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# PERCEPTION AND ATTITUDE OF HEALTH WORKERS TOWARD THE ADOPTION OF ELECTRONIC HEALTH RECORDS IN A NIGERIAN SECONDARY HOSPITAL

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## ABSTRACT

Successful adoption of electronic health records (EHRs) depends on more than technical installation; it depends on the beliefs, attitudes, and organizational conditions of the clinical workforce expected to use the system. This study assessed the perception and attitude of health workers toward EHR adoption at State Specialist Hospital, Lisaluwa, Ondo, Ondo State, Nigeria, examining perception, attitude, facilitating conditions, perceived barriers, and behavioral intention together, and their inter-relationships, among the hospital's clinical workforce.

An institution-based descriptive cross-sectional design with an analytical component was employed. Of 420 questionnaires distributed to clinical health workers across seven cadres, using Cochran's formula for sample-size determination, 357 were returned complete and analysed, a response rate of 85.0%. The structured, validated instrument (Cronbach's alpha 0.869–0.950 across scales) measured perception (15 items), attitude (10 items), facilitating conditions (8 items), perceived barriers (10 items), and behavioral intention (5 items). Data were analysed descriptively and inferentially in SPSS, including Pearson correlation, multiple linear regression with heteroscedasticity-consistent (HC3) standard errors, a Yates-corrected chi-square test, and Welch's one-way ANOVA.

Positive perception was recorded among 236 respondents (66.1%), 231 (64.7%) had a favourable attitude, and 221 (61.9%) had high behavioral intention. Mean scores were 3.77 (SD = 0.74) for perception, 3.72 (SD = 0.78) for attitude, 3.43 (SD = 0.79) for facilitating conditions, 3.36 (SD = 0.81) for perceived barriers, and 3.68 (SD = 0.81) for behavioral intention. Behavioral intention correlated positively with perception ($r = .513$), attitude ($r = .583$), and facilitating conditions ($r = .329$), and negatively with perceived barriers ($r = -.425$; all $p < .001$). The regression model explained 54.0% of the variance in intention ($F(7,349) = 58.62$, $p < .001$; adjusted $R^2 = .531$). Attitude ($\beta = .369$), computer proficiency ($\beta = .295$), perceived barriers ($\beta = -.201$), and facilitating conditions ($\beta = .150$) remained independently significant predictors, whereas perception, formal computer training, and prior EHR use did not remain significant after adjustment. Formal computer training was associated with high intention at the bivariate level (OR = 2.12, 95% CI [1.37, 3.28]).

The results indicate broad, conditional support for EHR adoption at the study hospital, but willingness is closely tied to digital competence and credible organizational support rather than to general approval alone. The hospital should prioritize competency-based training, workflow preparation, reliable connectivity, clear operating policies, and phased implementation with sustained technical support to translate this favourable disposition into effective, routine use.

**KEYWORDS:** Electronic Health Records; Health Workers; Perception; Attitude; Adoption; Health Information Management; Nigeria.

## 1. INTRODUCTION

Clinical care is organized around information: registration establishes patient identity, the case record documents assessment and treatment, laboratory and imaging requests connect clinicians with diagnostic services, and medication records guide dispensing and follow-up. In a paper-based system these details are distributed across folders, registers, and departmental files, and delayed retrieval, duplicate folders, illegible entries, and weak movement of information between service points can disrupt both care and administration. Electronic health records (EHRs) are intended to reduce these weaknesses by allowing authorized users to create, retrieve, and share structured patient information across the care pathway, combining identification, consultation notes, diagnoses, medication history, laboratory and imaging results, orders, alerts, coding, and billing, functions that have made EHR implementation a major component of digital-health policy (Negro-Calduch et al., 2021; Wang et al., 2023; World Health Organization, 2021).

Installing software does not by itself produce routine clinical use. A hospital has established roles, documentation habits, informal workarounds, and expectations about who records, verifies, and acts on information, and introducing an EHR may change the order of a consultation, redistribute clerical tasks, or create new authentication requirements. Adoption is therefore a sociotechnical process involving technology, workflow, governance, professional practice, and organizational culture, in which a technically functional system can still fail if these elements are poorly aligned (Iyanna et al., 2022; Luyten & Marneffe, 2021). Clinical health workers are central to that alignment because they generate and use most of the content in the patient record; if information is entered late, copied inaccurately, or not consulted, the value of the EHR declines, and workers may avoid parts of a system they consider cumbersome, unsafe, or unrelated to patient care (Akwaowo et al., 2022; Ngusie et al., 2024).

Perception, in this study, concerns how health workers judge the likely characteristics and consequences of EHR adoption, expected usefulness, ease of use, compatibility with clinical tasks, accessibility, efficiency, patient safety, and confidentiality, judgments that can shape behaviour before a worker has extensive direct experience with the system (Davis, 1989; Dube et al., 2025; Venkatesh et al., 2003). Attitude is treated separately because recognising that a technology may be useful does not necessarily produce willingness to use it; a worker may see potential benefits and still feel uncertain about digital competence, professional autonomy, or disruption of familiar routines. Studies in resource-constrained settings have linked favourable attitudes with computer skill, training, prior exposure, and access to supportive conditions, though the evidence is not uniform across institutions or professional groups (Mohammed et al., 2024; Wubante et al., 2023).

EHR adoption in Nigeria remains uneven: some tertiary and private facilities use integrated or modular systems, while many public facilities continue to rely substantially on paper records, and high patient volumes, infrastructure constraints, and variation in digital skills complicate implementation, alongside more explicit privacy obligations under the Nigeria Data Protection Act 2023 (Federal Republic of Nigeria, 2023). Recent Nigerian research does not present a single picture of readiness. Akwaowo et al. (2022), surveying 1,177 respondents across four Niger Delta states, found perceived usefulness, awareness, relative advantage, and critical success factors positively related to adoption propensity, and perceived risk and data-security concerns negatively related. In Ondo State specifically, Babatope et al. (2024) found high awareness alongside low utilization among 76 staff at the University of Medical Sciences Teaching Hospital (UNIMEDTH), with financial, ICT, power, connectivity, interoperability, and privacy concerns prominent, while Afolabi et al. (2022) examined adoption and implementation challenges at the same institution using a broader sample. Both

studies were conducted at UNIMEDTH with different populations and measures, and their results cannot be assumed to describe clinical workers at State Specialist Hospital, Lisaluwa.
The present study is located at State Specialist Hospital, Lisaluwa, Ondo, and concerns the workforce expected to document, retrieve, and act on electronic patient information. Whether EHR adoption is being planned, expanded, or evaluated, management needs evidence about what clinical workers expect from the system, the changes they are prepared to make, and the support they consider necessary, evidence that equipment inventories alone cannot provide. This study therefore assessed clinical health workers' perception and attitude toward EHR adoption at State Specialist Hospital, Lisaluwa, together with facilitating conditions, perceived barriers, and behavioral intention, with the specific objectives of: (i) determining health workers' perception of the usefulness, compatibility, and expected consequences of EHR adoption; (ii) assessing health workers' attitude toward learning, supporting, and routinely using an EHR system; (iii) identifying the principal barriers that health workers believe could hinder successful EHR adoption; and (iv) assessing the relationships between perception, attitude, facilitating conditions, perceived barriers, and behavioral intention to adopt EHRs.

## 2. Theoretical Framework

This study draws on the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Technology-Organization-Environment (TOE) perspective. None is used as a complete explanation of adoption: TAM and UTAUT help organize individual beliefs and intention, while TOE draws attention to organizational and environmental conditions. Their use in a cross-sectional survey identifies associations among constructs; it does not establish causal pathways.

### *2.1 Technology Acceptance Model*

TAM proposes that perceived usefulness and perceived ease of use influence attitude and behavioral intention, which are related to use (Davis, 1989). Its advantage for a pre-implementation study is parsimony: workers can evaluate expected benefit and effort before routine-use data exist. The model is less adequate when access is constrained by power, devices, training, policy, or management support, and mandatory use can weaken the link between attitude and observed behaviour; in a resource-constrained hospital, positive beliefs may coexist with an inability to use the system. TAM constructs are therefore retained in this study but not treated as sufficient on their own.

### *2.2 Unified Theory of Acceptance and Use of Technology*

UTAUT combines performance expectancy, effort expectancy, social influence, and facilitating conditions; performance and effort overlap with TAM's usefulness and ease-of-use constructs, while social influence and facilitating conditions add the expectations of colleagues, leaders, and the organization (Venkatesh et al., 2003). The distinction between intention and use is particularly useful here because workers may intend to adopt an EHR without having the resources or opportunity to do so. Later extensions of UTAUT include constructs developed mainly for consumer technologies (Venkatesh et al., 2012); the present study does not reproduce the full model or its original moderators, but selects constructs corresponding to the research questions and the proposed implementation context.

