

AI-Enabled IoT Mobile Health Platform for Telemedicine and Predictive Diagnostics in Underserved Communities in Rural Nigeria

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Abstract

Original Research Article

AI-enabled IoT mHealth could expand telemedicine and risk stratification in rural Nigeria, but implementation depends on infrastructure, awareness, trust, and clinical governance. Methods: A cross-sectional survey of 1,000 respondents from six rural communities assessed mobile access, telemedicine and IoT awareness, internet and electricity availability, willingness to use AI, trust, healthcare satisfaction, and perceived usefulness. Wilson 95% confidence intervals summarized binary outcomes. Results: Phone ownership was 74.1%, willingness 60.3%, and perceived usefulness 76.8%, whereas reliable internet was 20.0%, telemedicine awareness 26.9%, IoT awareness 17.9%, electricity availability 32.9%, and AI trust 50.0%. Poor or very poor healthcare access was reported by 59.5%. Conclusion: Social receptivity exceeds technical readiness. Deployment should prioritize offline-first telemedicine, clinician oversight, selective IoT integration, and local validation before predictive models are used clinically.

Keywords: Artificial intelligence; Internet of Things; mobile health; telemedicine; predictive diagnostics; edge computing; rural healthcare; Nigeria.

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1. Introduction

Digital health has moved from a peripheral innovation to a central component of health-system strengthening. Frameworks for mHealth emphasize that mobile technologies are most useful when embedded within health-system functions rather than treated as stand-alone applications (Labrique et al., 2013; Greenhalgh et al., 2017). The World Health Organization (WHO) frames digital health as a means of supporting equitable, efficient, and sustainable health services, while emphasizing that technology should reinforce rather than substitute for functioning health systems (WHO, 2019; WHO, 2025). In low-resource settings, this distinction is especially important: the value of a digital

intervention depends not only on the sophistication of its software but also on connectivity, electricity, user capability, institutional workflow, affordability, and trust. Telemedicine and mHealth are particularly relevant to geographically dispersed populations. Systematic reviews across Sub-Saharan Africa identify technological, organizational, financial, legal, cultural, and user-level determinants of sustainable adoption (Dodoo et al., 2021; Dodoo et al., 2022; Murray et al., 2026). Mobile devices can support asynchronous consultation, appointment coordination, health education, medication reminders, decision support, and remote monitoring. A recent systematic review of telemedicine in South Africa, Kenya, and Nigeria documented expanding



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use but also persistent constraints related to infrastructure, digital literacy, regulation, and workforce readiness (Agbeyangi and Lukose, 2025). Nigeria-specific evidence similarly identifies power outages, poor internet connectivity, limited technical expertise, organizational gaps, and inadequate training as recurring barriers to implementation (Cole et al., 2025).

AI and IoT technologies could extend these capabilities. IoT-enabled devices can collect physiological measurements, while AI can assist with pattern recognition, triage, prioritization, and clinical decision support. However, evidence of algorithmic performance in controlled settings does not establish that a system will be acceptable, equitable, safe, or usable in rural practice. Reviews of AI in healthcare highlight concerns related to bias, privacy, opacity, data quality, patient rights, and the risk of deploying systems beyond the populations in which they were validated (Botha et al., 2024; Younis et al., 2024). In African health systems, infrastructure, representative data, governance, and context-sensitive implementation remain decisive conditions for success.

Nigeria provides an important setting for readiness assessment because digital-health opportunity coexists with pronounced variation in electricity reliability, broadband access, digital literacy, healthcare availability, and institutional capacity. Recent empirical evidence from rural Oyo State found meaningful interest in digital health but also demonstrated that access, competency, and use are uneven across populations (Okeke et al., 2025). These conditions suggest that implementation studies should distinguish between social receptivity, whether users see value in a technology, and enabling readiness, whether communities have the infrastructure, knowledge, and trust required to use it reliably. This distinction is particularly important when the technology is described as AI-enabled or predictive. A community may believe that AI-assisted mHealth could improve care even when reliable connectivity, electricity, or familiarity with IoT devices remains low. If social enthusiasm is interpreted as full technological readiness, implementation plans can become overly ambitious,

potentially increasing exclusion or undermining trust. Conversely, low infrastructure readiness does not imply lack of demand; it may indicate that system architecture must be adapted to local constraints. Rural healthcare delivery adds a spatial and operational dimension to digital-health design. In communities where travel to referral facilities is difficult, digital tools can support continuity between infrequent face-to-face encounters through remote follow-up, symptom reporting, medication support, and clinician consultation. Recent evidence from Sub-Saharan Africa shows that digital tools can support chronic-care tasks, but uptake depends on digital literacy, communication between health workers, privacy protections, technical support, and access to devices and connectivity (Hinneht et al., 2025). These findings support an implementation model in which digital care extends existing primary-care pathways and community health-worker activities rather than creating a parallel technology service that users must navigate alone. Readiness should therefore be treated as a socio-technical construct. A community may have substantial mobile-phone access but limited experience using phones for healthcare; it may express interest in AI-assisted services while lacking stable connectivity or confidence in automated recommendations. Implementation frameworks similarly emphasize that adoption, scale-up, and sustainability depend on interactions among technology, users, organizations, regulation, and the wider health system (Greenhalgh et al., 2017; Murray et al., 2026). In rural Nigeria, this means that mobile ownership is only one layer of readiness. Practical deployment also requires workable charging options, low-data communication, trusted clinical pathways, locally appropriate training, device maintenance, and clear responsibility for escalation when remote monitoring identifies a potentially serious problem.

