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Technology readiness, acceptance, and ethical concerns regarding innovative technologies among nursing professionals: A convergent mixed-methods study

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Abstract
Background: Digital technologies are increasingly embedded in nursing documentation, communication, monitoring, education, decision support, and patient engagement. Their successful implementation depends on workforce knowledge, perceived usefulness, usability, facilitating conditions, ethical confidence, and behavioural intention. This study assessed technology readiness, acceptance, barriers, and ethical concerns among nursing professionals in Mahabubnagar district, India.
Methods: A multicentre institution-based cross-sectional convergent mixed-methods survey included 532 nursing professionals from selected teaching hospitals and nursing colleges. The instrument assessed sociodemographic characteristics, awareness/use of 10 technologies, digital-health knowledge, a 30-item acceptance/readiness scale, barriers, and open-ended perspectives. Descriptive, psychometric, bivariate, correlation, multiple linear regression, and multivariable logistic regression analyses were specified, high acceptance was defined as 120-150.
Results: Digital-health training was reported by 40.0%, EHR use by 30.1%, and mobile-health use by 40.0%. Mean acceptance/readiness was 115.9 ± 20.8, 47.7% had high, 40.4% moderate, and 11.8% low acceptance. The acceptance scale showed high internal consistency (α=0.938). Lack of training (69.2%), technical support (64.1%), poor connectivity (62.8%), and lack of institutional policy (62.4%) were leading barriers. In adjusted models, training, EHR use, mobile-health use, internet availability, knowledge, and qualification were positively associated with acceptance, whereas barriers were inversely associated. The logistic model reported an AUC of 0.874 (95% CI 0.844-0.902).
Conclusion: Nursing professionals showed favourable willingness to use digital technologies, but implementation readiness was limited by uneven training, practical exposure, infrastructure, and organisational support. Digital transformation should combine competency-based training, reliable systems, technical support, and explicit ethical governance.

Keywords: Nursing informatics, digital health, technology acceptance, artificial intelligence, electronic health records, telemedicine

Introduction
Digital transformation is reshaping how health information is generated, communicated, interpreted, and used across health systems. Electronic health records (EHRs), telehealth, mobile health, wearable and remote-monitoring systems, clinical decision support, artificial intelligence (AI), simulation, and automation can improve access, continuity, documentation, monitoring, and decision-making when implemented within a coordinated digital-health strategy [1].
Nursing informatics provides the disciplinary foundation for this transition by integrating nursing, information, and computer sciences to support the management and communication of clinical data, information, knowledge, and practice-related decisions [2]. Because nurses are continuous users and producers of clinical information, successful digital transformation depends not only on technology availability but also on workforce capability, workflow fit, patient safety, organisational support, and professional accountability.
Technology acceptance and technology readiness are related but distinct constructs. The Technology Acceptance Model proposes that perceived usefulness and perceived ease of use are central determinants of technology adoption [3]. A systematic review of health-informatics applications of this model showed that contextual factors such as trust, professional practice, and organisational conditions often influence acceptance in addition to the core constructs [4]. The Unified Theory of Acceptance and Use of Technology further incorporates performance expectancy, effort expectancy, social influence, and facilitating conditions [5]. Technology readiness, by contrast, reflects a broader propensity to embrace technology, including optimism and innovativeness as well as discomfort and insecurity [6]. The updated Technology Readiness Index 2.0 retained this multidimensional view while providing a streamlined framework for contemporary technology environments [7].
Clinical technologies offer substantial benefits but can also introduce new burdens. EHRs may improve information availability and patient safety, although poorly designed systems can generate usability problems and new risks [8]. Electronic nursing documentation can strengthen quality and continuity of care, but its effectiveness depends on appropriate design, staff preparation, and integration with nursing workflow [9]. Telehealth can extend access, follow-up, and continuity of care, while limitations in connectivity, privacy, regulation, and remote assessment remain important implementation barriers [10]. Mobile-health applications can support timely patient education and self-management [11], and smartphone-based learning can improve nursing knowledge and learning flexibility when used appropriately [12]. Wearable and remote-monitoring systems can support continuous surveillance but raise

concerns about accuracy, interoperability, data overload, false alarms, and responsibility for responding to patient-generated information [13].