### *2.3 Technology-Organization-Environment Perspective*

TOE explains organizational adoption through characteristics of the technology, the organization, and the external environment: compatibility and complexity belong to the technological domain; resources, leadership, and readiness belong to the organizational domain; and regulation, vendors, and sector expectations form the environment. TOE is usually applied at the organizational level, whereas the respondents in this study are individual workers; it is used here as a contextual perspective, not an individual-behaviour theory, so that workers' ratings of infrastructure, support, privacy, and interoperability represent perceptions of organizational conditions rather than an objective organizational audit.

### *2.4 Theoretical Framework Adopted for the Study*

The adopted framework retains perceived usefulness and ease of use from TAM and the broader performance, effort, and facilitating-condition ideas represented in UTAUT. Perception is defined broadly to include usefulness, ease, compatibility, relative advantage, safety, accessibility, and confidentiality, reflecting workers' overall evaluation of the proposed EHR, while attitude is measured separately to capture willingness, confidence, preference, and support rather than repeating beliefs about system attributes. Facilitating conditions are included because resources and organizational support may determine whether favourable beliefs can be acted upon, and perceived barriers are retained as a separate construct to capture anticipated cost, infrastructure, training, workload, resistance, privacy, and interoperability problems. Social influence, hedonic motivation, price value, and habit were not modelled as independent scales because they were not central to the stated objectives and some assume established or consumer use. Behavioral intention is the outcome because the study assesses adoption before actual routine use can be measured consistently, and formal computer training, prior EHR exposure, proficiency, and clinical cadre are treated as background characteristics that may relate to intention or to the main constructs. The framework predicts direction of association, not causality; a cross-sectional design cannot establish that perception or attitude preceded intention.

## 3. Conceptual Framework

Figure 1 presents the conceptual framework guiding this study, adapted from the Technology Acceptance Model (Davis, 1989) and UTAUT (Venkatesh et al., 2003). Perception, attitude, facilitating conditions, and perceived barriers are positioned as the principal individual and organizational predictors of behavioral intention to adopt an EHR, with formal computer training, prior EHR use, computer proficiency, and clinical cadre included as background characteristics that may additionally relate to intention. The framework guided both instrument development (Sections C–G of the questionnaire) and the analytical strategy (bivariate correlation followed by multivariable regression), allowing the study to distinguish which predictors retain independent explanatory value once their shared variance with related constructs is accounted for.

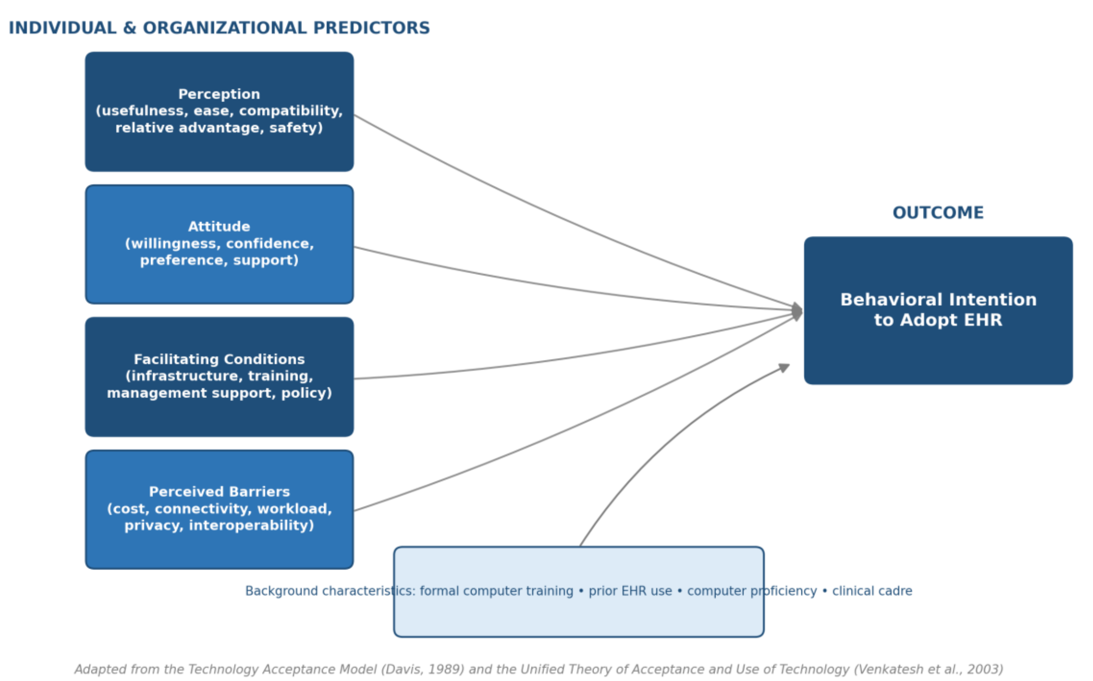


**Figure 1. Conceptual framework for behavioral intention to adopt electronic health records (adapted from Davis, 1989, and Venkatesh et al., 2003).**

## 4. Materials and Methods

### *4.1 Research Design and Setting*

An institution-based descriptive cross-sectional design with an analytical component was used. The descriptive component summarized perception, attitude, facilitating conditions, perceived barriers, and behavioral intention during the study period, while the analytical component examined relationships among the constructs and selected professional and digital-experience characteristics. The study was conducted at State Specialist Hospital, Lisaluwa, Ondo, in Ondo West Local Government Area, Ondo State, Nigeria, a secondary-level hospital whose work processes generate information across registration, consultation, nursing care, laboratory and imaging services, pharmacy, referral, discharge, and follow-up. The study assessed workers' views of EHR adoption; it did not independently audit the hospital's installed digital systems, electricity supply, network coverage, device inventory, or cybersecurity controls, and no unsupported institutional capacity figures are reported.

### *4.2 Study Population and Eligibility Criteria*

The target population consisted of eligible clinical health workers employed at the hospital during the data-collection period, comprising doctors, nurses and midwives, pharmacists, medical laboratory scientists, radiographers, physiotherapists, and other allied clinical workers whose duties involved direct patient care or the creation, retrieval, interpretation, or use of clinical information. The exact population of the eligible clinical workforce could not be ascertained from the hospital's human resources department at the time of the study. Inclusion required employment at the hospital during data collection, completion of at least three months of service, clinical duties, and informed consent; staff whose duties were entirely administrative or nonclinical, students, observers, short-placement personnel, and eligible workers on extended leave throughout fieldwork were excluded.

### *4.3 Sample Size and Sampling Technique*

Since the exact clinical-workforce population was unknown, Cochran's formula for an infinite population, $n_0 = Z^2p(1-p)/d^2$, was used to determine the minimum sample size. Using $Z = 1.96$ (95% confidence level), $p = .50$, and $d = .05$ produced $n_0 = 384.16$, rounded to 385; an additional 35 questionnaires (a 9.1% allowance) were prepared for nonresponse, giving a total of 420 questionnaires distributed. Clinical cadre served as the principal sampling stratum so that professional groups involved in patient care and clinical documentation were represented, with questionnaires allocated across cadres and departments and data-collection visits covering different work periods to reduce exclusion of staff with differing schedules. The final analysed distribution was 25 doctors, 152 nurses and midwives, 10 pharmacists, 14 medical laboratory scientists, 5 radiographers, 22 physiotherapists, and 129 other allied clinical workers. Of the 420 questionnaires distributed, 357 were returned and included in the analysis (63 were not returned), a response rate of 85.0%; no returned questionnaire was excluded, as none had missing responses that prevented calculation of the principal scales.

### *4.4 Instrument, Validity, and Reliability*

Data were collected with a structured, self-administered instrument, the Health Workers' Perception and Attitude Toward Electronic Health Record Adoption Questionnaire, developed from the study objectives and constructs drawn from TAM, UTAUT, and recent EHR-adoption research (Akwaowo et al., 2022; Ngusie et al., 2024; Venkatesh et al., 2003). Section A covered sociodemographic and professional characteristics; Section B measured digital experience and access; Section C contained 15 perception items; Section D, 10 attitude items; Section E, 8 facilitating-condition items; Section F, 10 perceived-barrier items; and Section G, 5 behavioral-intention items (48 Likert statements in total). Responses to Sections C–G used a five-point scale (1 = strongly disagree to 5 = strongly agree), with items P10, A4, and A8 negatively worded and reverse-scored before composite means were calculated.

The questionnaire underwent face and content review by the study supervisors and selected health information management experts before administration, focused on relevance, clarity, construct coverage, separation of perception from attitude, and suitability for clinical workers in the study setting; comments were used to simplify ambiguous wording and remove avoidable overlap. Factor analysis and test-retest reliability were not undertaken, so the validity evidence reported here is limited to pre-administration expert review and field internal consistency. Internal consistency, recalculated from the 357 analysed questionnaires, was strong for all five scales: Cronbach's alpha was .950 for perception, .933 for attitude, .916 for facilitating conditions, .930 for perceived barriers, and .869 for behavioral intention.

