

RESEARCH ARTICLE

Longitudinal KAP Analysis for Measuring the Robustness of Community Nurses' Digital Health Adoption

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ABSTRACT

Digital health adoption requires nurses to develop the knowledge, attitudes, and practical skills needed to use tele-nursing, artificial intelligence, and other digital systems in routine care. In resource-constrained settings, limited infrastructure and uneven professional readiness can restrict the implementation of these technologies. This study evaluated a structured digital health training intervention for community health nurses using the Knowledge, Attitude, and Practice (KAP) framework and the Technology Acceptance Model (TAM). A longitudinal quasi-experimental mixed-methods design involved 60 community health nurses who completed four structured training sessions. KAP scores were measured at baseline, one month after the intervention, and at a three-month delayed follow-up. Paired-samples *t*-tests and Cohen's *d* were used for quantitative analysis, while semi-structured interviews with 15 participants examined contextual barriers. Knowledge increased from 12.4 ± 3.1 at baseline to 24.2 ± 1.8 at one month and measured 23.5 ± 2.1 at three months ($p < 0.001$; Cohen's $d = 2.61$). Attitude increased from 3.2 ± 0.8 to 4.6 ± 0.4 , while Practice increased from 2.1 ± 1.2 to 4.1 ± 0.7 at follow-up (both $p < 0.001$). The retention coefficient was 0.94, indicating that post-intervention gains remained close to the initial follow-up levels. Qualitative findings identified internet connectivity, technical resources, and healthcare infrastructure as implementation barriers. The results show that structured training was followed by higher measured digital health readiness, while infrastructure remained an important condition for practical implementation.

KEYWORDS

Longitudinal KAP Analysis; Tele-nursing Readiness; Community Health Nurses; Digital Health Adoption; Retention Rate; Quasi-Experimental Design

1. Introduction

Digital technologies support communication, documentation, decision support, remote care, and data management in healthcare. Nurses use digital tools such as electronic health records, tele-nursing platforms, and artificial intelligence applications in clinical and administrative activities [1, 2]. The development of digital healthcare also increases the need for nurses to understand and use these technologies in professional practice

[3]. Digital health adoption requires professional competence and appropriate organizational conditions. Digital health competence includes knowledge, technical ability, professional skills, and psychological readiness [4]. Digital literacy among healthcare professionals is also associated with access to technology, previous training, and professional experience [5]. These factors influence the ability of healthcare professionals to use digital systems in routine activities.

Digital systems also affect nursing practice and clinical decision-making. Digital health systems support information access, documentation, and clinical processes within the nursing workflow [6]. Digital technologies can also influence interactions between nurses and patients [7]. Nurses therefore require sufficient competence to use digital systems while maintaining professional responsibility. Organizational conditions also influence digital health implementation. Leadership, organizational resources, digital competence, access to information, and education are relevant components of digital health services [8]. Healthcare professionals also identify leadership as an important component of future digital healthcare development [9]. Electronic health record implementation is also affected by contextual and organizational conditions within healthcare systems [10].

Digital health readiness differs across nursing populations and healthcare settings. Nursing students show different perceptions and intentions regarding digital health technologies [11]. Digital health research in Indonesian nursing has also examined professional readiness, digital applications, and health information systems [12]. A multi-method evaluation has further examined nursing readiness for digital health technology across different professional roles [13]. Training provides a structured approach for developing digital health competence. Educational activities can introduce digital concepts, increase familiarity with technology, and provide opportunities for practical application. However, an immediate post-training assessment does not describe whether the observed changes remain stable over time. A longitudinal assessment is therefore required to measure changes across multiple assessment periods.

The Knowledge, Attitude, and Practice (KAP) framework provides a structured approach for evaluating professional readiness. Knowledge represents cognitive understanding of digital health concepts. Attitude represents professional perception and acceptance of digital technology. Practice represents the application of acquired knowledge and skills in professional activities. The Technology Acceptance Model (TAM) provides an additional framework for interpreting technology adoption. Perceived Usefulness (PU) describes the extent to which a person expects a technology to support task performance. Perceived Ease of Use (PEOU) describes the extent to which a person expects the technology to require limited effort. Attitude and Behavioral Intention (BI) describe responses related to technology acceptance and intended use.