Adding IoT devices increases both opportunity and complexity. Connected blood-pressure monitors, pulse oximeters, thermometers, glucose meters, portable ECG devices, and wearable sensors can provide data that are more frequent than conventional clinic measurements. Edge computing can reduce dependence on continuous cloud access by performing basic checks, preprocessing, or

temporary storage near the point of care (Pereira et al., 2024). However, sensing accuracy, interoperability, maintenance, power consumption, missing data, cybersecurity, and user burden become part of the clinical safety problem. Reviews of AI-enabled wearable systems stress that technically impressive sensing and classification results do not guarantee reliable clinical use unless data quality, usability, privacy, and integration with professional workflows are addressed (Baumann et al., 2025). WHO regulatory considerations likewise emphasize risk management, data quality, transparency, performance evaluation, and monitoring across the AI system lifecycle (WHO, 2023). The evidentiary threshold becomes higher when a system moves from communication or monitoring to predictive diagnostics. A predictive model must demonstrate more than numerical accuracy on a development dataset. Transparent reporting should describe the target population, predictors, outcomes, missing-data handling, model development, discrimination, calibration, and validation strategy, consistent with TRIPOD+AI recommendations (Collins et al., 2024). Diagnostic AI studies also require clear reporting of the reference standard, data sources, model inputs, evaluation procedures, and subgroup performance, as emphasized by STARD-AI (Sounderajah et al., 2025). Before broad deployment, early clinical evaluation should assess workflow integration, human factors, safety, and the interaction between clinicians and AI outputs (Vasey et al., 2022). The FUTURE-AI consensus further highlights fairness, universality, traceability, usability, robustness, and explainability as core principles for trustworthy healthcare AI (Lekadir et al., 2025). These requirements are particularly relevant in underserved Nigerian communities because weak infrastructure can influence both access to a service and the quality of data used by an AI system. Interrupted synchronization can create incomplete longitudinal records, unstable power can reduce sensor availability, unfamiliar devices can increase measurement error, and low trust can alter whether users act on recommendations. As a result, a rural AI-IoT platform should be designed in stages: first establish dependable mobile communication and teleconsultation, then introduce selected

connected measurements, and only subsequently add locally validated predictive functions. The present study uses observed readiness indicators to identify where that sequence is most constrained and to translate the findings into explicit technical and clinical design requirements.

1.1 Study aim and objectives

The study aimed to assess readiness for an AI-enabled IoT mobile health platform for telemedicine and predictive diagnostics in underserved rural communities across Nigeria's six geopolitical zones. The specific objectives were to:

- quantify access to mobile phones, reliable internet, and electricity;
- assess previous health-related phone use, telemedicine awareness, and IoT-device awareness;
- estimate willingness to use AI-enabled health applications and trust in AI-assisted diagnosis;
- describe satisfaction with current healthcare access; and
- translate the observed readiness profile into design requirements for an AI-enabled IoT telemedicine platform and a staged pathway for clinically valid predictive diagnostics.

1.2 Contribution of the study

The study contributes in two linked ways. First, it provides empirical evidence on social, infrastructural, and awareness conditions relevant to AI-enabled mHealth deployment across six selected rural communities. Second, it converts those observed constraints into a context-sensitive platform architecture that connects IoT sensing, mobile/CHW interfaces, offline edge processing, secure synchronization, AI-assisted risk stratification, teleconsultation, and clinician-governed predictive diagnostics. The survey therefore informs platform design; it does not substitute for later clinical model development and validation.

1.3 Literature Review

1.3.1 Digital health and telemedicine in resource-constrained settings

WHO guidance emphasizes that digital interventions should be assessed in relation to benefits, harms, acceptability, feasibility, resource requirements, and equity (WHO, 2019). The WHO Global Strategy on Digital Health further stresses interoperability, privacy, security, sustainability, and alignment with national health priorities (WHO, 2025). These principles are especially pertinent in rural settings, where intermittent connectivity and power instability can convert apparently minor technical limitations into service-delivery failures. Osei and Mashamba-Thompson (2021) reviewed mHealth applications for disease screening and treatment support in low- and middle-income countries and identified stakeholder knowledge, attitudes, and perceptions as important implementation factors alongside technical constraints. This reinforces a multidimensional view of readiness: access to a device is necessary but not sufficient, and uptake depends on whether users understand, trust, and can repeatedly access the service.

1.3.2 Telemedicine in Nigeria and Sub-Saharan Africa

Recent reviews indicate that telemedicine adoption in Sub-Saharan Africa is increasing but remains heterogeneous. Earlier regional evidence identified recurring challenges in connectivity, power, policy, organizational readiness, cost, and user capability, while more recent implementation research continues to show that infrastructure and wider-system conditions shape scale-up and sustainability (Dodoo et al., 2021; Dodoo et al., 2022; Murray et al., 2026). Agbeyangi and Lukose (2025) found that infrastructure, digital literacy, policy, and implementation capacity shape adoption across South Africa, Kenya, and Nigeria. Focusing specifically on Nigeria, Cole et al. (2025) synthesized 29 studies and identified technical and institutional barriers, including power outages, poor internet connectivity, insufficient technical expertise, weak organizational policies, and

regulatory challenges. Education, training, mobile access, and low-technology communication pathways emerged as important facilitators. Nigeria-specific system development is also evolving. Nigerian studies have shown both the promise of context-appropriate digital tools and the practical importance of user acceptability, low-technology pathways, and locally workable service models (van Gurp et al., 2015; Itanyi et al., 2023). Kyado et al. (2025) described an IoT-based telemedicine system integrating mobile capture, remote consultation, clinician assignment, and cloud-based records. Such systems demonstrate technical feasibility, but widespread implementation requires an enabling environment. The present study therefore focuses on readiness conditions that would influence whether similar systems could be used consistently in underserved communities.

1.3.3 AI, IoT, edge computing, trust, and patient safety

AI-supported health systems can assist detection, classification, triage, risk stratification, and continuous monitoring, while IoT and wearable devices provide streams of physiological and behavioral data that can support those functions. Recent systematic mapping shows increasing use of machine learning with wearable devices and edge-computing architectures for cardiovascular monitoring, fall detection, and disease prediction (Pereira et al., 2024). Reviews of AI-enabled wearables likewise emphasize the potential for continuous or near-continuous monitoring, but also highlight sensing accuracy, usability, interoperability, privacy, and clinical integration as persistent barriers (Baumann et al., 2025). WHO guidance therefore stresses appropriate data, human oversight, accountability, transparency, and governance rather than autonomous algorithmic decision making (WHO, 2021). Trust is therefore not a superficial adoption variable. When AI is introduced into clinical care, users need to understand what the system does, what it does not do, who remains accountable, and how data are protected. In low-resource settings, these trust

requirements interact directly with infrastructure: a model cannot safely support diagnosis when sensor data are unreliable, synchronization is incomplete, or referral pathways are absent. The 50.0% trust estimate measured in the present study is therefore treated as a platform-design requirement for visible clinician oversight rather than as evidence for autonomous AI use.