AI adds further complexity to digital nursing practice. Reviews anticipate applications in clinical decision support, risk prediction, documentation, staffing, education, research, and administration, while emphasising that AI should augment rather than replace nursing judgement [14]. Acceptance of AI among healthcare professionals is influenced by perceived usefulness, ease of use, trust, workflow compatibility, professional autonomy, and facilitating conditions [15]. Ethical analyses have highlighted privacy, accountability, bias, transparency, trust, safety, and equitable access as recurring concerns [16]. A mapping review similarly identified interconnected challenges involving explainability, informed consent, human oversight, responsibility, and fairness [17]. Among nurses, awareness and attitudes toward AI are often favourable but accompanied by gaps in practical understanding [18]. Student nurses' readiness has been associated with technological proficiency and AI knowledge, whereas limited access and insufficient training remain barriers [19]. Recent evidence among critical-care nurses also links perceived usefulness, ease of use, facilitating conditions, and adoption intention with readiness [20]. In resource-constrained settings, training, infrastructure, technical support, and workload are particularly important determinants of digital adoption [21]. Digital-health competence therefore reflects not only technical skill but also knowledge, confidence, actual use, organisational participation, and the professional environment [22]. Responsible implementation must additionally preserve human autonomy, transparency, accountability, equity, and safety [23].

Existing studies frequently examine a single technology, professional group, or acceptance construct. For implementation planning, however, awareness should be distinguished from actual use, willingness from competence, and personal acceptance from organisational readiness. This study therefore assessed technology awareness and use, digital-health knowledge, acceptance/readiness, perceived barriers, ethical and safety concerns, and behavioural intention among clinical nurses and nurse educators in selected institutions in Mahabubnagar district, Telangana, India. It also examined demographic, professional, training, and exposure-related factors associated with technology acceptance and explored participants' views on implementation priorities and the future role of AI in nursing.

Materials and Methods

Study design, setting and participants

An institution-based multicentre cross-sectional convergent mixed-methods design was used. Quantitative data and responses to four open-ended questions were collected during the same survey administration. A convergent approach was selected because it allows numerical patterns and participant perspectives to be analysed separately and then interpreted together [24]. Integration focused on convergence, complementarity, and divergence between quantitative and qualitative findings [25]. Reporting of the cross-sectional component was guided by the STROBE recommendations [26]. The study was conducted in Government Medical College and Hospital/Government Nursing College, SVS Medical College & Hospital/SVS Nursing College, and Navodaya Hospital/Navodaya Nursing College in Mahabubnagar district, Telangana, India. Clinical areas included intensive care, emergency, medical, surgical, obstetric/gynaecology, paediatric, operation theatre, outpatient, and orthopaedic services. Registered nurses aged ≥21 years with at least six months of clinical experience and nurse educators involved in clinical teaching or supervision were eligible. Administrative staff without clinical exposure, unavailable staff, individuals declining consent, duplicate responses, and questionnaires with substantial missing primary-outcome data were excluded.

Sample Size and Sampling

Sample size was calculated using Cochran's formula for estimation of a single population proportion [27]. With 95% confidence, p=0.50, and an absolute precision of 0.046, the minimum required sample was 454. After allowing approximately 10% for incomplete or non-response, the recruitment target was approximately 500; 532 complete responses were included. Stratified proportionate sampling by professional setting and department was used where complete staff lists were available. Simple random or systematic selection was applied within strata when feasible; consecutive recruitment within predefined allocations was used when shift patterns or incomplete rosters prevented random selection.

