demanding clinical environments.

Trust, Privacy, Infrastructure, and Training

Trust refers to confidence that an AI system is reliable, competent, safe, and appropriate for its intended purpose. Ayorinde *et al.* (2024)^[1] identified trust and confidence, understanding of AI, perceived value, data limitations, time, governance, and collaboration as key themes in real-world use. Trust should be calibrated rather than absolute because excessive reliance may result in automation bias.

Data privacy concern reflects fear of unauthorized access, misuse, disclosure, or inappropriate sharing of sensitive health information. WHO guidance emphasizes privacy, autonomy, transparency, accountability, inclusiveness, safety, and equitable access as core governance principles (WHO, 2021, 2023, 2024).

Infrastructure readiness includes electricity, internet connectivity, digital devices, secure data storage, interoperable information systems, and technical support. It is expected to moderate AI's effect on healthcare delivery. Training is similarly critical because users need competencies in system operation, interpretation, limitations, bias, privacy, and ethical responsibilities.

Theoretical Review

The Technology Acceptance Model (TAM) developed by Davis (1989)^[5] proposes that perceived usefulness and perceived ease of use influence technology acceptance. Applied to healthcare AI, professionals are more likely to adopt diagnostic tools, predictive systems, AI-enhanced EHRs, and chatbots when they perceive practical performance benefits and manageable effort.

The Unified Theory of Acceptance and Use of Technology (UTAUT) integrates performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh *et al.*, 2003)^[15]. UTAUT is particularly useful because healthcare AI adoption occurs within institutions. A professional may perceive AI as useful but remain unable to use it where connectivity, equipment, institutional authorization, technical support, or training are absent.

The study is additionally informed by WHO's digital-health and responsible-AI perspective, which emphasizes science-based adoption, equity, ethics, regulation, safety, governance, accountability, privacy, and human oversight. This perspective broadens the analysis beyond adoption intentions to whether AI improves care while protecting patients.

Empirical Review and Gap in the Literature

Ayorinde *et al.* (2024)^[1] systematically reviewed healthcare professionals' real-world experiences with AI and identified substantial variation in perceived value, trust, understanding, data limitations, time pressures, governance concerns, and collaboration. Their findings demonstrate that availability of AI does not automatically generate improved healthcare delivery.

Within Nigeria, Egwudo *et al.* (2025)^[6] reviewed digital-health integration and found benefits in healthcare utilization, treatment adherence, community engagement, and data quality, alongside persistent network, operational, logistical, technological, cultural, and training challenges. The study is particularly relevant because AI applications depend on the wider digital-health ecosystem.

Several gaps remain. Much of the international evidence originates from technologically advanced systems; Nigerian studies often emphasize awareness, attitudes, or general digital health rather than direct healthcare-delivery outcomes; relatively few studies integrate doctors, nurses, patients, and administrators; and limited research simultaneously examines diagnostic AI, chatbot triage, EHR AI, telemedicine AI, and predictive analytics. The present study addresses these gaps by examining direct effects, trust as a mediator, and infrastructure and training as moderators across five South-East Nigerian cities.

Methodology

Research Design

The study adopts a quantitative cross-sectional survey design. The design is appropriate because data are collected from different categories of respondents during the study period to determine existing patterns of AI awareness, utilization, perceived usefulness, perceived ease of use, trust, infrastructure readiness, training, privacy concerns, and healthcare-delivery outcomes. The design permits descriptive, correlational, regression, mediation, and moderation analyses.

Area of the Study

The study covers Enugu, Owerri, Aba, Awka, and Abakaliki, representing the five states of South-East Nigeria. These cities are major administrative and healthcare centres containing public, private, specialist, and teaching hospitals and therefore provide an appropriate setting for examining variations in digital-health and AI adoption.

Population of the Study

The target population comprises healthcare professionals, patients, and hospital administrators in selected facilities. Respondents are classified as doctors, nurses, patients, and administrators. These groups capture clinical, organizational, and service-user perspectives on AI-enabled healthcare.

Sample Size and Sampling Technique

A total sample of 800 respondents is planned. A multistage sampling technique is used. The five cities are purposively selected; facilities are stratified into public, private, and teaching hospitals; and respondents are stratified by type. Healthcare workers and administrators are sampled proportionately where staff lists are available, while eligible patients are selected systematically during data collection.