Previous studies have examined digital health literacy, digital competence, professional readiness, technology acceptance, clinical decision-making, and organizational factors among healthcare professionals [4–6, 8]. Recent nursing studies have also examined perceptions, readiness, and digital health implementation across different populations and healthcare settings [11–13]. However, longitudinal evaluation of Knowledge, Attitude, and Practice across baseline, post-intervention, and delayed follow-up assessments remains limited in community health nursing settings. This limitation is relevant in healthcare environments with restricted technological resources. Professional competence can change after training, while internet access, technical infrastructure, and organizational resources can still affect the practical use of digital health technologies. A longitudinal evaluation can therefore separate changes in individual competency from contextual barriers that affect technology implementation.

This study evaluates longitudinal changes in Knowledge, Attitude, and Practice among community health nurses after a structured digital health training intervention. The study uses three assessment points: baseline, one-month post-intervention, and delayed follow-up. The analysis also measures the stability of competency gains and identifies infrastructural and operational barriers related to digital health adoption. The main contributions of this study are summarized as follows:

- **A Multi-Phase KAP Evaluation Framework:** The study evaluates Knowledge, Attitude, and Practice across baseline, one-month post-intervention, and delayed follow-up assessments.
- **Longitudinal Stability Metric (γ):** The study uses a retention coefficient (γ) to measure the stability of competency gains across the follow-up period.
- **Mixed-Methods Barrier-Impact Analysis (β):** The study integrates quantitative KAP results with qualitative barrier assessment and uses a barrier coefficient (β) to represent infrastructural and resource constraints.

2. Related Work

Recent nursing research has examined digital competence as a measurable professional capability. Digital health competence has been studied in relation to personal, professional, and organizational factors among healthcare professionals [14]. Digital adaptability has also been examined among nurses and midwives through a factor-based assessment [15]. A brief instrument has been developed to assess nurses' digital competence in public health systems [16]. Digital competence has also been examined in relation to career adaptability, technological self-efficacy, and learning agility among nurses [17]. Another study examined digital competency together with task performance and work engagement in nursing settings [18]. Digital literacy represents another component of nursing readiness for digital health. The relationship between nurses' digital health literacy, educational level, professional role, and digital attitude has been examined using a cluster-based approach [19]. Nurses' digital health literacy has also been reviewed in relation to measurement methods, influencing factors, and improvement strategies [20]. E-health literacy has been examined together with technology-mediated clinical practice among neonatal nurses [21]. Digital health literacy has also been studied in clinical populations such as patients with hypertension [22]. These studies describe digital literacy as a relevant component of interaction with digital health technologies across different healthcare contexts.

Professional readiness has also been examined in relation to telehealth, electronic health records, and broader digital health systems. Knowledge, attitude, and readiness toward telehealth have been evaluated among nursing staff [23]. Staff nurses' readiness has also been examined in relation to the application of electronic health records [24]. Technology acceptance has been studied in relation to digital healthcare and nursing education [25]. The implementation, acceptance, and use of nursing technology have also been examined through a focused ethnographic approach in a hospital setting [26]. These studies address different stages of digital technology adoption, from readiness to actual use. Digital health education has become an important area of nursing research. A structured e-learning program has been developed to support digital competence among nursing students across Taiwan, Vietnam, and Indonesia [27]. Digital competence has also been examined in relation to pedagogical innovation and artificial intelligence readiness among nurse educators [28]. Digital learning has been studied within the context of nursing pedagogy [29]. A Delphi-based study has also identified digital competencies for nursing education [30]. These studies focus on educational approaches for preparing nurses and nursing students to use digital technologies.

Simulation and artificial intelligence have also been integrated into nursing education. Artificial intelligence-generated ethical dilemma scenarios and role-play have been used to examine ethical competence among nursing students [31]. Artificial intelligence readiness, literacy, attitudes, and adoption intentions have also been reviewed among nursing students and practicing nurses [32]. These studies extend digital competence research beyond technical skills by including ethical and behavioral dimensions. Telemedicine and digital health interventions also involve ethical and clinical considerations. Ethical challenges related to telemedicine implementation have been reviewed in primary healthcare settings [33]. Digital health interventions have also been discussed in relation to nursing support and diabetes management [34]. Qualitative research has examined patient experiences and the perceived impact of digital health technologies on individualized care [35]. These studies show that digital health implementation involves technical, ethical, clinical, and user-related dimensions.