### *4.5 Data Collection, Measurement, and Scoring*

Eligible workers received information about the study's purpose, voluntary participation, confidentiality, and their right to decline. Questionnaires were self-administered and used study codes rather than names or personnel numbers; departmental contacts supported access and retrieval but did not receive individual responses. Perception was calculated as the mean of P1–P15 after reverse-scoring P10; attitude as the mean of A1–A10 after reverse-scoring A4 and A8; and facilitating conditions, perceived barriers, and behavioral intention as the means of F1–F8, B1–B10, and I1–I5 respectively. Higher perception, attitude, facilitating-condition, and intention scores represented more positive assessments; a higher barrier score represented stronger perceived obstacles. For descriptive classification, mean scores from

3.50 to 5.00 were categorized as positive/favourable/high, 2.50 to 3.49 as neutral/moderate, and below 2.50 as negative/unfavourable/low; these cutoffs are analytical conventions for this study rather than externally validated clinical thresholds, and continuous scale means were retained for inferential analysis. Formal computer training and prior EHR use were coded 0 = no, 1 = yes; self-rated computer proficiency was coded 0 = low, 1 = moderate, 2 = high for regression; and clinical cadre was treated as a categorical variable.

### *4.6 Statistical Analysis*

Frequencies and percentages summarized sociodemographic, professional, and digital-experience variables; item scores and composite scales were described with means and standard deviations; and internal consistency was evaluated with Cronbach's alpha. Pearson product-moment correlation examined the direction and strength of relationships among perception, attitude, facilitating conditions, perceived barriers, and behavioral intention. Multiple linear regression examined behavioral intention as the dependent variable, with perception, attitude, facilitating conditions, perceived barriers, formal computer training, prior EHR use, and self-rated computer proficiency entered simultaneously; the overall model was significant, $F(7, 349) = 58.62$, $p < .001$, explaining 54.0% of the variance in intention (adjusted $R^2 = .531$). Model diagnostics supported the specification: linearity was confirmed by the Ramsey RESET test, $F(1, 348) = 0.59$, $p = .442$; residual independence was acceptable (Durbin-Watson = 2.04); residuals were approximately normal (Shapiro-Wilk $W = .996$, $p = .551$); and variance inflation factors ranged from 1.09 to 1.97. Because the Breusch-Pagan test indicated heteroscedasticity, $\chi^2(7) = 17.02$, $p = .017$, HC3 heteroscedasticity-consistent standard errors and confidence intervals were used for coefficient tests.

Formal computer training was cross-tabulated with high versus not-high behavioral intention and evaluated with a Yates-corrected chi-square test, with the odds ratio and 95% confidence interval also reported. Clinical-cadre differences in mean intention were first checked with Levene's test; because homogeneity of variance was not supported, $F(6, 350) = 2.26$, $p = .037$, Welch's one-way ANOVA was used instead of conventional ANOVA, given group sizes ranging from 5 to 152. No post hoc test was conducted because the omnibus Welch test was not significant. All tests were two-sided, with statistical significance set at .05.

### *4.7 Control of Bias and Ethical Considerations*

The questionnaire was self-administered and did not request direct identifiers; participants were informed that responses would be reported in aggregate and would not affect employment. Coverage of multiple cadres and work periods reduced, but did not eliminate, selection bias; reverse-worded items were used sparingly and checked during scoring; and because all principal variables were measured in one questionnaire, common-method and social-desirability bias remain possible. Participation was voluntary, and informed consent was obtained before questionnaire completion; the dataset contained respondent codes rather than names, results were reported in aggregate, and data handling was guided by confidentiality principles and the Nigeria Data Protection Act 2023 (Federal Republic of Nigeria, 2023).

## 5. RESULTS

### *5.1 Response Rate and Sociodemographic Characteristics*

Of 420 questionnaires distributed, 357 were returned and included in the analysis (63 were not returned), a response rate of 85.0%. All demographic and Likert fields were complete, all Likert responses were within the permitted range of 1 to 5, and the reverse-scored items (P10, A4, A8) were applied correctly. Women accounted for 221 respondents (61.9%), and the largest age group was 30–39 years (134; 37.5%). Nurses and midwives formed the largest clinical cadre (152; 42.6%), followed by other allied clinical workers (129; 36.1%); doctors accounted for 25 (7.0%), physiotherapists for 22 (6.2%), medical laboratory scientists for 14 (3.9%), pharmacists for 10 (2.8%), and radiographers for 5 (1.4%) (Table 1). Formal computer training had been received by 172 respondents (48.2%), while 133 (37.3%) reported prior EHR/EMR use; computer proficiency was rated moderate by 139 (38.9%) and high by 134 (37.5%); and perceived internet reliability was more often described as sometimes reliable (181; 50.7%) than reliable (56; 15.7%).

**Table 1. Sociodemographic, professional, and digital-experience characteristics of respondents. (N = 357)**

| Characteristic | Category | Frequency | Percent |
|---|---|---|---|
| Sex | Female | 221 | 61.9 |
| | Male | 136 | 38.1 |
| Age group | 20–29 | 76 | 21.3 |
| | 30–39 | 134 | 37.5 |
| | 40–49 | 90 | 25.2 |
| | 50 years and above | 57 | 16.0 |
| Clinical cadre | Doctor | 25 | 7.0 |
| | Nurse/Midwife | 152 | 42.6 |
| | Pharmacist | 10 | 2.8 |

| Characteristic | Category | Frequency | Percent |
|---|---|---|---|
| | Medical Laboratory Scientist | 14 | 3.9 |
| | Radiographer | 5 | 1.4 |
| | Physiotherapist | 22 | 6.2 |
| | Other Allied Clinical Worker | 129 | 36.1 |
| Highest qualification | Diploma | 50 | 14.0 |
| | Bachelor's degree | 229 | 64.1 |
| | Postgraduate degree | 78 | 21.8 |
| Years of experience | Less than 5 years | 96 | 26.9 |
| | 5–9 years | 94 | 26.3 |
| | 10–14 years | 89 | 24.9 |
| | 15 years and above | 78 | 21.8 |
| Primary department | Medical | 89 | 24.9 |
| | Surgical | 45 | 12.6 |
| | Emergency | 49 | 13.7 |
| | Pediatrics | 40 | 11.2 |
| | Obstetrics/Gynecology | 37 | 10.4 |
| | Pharmacy | 27 | 7.6 |
| | Laboratory | 24 | 6.7 |
| | Radiology | 20 | 5.6 |
| | Rehabilitation/Other | 26 | 7.3 |
| Formal computer training | Yes | 172 | 48.2 |
| | No | 185 | 51.8 |
| Prior EHR use | Yes | 133 | 37.3 |
| | No | 224 | 62.7 |
| Computer proficiency | Low | 84 | 23.5 |
| | Moderate | 139 | 38.9 |
| | High | 134 | 37.5 |
| Perceived internet reliability | Unreliable | 120 | 33.6 |
| | Sometimes reliable | 181 | 50.7 |
| | Reliable | 56 | 15.7 |

*Source: Field survey (2026).*

### *5.2 Reliability and Overall Scale Scores*

Internal consistency was high for all five scales, with alpha coefficients ranging from .869 to .950 (Table 2), supporting the use of composite scores for group-level analysis in this sample, though these values do not by themselves establish full construct validity.

**Table 2. Descriptive statistics and internal consistency of the study scales.**

| Scale | Items | Mean | SD | Cronbach's α |
|---|---|---|---|---|
| Perception | 15 | 3.77 | 0.74 | 0.950 |
| Attitude | 10 | 3.72 | 0.78 | 0.933 |
| Facilitating conditions | 8 | 3.43 | 0.79 | 0.916 |
| Perceived barriers | 10 | 3.36 | 0.81 | 0.930 |
| Behavioral intention | 5 | 3.68 | 0.81 | 0.869 |

*Source: Field survey (2026), N = 357.*

### *5.3 Perception of EHR Adoption*

The overall perception mean was 3.77 (SD = 0.74) (Table 3). The highest-rated items were improved documentation accuracy and completeness (P2, M = 3.90), compatibility with clinical tasks (P11, M = 3.90), and better clinical decision-making (P5, M = 3.87). The lowest-scored item was the reverse-scored complexity statement (P10, M = 3.59), followed by easier reporting and audit (P8, M = 3.63) and the judgement that benefits would outweigh implementation difficulties (P12, M = 3.64). Two hundred and thirty-six respondents (66.1%) had a positive perception, 101 (28.3%) were neutral, and 20 (5.6%) had a negative perception (Figure 2).