Instrument for Data Collection

Data are collected using a structured questionnaire informed by TAM, UTAUT, and WHO digital-health principles. The instrument measures demographic characteristics; AI awareness and usage frequency; diagnostic AI, chatbot triage, and EHR AI use; perceived usefulness; perceived ease of use; trust in AI; privacy concerns; training;

infrastructure readiness; service-delivery time; diagnostic accuracy; patient satisfaction; and the Healthcare Delivery Index.

Validity and Reliability

Face and content validity are established through expert review in public health, health informatics, healthcare management, research methodology, and digital health. Internal consistency is assessed using Cronbach's alpha, with .70 or higher considered acceptable. The supplied codebook indicates expected reliability coefficients of approximately .91 for perceived usefulness, .88 for perceived ease of use, and .89 for trust in AI.

Data Collection Procedure and Ethics

Following relevant institutional and ethics approval, trained research assistants administer questionnaires to eligible participants without disrupting clinical services. Participation is voluntary and based on informed consent. Numerical respondent IDs are used, no unnecessary personally identifying information is collected, and research data are stored securely. The principles of confidentiality, privacy, autonomy, beneficence, non-maleficence, and responsible data handling guide the study.

Method of Data Analysis

Operationalization of Variables

Variable	Role	Measurement
AI Usage Frequency	Independent variable	1-5 scale
Perceived Usefulness	Independent variable	Multi-item 1-5 scale
Infrastructure Readiness	Moderator/Predictor	1-5 scale
Training Available	Moderator/Predictor	0=No, 1=Yes
Trust in AI	Mediator	Multi-item 1-5 scale
Data Privacy Concern	Barrier variable	1-5 scale
Service Delivery Time	Outcome	Minutes
Diagnostic Accuracy	Outcome/Mediator	1-5 scale
Patient Satisfaction	Outcome	1-10 scale
Healthcare Delivery Index	Main dependent variable	0-100

Model Specification

The principal multiple regression model is: $HDI_i = \beta_0 + \beta_1 AIU_i + \beta_2 PU_i + \beta_3 IR_i + \beta_4 TR_i + \epsilon_i$.

The proposed serial mediation pathway is: AI Usage → Trust in AI → Diagnostic Accuracy → Patient Satisfaction. Moderation is examined through interaction terms between AI usage and infrastructure readiness, and between AI usage and training availability.

Results and Discussion

Important analytical note: the dataset supplied for this manuscript is incomplete in the conversation record. Several respondent ranges are represented by ellipses or truncated rows. Consequently, the numerical findings below are limited to the study parameters explicitly supplied by the researchers and should not be presented as independently recomputed full-sample estimates. Final publication tables should be regenerated from the complete 800-row dataset before submission.

Respondent Distribution

The planned sample comprises 800 respondents distributed across Enugu, Owerri, Aba, Awka, and Abakaliki. Enugu contributes the largest allocation (25.0%), followed by

Data are screened for missing values, coding errors, outliers, and inconsistencies. Frequencies, percentages, means, and standard deviations summarize the sample and variables. Pearson correlation examines bivariate relationships. Multiple regression estimates the effects of AI usage, perceived usefulness, infrastructure readiness, and training on the Healthcare Delivery Index. Mediation and moderation are evaluated using an appropriate regression-based PROCESS framework with bootstrapped confidence intervals. Statistical significance is assessed at $p < .05$.

Sampling Distribution

City	Respondents	Percentage
Enugu	200	25.0%
Owerri	180	22.5%
Aba	160	20.0%
Awka	140	17.5%
Abakaliki	120	15.0%
Total	800	100.0%

Respondent Type	Expected Frequency	Percentage
Doctors	240	30.0%
Nurses	280	35.0%
Patients	200	25.0%
Hospital administrators	80	10.0%
Total	800	100.0%

Owerri (22.5%), Aba (20.0%), Awka (17.5%), and Abakaliki (15.0%). The framework further allocates approximately 30% of respondents to doctors, 35% to nurses, 25% to patients, and 10% to administrators, thereby incorporating provider, management, and service-user perspectives.

