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Empowering Patients through AI-Driven Care Navigation and e-Health Literacy Support: A Mixed-Methods Study and Nursing Policy Implications

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Abstract

Background

AI-driven tools have shown promise in assisting patients with healthcare navigation and improving e-health literacy, but research systematically examining their acceptance from the perspective of patients remains limited.

Objective

Assess patients' barriers to healthcare navigation, e-health literacy, and willingness to use AI-assisted nursing services, and use a mixed-methods approach to develop evidence-based nursing policy recommendations.

Methods

The study employed an explanatory mixed-methods design. The first phase consisted of quantitative analysis, using hierarchical multiple regression to identify independent predictors of use intention. In the second phase, purposeful sampling was conducted based on the results of the first phase, followed by semi-structured interviews, which were analyzed using Braun and Clarke's thematic analysis method. Data were integrated using connecting and merging strategies, and the results were presented in a joint presentation matrix.

Results

Perceived usefulness and e-health literacy were positive predictors of AI use intention, while perceived risk was a negative predictor. Barriers to accessing medical care did not reach statistical significance in the final model. The qualitative analysis identified five dimensions and 15 subthemes.

Conclusion

Perceived usefulness and e-health literacy are important factors driving patient's use intention of AI-based healthcare services, while multidimensional perceived risks—including distrust of technology, privacy concerns, and emotional detachment—constitute the primary barriers. The digital divide places older adults with chronic conditions, who have the most urgent healthcare needs, at a disadvantage when it comes to AI applications. Healthcare policies should promote a service model that combines AI systems with human triage and establish a nurse-led process for reviewing AI outputs.

1 Introduction

Advances in medical technology and the accelerating pace of population aging have made modern healthcare systems increasingly complex, and the challenges patients face throughout their care journeys have become more apparent. Patients must overcome multiple barriers related to information and processes, from navigating the hospital's complex layout and finding the right specialist to understanding highly specialized medical reports and adhering to post-discharge care instructions. Studies show that a significant proportion of adults worldwide have limited health literacy. This limits their ability to self-manage their conditions and participate effectively in healthcare decisions[1, 2].As of the end of 2024, China's population aged 60 and older exceeded 310 million[3].This group frequently uses healthcare services and is potentially vulnerable when it comes to digital technology applications. A global shortage of nursing staff has placed an overwhelming workload on clinical nurses, making it challenging to provide patients with sufficient personalized health education and in-depth communication beyond routine clinical tasks[4, 5]. Against this backdrop, exploring innovative support tools that can effectively empower patients and optimize the allocation of nursing resources has become a key issue in nursing management and health policy.

In recent years, the application of digital technologies, particularly generative AI and large language models, in the healthcare sector has received significant attention. Existing research suggests that AI-driven virtual navigators or health Q&A assistants may streamline the patient journey to some extent and translate complex medical terminology into everyday language[6]. In theory, these technological interventions are expected to enhance patients' sense of self-efficacy by improving access to medical information. At the same time, these interventions may alleviate the burden on healthcare providers associated with conveying basic information, allowing providers to devote more time to advanced care tasks that require empathy and complex clinical judgment[7, 8].

However, distance remains between the theoretical potential of AI to empower patients and its actual application in real-world clinical settings. Most existing research on AI in healthcare focuses on the technical validation of algorithmic accuracy or the acceptance of new technologies by healthcare professionals[9, 10]. Meanwhile, studies that systematically examine the genuine needs, perceived barriers, and behavioral motivations of patients, particularly vulnerable groups such as the elderly or those with chronic conditions, from the perspective of end users remain relatively limited. According to the Technology Acceptance Model (TAM), users' acceptance of new technologies depends not only on perceived usefulness and perceived ease of use, but is also significantly influenced by factors such as perceived risk [11–13]. In healthcare settings, where lives and health are at stake, patients' concerns about the ethical boundaries of AI, their sensitivity about data privacy, and their resistance to the emotional disconnect between humans and machines may undermine their willingness to adopt such technologies. Furthermore, Davies et al. has noted that digital transformation may inadvertently

exacerbate inequalities in access to technology, raising concerns about digital exclusion and health equity[14]. Perhaps more importantly, there is currently a lack of research that systematically integrates patients' acceptance of AI-based nursing technology with macro-level nursing policy formulation. This results in a lack of empirical patient-based evidence to inform the development of such policies.