**Table 3. Item-level perception scores.**

| Item | Statement | Mean | SD |
|---|---|---|---|
| P1 | Faster access to complete patient information | 3.85 | 0.97 |
| P2 | Improved accuracy and completeness of documentation | 3.90 | 0.91 |
| P3 | Reduced duplication, misfiling, and record loss | 3.75 | 0.96 |
| P4 | Improved continuity and coordination of care | 3.73 | 0.98 |
| P5 | Better clinical decision-making | 3.87 | 0.91 |
| P6 | Reduced waiting time and service delays | 3.82 | 0.97 |
| P7 | Improved patient safety and fewer preventable errors | 3.83 | 0.97 |
| P8 | Easier reporting, audit, and quality improvement | 3.63 | 0.99 |

| Item | Statement | Mean | SD |
|---|---|---|---|
| P9 | Increased efficiency and productivity | 3.65 | 0.96 |
| P10 | Clinical work would become unnecessarily complicated (reverse-scored) | 3.59 | 0.96 |
| P11 | Compatibility with tasks performed | 3.90 | 0.97 |
| P12 | Benefits outweigh implementation difficulties | 3.64 | 0.99 |
| P13 | Improved communication between departments | 3.68 | 1.02 |
| P14 | Improved confidentiality with access controls | 3.85 | 0.92 |
| P15 | Important for modernizing healthcare delivery | 3.84 | 0.94 |

*Source: Field survey (2026).*

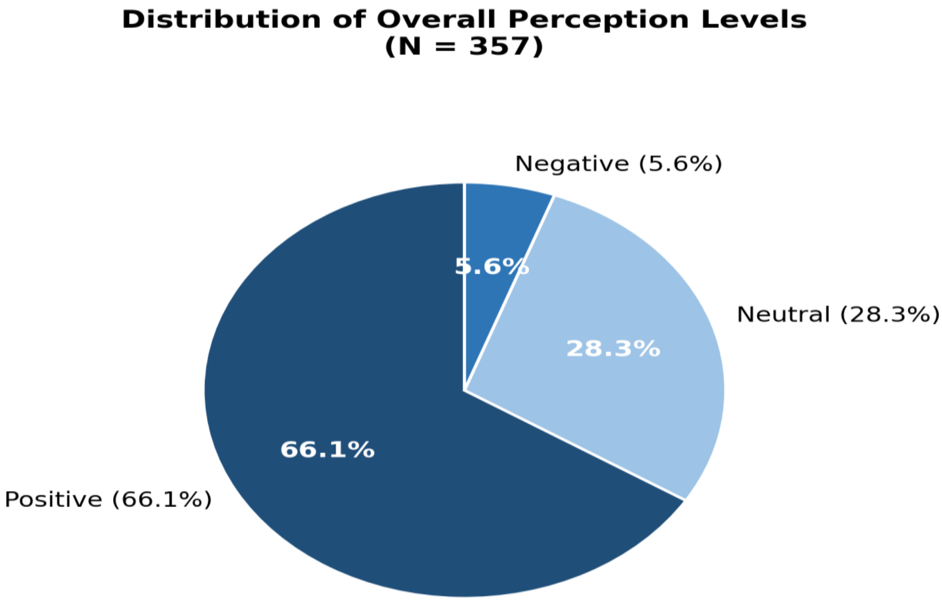


**Figure 2. Distribution of overall perception levels (N = 357).**

### *5.4 Attitude Toward EHR Adoption*

The overall attitude mean was 3.72 (SD = 0.78) (Table 4). Confidence in becoming competent (A9, M = 3.86), willingness to learn required skills (A2, M = 3.82), and the reverse-scored autonomy item (A8, M = 3.82) were strongest, while the general statement about feeling positive toward EHR introduction had the lowest mean (A1, M = 3.46), followed by support for phased and monitored introduction (A10, M = 3.56). This pattern suggests respondents were more confident about learning and adapting than uniformly enthusiastic about the introduction process itself. A favourable attitude was recorded for 231 respondents (64.7%), 107 (30.0%) were neutral, and 19 (5.3%) were unfavourable (Figure 3).

**Table 4. Item-level attitude scores.**

| Item | Statement | Mean | SD |
|---|---|---|---|
| A1 | Positive about introducing an HER | 3.46 | 1.02 |
| A2 | Willing to learn required skills | 3.82 | 0.96 |
| A3 | Comfortable replacing most paper records | 3.68 | 0.96 |
| A4 | Prefer paper even if a reliable EHR is available (reverse-scored) | 3.81 | 0.95 |
| A5 | Would use the EHR consistently | 3.64 | 1.02 |
| A6 | Would encourage colleagues to support implementation | 3.71 | 1.01 |
| A7 | Prepared to adjust workflow | 3.80 | 1.03 |
| A8 | EHR would threaten professional autonomy (reverse-scored) | 3.82 | 0.97 |
| A9 | Confident about becoming competent | 3.86 | 1.00 |
| A10 | Support phased and monitored introduction | 3.56 | 0.99 |

*Source: Field survey (2026).*

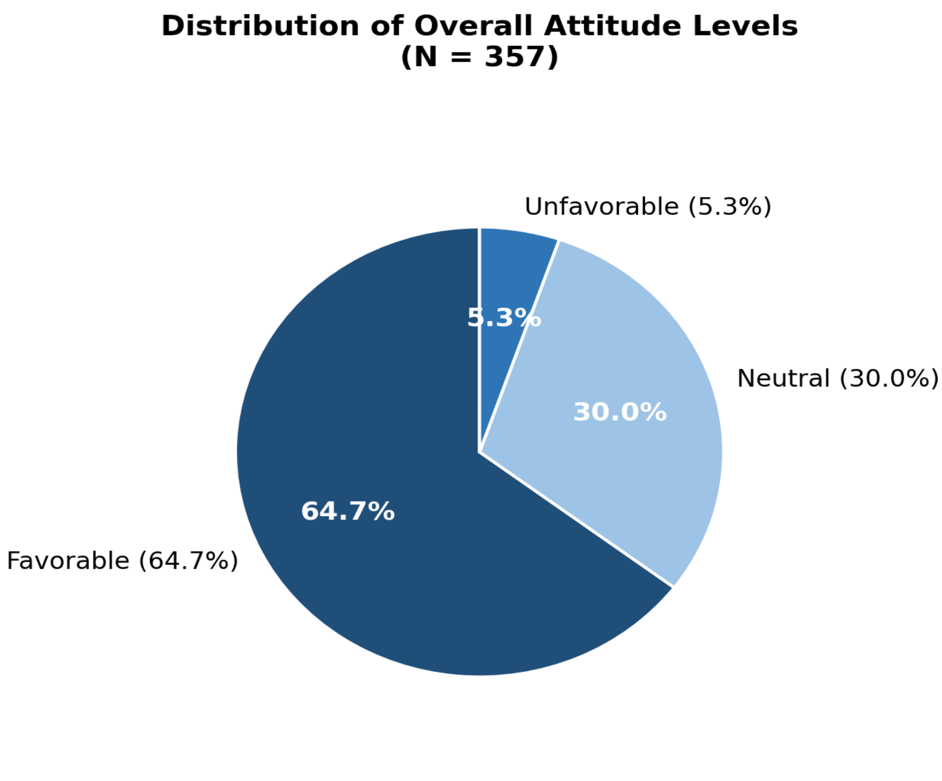


**Figure 3. Distribution of overall attitude levels (N = 357).**

### *5.5 Facilitating Conditions*

The facilitating-condition mean was 3.43 (SD = 0.79), lower than both perception and attitude (Table 5). Clear policies and procedures received the strongest rating (F7, M = 3.70), followed by timely technical support (F4, M = 3.56); adequate initial and refresher training was the weakest item (F5, M = 3.21), while reliable network/internet (F3, M = 3.32) and sufficient computers (F1, M = 3.35) also remained below the 3.50 benchmark used for descriptive classification. These responses do not establish the hospital's objective infrastructure status; they show where staff confidence was weakest and therefore where implementation planning may need clearer evidence and communication.

**Table 5. Item-level facilitating-condition scores.**

| Item | Statement | Mean | SD |
|---|---|---|---|
| F1 | Sufficient functional computers | 3.35 | 1.02 |
| F2 | Stable electricity or backup power | 3.45 | 0.99 |
| F3 | Reliable network and internet | 3.32 | 1.03 |
| F4 | Timely technical support | 3.56 | 0.98 |
| F5 | Adequate initial and refresher training | 3.21 | 1.00 |
| F6 | Visible and sustained management support | 3.45 | 1.01 |
| F7 | Clear policies and procedures | 3.70 | 1.00 |
| F8 | Protected time for training and workflow redesign | 3.43 | 0.96 |

*Source: Field survey (2026).*

### *5.6 Perceived Barriers to EHR Adoption*

The perceived-barrier mean was 3.36 (SD = 0.81) (Table 6). Poor network or internet connectivity was the highest-rated barrier (B3, M = 3.53), followed by lack of interoperability (B9, M = 3.46) and privacy, confidentiality, and cybersecurity concerns (B8, M = 3.44); unstable electricity had the lowest item mean (B2, M = 3.22), though it remained above the neutral midpoint. Barrier ratings were moderate rather than uniformly high; their importance became clearer in the relationship analyses, where stronger barrier perceptions were consistently associated with lower intention.