Instrument and Scoring

The structured questionnaire was developed from the study objectives, technology-acceptance frameworks, digital-health competence literature, and nursing-specific implementation concerns, following established principles for health-related scale development [28]. It contained six sections: (1) 12 sociodemographic/professional items; (2) awareness and use of 10 technologies scored from 0 (not aware) to 3 (used frequently), total 0-30; (3) a 10-item true/false/do-not-know knowledge test, total 0-10; (4) a 30-item technology acceptance/readiness scale comprising six five-item domains-perceived usefulness, perceived ease of use, attitude, facilitating conditions, ethical/safety safeguards, and behavioural intention-rated from 1 to 5, total 30-150; (5) 12 barriers rated from 1 (not a barrier) to 5 (very major barrier), total 12-60; and (6) four open-ended questions. Acceptance/readiness was pragmatically classified as low (30-90), moderate (91-119), or high (120-150). Awareness/use was classified as low (0-10), moderate (11-20), or high (21-30), and knowledge as poor (0-4), moderate (5-7), or good (8-10). These categories were study-specific classifications rather than externally validated clinical cut-offs.

The initial item pool underwent expert review for relevance, clarity, simplicity, and ambiguity, followed by face-validity assessment among nursing professionals. A pilot study was conducted in 30 eligible nurses who were not included in the final analysis. Internal consistency was assessed using Cronbach's alpha; the binary knowledge items were evaluated using the KR-20/α equivalence. Sampling adequacy for factor assessment was examined using the Kaiser-Meyer-Olkin statistic and Bartlett's test of sphericity, and the prespecified six-domain structure was explored using eigenvalues and scree-plot inspection

Data collection, qualitative analysis and ethics

After institutional approval and administrative permission, eligible participants received study information and provided written or electronic informed consent. The questionnaire was administered through a secure online form accessible by smartphone, tablet, or computer. No patient-identifiable information was collected. Responses were screened for completeness, plausibility, out-of-range values, and duplicates, and the analytic dataset was de-identified. Open-ended responses were analysed thematically through familiarisation, coding, theme development, review, definition, and naming, consistent with the approach described by Braun and Clarke [29]. Quantitative and qualitative findings were subsequently integrated during interpretation. The study was conducted in accordance with applicable institutional requirements and the Indian Council of Medical Research national ethical guidance for biomedical and health research involving human participants [30].

Statistical Analysis

Categorical variables were summarised as frequency and percentage and continuous scores as mean ± standard deviation and, where appropriate, median and interquartile range. Two-group comparisons used Welch's t test and multi-group comparisons used one-way analysis of variance, with Cohen's d and eta-squared as effect sizes. Categorical associations used chi-square tests with Cramer's V, and Spearman correlation assessed relationships among awareness/use, knowledge, barriers, and acceptance/readiness. Multiple linear regression identified independent predictors of continuous acceptance/readiness, while multivariable logistic regression modelled high versus low/moderate acceptance. Adjusted odds ratios (ORs) with 95% confidence intervals (CIs) were reported. Logistic-model discrimination was assessed using the area under the receiver-operating-characteristic curve (AUC) with 95% CI, and calibration using the Hosmer-Lemeshow statistic and Brier score. All tests were two-sided with $p<0.05$.

Results

Participant profile and digital exposure

The analytic sample comprised 532 nursing professionals. Females accounted for 474 (89.1%) participants. BSc Nursing was the most common qualification (269, 50.6%), followed by GNM (215, 40.4%), and most participants were Nursing Officers (415, 78.0%). Experience was <1 year in 187 (35.2%) and 1-5 years in 291 (54.7%). Government institutions contributed 245 (46.1%) participants, private institutions 219 (41.2%), and nursing colleges 68 (12.8%). Prior digital-health or hospital-information-system training was reported by 213 (40.0%), EHR use by 160 (30.1%), and mobile-health application use by 213 (40.0%). Workplace internet was always available to only 53 (10.0%), although 478 (89.8%) reported at least intermittent access (Table 1).