Availability and Utilization of Artificial Intelligence

The supplied study parameters indicate that approximately 32% of participating healthcare settings have functional AI-related tools. This suggests that adoption remains at an emerging stage and that diagnostic decision support, chatbot-assisted triage, AI-supported EHR functions, and predictive technologies are more likely to be concentrated in better-equipped facilities. This pattern is consistent with Nigerian digital-health evidence showing that network coverage, logistics, operational capacity, technology, and training remain important implementation constraints (Egwudo *et al.*, 2025)^[6].

AI Usage and Service-Delivery Time

A central supplied finding is a statistically significant moderate negative relationship between AI usage and

service-delivery time ($r = -.48, p < .01$). Higher AI use is therefore associated with shorter patient waiting or processing time. This relationship is plausible because automated triage, AI-supported diagnosis, predictive alerts,

and intelligent information retrieval can reduce delays. The magnitude does not imply that AI alone determines waiting time; staffing, patient volume, clinical complexity, facility type, and organizational procedures remain relevant.

Variables	r	p	Interpretation
AI Usage Frequency × Service-Delivery Time	-.48	< .01	Moderate significant negative relationship

Training and Perceived Usefulness

The study parameters further indicate that respondents who received AI-related training recorded perceived usefulness scores approximately 0.8 points higher than those without training. Training may therefore influence both competence and the perceived practical value of AI. Professionals who understand system capabilities, limitations, interpretation, and workflow integration are more likely to recognize benefits and use AI appropriately.

Indicator	Supplied Result
Difference in perceived usefulness associated with AI training	+0.8 points

Data Privacy Concerns

Approximately 61% of respondents were reported to identify data privacy as the leading AI-related barrier. This finding is important because healthcare AI may process highly sensitive medical histories, diagnoses, prescriptions, laboratory results, images, and identifiers. Strong data governance, consent, cybersecurity, access controls, and accountability are therefore necessary to sustain public and professional trust.

Indicator	Supplied Result
Respondents identifying data privacy as the leading barrier	61%

Infrastructure Readiness and Healthcare Delivery

The study framework anticipates that respondents in facilities with stronger electricity supply, internet connectivity, digital devices, and functioning information

systems will demonstrate higher AI utilization and better healthcare-delivery outcomes. Infrastructure readiness is therefore conceptualized as a moderator: the same nominal AI technology may produce substantially different results in a well-equipped teaching hospital than in a facility with unstable electricity, weak connectivity, or fragmented paper records.

Trust, Diagnostic Accuracy, and Patient Satisfaction

The proposed serial mediation model assumes that greater AI use can build appropriate trust where systems perform reliably; trust can encourage effective use of diagnostic support; and improved diagnostic accuracy can contribute to higher patient satisfaction. The pathway is AI Usage → Trust in AI → Diagnostic Accuracy → Patient Satisfaction. Trust should remain calibrated because insufficient trust can impede useful adoption while excessive trust may generate automation bias. Ayorinde *et al.* (2024) ^[1] similarly found that understanding, trust, confidence, perceived added value, data limitations, time pressures, governance, and collaboration shape professionals' real-world experience with AI.

Multiple Regression and Moderation

The principal regression model specifies the Healthcare Delivery Index as a function of AI usage, perceived usefulness, infrastructure readiness, and training. The expected directions of all four predictors are positive. The moderation models further propose that the positive association between AI use and healthcare delivery will be stronger where infrastructure readiness is high and where users have received appropriate training.

Predictor	Expected Direction	Interpretation
AI Usage Frequency	Positive	Greater appropriate AI use is associated with better delivery
Perceived Usefulness	Positive	Perceived value supports adoption and outcomes
Infrastructure Readiness	Positive	Better infrastructure enables effective use
Training Available	Positive	Training strengthens competent AI utilization

Discussion

Taken together, the findings support a conditional-benefit interpretation of healthcare AI. Artificial intelligence can contribute to operational efficiency, diagnostic support, and patient experience, but benefits are not automatic. They depend on infrastructure, competent users, trustworthy systems, secure data governance, and effective human oversight.

The results support TAM by highlighting perceived usefulness and ease of use as important acceptance mechanisms, while UTAUT is particularly relevant because facilitating conditions such as infrastructure, training, and institutional support shape whether positive attitudes translate into actual use. The WHO responsible-AI perspective further underscores that safety, equity, privacy,

accountability, and human oversight must accompany implementation.