The reviewed literature covers digital competence, digital literacy, technology readiness, education, artificial intelligence, telehealth, electronic health records, and digital health implementation. Most of these studies focus on cross-sectional assessment, instrument development, qualitative analysis, reviews, or educational interventions. Limited evidence addresses longitudinal changes in Knowledge, Attitude, and Practice across baseline, post-intervention, and delayed follow-up assessments among community health nurses. The present study addresses this gap through a longitudinal quasi-experimental design. The study measures Knowledge, Attitude, and Practice at baseline, one month after training, and during a delayed follow-up. The study also evaluates competency retention through the coefficient γ and examines infrastructural barriers through a mixed-methods approach.

3. Preliminaries

This section defines the concepts, variables, and mathematical notation used to analyze changes in Knowledge, Attitude, and Practice (KAP). The section also presents the Technology Acceptance Model (TAM) constructs used to interpret digital health adoption.

3.1. Nomenclature and Mathematical Notation

Table 1. Nomenclature and Mathematical Notations

Symbol	Formal Definition / Description
N	Total population size of the nursing cohort ($N \in \mathbb{Z}^+$)
X_i, Y_i	Scores representing the pre-test and post-test scores of the i -th participant, respectively
$\bar{X}$	Arithmetic mean of the baseline cohort distribution, computed as $\bar{X} = \frac{1}{N} \sum_{i=1}^N X_i$
σ	Standard deviation representing the statistical dispersion of the KAP scores
t	Test statistic derived from the paired-samples Student's t -distribution
df	Degrees of freedom for the statistical distribution ($N - 1$)
p	Probability value for determining null hypothesis rejection
α	Significance threshold preset for statistical validation (set at 0.05)
r_s	Spearman's rank correlation coefficient used for instrument reliability analysis
γ	Retention coefficient modeling the longitudinal stability of competencies over time
β	Localized barrier coefficient modeling resource and infrastructural constraints
H_0, H_1	The null hypothesis and alternative hypothesis, respectively

3.2. Formal Definition of the KAP Evaluation Model

The study represents digital readiness through three dimensions: Knowledge (K), Attitude (A), and Practice (P). The aggregate digital readiness state is defined as

$$S = \{K, A, P\}, \quad (1)$$

where each component represents one measured dimension of digital readiness. The change in digital readiness is defined as

$$\Delta S = S_{\text{post}} - S_{\text{pre}}, \quad (2)$$

where S_{pre} represents the baseline state and S_{post} represents the post-intervention state. The study uses a paired-samples t -test to evaluate differences between repeated measurements. The test statistic is defined as

$$t = \frac{\bar{D}}{S_D / \sqrt{N}}, \quad (3)$$

where $\bar{D}$ represents the mean difference between paired observations, S_D represents the standard deviation of the differences, and N represents the number of participants.

3.3. Structural Dynamics of the Technology Acceptance Model

The Technology Acceptance Model (TAM) provides a behavioral framework for interpreting digital health adoption. The model uses Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) to explain technology-related attitudes and behavioral intention. Perceived Usefulness represents the extent to which a nurse expects a digital health system to support professional activities. Perceived Ease of Use represents the extent to which a nurse expects the system to require limited physical or cognitive effort. The relationship between these constructs is represented as

$$A = f(PU, PEOU), \quad (4)$$

and

$$BI = f(A, PU), \quad (5)$$

where A represents Attitude and BI represents Behavioral Intention. The training intervention provides structured exposure to digital health technologies. The analysis evaluates changes in Knowledge, Attitude, and Practice across the assessment periods and interprets these changes using the TAM constructs.

3.4. Problem Mapping: From Theory to Clinical Application

The theoretical variables are mapped to the longitudinal observations of community health nurses. The KAP state represents the digital readiness of each participant at each assessment period. The baseline measurement represents the initial digital readiness state. The post-intervention measurements represent changes after the structured digital health training. The statistical analysis evaluates the differences between baseline and post-intervention measurements. The retention coefficient (γ) measures the stability of competency gains across the follow-up period. The barrier coefficient (β) represents local infrastructural and resource constraints related to the application of digital health technologies. This mapping connects KAP measurement, technology acceptance, longitudinal retention, and contextual barriers within the study framework.