**Table 6. Item-level perceived-barrier scores.**

| Item | Statement | Mean | SD |
|---|---|---|---|
| B1 | High implementation and maintenance costs | 3.27 | 1.07 |
| B2 | Unstable electricity | 3.22 | 1.05 |
| B3 | Poor network or internet connectivity | 3.53 | 1.05 |
| B4 | Inadequate computers and hardware | 3.36 | 1.04 |

| Item | Statement | Mean | SD |
|---|---|---|---|
| B5 | Insufficient training and limited digital skills | 3.28 | 1.04 |
| B6 | Resistance to organizational change | 3.38 | 1.02 |
| B7 | Increased documentation time or workload | 3.37 | 0.99 |
| B8 | Privacy, confidentiality, and cybersecurity concerns | 3.44 | 1.03 |
| B9 | Lack of interoperability | 3.46 | 1.03 |
| B10 | Inadequate technical support and maintenance | 3.26 | 1.04 |

*Source: Field survey (2026).*

### *5.7 Behavioral Intention to Adopt EHRs*

The overall behavioral-intention mean was 3.68 (SD = 0.81) (Table 7). Planning to use an EHR regularly (I2, M = 3.88) and willingness to participate in training and a pilot implementation (I4, M = 3.86) were strongest, while the general intention statement (I1, M = 3.41) and willingness to recommend implementation (I5, M = 3.46) were lower, cautioning against treating a single broad intention item as a complete readiness measure. High intention was recorded for 221 respondents (61.9%), 105 (29.4%) had moderate intention, and 31 (8.7%) had low intention (Figure 4).

**Table 7. Item-level behavioral-intention scores.**

| Item | Statement | Mean | SD |
|---|---|---|---|
| I1 | Intend to use the EHR | 3.41 | 1.05 |
| I2 | Plan to use the EHR regularly | 3.88 | 0.95 |
| I3 | Would choose the EHR over paper where feasible | 3.77 | 0.98 |
| I4 | Would participate in training and pilot implementation | 3.86 | 0.94 |
| I5 | Would recommend EHR implementation | 3.46 | 1.05 |

*Source: Field survey (2026).*

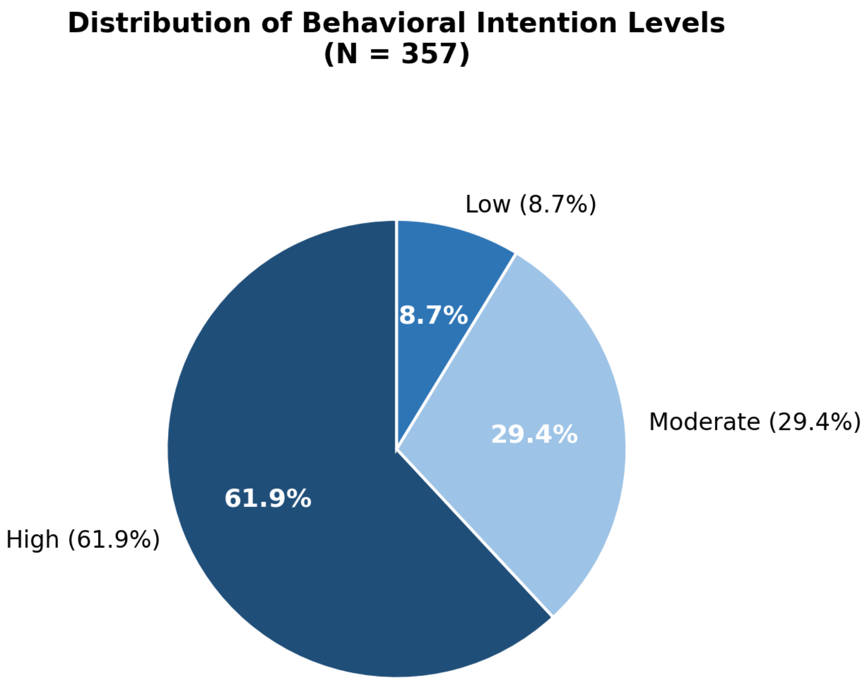


**Figure 4. Distribution of behavioral intention levels (N = 357).**

### *5.8 Relationships Among the Main Constructs*

Behavioral intention had a moderate positive correlation with attitude ($r = .583$, $p < .001$) and perception ($r = .513$, $p < .001$) (Table 8). Facilitating conditions were positively related to intention ($r = .329$, $p < .001$), while perceived barriers were negatively related ($r = −.425$, $p < .001$). Perception and attitude were strongly related ($r = .645$, $p < .001$); their overlap is important when the regression results are interpreted, because a construct may show a clear bivariate relationship with intention but contribute little unique variance once a related construct is included.

**Table 8. Correlations among the main study constructs.**

| Construct | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| 1. Perception | 1.000 | | | | |
| 2. Attitude | .645*** | 1.000 | | | |
| 3. Facilitating conditions | .156** | .118* | 1.000 | | |
| 4. Perceived barriers | −.213*** | −.218*** | −.437*** | 1.000 | |
| 5. Behavioral intention | .513*** | .583*** | .329*** | −.425*** | 1.000 |

*Source: Field survey (2026), N = 357. *p < .05, **p < .01, ***p < .001.*

### *5.9 Multivariable Prediction of Behavioral Intention*

The regression model explained 54.0% of the variance in behavioral intention (Table 9). Attitude had the largest adjusted association ($\beta = .369$, $p < .001$), followed by computer proficiency ($\beta = .295$, $p < .001$). Stronger perceived barriers were associated with lower intention ($\beta = -.201$, $p < .001$), while facilitating conditions retained a smaller positive association ($\beta = .150$, $p = .001$). Perception was not significant after attitude and the other variables were included ($\beta = .065$, $p = .175$), which does not contradict its bivariate correlation with intention but reflects shared variance between perception and attitude. Formal computer training ($p = .178$) and prior EHR use ($p = .174$) were also not independent predictors after adjustment.

**Table 9. Multiple linear regression of behavioral intention. (HC3 robust standard errors)**

| Predictor | B | HC3 SE | β | t | p | 95% CI for B |
|---|---|---|---|---|---|---|
| Intercept | 1.799 | 0.314 | — | 5.73 | <.001 | [1.181, 2.417] |
| Perception | 0.071 | 0.053 | 0.065 | 1.36 | .175 | [−0.032, 0.175] |
| Attitude | 0.380 | 0.052 | 0.369 | 7.34 | <.001 | [0.278, 0.482] |
| Facilitating conditions | 0.152 | 0.045 | 0.150 | 3.35 | <.001 | [0.063, 0.241] |
| Perceived barriers | −0.199 | 0.045 | −0.201 | −4.41 | <.001 | [−0.288, −0.110] |
| Formal computer training | −0.086 | 0.064 | −0.054 | −1.35 | .178 | [−0.212, 0.039] |
| Prior EHR use | 0.090 | 0.066 | 0.054 | 1.36 | .174 | [−0.040, 0.221] |
| Computer proficiency | 0.308 | 0.048 | 0.295 | 6.48 | <.001 | [0.215, 0.402] |

*Dependent variable: behavioral intention. Model: $F(7, 349) = 58.62$, $p < .001$; $R^2 = .540$; adjusted $R^2 = .531$. Source: Field survey (2026).*

### *5.10 Test of Research Hypotheses*

The two null hypotheses were both rejected (Table 10). $H_{01}$, that there is no significant relationship between health workers' perception and attitude toward EHRs and their behavioral intention, was rejected on the basis of the significant positive correlations of both perception ($r = .513$, $p < .001$) and attitude ($r = .583$, $p < .001$) with intention. $H_{02}$, that facilitating conditions and perceived barriers do not significantly predict behavioral intention, was rejected on the basis of the significant regression coefficients for facilitating conditions ($\beta = .150$, $p = .001$) and perceived barriers ($\beta = -.201$, $p < .001$) reported in Table 9.