Due to the multifaceted and intricate nature of the aforementioned issues, a single quantitative measurement or qualitative description cannot adequately capture the psychosocial mechanisms underlying patients' acceptance of AI-assisted nursing services. This study uses an explanatory mixed-methods design to assess the barriers patients face in healthcare navigation and health literacy, as well as their acceptance of AI-assisted nursing services. The study also aims to identify independent predictors of acceptance through a cross-sectional survey. Based on significant findings from the quantitative phase, purposeful sampling was conducted to explore the underlying behavioral motivations, experiences of the digital divide, and ethical considerations behind the quantitative results through in-depth interviews. Finally, by systematically integrating data from both phases, this study provides targeted nursing policy recommendations for the clinical implementation of AI-assisted nursing services.

2 Methods

2.1 Research Design

This study employs an explanatory sequential mixed methods design. This design consists of two consecutive phases: Phase 1 is a cross-sectional quantitative study aimed at assessing barriers to care navigation and health literacy among patients, as well as exploring the demand for and use intention of AI-assisted nursing services. The second phase is a descriptive qualitative study designed to provide an in-depth interpretation of the quantitative results from the first phase and to explore ethical considerations and nursing policy needs in the process of AI-empowering patients. This study report adheres to the Guidelines for Reporting Mixed Methods Studies (GRAMMS)[15] and the Common Reporting Standards for Qualitative Research (COREQ)[16].The research flowchart is shown in Fig. 1.

2.2 Phase 1: Quantitative Study

2.2.1 Study Population and Sample Size Calculation

This study was conducted from March 2025 to January 2026 at a large, comprehensive Grade A tertiary hospital in Shenyang, Liaoning Province, China. Outpatients and inpatients were recruited using convenience sampling. The inclusion criteria were: 1) Age ≥ 18 years; 2) Possession of basic Chinese reading and communication skills; 3) Ownership of a smartphone and basic internet usage experience (or a primary caregiver meeting these criteria); 4) Voluntary participation in the study and signing of an informed consent form. The following subjects were excluded: 1) Those with severe cognitive impairment or mental illness who were unable to cooperate; 2) Those in critical condition who were unable to complete the questionnaire.

This study intentionally adopted a broad inclusion strategy spanning multiple departments and disease types. This design choice was based on the following considerations: the core objective of this study is to assess, from a macro-level perspective, patients' overall use intention of AI-assisted nursing services and the predictive factors related to demographics, cognition, and technological perceptions, rather than the effectiveness of AI interventions for a specific disease group. Barriers to accessing medical care, insufficient health literacy, and perceptions of AI risks are common issues across departments and disease types. A broad inclusion strategy enhances the generalizability and reference value of the study's findings for nursing policy formulation. The study also collected information on the departments where patients received care to examine, in the analysis, whether department type has a significant impact on AI use intention .

The sample size for the quantitative phase of this study was estimated using the formula for cross-sectional survey sample size. Given the current lack of large-scale data on the exact demand rate for AI-assisted nursing services among patients, to obtain the largest possible sample size and ensure statistical power, this study set the expected proportion (p) at 0.5, the margin of error (d) at 0.05, and the significance level (α) at 0.05. resulting in Z = 1.96. Calculations indicate that the theoretical minimum sample size is 384 cases. Considering that approximately 20% of questionnaires may be invalid or result in refusal to answer in the actual survey, this study plans to recruit at least 480 patients.

$$n = \frac{Z^2_{\alpha/2} \times p \times (1-p)}{\delta^2}$$

2.2.2 Research Tools

a. Demographic Questionnaire

This includes age, gender, educational level, place of residence, method of medical expense payment, history of chronic diseases, and department visited.

b. Assessment of e-Health Literacy and Barriers to Healthcare Access

The Chinese version of the e-Health Literacy Scale (eHEALS)[17] was used to assess patients' ability to use digital technologies to access and understand health information. This scale consists of 8 items and uses a 5-point Likert scale; a higher score indicates better e-health literacy. Additionally, drawing on the Treatment Burden Questionnaire (TBQ)[18], 5 items were extracted and adapted to assess specific barriers patients face

during the healthcare process (e.g., difficulty navigating the hospital, difficulty registering for appointments, insufficient time to communicate with nurses, etc.); a higher score indicates more severe barriers to healthcare.