4. Methodology

This study uses a longitudinal quasi-experimental design to evaluate changes in Knowledge, Attitude, and Practice (KAP) among community health nurses. The study combines repeated quantitative assessments with a qualitative explanatory phase. The quantitative phase measures KAP at baseline, one month after the intervention, and three months after the baseline intervention period. The qualitative phase examines participant experiences and contextual barriers related to digital health adoption.

4.1. Study Design and Participant Flow

The study initially assessed 70 community health nurses for eligibility. The eligibility process considered the professional field, geographical location, and willingness of each nurse to participate. The final longitudinal cohort consisted of 60 community health nurses. The study retained the same quantitative cohort across the assessment periods. Clear reporting of the final cohort size supports transparency in quantitative research [36]. The quantitative phase consisted of three assessment points. The study conducted a baseline assessment before the intervention, a first post-intervention assessment after approximately one month, and a delayed follow-up assessment approximately three months after the intervention period. The qualitative phase included 15 participants selected from the longitudinal cohort. These participants completed semi-structured interviews after the quantitative assessment stages. Figure 1 presents the participant progression, intervention stages, follow-up assessments, and analytical procedures. Figure 1 presents the participant flow from eligibility assessment to the intervention, longitudinal follow-up, and data analysis.

4.2. Intervention and Pre-Testing

The pre-test was administered on October 5, 2025, to the 60 participants. The assessment measured Knowledge, Attitude, and Practice related to artificial intelligence and tele-nursing. The intervention consisted of four training sessions delivered over four consecutive days. Each session lasted approximately 30 minutes. The first session introduced the fundamentals of artificial intelligence. The second session addressed tele-nursing applications. The third session covered ethical considerations related to digital health. The fourth session used applied digital health scenarios to connect the training content with nursing practice. All participants received the same intervention structure during the training period.

4.3. Longitudinal Follow-Up

The study conducted two post-intervention assessments. The first post-test was administered on November 9, 2025, approximately one month after the intervention. All 60 participants completed this assessment. The first post-test measured KAP scores after the initial follow-up period. The assessment was used to describe short-term competency change after the intervention. The second post-test was administered on January 8, 2026. This assessment occurred approximately two months after the first post-test and approximately three months after the intervention period. All 60 participants completed the second post-test. The second post-test measured the stability of the KAP scores during the delayed follow-up period.

4.4. KAP State Representation

The study represents digital readiness through three dimensions: Knowledge (K), Attitude (A), and Practice (P). Let