**Table 10. Summary of hypothesis tests.**

| Hypothesis | Test | Statistic | p | Decision |
|---|---|---|---|---|
| $H_{01}$: No significant relationship between perception/attitude and behavioral intention | Pearson correlation | r = .513 (perception); r = .583 (attitude) | <.001 | Rejected |
| $H_{02}$: Facilitating conditions and perceived barriers do not significantly predict behavioral intention | Multiple regression | $\beta$ = .150 (facilitating conditions); $\beta = -.201$ (barriers) | <.001 | Rejected |

*Source: Field survey (2026).*

Additional supporting analyses reinforced these findings. Formal computer training was associated with the high-intention classification at the bivariate level: high intention was observed among 122 of 172 trained respondents (70.9%) versus 99 of 185 untrained respondents (53.5%), with the odds of high intention approximately twice as high among trained respondents (OR = 2.12, 95% CI [1.37, 3.28]); training did not, however, remain significant in the multivariable model, suggesting its bivariate association was partly accounted for by proficiency and the main study constructs. Clinical-cadre groups differed considerably in size, and Levene's test indicated unequal variances, so Welch's ANOVA was used; mean intention ranged from 3.38 among pharmacists to 3.78 among nurses and midwives, but the overall difference was not statistically significant, with a small descriptive effect size ($\eta^2 = .020$).

## 6. DISCUSSION

Health workers at State Specialist Hospital, Lisaluwa, generally held a favourable disposition toward EHR adoption, though the pattern is better described as conditional support than complete readiness. Positive perception was recorded among 66.1% of respondents, 64.7% demonstrated a favourable attitude, and 61.9% reported high behavioral intention, a pattern suggesting that favourable beliefs about digital records are accompanied by substantial willingness to engage with them. Nevertheless, about one-third of respondents remained neutral or negative on the major constructs, a minority that matters because implementation experience often exposes practical difficulties not fully captured by pre-implementation optimism. Finnegan and Mountford (2025), reviewing 25 years of EHR implementation research, emphasised that successful implementation is a process of preparation, engagement, configuration, training, support, and continual adjustment rather than a single technology-acquisition event; the present findings support that view by showing that willingness exists, but its translation into sustained use will depend on the conditions created around the technology.

The positive perception observed was strongly connected to concrete clinical and administrative benefits rather than to the general idea of modernization: the highest-rated perception items concerned improved documentation accuracy and completeness (M = 3.90), compatibility with clinical tasks (M = 3.90), and better clinical decision-making (M = 3.87). This is consistent with Akwaowo et al. (2022), who reported that perceived usefulness and relative advantage were important positive influences on EHR adoption propensity across several Nigerian states, and with Babalola et al. (2025), who found highly positive overall perception among physicians and nurses in Lagos despite substantial operational barriers. Health workers therefore appear more likely to value EHRs when expected benefits directly address everyday problems such as missing records, duplication, delayed retrieval, and fragmented information, rather than technology enthusiasm alone. At the same time, respondents were not fully convinced that benefits would automatically outweigh implementation difficulties (P12, M = 3.64), a caution consistent with evidence that poor usability and excessive documentation demands can offset expected gains (Alobayli et al., 2023; Wu et al., 2024).

The attitude findings add a more nuanced picture: respondents were more confident about their ability to learn and adapt (A9, A2 both above 3.8) than about the implementation process itself (A1, M = 3.46, the lowest attitude item). Similar patterns, in which favourable attitudes toward electronic records are associated with computer skills, training, and organizational support, have been reported in Ethiopian settings (Mohammed et al., 2024; Wubante et al., 2023), suggesting that positive attitude at Lisaluwa is partly a reflection of confidence and perceived preparedness, with uncertainty persisting where staff do not yet know what the transition will require of them.

Digital competence emerged as particularly consequential. Computer proficiency was independently associated with intention in the multivariable model ($\beta = .295$, $p < .001$), the second-strongest adjusted predictor after attitude, and formal computer training showed a significant bivariate association with high intention (70.9% vs 53.5%; OR = 2.12) that did not survive adjustment. This distinction suggests that training exposure alone matters less than the competence actually acquired, consistent with Nguyen et al. (2024), whose scoping review of EHR training for inpatient nurses emphasised practice opportunities, role-specific personalisation, and implementation support over mere attendance. For Lisaluwa, this implies training should be competency-oriented rather than attendance-oriented, with practical exercises matched to each professional group's responsibilities.

Facilitating conditions (M = 3.43) and perceived barriers (M = 3.36) point in a consistent direction: clear policies scored highest among facilitating conditions (M = 3.70) while training adequacy scored lowest (M = 3.21), and poor connectivity was the leading perceived barrier (M = 3.53), followed by interoperability (M = 3.46) and privacy/security concerns (M = 3.44). These findings echo Babatope et al. (2024) at UNIMEDTH in Ondo State and Babalola et al. (2025) in Lagos, both of which identified infrastructure, connectivity, and related concerns as prominent implementation barriers, suggesting facilitating conditions should be treated as central to readiness rather than technical details to be addressed after implementation begins. Because the study measured perceived barriers rather than conducting an independent technical audit, these results should not be read as evidence that a specific network failure or security weakness already exists at the hospital, but as evidence that staff anticipate these as credible risks that could weaken trust absent visible arrangements for access control, downtime management, and technical support.

The multivariable regression provides the strongest evidence on which factors retain unique statistical association with intention. That perceived barriers remained significantly and negatively associated with intention even after adjustment for attitude, perception, facilitating conditions, training, prior use, and proficiency ($\beta = -.201$, $p < .001$) supports the view that adoption is not purely an individual acceptance decision but also a response to the anticipated working environment: a favourable attitude may not be sufficient when workers anticipate unreliable connectivity, inadequate equipment, poor interoperability, or insufficient support. The absence of a statistically significant cadre difference in mean intention ($\eta^2 = .020$) suggests broad readiness may not vary substantially by professional group in this workforce, though the highly uneven cadre group sizes (5 radiographers to 152 nurses) warrant caution in generalising this null finding, and role-specific workflow mapping and usability testing remain warranted given that different professionals interact with records differently.

## 7. CONCLUSION

This study assessed the perception and attitude of health workers toward EHR adoption at State Specialist Hospital, Lisaluwa, and found broad but conditional support: most respondents perceived clear benefits, expressed confidence in learning the necessary skills, and reported intention to participate in implementation, with 66.1% holding positive perception, 64.7% a favourable attitude, and 61.9% high behavioral intention. At the same time, concerns about connectivity, interoperability, privacy, training adequacy, and equipment availability remained sufficiently strong to shape behavioral intention, and the multivariable analysis showed that attitude and computer proficiency, not general perception, carried the strongest independent statistical association with intention, while perceived barriers retained a significant negative association even after full adjustment. Behavioral intention is not evidence of actual use, and the findings provide a baseline for implementation preparation and later evaluation rather than a guarantee that an EHR will be used consistently or improve patient outcomes once deployed. The study concludes that successful EHR adoption at State Specialist Hospital, Lisaluwa, will depend less on persuading staff that EHRs are useful, since most already believe this, and more on building digital competence, demonstrating credible organizational support, and directly addressing the connectivity, interoperability, and privacy concerns that continue to temper an otherwise favourable disposition toward adoption.

## 8. RECOMMENDATIONS

Based on the findings, the following five recommendations are made, each specifying the responsible party and the corresponding action:

**1. State Specialist Hospital Management and the Health Information Management (HIM) Department:** should design and deliver competency-based, role-specific EHR training, incorporating supervised practice, competency checks, and correction of errors rather than a single general orientation, given that computer proficiency ($\beta = .295$, $p < .001$) was a stronger independent predictor of intention than formal training exposure alone (not significant after adjustment, $p = .178$), and that adequate training was the weakest-rated facilitating condition ($M = 3.21$).

**2. Hospital Management, in partnership with the Ondo State Ministry of Health and Internet/Telecommunications Service Providers:** should verify and strengthen network coverage, device availability, and points of technical support in the clinical areas selected for initial implementation, given that poor network/internet connectivity was the single highest-rated perceived barrier ($M = 3.53$) and that facilitating conditions retained a significant positive association with intention ($\beta = .150$, $p = .001$).

**3. Hospital Management and the proposed EHR Governance Committee:** should publish clear operating rules before go-live, covering user access, password practice, correction of records, confidentiality, incident reporting, downtime procedures, and responsibility for data quality, given that clear policies and procedures was the strongest-rated facilitating-condition item ($M = 3.70$) and can provide an early foundation for staff trust.

**4. A Multidisciplinary EHR Governance Group (Health Information Management, clinical cadre representatives, information technology, and hospital leadership):** should map clinical workflows with the staff who perform them, from registration through consultation, nursing, laboratory, pharmacy, referral, and discharge, and should incorporate interoperability and privacy requirements into procurement and configuration criteria, given that lack of interoperability ($M = 3.46$) and privacy/cybersecurity concerns ($M = 3.44$) were among the leading perceived barriers.