c. AI-Assisted Nursing Service Acceptance Scale

This study adopts the Technology Acceptance Model (TAM) as its theoretical framework. The development of the scale items primarily drew upon the original Perceived Usefulness and Perceived Ease of Use scales developed by Davis (1989) [12], combined with the measurement items regarding usage intention from Venkatesh et al.'s (2003) Unified Theory of Acceptance and Use of Technology (UTAUT) [19]. Items for the perceived risk dimension were adapted from the Perceived Risk Scale by Featherman and Pavlou (2003) [20] and semantically modified to reflect the specific contexts of AI-assisted nursing services (e.g., report interpretation, healthcare navigation, and home care appointments).

The scale comprises two functional modules, totaling 16 items. The first module is the AI Technology Perception Scale, comprising three dimensions: perceived usefulness (4 items, e.g., "AI can help me better understand test reports"), perceived ease of use (4 items, e.g., "I believe learning to use an AI nursing assistant does not require much effort"), and perceived risk (3 items, e.g., "I am concerned that AI will provide incorrect home care advice"). This module consists of 11 items in total and serves as an independent variable in the regression model. The second module is the AI Nursing Service Usage Intention Scale, comprising 5 items (e.g., "If the hospital provided AI-assisted navigation services, I would be willing to try them"), used to assess patients' ultimate willingness to use AI-assisted nursing services, and serving as the dependent variable in the regression model. Both modules employ a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). The total score range for the willingness-to-use module is 5–25 points, with higher scores indicating stronger willingness to accept the service.

Prior to the formal survey, five experts in nursing informatics and nursing management were invited to evaluate the content validity of the adapted questionnaire. The scale-level content validity index (S-CVI) was 0.92, and the item-level content validity indices (I-CVI) were all ≥ 0.80, indicating good content validity. Subsequently, a pilot survey was conducted among 50 patients. The results showed that the Cronbach's α coefficient for the barriers to healthcare access section was 0.85, the Cronbach's α coefficients for each dimension of the AI Technology Perception Scale were all ≥ 0.78, and the Cronbach's α coefficient for the willingness-to-use scale was 0.88, indicating that the questionnaire possesses good internal consistency reliability.

2.2.3 Data Collection

Nursing graduate students who had undergone standardized training served as interviewers. Electronic questionnaires (accessed by scanning a QR code) or paper questionnaires were distributed in outpatient waiting areas or inpatient wards. Interviewers used standardized instructions to explain the purpose of the study to patients and provided objective explanations when patients encountered difficulties in understanding, but did not offer leading prompts.

2.2.4 Data Analysis

Statistical analysis for this study was performed using SPSS 27.0 software. For categorical variables (e.g., gender, educational level), independent samples t-tests or one-way analysis of variance (ANOVA) were used to compare differences in AI use intention among patients with different characteristics. For continuous variables (e.g., e-health literacy, barriers to healthcare access scores, and TAM core variables), Pearson correlation analysis was used to explore bivariate correlations with AI use intention. Variables found to be statistically significant in the one-way analysis and correlation analyses will be included in subsequent regression models.

To investigate the independent predictive roles of barriers to healthcare access, e-health literacy, and technology perceptions on the willingness to use AI-assisted nursing services while controlling for demographic confounders, this study employed stratified multiple linear regression analysis. The model used willingness to use AI nursing services as the dependent variable, representing patients' ultimate willingness to accept AI-assisted nursing services. Scores from the three dimensions of the AI Perception Scale—perceived usefulness, perceived ease of use, and perceived risk—were included as independent variables in the third step. Prior to model construction, the data underwent tests for multicollinearity (variance inflation factor VIF < 10, tolerance > 0.1) and residual independence (Durbin-Watson statistic close to 2) to ensure compliance with the basic assumptions of linear regression.

Independent variables were incorporated into the regression model in three steps: Step 1 (Model 1) included demographic characteristics (such as age and educational level) as control variables; Step 2 (Model 2) included scores for e-health literacy and barriers to healthcare navigation; Step 3 (Model 3) included the core variables of the Technology Acceptance Model (TAM) (perceived usefulness, perceived ease of use, and perceived risk). The incremental explanatory power of each set of independent variables on patient willingness to use the service was assessed by observing changes in R^2 and their significance across the steps. The significance level was set at a two-tailed $\alpha = 0.05$.