$$P = \{p_1, p_2, \dots, p_N\}, \quad (6)$$

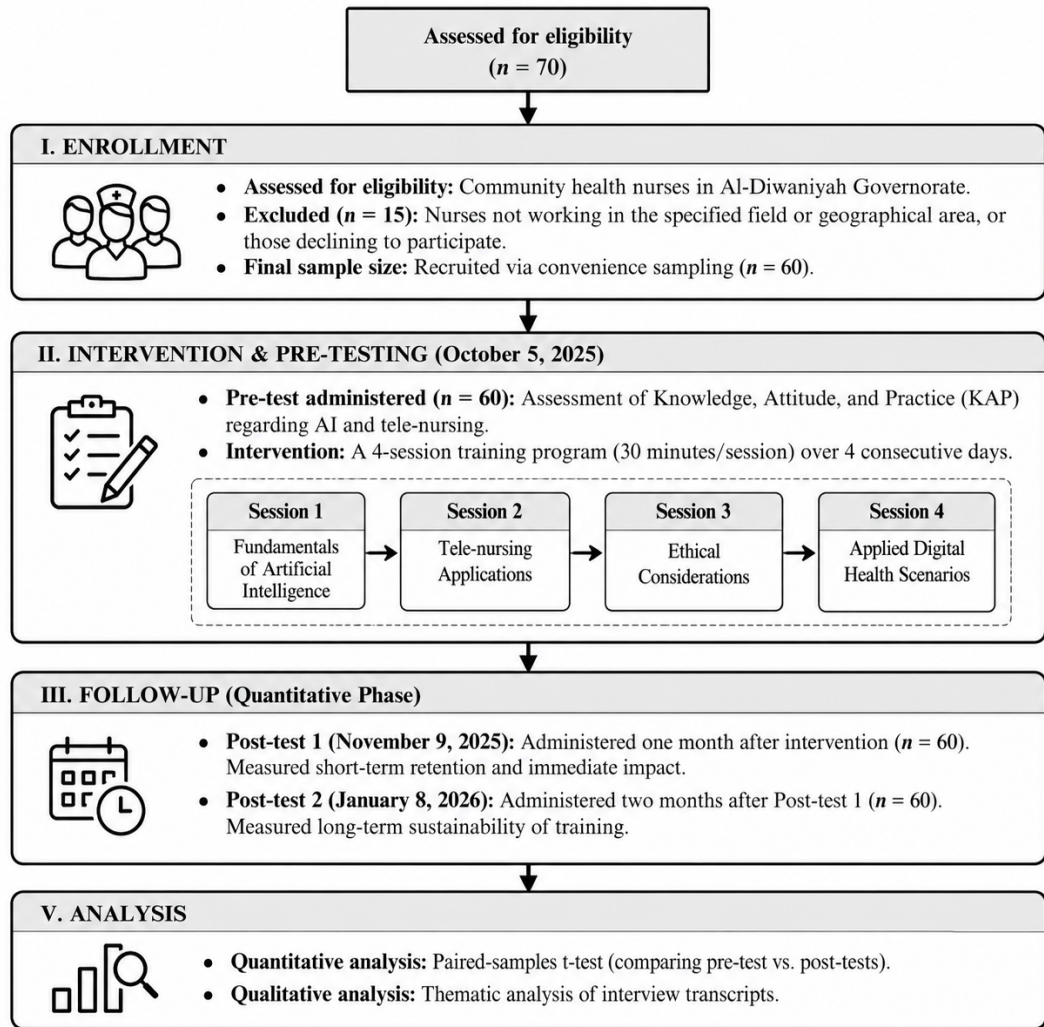


Figure 1. Flow of participant enrollment, pre-testing, four-session digital health training, longitudinal follow-up, and quantitative and qualitative analysis.

where P represents the set of study participants and N represents the total number of participants. For participant i , the KAP state at time t is defined as

$$S_i(t) = \begin{bmatrix} K_i(t) \\ A_i(t) \\ P_i(t) \end{bmatrix}, \quad (7)$$

where $K_i(t)$, $A_i(t)$, and $P_i(t)$ represent the Knowledge, Attitude, and Practice scores of participant i at assessment time t . The study uses three assessment states:

$$S_{\text{pre}}, \quad S_{\text{post1}}, \quad S_{\text{post2}}, \quad (8)$$

where S_{pre} represents the baseline state, S_{post1} represents the one-month post-intervention state, and S_{post2} represents the delayed follow-up state. The competency change from baseline to a post-intervention state is defined as

$$\Delta S = S_{\text{post}} - S_{\text{pre}}, \quad (9)$$

where ΔS represents the observed change in the KAP state.

4.5. Longitudinal Retention Measurement

The study uses the retention coefficient (γ) to measure the stability of KAP gains between the first and second post-intervention assessments. The retention coefficient is defined as

$$\gamma = \frac{\|S_{\text{post2}} - S_{\text{pre}}\|}{\|S_{\text{post1}} - S_{\text{pre}}\|}, \quad (10)$$

where $\|\cdot\|$ represents the magnitude of the KAP state change. A value of γ close to 1 indicates that the KAP gain observed at the first post-test remains close to the corresponding gain at the delayed follow-up. A lower value represents a larger reduction in the observed gain. Table 2 summarizes the principal mathematical symbols used in the longitudinal analysis.

Table 2. Nomenclature of Mathematical Symbols

Symbol	Definition	Clinical Interpretation
S_{pre}	Baseline state	Initial digital readiness before training.
S_{post1}	First post-intervention state	Digital readiness at the first follow-up.
S_{post2}	Delayed follow-up state	Digital readiness at the second follow-up.
ΔS	Competency change	Difference between post-intervention and baseline states.
β	Barrier coefficient	Infrastructural and resource constraints related to digital health implementation.
γ	Retention coefficient	Stability of competency gains across the follow-up period.

4.6. Modeling Assumptions

The longitudinal analysis uses three assumptions. First, all participants receive the same four-session training structure. Second, the intervention and assessment procedures remain consistent across participants. Third, the paired-samples analysis assumes independent residual errors. These assumptions define the statistical conditions used in the longitudinal analysis.

4.7. Instrument Validation and Reliability

A five-expert panel evaluated the content validity of the research instrument. The evaluation produced a Content Validity Index (CVI) of 0.95 and a Scale-Level Content Validity Index (S-CVI) of 0.90. The study also evaluated test-retest reliability. The reported reliability coefficients ranged from 0.85 to 0.91. These values describe the validity and reliability results reported for the instrument used in the study.