The evidence also extends recent Nigerian digital-health literature. Egwudo *et al.* (2025) ^[6] demonstrate that digital technologies can improve utilization, adherence, engagement, and data quality while remaining constrained by network, operational, logistical, technological, cultural, and training barriers. The present study applies this broader digital-health reality specifically to AI-enabled healthcare in South-East Nigeria.

The optimal model is therefore human-AI collaboration rather than professional replacement. AI can contribute computational speed, pattern recognition, prediction, and information processing, while healthcare professionals retain clinical responsibility, contextual judgement, ethical accountability, and interpersonal care.

Conclusion and Recommendations

Conclusion

This study examined the effects of artificial intelligence on healthcare delivery in Enugu, Owerri, Aba, Awka, and Abakaliki, focusing on diagnostic AI, chatbot-assisted triage, AI-supported EHRs, telemedicine AI, predictive analytics, awareness, usage, perceived usefulness, ease of use, trust, privacy, training, infrastructure, service-delivery time, diagnostic accuracy, patient satisfaction, and the Healthcare Delivery Index.

The study concludes that AI has considerable potential to improve healthcare efficiency, diagnostic support, and patient experience. The supplied negative relationship between AI usage and service-delivery time suggests that greater utilization may contribute to shorter waiting periods, while the training-related difference in perceived usefulness highlights the importance of workforce development. Data privacy concerns and infrastructure limitations, however, demonstrate that adoption must be embedded in broader institutional and governance reforms.

AI should augment rather than replace healthcare professionals. Clinical responsibility, contextual interpretation, ethical judgement, and final decision-making should remain under competent human oversight. Sustainable AI-enabled healthcare in South-East Nigeria will therefore require coordinated investment in technology, infrastructure, workforce competence, data governance, ethical safeguards, regulation, and patient trust.

Recommendations

1. Healthcare institutions should progressively integrate clinically validated AI technologies in areas with measurable service needs, including diagnostic support, medical imaging, EHRs, triage, telemedicine, documentation, and predictive analytics.
2. Government and healthcare institutions should strengthen electricity supply, broadband connectivity, secure networks, digital devices, EHR systems, data storage, cybersecurity, and technical support.
3. Structured AI training programmes should be provided for doctors, nurses, administrators, health-information personnel, and other relevant staff, covering system operation, interpretation, limitations, bias, privacy, ethics, and human oversight.
4. Universities and health-professional training institutions should integrate AI literacy, health informatics, digital health, data analytics, and responsible AI into relevant curricula.
5. Healthcare facilities should establish robust health-data governance policies covering consent, collection, storage, access, sharing, retention, anonymization, cybersecurity, and accountability.
6. Human oversight should remain mandatory for high-impact AI-supported clinical decisions involving diagnosis, treatment, medication, referral, and other consequential actions.
7. Healthcare institutions should build calibrated trust by communicating the intended purpose, performance, limitations, and validation status of AI systems and by creating mechanisms for reporting questionable outputs.
8. AI systems intended for Nigerian healthcare should undergo appropriate local validation using representative populations and relevant clinical settings before large-scale deployment.

9. Priority should be given to AI applications that address major health-system bottlenecks such as long waiting times, specialist shortages, imaging interpretation, laboratory decision support, emergency triage, appointment management, chronic-disease monitoring, and resource planning.
10. AI-supported telemedicine should be expanded cautiously to underserved populations while accounting for digital literacy, affordability, internet access, accessibility, language, and referral continuity.
11. Hospital administrators should continuously evaluate diagnostic performance, waiting time, patient satisfaction, workflow effects, errors, staff acceptance, system downtime, cybersecurity incidents, and cost-effectiveness.
12. Relevant Nigerian health, professional, data-protection, and technology regulators should strengthen coherent standards for clinical validation, accountability, transparency, patient safety, privacy, procurement, cybersecurity, and post-deployment monitoring.
13. Public-private partnerships involving government, universities, teaching hospitals, technology companies, telecommunications providers, professional associations, and development partners should be encouraged to build affordable and context-appropriate solutions.
14. Patients should receive clear information where AI materially contributes to patient-facing or consequential clinical processes, including information on benefits, limitations, relevant data practices, and complaint channels.
15. Future studies should employ longitudinal, experimental, rural-urban comparative, and technology-specific designs and should validate the complete 800-case dataset before drawing definitive inferential conclusions.

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