2.3 Phase 2: Qualitative Research

2.3.1 Research Participants and Sampling

Based on the quantitative results from Phase 1, purposive sampling was used to select representative respondents. To obtain rich and multidimensional perspectives, a maximum diversity sampling strategy was adopted, selecting: 1) Patient representatives (N = 15–20): including patients with extremely high and extremely low use intention of AI, elderly and young patients, and patients with high and low educational levels; 2) Stakeholders (N = 5–8): We invited nursing administrators with over five years of management experience, clinical nurses, and personnel from hospital IT departments or policy-making units to discuss feasibility at the policy level. The sample size was determined based on data saturation (i.e., when no new themes emerged).

2.3.2 Data Collection

Semi-structured in-depth interviews were conducted. The interview guidelines were developed based on outliers or significant trends identified in the quantitative analysis of Phase 1. To ensure the psychological comfort, privacy, and authenticity of the data to the greatest extent possible, this study adopted a differentiated strategy for interview locations based on the specific characteristics of the respondent groups. For patient representatives, interviews were primarily conducted in dedicated health education rooms within outpatient areas or in quiet family consultation rooms within hospital wards to reduce the burden of walking for patients and alleviate their anxiety in a clinical setting. For patients who had been discharged or lived far away, interviews were conducted via encrypted online video conferencing platforms (such as Tencent Meeting or Zoom) after obtaining consent, ensuring they were in a relaxed environment such as their homes. For nursing administrators, considering the nature of their work and time constraints, interviews were primarily conducted in their private offices or in secure conference rooms within the hospital's administrative area to ensure they could discuss policy challenges and sensitive management issues without external interference.

By conducting interviews in environments tailored to each stakeholder group, the researchers aimed to mitigate potential power imbalances (particularly for patients) and foster an environment conducive to open, authentic dialogue regarding AI integration and nursing policies. Each interview lasted approximately 20–30 minutes. Before formally beginning, the researchers reiterated the principle of confidentiality and had participants sign informed consent forms. With the explicit consent of the interviewees, two voice recorders were used to record the entire session (as a precaution against equipment failure), and two researchers independently transcribed the recordings into verbatim transcripts within 24 hours of the interview's conclusion.

a. Sample interview guide for patients:

In our survey, we found that many patients are concerned about AI interpreting medical reports. Could you elaborate on what specifically worries you?

If you got lost in the hospital or didn't know which department to visit, how would you like the AI assistant on your phone to help you?

What suggestions do you have for situations where older adults might not know how to use AI tools?

b. Sample interview guide for nursing administrators/policy makers:

If hospitals introduce AI to assist with patient triage or report interpretation, how do you think the role of nursing staff will change?

If AI provides inaccurate home care advice to patients, how do you think responsibility should be defined in terms of policy and ethics?

The complete English version of the interview guide is provided in **Supplementary File 1**.

2.3.3 Data Analysis

We employed the thematic analysis method developed by Braun and Clarke[21]. NVivo 12 software was used to assist with data management. The analysis steps included: (1) repeated reading of the transcripts to familiarize ourselves with the data; (2) generating initial codes; (3) identifying themes; (4) reviewing themes; (5) defining and naming themes; (6) writing the report. Two researchers conducted the coding independently; when discrepancies arose, they were resolved through discussion or by consulting a third senior researcher.

2.3.4 Research Rigor

This study adhered to the evaluation criteria established by Lincoln and Guba[22]. Member validation was employed, whereby preliminarily identified themes were presented to a subset of participants to confirm whether they accurately reflected their intended meanings, thereby ensuring credibility. A detailed audit trail of the research process was maintained, and peer review was conducted by nursing experts who were not involved in data collection to ensure reliability.

2.4 Integration of Mixed Methods

In accordance with the core principles of an explanatory time-series mixed-methods design, this study achieved a deep integration of quantitative and qualitative data at two critical stages: methodology and data interpretation. Methodologically, the study employed a bridging strategy: significant trends, outliers, or specific demographic differences identified in the first phase of quantitative analysis (such as a significant decline in willingness to use AI among older adults or the frequent occurrence of specific barriers to healthcare access) directly guided the purposeful sampling strategy and the development of the semi-structured interview guide for the second phase of qualitative research, thereby ensuring that the qualitative inquiry could accurately explain the underlying causes behind the quantitative results. In terms of interpretation and reporting, the study employed a consolidation strategy. By constructing a joint presentation matrix in the discussion section, it presented side-by-side and cross-validated the statistical findings from the quantitative phase (such as specific scores for barriers to healthcare access and independent predictors of AI demand), the core themes distilled from the qualitative phase (such as patients' real-life experiences with the digital divide and concerns regarding AI's ethical responsibilities), and the macro-level nursing policy recommendations derived therefrom.