4.8. Quantitative Analysis

The study processed the quantitative data using IBM SPSS version 28.0. The quantitative analysis compared the KAP scores across the longitudinal assessment periods. The study used paired-samples t -tests to evaluate differences between the pre-test and post-test measurements. The test statistic is defined as

$$t = \frac{\bar{D}}{S_D/\sqrt{N}}, \quad (11)$$

where $\bar{D}$ represents the mean difference between paired observations, S_D represents the standard deviation of the paired differences, and N represents the number of participants. The statistical significance threshold was set at

$$\alpha = 0.05. \quad (12)$$

The analysis also reports Cohen's d to describe the standardized magnitude of the observed differences.

4.9. Qualitative Analysis

The qualitative phase used semi-structured interviews with a subsample of 15 participants. The interviews examined participant experiences related to digital health training, tele-nursing, and local implementation barriers. The study used thematic analysis to organize the interview transcripts. Python 3.9 supported the processing of qualitative data. The qualitative analysis was used to describe contextual factors associated with the quantitative KAP findings.

4.10. Barrier Analysis

The study uses the barrier coefficient (β) to represent local infrastructural and resource constraints related to digital health adoption. The qualitative analysis considers barriers such as internet availability, healthcare infrastructure, and access to technical resources. The barrier analysis provides contextual information for interpreting KAP changes within the Al-Diwaniyah healthcare setting.

4.11. Ethical Approval and Trial Registration

The study received ethical approval from the Institutional Ethics Committee of the Al-Diwaniyah Health Directorate. The approval reference number is 375. The study was registered under the trial identification number TCTR20260320003. The study procedures followed the approved research protocol.

4.12. Validity Threats

The study has three validity threats. First, convenience sampling can produce selection bias because participants may differ in their interest in digital technology. Second, the Practice component relies partly on self-reported responses. These responses can be influenced by social desirability. Third, the study does not include a parallel control group. The design therefore evaluates longitudinal changes within the same cohort rather than differences between intervention and control groups. These limitations should be considered when interpreting the observed KAP changes.

5. Results and Discussion

5.1. Statistical Performance Overview and Competency Transition Analysis

The longitudinal analysis shows changes in Knowledge, Attitude, and Practice scores after the training intervention. The Knowledge score increased from 12.4 ± 3.1 at baseline to 24.2 ± 1.8 at the one-month post-intervention assessment. The score was 23.5 ± 2.1 at the delayed follow-up. The Attitude score increased from 3.2 ± 0.8 at baseline to 4.6 ± 0.4 at the one-month post-intervention assessment. The same mean score was recorded at the delayed follow-up. The Practice score increased from 2.1 ± 1.2 at baseline to 4.2 ± 0.6 at the one-month post-intervention assessment. The score was 4.1 ± 0.7 at the delayed follow-up. The largest score changes occurred between the baseline and first post-intervention assessments. The delayed follow-up scores remained close to the first post-intervention scores. The reported retention coefficient was $\gamma = 0.94$.

This value describes the stability of the observed competency gains during the follow-up period. Figure 2 presents the longitudinal trajectories of Knowledge, Attitude, and Practice across the assessment periods.