Table 1: Participant characteristics and digital-health exposure (N=532)

Variable	Category	n	%
Gender	Female	474	89.1
	Male	58	10.9
Qualification	ANM	15	2.8
	GNM	215	40.4
	BSc Nursing	269	50.6
	MSc Nursing	31	5.8
	PhD	2	0.4
Designation	Nursing Officer	415	78.0
	Senior Nursing Officer	40	7.5
	Chief Nursing Officer	9	1.7
	Nurse Educator	68	12.8
Experience	<1 year	187	35.2
	1-5 years	291	54.7
	6-10 years	42	7.9
	>10 years	12	2.3
Institutional category	Government	245	46.1
	Private	219	41.2
	Nursing college	68	12.8
Digital-health/HIS training	Yes	213	40.0
	No	319	60.0
EHR use at workplace	Yes	160	30.1
	No	372	69.9
Mobile-health application use	Yes	213	40.0
	No	319	60.0
Daily digital-device use	1-3 hours	426	80.1
	>3 hours	106	19.9
Workplace internet access	Always	53	10.0
	Sometimes	319	60.0
	Rarely	106	19.9
	Never	54	10.2

Readiness, knowledge and barriers

Mean awareness/use was 12.11 ± 5.17 of 30 and mean knowledge was 6.58 ± 2.70 of 10. The mean technology acceptance/readiness score was 115.91 ± 20.85 of 150; 254 (47.7%) participants were classified as high, 215 (40.4%) as moderate, and 63 (11.8%) as low acceptance/readiness.

Domain means were similar (19.08-19.48 of 25), with ethical/safety safeguards (19.48 ± 4.39) and behavioural intention (19.45 ± 4.52) highest. Internal consistency was high for the total acceptance/readiness scale (α=0.938), barrier scale (α=0.902), awareness/use scale (α=0.869), and knowledge measure (KR-20/α=0.774); domain α values ranged from 0.797 to 0.834 (Table 2). KMO was 0.950 and Bartlett's test was significant (χ^2=6647.0, df=435, p<0.001); six eigenvalues exceeded 1 and accounted for 59.1% of variance.

The mean barrier score was 43.47 ± 11.22 of 60. Lack of training was the most frequently rated major/very major barrier (368, 69.2%), followed by lack of technical support (341, 64.1%), poor internet connectivity (334, 62.8%), lack of institutional policy (332, 62.4%), and implementation cost (319, 60.0%). Increased workload (58.1%), lack of confidence (56.4%), medico-legal concerns (55.5%), fear of errors (53.0%), software/language issues (53.0%), and privacy concerns (52.8%) were also common (Table 3).

Table 2: Descriptive statistics and reliability of study scales/domains

Scale/domain	Range	Mean ± SD	Median (IQR)	Observed range	Reliability
Awareness/use	0-30	12.11 ± 5.17	11.0 (9.0-15.0)	0-30	0.869
Knowledge	0-10	6.58 ± 2.70	7.0 (5.0-9.0)	0-10	0.774
Acceptance/readiness	30-150	115.91 ± 20.85	118.0 (101.75-133.25)	44-150	0.938
Barrier score	12-60	43.47 ± 11.22	45.0 (35.0-53.0)	13-60	0.902
Perceived usefulness	5-25	19.08 ± 4.57	20.0	5-25	0.832
Perceived ease of use	5-25	19.27 ± 4.26	20.0	7-25	0.797
Attitude	5-25	19.43 ± 4.32	20.0	7-25	0.811
Facilitating conditions	5-25	19.20 ± 4.59	20.0	6-25	0.834
Ethical/safety safeguards	5-25	19.48 ± 4.39	20.0	5-25	0.822
Behavioural intention	5-25	19.45 ± 4.52	20.0	6-25	0.830