2.5 Ethical Considerations

This study protocol has received ethical approval from the Institutional Review Board of the First Affiliated Hospital of China Medical University (Approval No.: [2025] 2025-805-2). All participants were fully informed of the study's objectives, procedures, potential risks, and benefits prior to participation and

signed a written informed consent form. The study guarantees strict confidentiality of participants' personal information; all data will be anonymized and used solely for academic research. Participants have the right to withdraw from the study unconditionally at any stage.

3 Results

3.1 Phase 1: Quantitative Study

3.1.1 Univariate Analysis of Participants' Demographic Characteristics and Willingness to Use AI

A total of 480 valid questionnaires were collected during this phase. As shown in Table 1, the patient sample was well-represented, with a wide distribution across age, educational attainment, place of residence, and history of chronic diseases. Univariate analysis revealed significant differences in willingness to use AI among patients with different demographic characteristics. Young adults aged 18–35 (20.35 ± 2.61), those with a college degree or higher (19.73 ± 2.70), urban residents (18.84 ± 2.97), and those without a history of chronic diseases (18.92 ± 2.96) exhibited significantly higher willingness to use AI nursing services ($P < 0.001$). There were no statistically significant differences in willingness to use AI based on gender or method of medical payment ($P > 0.05$). Furthermore, differences in willingness to use AI across different clinical departments and patient types (outpatients vs. inpatients) did not reach statistical significance ($P > 0.05$).

Table 1
Demographic Characteristics and Bivariate Analysis of AI use intention (N = 480)

Variables	N (%)	Use Intention (Mean ± SD)	*t/F*	*P*	Effect Size
Age(years)	-	-	76.824	< 0.001	0.245 (η^2)
18–35	143 (29.8)	20.35 ± 2.61[a]			
36–59	211 (44.0)	18.33 ± 2.94[b]			
≥ 60	126 (26.3)	15.88 ± 3.45[c]			
Gender			0.982	0.327	0.090 (Cohen's *d*)
Male	227 (47.3)	18.45 ± 3.27			
Female	253 (52.7)	18.16 ± 3.13			
Education Level			53.417	< 0.001	0.183 (η^2)
Under middle school	108 (22.5)	16.04 ± 3.36[a]			
High school/Vocational	179 (37.3)	18.10 ± 2.87[b]			
Above college	193 (40.2)	19.73 ± 2.70[c]			
Residence			5.214	< 0.001	0.495(Cohen's *d*)
Urban	314 (65.4)	18.84 ± 2.97			
Rural	166 (34.6)	17.26 ± 3.38			
Payment Method			2.618	0.074	0.011 (η^2)
Basic Insurance	307 (64.0)	18.19 ± 3.16[a]			
Out-of-pocket	98 (20.4)	17.79 ± 3.51[a]			
Commercial/Public	75 (15.6)	19.33 ± 2.80[a]			
Chronic Disease History			-4.753	< 0.001	0.436(Cohen's *d*)
Yes	218 (45.4)	17.54 ± 3.35			
No	262 (54.6)	18.92 ± 2.96			
Department			2.156	0.074	0.018 (η^2)
Internal Medicine	168 (35.0)	18.07 ± 3.23[a]			
Surgery	132 (27.5)	18.48 ± 3.08[a]			
Obstetrics & Gynecology	62 (12.9)	16.28 ± 2.09[a]			
Oncology	58 (12.1)	17.73 ± 3.52[a]			
Others (Ophthalmology, ENT, etc.)	60 (12.5)	18.65 ± 3.14[a]			
Patient Type			-1.824	0.069	0.167 (Cohen's *d*)
Outpatient	296 (61.7)	18.50 ± 3.08			
Inpatient	184 (38.3)	17.96 ± 3.35			

Notes: For between-group comparisons, the effect size is reported as Cohen's d (0.2 for a small effect, 0.5 for a medium effect, and 0.8 for a large effect). For comparisons of three groups or more, the effect size is reported as η^2 (Eta-squared) (0.01 for a small effect, 0.06 for a medium effect, and 0.14 for a large effect). Groups with different superscript letters indicate that there are statistically significant differences in pairwise comparisons in the Bonferroni post-hoc test. If the letters are the same, it indicates that there is no significant difference between the groups.