1.3.4 Predictive diagnostics from IoT data

Predictive diagnostics in an AI-IoT platform refers to the use of validated algorithms to estimate clinically meaningful risks from patient history, symptoms, physiological measurements, and longitudinal sensor data. A deployable pathway must include signal-quality checks, preprocessing, feature engineering, model development, calibration, internal validation, external validation in the intended population, prospective clinical evaluation, and post-deployment monitoring. Wearable and edge-AI research shows that performance obtained in controlled datasets cannot be assumed to transfer automatically to rural clinical practice because missingness, device variation, population differences, connectivity failures, and workflow constraints can materially alter model behavior (Pereira et al., 2024; Baumann et al., 2025). In this paper, predictive diagnostics is therefore treated as a future clinical layer of the proposed platform whose implementation requirements are informed by the readiness survey, not as an already validated outcome of the survey itself.

1.3.5 Research gap

The literature documents the technological potential of AI-IoT healthcare and the barriers to digital-health implementation, but fewer studies explicitly connect community readiness evidence to the architecture and validation sequence required for predictive telemedicine in rural Nigeria. In particular, there is a need to distinguish enthusiasm for AI-enabled care from the operational conditions required to generate trustworthy sensor data, transmit them reliably, support clinician review, and validate predictive models locally. This study addresses that gap by combining a six-zone readiness survey with an implementation-oriented platform and predictive-diagnostics framework.

2. Methods

2.1 Study design and analytical scope

This study employed a descriptive cross-sectional survey design involving 1,000 respondents across six rural communities representing Nigeria's six geopolitical zones. The empirical component assessed enabling infrastructure, prior digital-health exposure, awareness, trust, willingness to use AI-enabled health applications, satisfaction with current healthcare access, and perceived usefulness of AI-mHealth. All numerical analyses use the observed survey counts and percentages. The survey findings are complemented by an implementation framework that translates the readiness constraints into design requirements for an AI-enabled IoT telemedicine platform and a staged pathway toward predictive diagnostics.

2.2 Geographic structure of the dataset

Geopolitical zone	Community	Records (n)	Share (%)
North-Central	Tse-Agberagbe, Benue State	167	16.7
North-East	Geidam, Yobe State	167	16.7
North-West	Maradun, Zamfara State	167	16.7

South-East	Igbo-Eze, Enugu State	166	16.6
South-South	Sagbama, Bayelsa State	167	16.7
South-West	Saki, Oyo State	166	16.6
Total		1,000	100.0

Table 1. Distribution of the 1,000 survey respondents across the six selected rural communities. The allocation was nearly equal across zones (166–167 respondents per community). Because the available study records do not establish probability sampling or recruitment procedures, the results are interpreted as evidence from the selected communities rather than national prevalence estimates.

2.3 Proposed AI-enabled IoT mHealth platform architecture

The proposed architecture in Figure 1 translates the observed readiness profile into an end-to-end implementation model for rural telemedicine. It comprises six linked components: (1) community-level acquisition of symptoms and optional IoT measurements; (2) a patient/community-health-worker mobile interface that supports local capture and offline operation; (3) secure cloud or edge infrastructure for encrypted storage, preprocessing, synchronization, and interoperability; (4) AI

analytics for risk stratification and predictive decision support; (5) clinician-led telemedicine and integration with primary, secondary, specialist, laboratory, pharmacy, and health-information services; and (6) cross-cutting enablers covering privacy, power, connectivity, workforce capacity, governance, and monitoring. The design is intentionally modular: core telemedicine functions can operate without continuous connectivity or advanced sensing, while IoT monitoring and predictive functions can be introduced progressively as infrastructure, training, data quality, and clinical validation mature.



Figure 1. Proposed end-to-end architecture of the AI-enabled IoT mobile health platform for telemedicine and predictive diagnostics in underserved rural Nigeria. The platform links community-based data acquisition, an offline-capable mobile/CHW interface, secure cloud/edge data management, AI-assisted risk stratification, clinician-supervised telemedicine, and health-system integration. Cross-cutting requirements include privacy and security, reliable power, connectivity, capacity building, regulatory and ethical governance, and monitoring and evaluation. The figure represents the proposed system design; the present survey evaluates deployment readiness and does not constitute clinical validation of the predictive model layer.

2.4 Study variables and instrument

The instrument contained ten items. Nine were dichotomous (Yes/No), and one assessed satisfaction with current healthcare access on a five-point scale from 1 = Very Poor to 5 = Very Good. The measured domains were mobile-phone ownership, previous

use of a phone for health advice, telemedicine awareness, reliable internet access, willingness to use an AI-enabled health application for diagnosis, healthcare-access satisfaction, IoT-device awareness, trust in AI-assisted diagnosis, electricity availability, and perceived usefulness of AI-mHealth.

Item	Construct	Response format
Q1	Ownership of a smartphone or basic mobile phone	Yes / No
Q2	Previous use of a mobile phone to seek health advice	Yes / No

Q3	Awareness of telemedicine services in the area	Yes / No
Q4	Reliable internet access in the community	Yes / No
Q5	Willingness to use an AI-enabled health app for diagnosis	Yes / No
Q6	Satisfaction with current healthcare access	1 (Very Poor) to 5 (Very Good)
Q7	Awareness of IoT health devices such as smart wristbands	Yes / No
Q8	Trust in AI to assist diagnosis	Yes / No
Q9	Electricity for at least eight hours per day	Yes / No
Q10	Belief that AI-mHealth can improve community healthcare	Yes / No

Table 2. Survey variables and questionnaire items used in the study.

2.5 Statistical analysis

Binary survey items were summarized using observed counts, percentages, and Wilson 95% confidence intervals. The five-point satisfaction item was summarized using frequencies, percentages, mean, standard deviation, median, and mode. The analysis was intentionally descriptive because the available dataset did not contain respondent-level joint-response information required for valid cross-tabulations, subgroup comparisons, or multivariable modelling. Five figures support the analysis. Figure 1 presents the proposed AI-IoT telemedicine architecture; Figures 2–4 visualize the observed readiness and healthcare-access results; and Figure 5 presents the staged validation pathway required before predictive diagnostic outputs can be used clinically. Figures 2–4 are empirical, whereas Figures 1 and 5 are conceptual implementation frameworks derived from the study findings and current digital-health governance principles.

2.6 Ethical and data-protection framework

Any AI-mHealth implementation involving

identifiable health information should comply with applicable Nigerian data-protection requirements, including safeguards for sensitive health data, purpose limitation, security controls, accountable processing, and appropriate consent. Predictive outputs should not be used as autonomous diagnoses; responsibility for clinical decisions should remain with qualified health professionals, with model outputs treated as decision support and subjected to audit and safety monitoring (WHO, 2021; Nigeria Data Protection Commission, 2023).