Table 3: Perceived barriers to digital technology adoption

Barrier	Mean ± SD	Median	Major/very major, n (%)
Lack of training	3.99 ± 1.21	4.0	368 (69.2%)
Lack of technical support	3.78 ± 1.30	4.0	341 (64.1%)
Poor internet connectivity	3.74 ± 1.34	4.0	334 (62.8%)
Lack of institutional policy	3.75 ± 1.30	4.0	332 (62.4%)
Cost of implementation	3.74 ± 1.33	4.0	319 (60.0%)
Increased workload	3.60 ± 1.33	4.0	309 (58.1%)
Lack of confidence	3.63 ± 1.34	4.0	300 (56.4%)
Medico-legal concerns	3.56 ± 1.38	4.0	295 (55.5%)
Fear of making errors	3.47 ± 1.42	4.0	282 (53.0%)
Language/software-usability issues	3.45 ± 1.40	4.0	282 (53.0%)
Patient-privacy concerns	3.42 ± 1.41	4.0	281 (52.8%)
Staff resistance	3.33 ± 1.40	3.0	262 (49.2%)

Associations and multivariable models

Acceptance/readiness was substantially higher among participants with previous digital-health training (130.1 ± 13.1 vs 106.4 ± 19.7; p<0.001; d=1.36), EHR users (126.3 ± 16.7 vs 111.4 ± 20.9; p<0.001; d=0.75), and mobile-health users (125.7 ± 16.3 vs 109.4 ± 21.0; p<0.001; d=0.84). Qualification, designation, institutional category, and workplace internet frequency were associated with acceptance, whereas experience and department were not. Acceptance correlated positively with awareness/use (Spearman ρ=0.411, p<0.001) and knowledge (ρ=0.492, p<0.001) and inversely with barrier score (ρ=-0.408, p<0.001).

The linear regression model was significant (F(11,520)=59.20, p<0.001) and explained 55.6% of variance (adjusted R^2=0.547). Higher knowledge (standardised β=0.263), prior training (β=0.233), EHR use (β=0.203), greater workplace internet availability (β=0.185), mobile-health use (β=0.149), and qualification (β=0.127) independently predicted higher acceptance, whereas barriers were inversely associated (β=-0.191). Awareness/use score, daily device duration, age, and gender were not independently significant (Table 4).

In logistic regression, prior training was associated with higher odds of high acceptance (adjusted OR 3.18, 95% CI 1.90-5.34), as were EHR use (OR 4.01, 95% CI 2.20-7.29) and mobile-health use (OR 2.41, 95% CI 1.41-4.12). Internet availability (OR 1.65 per category), knowledge (OR 1.27 per point), and qualification (OR 1.65 per level) were positive predictors, whereas barrier score was inversely associated (OR 0.94 per point). The model AUC was 0.874 (95% CI 0.844-0.902), the Hosmer-Lemeshow p value was 0.702, and the Brier score was 0.144 (Table 5).

Table 4: Multiple linear regression predicting continuous acceptance/readiness

Predictor	B	SE	Standardised β	95% CI for B	p
Prior digital-health training	9.90	1.57	0.233	6.82 to 12.99	<0.001
EHR use	9.23	1.56	0.203	6.16 to 12.31	<0.001
Mobile-health use	6.35	1.47	0.149	3.46 to 9.24	<0.001
Internet access frequency	4.91	0.81	0.185	3.33 to 6.50	<0.001
Knowledge score	2.03	0.25	0.263	1.55 to 2.52	<0.001

Barrier score	-0.35	0.06	-0.191	-0.47 to -0.24	<0.001
Awareness/use score	0.04	0.15	0.010	-0.25 to 0.33	0.782
Qualification level	4.03	0.99	0.127	2.09 to 5.97	<0.001
>3 h/day digital-device use	-0.52	1.71	-0.010	-3.87 to 2.83	0.759
Age (years)	-0.15	0.13	-0.034	-0.42 to 0.11	0.257
Female gender	2.62	1.98	0.039	-1.27 to 6.51	0.186

Table 5: Multivariable logistic regression predicting high technology acceptance/readiness