3.1.2 Descriptive Statistics and Correlation Analysis of Core Continuous Variables

The means, standard deviations, and Pearson correlation coefficients for the core variables in this study are presented in **Supplementary Table S1**. Patients' e-health literacy, barriers to accessing medical care, perceived usefulness, and perceived ease of use were all significantly positively correlated with willingness to use AI ($0.175 < r < 0.512$). Conversely, perceived risk was significantly negatively correlated with willingness to use AI ($r = -0.318$, $P < 0.01$). Additionally, age was significantly negatively correlated with e-health literacy ($r = -0.315$, $P < 0.01$) and significantly positively correlated with barriers to healthcare navigation ($r = 0.242$, $P < 0.01$).

3.1.3 Predictors of Willingness to Use AI-Assisted Nursing Services: Hierarchical Multiple Regression Analysis

To investigate the independent predictive power of various factors on patients' willingness to use AI-assisted nursing services after controlling for potential confounders, this study constructed a three-step hierarchical linear regression model, as shown in Table 2. In Model 1, demographic characteristics were included as control variables; the results showed that age (β = −0.22, P < 0.001) and history of chronic disease (β=−0.12, P < 0.01) were significant negative predictors of willingness to use AI, while educational attainment (β = 0.15, P < 0.01) had a significant positive effect; this baseline model explained 12.4% of the total variance. In Model 2, after introducing e-health literacy and barriers to healthcare access, eHEALS demonstrated a very strong positive predictive effect (β = 0.28, P < 0.001), significantly increasing the model's explanatory power (ΔR^2) by 11.1% (P < 0.001). However, after controlling for demographic and e-health literacy factors, patients' barriers to navigating healthcare services did not exhibit a significant predictive role in the model (β = 0.05, P > 0.05). In Model 3, core variables from the Technology Acceptance Model (TAM) were incorporated, and the final model explained 39.2% of the variance in AI acceptance (F = 40.85, P < 0.001). The results indicated that perceived usefulness (PU) was a strong positive predictor (β = 0.25, P < 0.001), while perceived risk was a strong negative predictor (β = −0.22, P < 0.001). Furthermore, in the final model, barriers to seeking medical care did not reach statistical significance (β = 0.02, P > 0.05), suggesting that the direct impact of this variable on willingness to use AI may be masked or moderated by factors such as health literacy or perceived risk; this phenomenon was explored and explained in subsequent qualitative interviews.

Table 2
Hierarchical Multiple Regression Analysis Predicting use intention of AI-Assisted Nursing Services

Predictors	**Model 1**		**Model 2**		**Model 3**	
	***B* (*SE*)**	***β***	***B* (*SE*)**	***β***	***B* (*SE*)**	***β***
Step 1						
Age(years)	-0.16 (0.03)	-0.22***	-0.10 (0.03)	-0.14**	-0.07 (0.03)	-0.10*
Education[a]	1.95 (0.58)	0.15**	0.78 (0.55)	0.06	0.52 (0.48)	0.04
Residence: Urban[b]	1.66 (0.85)	0.08	0.85 (0.82)	0.04	0.45 (0.71)	0.02
Chronic Disease: Yes[c]	-2.45 (0.82)	-0.12**	-1.84 (0.78)	-0.09*	-1.42 (0.68)	-0.07*
Step 2						
eHealth Literacy			0.43 (0.07)	0.28***	0.23 (0.06)	0.15**
Navigation Barriers			0.12 (0.10)	0.05	0.05 (0.08)	0.02
Step 3						
Perceived Usefulness					0.82 (0.12)	0.25***
Perceived Ease of Use					0.53 (0.11)	0.18***
Perceived Risk					-0.54 (0.09)	-0.22***
R^2	0.124		0.235		0.392	
Adjusted R^2	0.116		0.225		0.38	
ΔR^2	0.124		0.111		0.157	
F	16.82***		34.25***		40.85***	