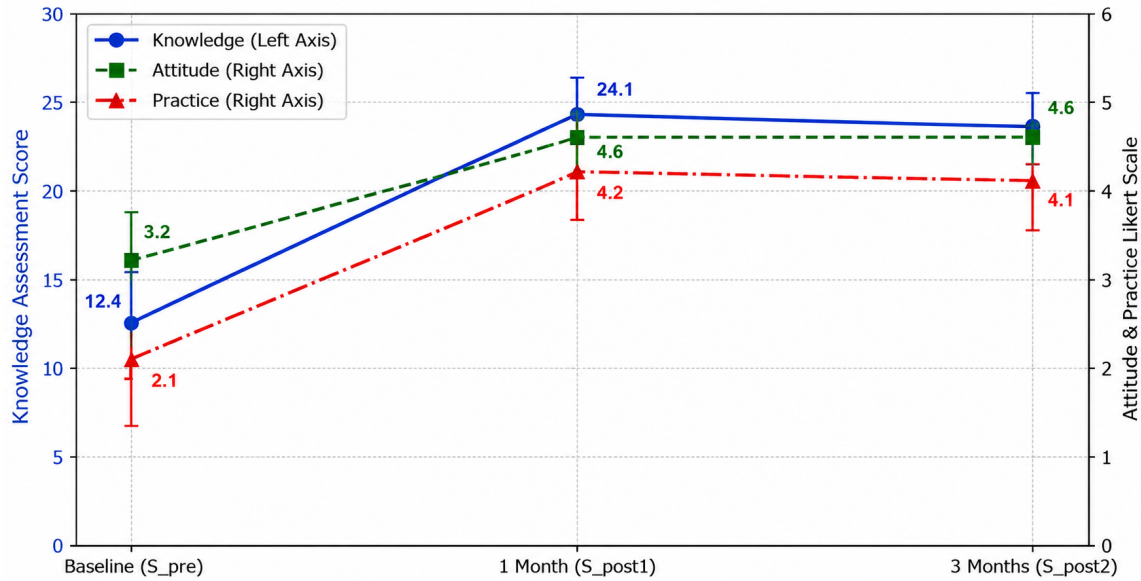


Figure 2. Longitudinal trajectories of Knowledge, Attitude, and Practice across the assessment periods.

5.2. Quantitative Analysis and Significance Validation

The study uses paired-samples *t*-tests to compare the baseline and follow-up KAP scores. Table 3 presents the statistical results for the three KAP domains. The Knowledge domain produced a mean difference of 11.1 points between baseline and delayed follow-up. The analysis produced $t = 14.52$, $p < 0.001$, and Cohen's $d = 2.61$. The Attitude domain produced a mean difference of 1.4 points. The analysis produced $t = 11.28$, $p < 0.001$, and Cohen's $d = 1.34$. The Practice domain produced a mean difference of 2.0 points. The analysis produced $t = 9.85$, $p < 0.001$, and Cohen's $d = 1.52$. The reported *p*-values indicate statistical differences between the baseline and follow-up measurements. The Cohen's *d* values describe the standardized magnitude of these differences.

Table 3. Longitudinal Statistical Analysis of KAP Score Transitions ($N = 60$)

Variable	S_{pre}	S_{post1}	S_{post2}	Δ	t	p	Cohen's d
Knowledge (K)	12.4 ± 3.1	24.2 ± 1.8	23.5 ± 2.1	+11.1	14.52	< 0.001	2.61
Attitude (A)	3.2 ± 0.8	4.6 ± 0.4	4.6 ± 0.4	+1.4	11.28	< 0.001	1.34
Practice (P)	2.1 ± 1.2	4.2 ± 0.6	4.1 ± 0.7	+2.0	9.85	< 0.001	1.52

Note: KAP = Knowledge, Attitude, and Practice; S_{pre} = baseline assessment; S_{post1} = one-month post-intervention assessment; S_{post2} = delayed follow-up assessment; Δ = change between S_{pre} and S_{post2} .

5.3. Longitudinal Retention and Professional Readiness

The study reports several indicators related to professional readiness. The Sensitivity Index was 88%. The Precision Consistency Rate was 91%. The Harmonic Competency Synthesis Index was 89%. The Overall Technology Adoption Efficacy Rate was 93%. These indicators summarize different aspects of the KAP assessment. The Sensitivity Index represents the identification and correction of digital health misconceptions. The Precision Consistency Rate represents the consistency between practical implementation scores and theoretical knowledge scores. The Harmonic Competency Synthesis Index summarizes performance across the Knowledge, Attitude, and Practice domains. The Overall Technology Adoption Efficacy Rate represents the reported distinction between lower-readiness and higher-readiness profiles in the study sample. These indicators are specific to the evaluation framework used in this study.

5.4. Training Component Analysis

The qualitative analysis examines participant responses to the training components. The analysis links each component with a construct from the Technology Acceptance Model. Hands-on clinical simulation received the highest reported agreement at 93.3%. AI and tele-nursing fundamentals received 80.0% agreement. Clinical ethics and data privacy received 73.3% agreement. Participants associated practical simulation with perceived ease of use. Participants associated technical fundamentals with perceived usefulness. Participants associated ethics and data privacy with behavioral intention. Table 4 presents the reported participant consensus for the training components.