3. Results

3.1 Overall readiness profile

The clearest pattern in the dataset is a separation between social receptivity and enabling infrastructure. Three relatively strong positive indicators were mobile-phone ownership (74.1%), perceived usefulness of AI-mHealth (76.8%), and willingness to use an AI-enabled health application (60.3%). By contrast, reliable internet access (20.0%), telemedicine awareness (26.9%), IoT-device awareness (17.9%), and electricity

availability for at least eight hours per day (32.9%)

were substantially lower.

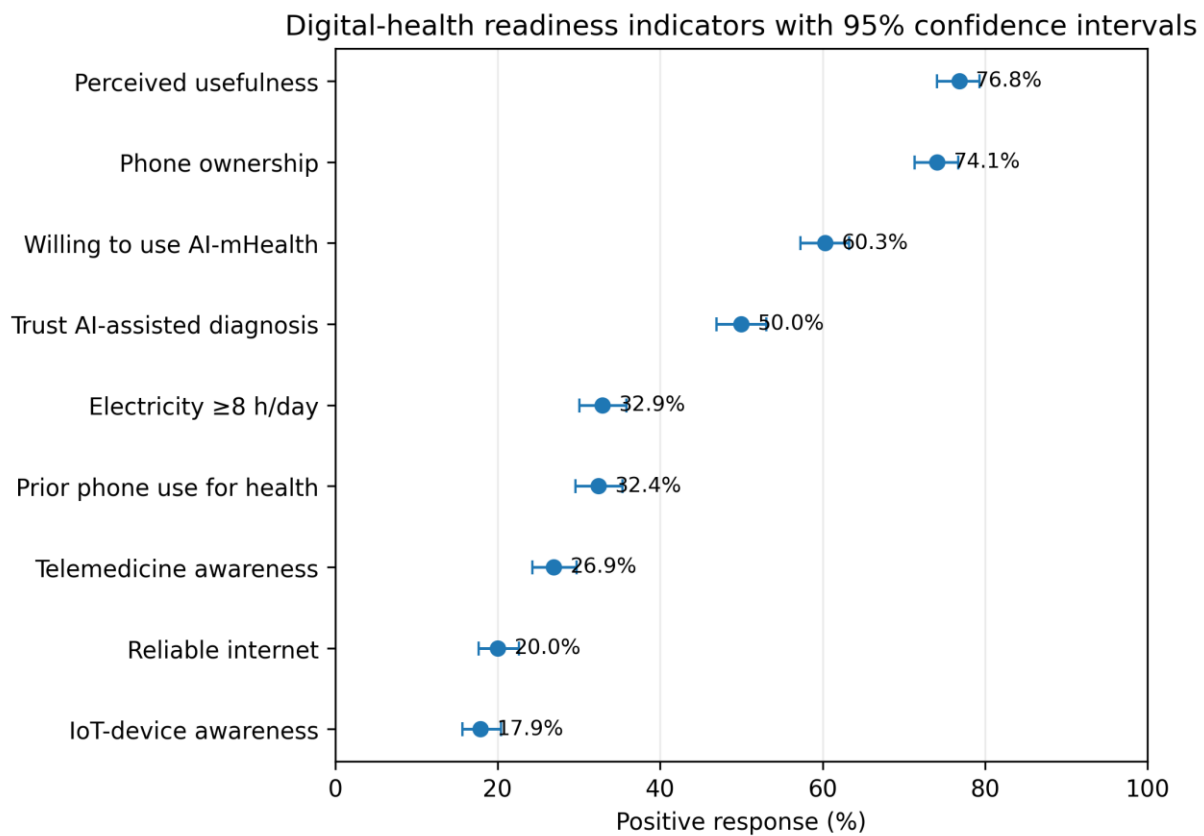


Figure 2. Positive-response estimates for nine binary digital-health readiness indicators. Points show observed percentages and whiskers show Wilson 95% confidence intervals ($N = 1,000$).

Indicator	Yes n (%)	No n (%)	95% CI for Yes (%)
Mobile phone ownership	741 (74.1)	259 (25.9)	71.3–76.7
Previous phone use for health advice	324 (32.4)	676 (67.6)	29.6–35.4
Telemedicine awareness	269 (26.9)	731 (73.1)	24.2–29.7
Reliable internet access	200 (20.0)	800 (80.0)	17.6–22.6
Willingness to use AI-enabled health app	603 (60.3)	397 (39.7)	57.2–63.3

IoT health-device awareness	179 (17.9)	821 (82.1)	15.6–20.4
Trust in AI-assisted diagnosis	500 (50.0)	500 (50.0)	46.9–53.1
Electricity ≥ 8 hours/day	329 (32.9)	671 (67.1)	30.1–35.9
AI-mHealth perceived as beneficial	768 (76.8)	232 (23.2)	74.1–79.3

Table 3. Descriptive results for binary digital-health readiness indicators (N = 1,000).

3.1.1 Precision of the principal estimates

The confidence intervals are sufficiently narrow to distinguish the strongest and weakest indicators descriptively. Perceived usefulness was estimated at 76.8% (95% CI 74.1–79.3), whereas reliable internet access was 20.0% (17.6–22.6) and IoT-device awareness was 17.9% (15.6–20.4). The separation between these estimates is much larger than their sampling uncertainty, supporting the interpretation that social receptivity currently exceeds technical readiness in the surveyed communities.

3.2 Mobile access and prior digital-health behavior

Mobile-phone ownership was high relative to other enabling conditions: 741 respondents (74.1%; 95% CI 71.3–76.7) reported owning a smartphone or basic mobile phone. However, only 324 (32.4%; 95% CI 29.6–35.4) had previously used a phone to seek health advice. This gap suggests that physical access to a handset does not automatically translate into established digital-health behavior.

3.3 Awareness and connectivity

Telemedicine awareness was reported by 269 respondents (26.9%; 95% CI 24.2–29.7), while reliable internet access was reported by only 200 (20.0%; 95% CI 17.6–22.6). Awareness of IoT-based health devices was the lowest measured positive indicator at 17.9% (95% CI 15.6–20.4). These values support an implementation strategy that does not assume prior familiarity with telemedicine or connected health devices.

3.4 Willingness, trust, and perceived usefulness

Willingness to use an AI-enabled health application was reported by 603 respondents (60.3%; 95% CI 57.2–63.3). Perceived usefulness was stronger: 768 (76.8%; 95% CI 74.1–79.3) believed AI-mHealth could improve healthcare in their community. Trust in AI-assisted diagnosis was evenly divided at 50.0% (95% CI 46.9–53.1), indicating that perceived benefit does not eliminate concerns about reliance on AI in clinical decision making.