Predictor	Adjusted OR	95% CI	p
Prior digital-health training	3.18	1.90-5.34	<0.001
EHR use	4.01	2.20-7.29	<0.001
Mobile-health use	2.41	1.41-4.12	0.001
Internet access frequency	1.65	1.20-2.26	0.002
Knowledge score	1.27	1.16-1.40	<0.001
Barrier score	0.94	0.92-0.96	<0.001
Awareness/use score	1.00	0.95-1.06	0.988
Qualification level	1.65	1.13-2.41	0.010
>3 h/day digital-device use	0.84	0.44-1.59	0.592
Age (years)	1.02	0.97-1.07	0.450
Female gender	1.61	0.75-3.43	0.219

Qualitative findings and integration

The developmental qualitative analysis identified four principal themes: training before transformation; reliable infrastructure as a prerequisite; technology should augment rather than replace nursing judgement; and practical exposure builds confidence. Hands-on workshops or simulation were the most commonly represented preferred training format, while training gaps and connectivity were the leading implementation challenges. AI was predominantly represented as supportive or supportive with safeguards (Table 6). Integration suggested convergence around training and infrastructure, as factors strongly associated with quantitative acceptance were also prominent in the qualitative interpretation.

Data-integrity note: the source manuscript explicitly states that the continuous-scale, item-level psychometric, subgroup, regression, and qualitative findings reported in this manuscript were modelled/hypothetical and must be reproduced from the original participant-level dataset before they are represented as observed empirical results. It also states that the EHR non-use value was arithmetically corrected to 69.9% and that the modelled age distribution requires verification.

Table 6: Developmental thematic coding summary for open-ended responses

Question/theme	Category	n	%
Technology most likely to improve nursing	EHR/decision support	168	31.6
	Remote monitoring/wearables	129	24.2
	Telehealth/telenursing	92	17.3
	Mobile-health applications	73	13.7
	Simulation/VR	44	8.3
	Robotics/automation	26	4.9
Greatest implementation challenge	Training/competency gaps	206	38.7
	Connectivity/infrastructure	167	31.4
	Workload/time	82	15.4
	Privacy/data security	44	8.3
	Resistance/usability	33	6.2
Preferred training approach	Hands-on simulation/workshops	278	52.3
	Periodic in-service sessions	119	22.4
	Blended e-learning	82	15.4
	Vendor/bedside supervised training	53	10.0
Perceived role of AI	Supportive	362	68.0
	Supportive with safeguards/human oversight	117	22.0
	Potentially threatening or harmful	53	10.0

\Discussion

This study portrays a nursing workforce that is generally receptive to digital transformation but not uniformly prepared for implementation. Nearly half of participants were classified as having high acceptance/readiness and another two-fifths had moderate acceptance, yet only 40.0% reported previous digital-health training, 30.1% reported EHR use, and 40.0% reported mobile-health use. Continuous workplace internet access was uncommon. These findings reinforce the distinction between attitudinal acceptance and operational readiness: clinicians may value technology while lacking the infrastructure, exposure, competence, or organisational conditions needed for safe and sustained use. This interpretation is consistent with the broader view of digital transformation as a health-system strategy rather than simple technology procurement [1] and with evidence that digital-health competence is shaped by both individual capability and contextual factors [22].

Training was the most consistent modifiable factor. Participants with previous digital-health training had markedly higher acceptance, and training remained independently associated with acceptance in both multivariable models. Evidence from critical-care nursing similarly indicates that readiness is closely related to perceived usefulness, ease of use, and facilitating conditions [20]. Student-nurse research also identifies knowledge, technological proficiency, and access to training as important determinants of readiness [19]. These findings support competency-based programmes that combine introductory digital literacy with hands-on practice, role-specific application, supervised implementation, and periodic reinforcement rather than relying on one-time orientation.

EHR use was strongly associated with acceptance, suggesting that practical exposure may reduce uncertainty and demonstrate the clinical value of structured documentation and information continuity. However, adoption should not be equated with effective implementation. EHRs may improve patient-safety processes while also creating new problems when usability or workflow integration is poor [8]. Evidence specific to electronic nursing documentation likewise indicates that benefits depend on system design, staff preparation, and appropriate incorporation into nursing work [9]. Institutions should therefore combine training with usability testing, workflow redesign, nurse involvement in configuration, rational alert design, and accessible technical support.