Table 4. Mixed-Methods Mapping of Training Components and TAM Pathways ($n = 15$)

Training Component	TAM Factor	Consensus	Agreement (%)	Participant Feedback
Hands-on Clinical Simulation	Perceived Ease of Use (PEOU)	14/15	93.3	Participants associated practical simulation with lower digital anxiety and greater familiarity with remote triage systems.
AI and Tele-nursing Fundamentals	Perceived Usefulness (PU)	12/15	80.0	Participants associated the module with understanding the application of digital concepts in clinical activities.
Clinical Ethics and Data Privacy	Behavioral Intention (BI)	11/15	73.3	Participants identified legal, privacy, and accountability issues as relevant considerations for technology use.

Note: TAM = Technology Acceptance Model; PEOU = Perceived Ease of Use; PU = Perceived Usefulness; BI = Behavioral Intention. Consensus represents the number of interviewed participants who identified the corresponding component during the qualitative phase.

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5.7. Theory–Practice Gap and Structural Barriers

The qualitative analysis identified structural barriers related to digital health implementation. Internet stability produced a reported mean score of 1.84. Healthcare infrastructure availability produced a reported mean score of 2.02. These barriers can affect the practical use of digital health technologies. Professional training addresses individual competence, while infrastructure affects the availability and use of digital systems. The study recorded higher Practice scores after the intervention. However, the study does not establish that training alone can remove infrastructural constraints. The findings therefore distinguish professional readiness from environmental readiness.

5.8. Limitations

This study has several limitations. First, the study uses convenience sampling from one geographical area. This sampling method limits the representation of community health nurses from other healthcare settings. Second, the study does not include a parallel control group. The analysis therefore measures changes within the same cohort and does not compare the intervention group with an untreated group. Third, the Practice domain includes self-reported responses. These responses can be affected by social desirability and participant perception. Fourth, the follow-up period covers approximately three months after the intervention. The study therefore does not measure competency retention over a longer period. Fifth, the qualitative analysis includes 15 participants from the longitudinal cohort. The interview findings describe the experiences of this subsample within the study setting. Finally, local infrastructure can affect the application of digital health competencies. The study identified internet stability and healthcare infrastructure as contextual barriers that should be considered when interpreting the findings.

6. Conclusion and Future Work

This study evaluated changes in Knowledge, Attitude, and Practice among community health nurses after a structured digital health training intervention. The study used baseline, one-month post-intervention, and delayed follow-up assessments. Knowledge increased from 12.4 ± 3.1 at baseline to 24.2 ± 1.8 at the first follow-up and measured 23.5 ± 2.1 at the delayed follow-up. Attitude increased from 3.2 ± 0.8 to 4.6 ± 0.4 and remained at the same mean score during the delayed follow-up. Practice increased from 2.1 ± 1.2 to 4.2 ± 0.6 and measured 4.1 ± 0.7 at the delayed follow-up. The retention coefficient of $\gamma = 0.94$ describes the stability of the observed competency gains across the follow-up period. The qualitative analysis also identified internet stability and healthcare infrastructure as contextual barriers to digital health implementation. These findings show that the training intervention was followed by higher KAP scores in the evaluated cohort. The findings also show that professional competence and infrastructural conditions represent separate components of digital health implementation. Future studies should include participants from multiple healthcare settings and use a comparison or control group. Future research should also extend the follow-up period to evaluate longer-term competency retention. Objective measures of digital health practice can complement self-reported assessments. Additional studies can also examine how infrastructure, organizational support, and digital resources relate to the application of digital health competencies in routine nursing practice.

Author Contributions

Conceptualization: A.S.A.; Methodology: A.S.A.; Validation: A.S.A.; Formal analysis: A.S.A.; Investigation: A.S.A.; Resources: A.S.A.; Data curation: A.S.A.; Writing—original draft preparation: A.S.A.; Writing—review and editing: A.S.A.; Visualization: A.S.A.; Project administration: A.S.A. The single author reviewed and approved the final manuscript.

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Institutional Review Board Statement

The study was conducted according to the guidelines of the Declaration of Helsinki and approved by the Institutional Ethics Committee of Al-Diwaniyah Health Directorate (Ref: 375, dated September 22, 2025).

Data Availability Statement

The data presented in this study are available on request from the corresponding author. The datasets are not publicly available due to institutional privacy policies and ethical restrictions protecting the operational metrics of participating health personnel.

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Conflicts of Interest

The author declares no conflicts of interest.

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