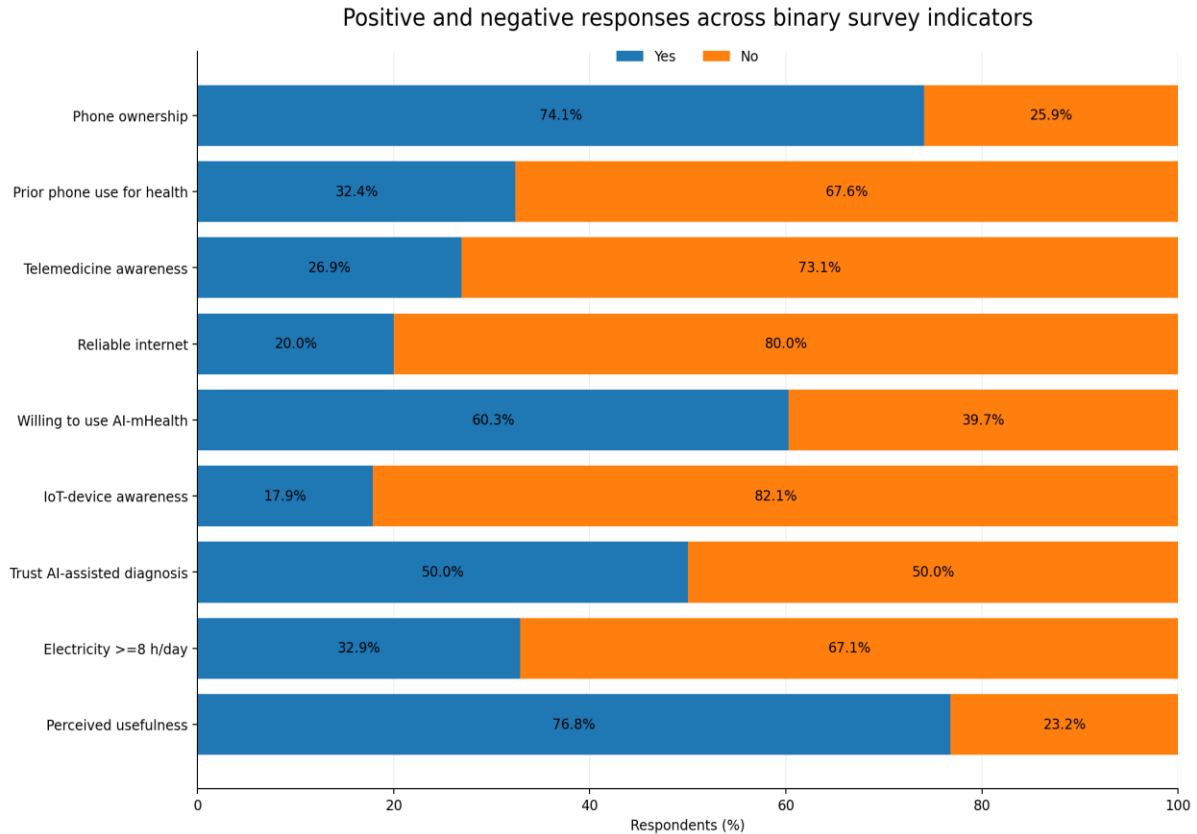


Figure 3. Positive and negative responses across the nine binary digital-health readiness indicators (N = 1,000).

3.5 Electricity and infrastructure readiness

Only 329 respondents (32.9%; 95% CI 30.1–35.9) reported electricity availability for at least eight hours per day. Together with the 20.0% estimate for

reliable internet access, this argues against an architecture that depends on continuous cloud connectivity, uninterrupted charging, or always-on sensor streaming.

3.6 Satisfaction with current healthcare access

Rating	Score	n	%
Very Poor	1	289	28.9
Poor	2	306	30.6
Fair	3	217	21.7
Good	4	127	12.7
Very Good	5	61	6.1

Table 4. Satisfaction with current healthcare access.

Healthcare-access satisfaction was generally low. The mean score was 2.37 out of 5 (SD 1.20), the median was 2 (Poor), and the mode was 2. The complete distribution was Very Poor = 289 (28.9%), Poor = 306 (30.6%), Fair = 217 (21.7%), Good = 127 (12.7%), and Very Good = 61 (6.1%). In total, 595

respondents (59.5%) rated access as Poor or Very Poor, compared with 188 (18.8%) who selected Good or Very Good. Thus, unfavorable ratings exceeded favorable ratings by 407 respondents, or 40.7 percentage points, and were approximately 3.2 times as common as favorable ratings.

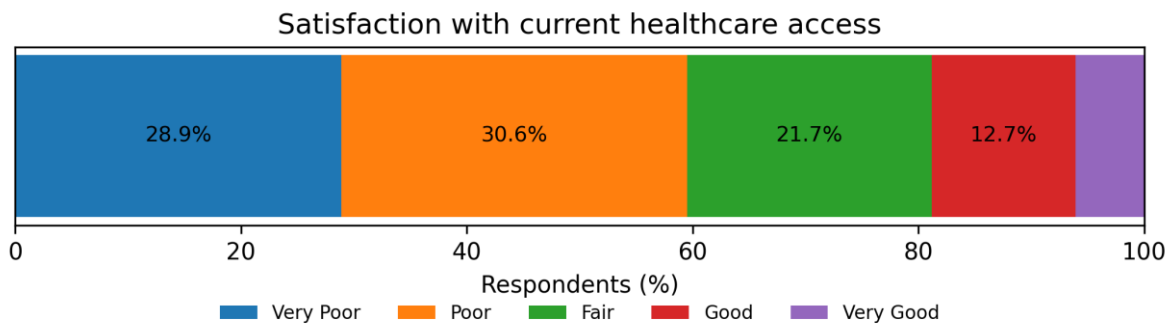


Figure 4. Distribution of satisfaction with current healthcare access (Q6). Percentages sum to 100% across the five ordered categories.

3.7 Design implications of the observed readiness gaps

Perceived usefulness exceeded reliable internet access by 56.8 percentage points and electricity availability by 43.9 points, while willingness to use AI-mHealth exceeded IoT-device awareness by 42.4 points. These are descriptive aggregate contrasts, not paired individual-level effects. Their practical meaning is architectural: the platform should not assume continuous connectivity, constant power, or prior familiarity with IoT technologies.