**5. Hospital Management, supported by the HIM Department:** should implement the EHR through a defined pilot with measurable entry and exit criteria (uptime, documentation completeness, support requests, task time, user-reported problems), rather than an institution-wide launch, and should repeat this survey alongside objective indicators of use after implementation, given that perceived barriers remained a statistically significant negative predictor of intention even after adjustment ($\beta = -.201$, $p < .001$), indicating that anticipated barriers must be directly addressed and monitored rather than assumed to resolve on their own.

## 9. Implications of the Study

The findings carry several practical and policy implications. First, because attitude ($\beta = .369$) and computer proficiency ($\beta = .295$) were the strongest independent predictors of intention, while perception alone was not significant after adjustment ($\beta = .065$, $p = .175$), implementation strategy should shift from simply promoting the perceived usefulness of EHRs, an argument respondents largely already accept, toward building confidence, willingness, and demonstrable digital competence among staff. Second, the persistence of a significant negative association between perceived barriers and intention after full adjustment ($\beta = -.201$, $p < .001$) indicates that hospital management cannot rely on favourable attitudes to override unresolved practical concerns; connectivity, interoperability, and privacy safeguards must be visibly and credibly addressed as part of, not after, implementation planning. Third, the gap between the general statement of positivity toward EHR introduction (the lowest attitude item, $M = 3.46$) and specific confidence in learning and adapting ($M = 3.82$–$3.86$) suggests that communication about the implementation process itself, not only the technology's benefits, deserves particular management attention. Fourth, the finding that formal computer training was associated with intention at the bivariate level but not after adjustment for proficiency implies that hospital and Ministry of Health training investments should be evaluated by competency outcomes achieved, not simply attendance recorded, when assessing return on training expenditure.

## 10. Contributions to Knowledge

1. Provision of the first institution-specific assessment identified in the literature to measure perception, attitude, facilitating conditions, perceived barriers, and behavioral intention together among all clinical cadres at a Nigerian secondary hospital, addressing a gap left by prior Nigerian studies conducted at tertiary/teaching hospitals (UNIMEDTH, Lagos general hospitals) or restricted to single cadres or medical students.
2. Empirical demonstration, through HC3 heteroscedasticity-robust multivariable regression, that computer proficiency and attitude retain independent statistical association with behavioral intention while general perception and formal training exposure do not survive adjustment, a distinction between believing a technology is useful and being practically ready to use it that is often blurred in pre-implementation EHR surveys.
3. Quantification of the independent, adjusted contribution of perceived barriers to reduced adoption intention ($\beta = -.201$, $p < .001$) even after accounting for favourable attitude and perception, providing statistical evidence that anticipated organizational and infrastructural barriers are not simply attitudinal noise but a distinct, actionable predictor of readiness.
4. Application of an integrated TAM-UTAUT-TOE framework, together with rigorous model diagnostics (Ramsey RESET, Durbin-Watson, Shapiro-Wilk, variance inflation factors, Breusch-Pagan-informed HC3 correction, Welch's ANOVA for unequal cadre variances), offering a methodologically transparent and replicable analytical template for future EHR-readiness research in comparable Nigerian and sub-Saharan African hospital settings.

## 11. Limitations of the Study

This study has several limitations. First, the cross-sectional design measured all variables at one point in time and cannot establish temporal order or causality among perception, attitude, and intention. Second, the study relied on self-report, so social-desirability and common-method bias may have inflated the apparent consistency among constructs; anonymous administration and balanced item wording reduced but did not eliminate this risk. Third, behavioral intention was measured rather than observed EHR use, and intention is not equivalent to actual, sustained adoption after implementation. Fourth, the study was conducted at a single hospital, so findings cannot automatically be generalised to other secondary facilities in Ondo State or Nigeria. Fifth, the clinical-cadre distribution was highly uneven (radiographers, pharmacists, and medical laboratory scientists had small group sizes of 5–14, while nurses and other allied clinical workers accounted for most respondents), limiting the precision of cadre-specific estimates and the generalisability of the non-significant cadre comparison. Finally, although the questionnaire showed high internal consistency (Cronbach's alpha .869–.950), factor analysis, test-retest reliability, and external validation of the descriptive category cutoffs were not undertaken, and formal computer training was measured as a yes/no variable that did not capture duration, content, quality, or competence achieved.

**Author Contributions**

Oyeneyin Ajike Esther: Conceptualisation, methodology, investigation, formal analysis, data curation, writing — original draft, writing — review and editing. Folasade A. Adediran: Supervision, conceptualisation, validation, writing — review and editing. Adebola Samuel Adeoye: Co-supervision, methodology review, validation, writing — review and editing. All authors read and approved the final manuscript.

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**Conflict of Interest**

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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**Data Availability Statement**

The datasets generated and/or analysed during the current study are available from the corresponding author on reasonable request, subject to institutional approval and participant confidentiality safeguards.

## Ethical Approval

This study was conducted in accordance with institutional ethical guidelines. Participation was voluntary, and informed consent was obtained from all participants before questionnaire completion. Data handling was guided by confidentiality principles and the Nigeria Data Protection Act 2023. No respondent names or personnel numbers were collected, and results are reported in aggregate.

## REFERENCES


1. Abore, K. W., Debiso, A. T., Birhanu, B. E., Bua, B. Z., & Negeri, K. G. (2022). Health professionals' readiness to implement electronic medical recording system and associated factors in public general hospitals of Sidama Region, Ethiopia. PLOS ONE, 17(10), e0276371.
2. Adedeji, T., Fraser, H. S. F., & Scott, P. (2022). Implementing electronic health records in primary care using the theory of change: Nigerian case study. JMIR Medical Informatics, 10(8), e33491.
3. Adepoju, E. O., & Opele, J. K. (2021). Barriers to implementing electronic health information management in patient care. IOSR Journal of Research & Method in Education, 11(2), 31–43.
4. Adeyeye, A. A., Ajose, A. O., Oduola, O. M., Akodu, B. A., & Olufadeji, A. (2024). Usage and perception of electronic medical records among medical students in southwestern Nigeria. Discover Public Health, 21, 143.
5. Afolabi, O. A., Oladipo, E. K., & Popoola, Y. A. (2022). The adoption and challenges associated with the use of electronic health records management system in UNIMEDTH, Ondo, Ondo State. Adeleke University Journal of Science, 1(1), 107–117.
6. Akwaowo, C. D., Sabi, H. M., Ekpenyong, N., Isiguzo, C. M., Andem, N. F., Maduka, O., Dan, E., Umoh, E. U., Ekpin, V., & Uzoka, F.-M. E. (2022). Adoption of electronic medical records in developing countries—A multi-state study of the Nigerian healthcare system. Frontiers in Digital Health, 4, 1017231.
7. Alobayli, F., O'Connor, S., Holloway, A., Cresswell, K., & McClelland, G. T. (2023). Electronic health record stress and burnout among clinicians in hospital settings: A systematic review. Digital Health, 9, 20552076231220241.
8. Babatope, A. E., Adewumi, I. P., Ajisafe, D. O., Adepoju, K. O., & Babatope, A. R. (2024). Assessing the factors militating against the effective implementation of electronic health records in Nigeria. Scientific Reports, 14, 31398.

9. Babalola, O. A., Olufunlayo, T. F., Akinlawon, O. O., Odukoya, T. O., Fagbo, O. O., & Akinlawon, D. (2025). Perception and barriers to electronic medical record use among physicians and nurses in general hospitals in Lagos State. African Health Sciences, 25(3), 154–162.
10. Bekele, T. A., Gezie, L. D., Willems, H., Metzger, J., Abere, B., Seyoum, B., Abraham, L., Wendrad, N., Meressa, S., Desta, B., & Bogale, T. N. (2024). Barriers and facilitators of electronic medical record adoption among healthcare providers in Addis Ababa, Ethiopia. Digital Health, 10, 20552076241301946.
11. Campione, J., & Liu, H. (2024). Perceptions of hospital electronic health record (EHR) training, support, and patient safety by staff position and tenure. BMC Health Services Research, 24, 955.
12. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340.
13. de Mello, B. H., Rigo, S. J., da Costa, C. A., da Rosa Righi, R., Donida, B., Bez, M. R., & Schunke, L. C. (2022). Semantic interoperability in health records standards: A systematic literature review. Health and Technology, 12, 255–272.
14. do Nascimento, I. J. B., Abdulazeem, H., Vasanthan, L. T., Martinez, E. Z., Zucoloto, M. L., Østengaard, L., Azzopardi-Muscat, N., Zapata, T., & Novillo-Ortiz, D. (2023). Barriers and facilitators to utilizing digital health technologies by healthcare professionals. npj Digital Medicine, 6, 161.
15. Dube, G. N., Asemahagn, M. A., Mulu, Y., Guadie, H. A., Ahmed, M. H., Walle, A. D., Bitacha, G. K., Alameraw, T. A., & Meshasha, N. A. (2025). Intention to use personal health records and associated factors among healthcare providers in Southwest Oromia Region referral hospitals, Ethiopia: Using the modified UTAUT2 model. Frontiers in Digital Health, 7, 1368588.
16. Federal Republic of Nigeria. (2023). Nigeria Data Protection Act, 2023.
17. Fennelly, O., Cunningham, C., Grogan, L., Cronin, H., O'Shea, C., Roche, M., Lawlor, F., & O'Hare, N. (2020). Successfully implementing a national electronic health record: A rapid umbrella review. International Journal of Medical Informatics, 144, 104281.
18. Finnegan, H., & Mountford, N. (2025). Twenty-five years of electronic health record implementation processes: A scoping review. Journal of Medical Internet Research, 27, e60077.
19. Fraser, H. S. F., Mugisha, M., Remera, E., Ngenzi, J. L., Richards, J., Santas, X., Naidoo, W., Seebregts, C., Condo, J., & Umubyeyi, A. (2022). User perceptions and use of an

enhanced electronic health record in Rwanda with and without clinical alerts: Cross-sectional survey. JMIR Medical Informatics, 10(5), e32305.