Mobile health, telehealth, remote monitoring, and AI require similar attention to clinical context. Telehealth can improve access and follow-up, but its effectiveness depends on connectivity, privacy protection, communication skills, and clear clinical responsibilities [10]. Mobile-health tools can support timely patient education and engagement [11], while remote-monitoring systems require reliable devices, interoperable data flows, manageable alert volumes, and explicit escalation pathways [13]. AI may enhance nursing decision support and operational efficiency [14], but willingness to use AI is influenced by trust, workflow compatibility, perceived usefulness, and professional autonomy [15]. Technology-specific preparation is therefore preferable to assuming that general familiarity with smartphones or computers automatically translates into clinical digital competence.

The barrier profile was predominantly organisational and capability-related. Lack of training, technical support, reliable internet, institutional policy, and implementation resources ranked above staff resistance. This pattern is consistent with evidence from resource-limited settings showing that digital adoption can be constrained by infrastructure, workload, access, and support rather than by unwillingness alone [21]. It also supports a multidimensional interpretation of competence in which organisational conditions and opportunities for actual technology use matter alongside individual knowledge [22]. Practical implementation should include protected training time, ward-level digital champions, rapid troubleshooting, documented downtime procedures, and staged deployment with frontline nurse participation.

Ethical caution should not be interpreted as opposition to innovation. The high ethical/safety domain score coexisted with strong behavioural intention, indicating that participants could support technology while still expecting safeguards. AI ethics literature consistently identifies privacy, bias, transparency, accountability, and trust as core concerns [16]. Broader health-care mapping also emphasises explainability, human oversight, informed consent, fairness, and the distribution of responsibility when algorithmic systems influence care [17]. International guidance recommends protecting human autonomy, well-being, transparency, responsibility, inclusiveness, equity, and safety throughout the AI lifecycle [23]. Nursing digital-health education should therefore integrate AI literacy, cybersecurity, data governance, verification of machine-generated outputs, recognition of bias, and preservation of person-centred communication.

The study has several strengths, including a relatively large multicentre sample, representation of both clinical and educational nursing roles, and a multidimensional framework covering knowledge, exposure, acceptance, facilitating conditions, ethical safeguards, behavioural intention, and barriers. The analytic framework also incorporated effect sizes, multivariable modelling, and integration of open-ended responses. Nevertheless, the cross-sectional design cannot establish temporal or causal relationships, and self-reported exposure and competence are vulnerable to recall and social-desirability bias. Sampling from selected institutions within one district limits generalisability. The study-specific acceptance categories require external validation, and brief open-ended survey responses provide less qualitative depth than interviews or focus groups.

Most importantly, the source manuscript identifies the psychometric, continuous-scale, subgroup, regression, and qualitative extensions as hypothetical/modelled rather than directly reproduced from participant-level data. These findings therefore require verification before empirical submission. The EHR non-use denominator and age distribution also require confirmation. Until this verification is completed, the inferential findings should be treated as a developmental analytic framework rather than definitive empirical evidence. After verification, further assessment of the study-developed instrument should include confirmatory factor analysis in an independent sample, test-retest reliability, convergent validity, and measurement invariance across clinical and educational roles.

Conclusion

Nursing professionals in the selected Mahabubnagar institutions showed generally favourable technology acceptance, but practical readiness was constrained by uneven training, limited digital-health exposure, intermittent connectivity, and organisational barriers. Prior training, EHR and mobile-health use, knowledge, internet availability, and qualification were associated with greater acceptance, whereas perceived barriers were inversely associated. Sustainable digital transformation should therefore be approached as a workforce-development and governance programme that combines role-specific competency training, reliable infrastructure, usable systems, technical support, clear policies, ethical safeguards, and meaningful nurse involvement in technology selection and evaluation. All modelled inferential and qualitative findings must be verified against the original participant-level data before submission as empirical results.

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