3.8 Ranking and majority-response pattern

Across the nine binary indicators, perceived usefulness of AI-mHealth was the highest positive response at 76.8%, followed by mobile-phone ownership at 74.1%, willingness to use an AI-enabled health application at 60.3%, and trust in AI-assisted diagnosis at 50.0%. The remaining positive-response estimates were electricity availability for at

least eight hours per day (32.9%), previous use of a phone for health advice (32.4%), telemedicine awareness (26.9%), reliable internet access (20.0%), and IoT-device awareness (17.9%). The difference between the highest and lowest positive-response estimates was 58.9 percentage points. Only three of the nine binary indicators had a positive majority above 50%: phone ownership, willingness to use AI-mHealth, and perceived usefulness. Five indicators had a negative majority, while trust in AI-assisted diagnosis was exactly balanced at 50.0%. This distribution reinforces the distinction between interest in digital care and readiness to sustain more infrastructure-dependent services.

3.9 Implementation-critical contrasts

Several contrasts quantify the implementation gap more directly. Phone ownership exceeded prior health-related phone use by 41.7 percentage points, showing that device access is substantially greater

than established digital-health behavior. Perceived usefulness exceeded trust in AI-assisted diagnosis by 26.8 points, indicating that respondents could see potential value in AI-mHealth without being equally willing to rely on AI for diagnosis. Willingness to use AI-mHealth exceeded IoT-device awareness by 42.4 points. In infrastructure terms, electricity availability

exceeded reliable internet access by 12.9 points, but both remained well below mobile ownership and perceived usefulness. Table 5 summarizes the largest descriptive contrasts. These are aggregate comparisons and should not be interpreted as paired individual-level effects because respondent-level joint-response data were not available.

Table 5. Descriptive implementation-critical contrasts derived from the observed survey estimates.

Contrast	Estimate A (%)	Estimate B (%)	Gap (pp)	Interpretation
Perceived usefulness vs reliable internet	76.8	20.0	56.8	High perceived value despite limited connectivity
Perceived usefulness vs electricity availability	76.8	32.9	43.9	Interest exceeds power readiness
Mobile-phone ownership vs prior health-phone use	74.1	32.4	41.7	Access has not translated into routine digital-health use
Willingness to use AI-mHealth vs IoT awareness	60.3	17.9	42.4	Willingness precedes familiarity with connected devices
Perceived usefulness vs AI diagnostic trust	76.8	50.0	26.8	Perceived benefit is stronger than diagnostic trust
Poor/very poor vs good/very good healthcare access	59.5	18.8	40.7	Negative access experience substantially exceeds favorable ratings

Note: Percentage-point gaps are descriptive contrasts between aggregate survey estimates. They are not paired differences or causal effects.

3.10 Consolidated empirical interpretation

Taken together, the results identify three distinct layers of readiness. The first is access potential, represented most clearly by mobile-phone ownership. The second is social receptivity, reflected in willingness and perceived usefulness. The third is operational readiness, represented by connectivity,

electricity, prior telemedicine exposure, IoT familiarity, and trust in AI-supported diagnosis. Access potential and social receptivity were substantially stronger than most operational indicators. This pattern supports beginning with functions that can operate on basic mobile devices and intermittent networks, while treating connected sensing and predictive diagnostics as later

implementation stages that require additional infrastructure, training, governance, and clinical evidence.

4. Discussion and Proposed AI-IoT Telemedicine Framework

4.1 From survey evidence to platform requirements

The empirical profile supports the staged platform shown in Figure 1. Mobile-phone ownership (74.1%) provides a plausible entry channel for patient- and CHW-facing services, but low reliable internet access (20.0%) and limited electricity availability (32.9%) require store-and-forward workflows, local caching, low-bandwidth interfaces, and energy-efficient devices. Low IoT awareness (17.9%) argues against making wearables or connected sensors mandatory at initial deployment; instead, basic telemedicine should function with manually entered symptoms and measurements, while validated IoT devices are introduced selectively. The evenly divided trust in AI-assisted diagnosis (50.0%) further supports a clinician-in-the-loop design in which AI outputs prioritize or flag cases but do not replace professional judgment. Accordingly, the architecture separates core telemedicine from the predictive layer and allows progressively greater automation only as local evidence, governance, and validation requirements are satisfied.

4.2 Telemedicine workflow

A practical workflow begins when a patient or community health worker records symptoms and, where available, measurements such as blood pressure, oxygen saturation, temperature, glucose, respiratory rate, ECG, or activity data. The mobile interface performs basic completeness and plausibility checks and stores records locally whenever connectivity is unavailable. Once a secure connection becomes available, encrypted

synchronization transfers data to the cloud/edge layer, where ingestion, quality control, longitudinal storage, and interoperability services prepare the information for clinical use. AI analytics may then generate risk scores, alerts, or prioritization cues, but these outputs are reviewed by a clinician during asynchronous or synchronous teleconsultation before referral, treatment review, e-prescription, follow-up, or escalation decisions are made. This workflow preserves clinical accountability and allows the telemedicine service to remain functional even when the predictive component is unavailable.

4.3 Predictive diagnostics: required validation sequence

Predictive diagnostics should be introduced only after the platform can collect sufficiently reliable and clinically relevant data. Candidate models may estimate deterioration risk, abnormal vital-sign patterns, or disease-specific events, but each target outcome must be defined clinically before model development. As summarized in Figure 5, the pathway should proceed through data curation, feature engineering, model development, internal validation, independent local validation, and prospective clinical evaluation before deployment. Performance assessment should include discrimination, calibration, clinically meaningful thresholds, subgroup performance, false-alert burden, and transportability to the intended Nigerian population. Post-deployment monitoring should then evaluate calibration drift, safety, workflow burden, auditability, and ongoing clinical utility under clinician supervision. Future model-development studies should be reported in accordance with TRIPOD+AI, while diagnostic-accuracy evaluations should follow STARD-AI where applicable (Collins et al., 2024; Sounderajah et al., 2025). Early live clinical testing should also assess workflow, human factors, and safety using principles reflected in DECIDE-AI (Vasey et al., 2022).