20. Hailegebreal, S., Dileba, T., Haile, Y., & Abebe, S. (2023). Health professionals' readiness to implement electronic medical record systems in Gamo Zone public hospitals, southern Ethiopia. BMC Health Services Research, 23, 773.
21. Harerimana, A., Wicking, K., Biedermann, N., Yates, K., Pillay, J. D., & Mchunu, G. (2025). Adoption of electronic health records by nurses in Africa: A scoping review. Digital Health, 11, 20552076251357401.
22. Holmgren, A. J., Hendrix, N., Maisel, N., Everson, J., Bazemore, A., Phillips, R. L., Rotenstein, L. S., & Adler-Milstein, J. (2024). Electronic health record usability, satisfaction, and burnout for family physicians. JAMA Network Open, 7(8), e2426956.
23. Iyanna, S., Kaur, P., Ractham, P., Talwar, S., & Islam, A. K. M. N. (2022). Digital transformation of healthcare sector: What is impeding adoption and continued usage of technology-driven innovations by end-users? Journal of Business Research, 153, 150–161.
24. Jung, S. Y., Hwang, H., Lee, K., Lee, D., Yoo, S., Lim, K., Kim, J., & Kim, E. (2021). User perspectives on barriers and facilitators to the implementation of electronic health records in behavioral hospitals: Qualitative study. JMIR Formative Research, 5(4), e18764.
25. Kessy, E. C., Kibusi, S. M., & Ntwenya, J. E. (2024). Electronic medical record systems data use in decision-making and associated factors among health managers at public primary health facilities, Dodoma Region. Frontiers in Digital Health, 5, 1259268.
26. Khan, R., Khan, S., Almohaimeed, H. M., Almars, A. I., & Pari, B. (2025). Utilization, challenges, and training needs of digital health technologies: Perspectives from healthcare professionals. International Journal of Medical Informatics, 201, 105833.
27. Luyten, J., & Marneffe, W. (2021). Examining the acceptance of an integrated electronic health records system: Insights from a repeated cross-sectional design. International Journal of Medical Informatics, 150, 104450.
28. Modi, S., & Feldman, S. S. (2022). The value of electronic health records since the Health Information Technology for Economic and Clinical Health Act: Systematic review. JMIR Medical Informatics, 10(9), e37283.
29. Mohammed, A. S., Wudu, D., Minda, Z., & Diress, G. M. (2024). Attitudes toward implementation of electronic medical record and its associated factors among health

professional workers in selected public hospitals in Addis Ababa, Ethiopia. Digital Health, 10, 20552076241277034.
30. Negro-Calduch, E., Azzopardi-Muscat, N., Krishnamurthy, R. S., & Novillo-Ortiz, D. (2021). Technological progress in electronic health record system optimization: Systematic review of systematic literature reviews. International Journal of Medical Informatics, 152, 104507.
31. Ngugi, P., Were, M. C., & Babic, A. (2021). Users' perception of factors contributing to electronic medical records systems use: A focus-group discussion study in health care facilities in Kenya. BMC Medical Informatics and Decision Making, 21, 362.
32. Ngusie, H. S., Kassie, S. Y., Chereka, A. A., & Enyew, E. B. (2022). Healthcare providers' readiness for electronic health record adoption: A cross-sectional study during the pre-implementation phase. BMC Health Services Research, 22, 282.
33. Ngusie, H. S., Kassie, S. Y., Zemariam, A. B., Walle, A. D., Enyew, E. B., Kasaye, M. D., Seboka, B. T., & Mengiste, S. A. (2024). Understanding the predictors of health professionals' intention to use an electronic health record system: Extension and application of the UTAUT3 model. BMC Health Services Research, 24, 889.
34. Nguyen, O. T., Vo, S. D., Lee, T., Cato, K. D., & Cho, H. (2024). Implementation and delivery of electronic health records training programs for nurses working in inpatient settings: A scoping review. Journal of the American Medical Informatics Association, 31(11), 2740–2748.
35. Oo, H. M., Htun, Y. M., Win, T. T., Han, Z. M., Zaw, T., & Tun, K. M. (2021). Information and communication technology literacy, knowledge, and readiness for electronic medical record system adoption among health professionals in a tertiary hospital, Myanmar. PLOS ONE, 16(7), e0253691.
36. Ope-Babadele, O. O., Ndurue, L. O., & Isaiah, R. (2021). Challenges of electronic health recording implementation by nurses in Babcock University Teaching Hospital, Ogun State. Commonwealth Journal of Academic Research, 2(8), 1–12.
37. Palojoki, S., Saranto, K., Reponen, E., Skants, N., Vakkuri, A., & Vuokko, R. (2021). Classification of electronic health record–related patient safety incidents: Development and validation study. JMIR Medical Informatics, 9(8), e30470.
38. Rahal, R. M., Mercer, J., Kuziemsky, C., & Yaya, S. (2021). Factors affecting the mature use of electronic medical records by primary care physicians: A systematic review. BMC Medical Informatics and Decision Making, 21, 67.

39. Sekoai, T. E., Turner, A., & Mitchell, J. (2025). Insights into healthcare workers' perceptions of electronic medical record system utilization: A cross-sectional study in Mafeteng District, Lesotho. BMC Medical Informatics and Decision Making, 25, 181.
40. Sibiya, M. N., Akinyemi, O. R., & Oladimeji, O. (2023). Computer skills and electronic health records in a state tertiary hospital in Southwest Nigeria. Epidemiologia, 4(2), 137–147.
41. Steenkamp, I., Peltonen, L. M., & Chipps, J. (2025). Digital health readiness: Insights from healthcare leaders in operational management. BMC Health Services Research, 25, 240.
42. Tolera, A., Oljira, L., Dingeta, T., Abera, A., & Roba, H. S. (2022). Electronic medical record use and associated factors among healthcare professionals at public health facilities in Dire Dawa, eastern Ethiopia. Frontiers in Digital Health, 4, 935945.
43. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425–478.
44. Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the Unified Theory of Acceptance and Use of Technology. MIS Quarterly, 36(1), 157–178.
45. Wang, W., Ferrari, D., Haddon-Hill, G., & Curcin, V. (2023). Electronic health records as a source of research data. In O. Colliot (Ed.), Machine learning for brain disorders (pp. 331–354). Springer.
46. Woldemariam, M. T., & Jimma, W. (2023). Adoption of electronic health record systems to enhance the quality of healthcare in low-income countries: A systematic review. BMJ Health & Care Informatics, 30(1), e100704.
47. World Health Organization. (2021). Global strategy on digital health 2020–2025. World Health Organization.
48. Williams, G. A., Falkenbach, M., van Schaaijk, A., Batenburg, R. S., & Wismar, M. (2025). Closing the digital skills gap in healthcare: Identifying core digital skills and competencies and education and training opportunities for health professionals in the European Union. World Health Organization Regional Office for Europe.
49. Wosny, M., Strasser, L. M., & Hastings, J. (2023). Experience of health care professionals using digital tools in the hospital: Qualitative systematic review. JMIR Human Factors, 10, e50357.

50. Wu, Y., Wu, M., Wang, C., Lin, J., Liu, J., & Liu, S. (2024). Evaluating the prevalence of burnout among health care professionals related to electronic health record use: Systematic review and meta-analysis. JMIR Medical Informatics, 12, e54811.

51. Wubante, S. M., Tegegne, M. D., Melaku, M. S., Mengiste, N. D., Fentahun, A., Zemene, W., Fikadie, M., Musie, B., & Keleb, D. (2023). Healthcare professionals' knowledge, attitude and its associated factors toward electronic personal health record system in a resource-limited setting: A cross-sectional study. Frontiers in Public Health, 11, 1114456.