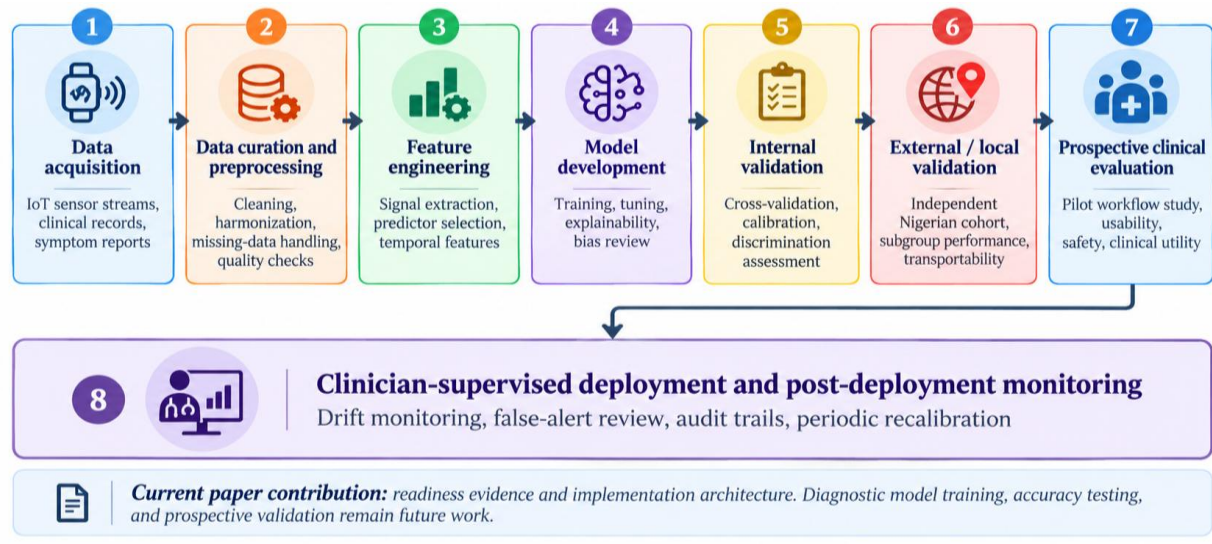


Figure 5. Staged validation pathway for predictive diagnostics within the proposed AI-IoT mHealth platform. Clinical use requires progression from data acquisition and preprocessing through feature engineering, model development, internal and external validation, prospective clinical evaluation, and clinician-supervised post-deployment monitoring.

4.4 Discussion of Findings

4.4.1 Principal findings

The analysis identifies a consistent readiness gap. The strongest indicators, perceived usefulness of AI-mHealth, mobile-phone ownership, and willingness to use an AI-enabled application, reflect social or access potential. The weakest indicators, IoT awareness, reliable internet, telemedicine awareness, and electricity availability, reflect the operational conditions required for sustained deployment. Trust occupies an intermediate position. This pattern suggests that the principal constraint is not simple rejection of digital health; rather, the environment may not yet support sophisticated, always-connected AI-IoT services at scale. The result also illustrates why technology acceptance should be decomposed into distinct constructs. A person can own a phone without using it for health, believe AI-mHealth would be useful without trusting an AI-generated diagnosis, and express willingness to try an application despite unreliable internet. Treating these indicators as interchangeable would obscure the practical sequence required for implementation.

4.4.2 Relationship to Nigerian and regional evidence

The observed infrastructure pattern is consistent with recent Nigerian telemedicine literature. Cole et al. (2025) identified power outages, internet limitations, technical capacity, and institutional factors as recurring barriers, while training and accessible technology were important facilitators. Agbeyangi and Lukose (2025) similarly reported that telemedicine adoption in Sub-Saharan Africa is shaped by infrastructure, workforce readiness, digital literacy, and regulatory conditions. The present dataset adds a useful descriptive contrast: perceived usefulness can remain high despite weak enabling conditions. These findings are also consistent with earlier Nigerian qualitative evidence showing that irregular bandwidth, network limitations, and unstable power can make low-technology asynchronous telemedicine more practical than continuously connected models (van Gurp et al., 2015).

The findings also align conceptually with Okeke et al. (2025), whose rural Oyo State study examined digital-health knowledge, use, competency, and

adoption. Although the populations and methods should not be treated as directly equivalent, both studies support the argument that rural digital-health strategy must address capability and infrastructure alongside willingness. This matters because adoption programs that emphasize only awareness campaigns may fail if users cannot maintain connectivity or power devices, while infrastructure investment alone may fail if trust and digital literacy are ignored. Related Nigerian work on patient-held digital records has likewise highlighted the importance of acceptability, user experience, and fit with local service delivery (Itanyi et al., 2023).

4.4.3 Implications for AI-enabled telemedicine architecture

The results favor a staged architecture. Phase 1 should prioritize functions that tolerate intermittent connectivity: appointment requests, asynchronous messaging, SMS reminders, symptom questionnaires, health education, and store-and-forward teleconsultation. Data should be cached securely on the device and synchronized when connectivity becomes available. Interfaces should minimize bandwidth, support low-cost Android devices where appropriate, and avoid assuming continuous access to wearable sensors.

Phase 2 could introduce supervised remote monitoring using selected IoT devices where charging, maintenance, and connectivity can be supported. Community health workers or primary-care staff could act as intermediaries for onboarding, measurement quality, and escalation. This approach is more consistent with the dataset than a consumer-only model that assumes widespread familiarity with smart wearables.

Phase 3 could incorporate AI decision support only after local validation. AI should initially assist clinicians with prioritization or risk flagging rather than replace clinical judgment. Any predictive function would require real patient-level clinical data, prespecified outcomes, representative training and validation samples, appropriate performance metrics, calibration, subgroup evaluation, prospective testing, and clinical governance. The present survey data cannot establish diagnostic

accuracy and should not be cited as evidence that an AI model performs clinically. This staged approach is consistent with WHO regulatory considerations for AI in health and with recent consensus guidance emphasizing lifecycle evaluation, robustness, explainability, and monitoring (WHO, 2023; Lekadir et al., 2025).

4.4.4 Trust, explainability, and human oversight

The 50.0% trust estimate is a central implementation finding. It argues against presenting AI as an autonomous authority. Instead, the user interface should make clinician involvement visible, distinguish algorithmic suggestions from confirmed diagnoses, explain why information is being requested, and provide a pathway to human review. Such design choices may be particularly important where familiarity with IoT and telemedicine is low. Trust also depends on data governance. WHO guidance on AI for health treats transparency, human oversight, accountability, inclusiveness, and protection of autonomy as core governance principles, while Nigeria's data-protection framework establishes legal safeguards for sensitive personal information (WHO, 2021; Nigeria Data Protection Commission, 2023). Health information can be highly sensitive, and rural users may reasonably be concerned about who can access records, whether data are reused, and what happens when an automated system is wrong. Privacy notices, consent processes, role-based access, encryption, audit trails, and procedures for correcting inaccurate records should therefore be part of the platform design from the outset. These principles are consistent with Nigeria's data-protection framework and broader WHO guidance on safe, equitable digital health.

4.4.5 Interpretation of uncertainty and figure-based evidence

The visual analysis places uncertainty beside each observed binary proportion and therefore avoids treating the sample percentages as exact population parameters. The confidence intervals quantify sampling uncertainty around the reported survey estimates, although they do not by themselves

establish national representativeness. Their main value here is comparative: the high perceived-usefulness and phone-ownership estimates remain clearly separated from the much lower internet-access and IoT-awareness estimates. This reinforces the descriptive conclusion that enthusiasm for digital health is not matched by equivalent infrastructural readiness. The observed implementation gaps are intentionally interpreted descriptively rather than as causal or paired effects. For example, the 56.8-percentage-point difference between perceived usefulness and reliable internet access indicates that perceived value currently exceeds a key enabling condition, but it does not establish that poor connectivity caused any individual response. These aggregate contrasts are used to guide system design rather than to test causal hypotheses.

4.4.6 Health-system and policy implications

The dataset suggests that policy should not equate national digital-health ambition with uniform local readiness. Rural implementation plans should include minimum infrastructure assessments, community-level onboarding, workforce training, and service-continuity planning. Where broadband is unstable, investments in alternative connectivity, local caching, and asynchronous workflows may produce greater practical value than adding computationally intensive features. The low satisfaction with existing healthcare access also deserves attention. Digital services should be positioned as extensions of care pathways, not as substitutes for staffing, medicines, referral systems, or emergency services. WHO guidance explicitly cautions that digital interventions cannot compensate for a non-functioning health system. Accordingly, AI-mHealth programs should be evaluated on whether they reduce delay, improve continuity, support appropriate referral, and expand access without creating new exclusion for users with limited devices, literacy, electricity, or connectivity.

4.4.7 Strengths and limitations

A strength of the study is the inclusion of 1,000 respondents distributed across six rural communities spanning all six geopolitical zones, together with

indicators covering social receptivity, awareness, access, infrastructure, and trust. A second strength is the direct translation of those constraints into a platform design and predictive-diagnostics validation pathway, improving alignment between the empirical evidence and the technological focus. The principal limitations are the absence of respondent-level demographic covariates, the inclusion of one selected rural community per zone, the descriptive cross-sectional design, and the fact that no IoT sensor stream or clinical AI model was tested. Accordingly, the paper supports readiness assessment and system design rather than claims of diagnostic accuracy or clinical effectiveness.

Several limitations constrain interpretation. First, only one selected rural community from each geopolitical zone is represented, so the findings should not be interpreted as nationally representative estimates for all rural Nigerians. Second, participant demographic characteristics were not available in the study dataset used for analysis, preventing stratified assessment by age, sex, education, occupation, digital literacy, or socioeconomic status. Third, respondent-level joint-response data were unavailable, so predictors of willingness, trust, or perceived usefulness could not be evaluated using cross-tabulation or multivariable regression. Fourth, most readiness indicators are single-item self-reports and may be affected by recall, interpretation, or social-desirability bias. Finally, the study measures readiness and perceptions rather than actual platform use, clinical outcomes, IoT sensor performance, or AI diagnostic accuracy.

4.4.8 Priorities for future research

Future research should use a documented multistage sampling strategy, collect demographic and socioeconomic covariates, validate the questionnaire, and preserve respondent-level joint-response data. The next technical phase should pilot the proposed platform with selected IoT measurements, quantify connectivity and power interruptions, assess measurement completeness and sensor reliability, and evaluate teleconsultation workflow performance. Only after an adequate local clinical dataset exists should predictive models be

developed and tested using prespecified outcomes, internal and external validation, calibration analysis, subgroup performance assessment, prospective clinical evaluation, and post-deployment monitoring. Reporting of any subsequent prediction-model study should follow TRIPOD+AI, and any diagnostic-accuracy study should use STARD-AI as appropriate; early prospective deployment should document human factors and workflow effects consistent with DECIDE-AI (Collins et al., 2024; Sounderajah et al., 2025; Vasey et al., 2022).

5. Conclusion and Practical Recommendations

The survey findings indicate meaningful interest in an AI-enabled IoT mobile-health platform, but they also identify the operational constraints that must shape telemedicine and predictive diagnostics in underserved rural Nigeria. Mobile-phone ownership (74.1%), willingness to use AI-enabled health applications (60.3%), and perceived usefulness (76.8%) support a mobile-first entry point, whereas low reliable internet access (20.0%), limited electricity availability (32.9%), low IoT awareness (17.9%), and evenly divided trust in AI-assisted diagnosis (50.0%) argue for offline-first architecture, selective sensor deployment, community-supported onboarding, and visible clinician oversight. The proposed platform therefore separates telemedicine functionality from the predictive layer: remote care should remain usable without AI, and predictive diagnostics should be activated only after local clinical data, model validation, safety evaluation, and workflow integration requirements have been satisfied.

The most defensible interpretation is therefore one of conditional readiness rather than full technological readiness. Rural AI-mHealth in Nigeria should begin with resilient, low-bandwidth, clinically supervised services and progress toward IoT monitoring and predictive decision support only after infrastructure, trust, governance, and local validation improve. These observed survey data do not demonstrate diagnostic performance; they identify the conditions that a future AI-IoT telemedicine program would need to address.

5.1 Practical Recommendations

- Adopt offline-first and low-bandwidth platform architecture, with secure delayed synchronization.
- Use SMS, asynchronous consultation, and lightweight mobile workflows before introducing continuous remote monitoring.
- Build community sensitization and digital-health literacy into implementation budgets.
- Keep clinicians and trained community health workers visibly involved in AI-supported pathways.
- Introduce IoT devices selectively, with charging, maintenance, training, and measurement-quality support.
- Apply privacy-by-design, role-based access, encryption, clear consent, and auditability for sensitive health data.
- Validate any future predictive algorithm on Nigerian clinical data and report discrimination, calibration, subgroup performance, and prospective clinical utility.
- Collect respondent-level demographic and joint-response data in the next study so that predictors of willingness and trust can be estimated.

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