Notes: ***: <0.001, **: <0.01, *: <0.05, β = Standardized coefficients. B = Unstandardized regression coefficients, SE = Standard error, Education[a](1 = Under middle school, 2 = High school/Vocational, 3 = Above college),Residence: Urban[b](0 = rural, 1 = urban),Chronic Disease: Yes[c](0 = No, 1 = Yes)

3.2 Phase Two: Qualitative Research

3.2.1 Respondent Characteristics and Sampling Logic

Based on the significant trends identified in the regression model from Phase One (such as the negative impact of age on risk) and anomalous phenomena (such as the failure of the barriers to care variable), this phase involved in-depth interviews with 20 patient representatives (P01–P20) and 8 stakeholders (M01–M08). As shown in Table 3, the patient sample included typical high- and low-scoring cases from the quantitative phase, as well as anomalous cases of high research value. The stakeholders represented diverse perspectives, including nursing managers, the director of the information technology department, and ethics experts.

Table 3
Characteristics of Qualitative Phase Participants and Purposive Sampling Rationale

Part A: Patient representatives (P01 - P20)											
ID	Age	Gender	Education	Residence	Chronic	eHEALS (8–40)	Nav. Barriers (5–25)	PU / PEOU (4–20) / (4–20)	Perceived Risk (3–15)	BI Score (5–25)	Sampling Rationale / QUAN Link
P01	25	male	Above college	Urban	No	36	10	19 / 18	5	24	Typical high scores: Both PU and PEOU are extremely high. Explore the specific nursing scenarios in which they consider AI "most useful" (report interpretation? Triage? Home appointment?)
P02	74	female	Under middle school	Rural	Yes	14	22	8 / 7	14	10	Typical low scores: Both PU and PEOU are extremely low. Explore the fundamental reasons why the elderly "think AI is useless" - is it because they don't know what AI can do, or do they still not trust it after understanding?
P03	66	male	Under middle school	Rural	Yes	16	23	10 / 9	14	12	Explain non-significant variables: The navigation obstacles are extremely high but the AI score is extremely low. Both PU/PEOU are low, indicating that patients neither think AI is useful nor easy to use - explore whether it is because they have never come into contact with AI medical tools.
P04	30	female	Above college	Urban	No	34	9	17 / 16	14	14	Abnormal cases: PU/PEOU is above the middle level, but the extremely high Risk leads to a low AI score. Explore the psychological mechanisms of "knowing AI is useful but daring not to use it" - privacy anxiety? Fear

Part A: Patient representatives (P01 - P20)											
											of AI hallucinations?
P05	70	male	High school/Vocational	Urban	Yes	27	16	16 / 13	8	21	Abnormal cases: Elderly patients with chronic diseases but a relatively high PU. Explore what specific medical treatment hardships make them consider AI "useful" (such as repeatedly going to the hospital to pick up reports).
P06	46	female	High school/Vocational	Rural	Yes	26	19	14 / 13	12	18	Typical mean case: All variables are close to the mean. Explore the contradictory game between the middle - aged chronic disease group in PU and Risk.
P07	33	male	Above college	Urban	No	35	21	18 / 17	6	23	Explain non-significant variables: When there is high literacy + high PU/PEOU + low risk, high navigation barriers do drive AI usage. Verify that Nav. Barriers is not significant in the regression because it is moderated by Risk and eHEALS.
P08	56	female	Under middle school	Urban	Yes	18	20	9 / 8	15	11	Exploration of Extreme Variables: Risk reaches the full score (15) and PU/PEOU are extremely low. Dig deep into the specific content of "AI fear" - fear of machine indifference? Fear of data being sold? Fear of not understanding the AI interface?
P09	40	male	High school/Vocational	Urban	No	29	14	15 / 17	10	19	Exploration of specific variables: PEOU is higher than PU. Explore the group for whom "usability is more important than usefulness" -

Part A: Patient representatives (P01 - P20)											
											are they willing to try just because of a friendly interface?
P10	78	female	Under middle school	Rural	Yes	11	24	6 / 5	15	9	Extremely elderly cases: PU/PEOU scores are almost at the lowest. Explore the current situation of complete dependence on family members for operation and the sense of powerlessness of being "abandoned by the technological era".
P11	23	female	Above college	Urban	No	38	8	16 / 18	13	15	Anomalous cases: High PEOU but also high Risk. Explore the psychological dividing line of digital natives' trust in "daily AI" but prudence towards "medical AI".
P12	62	male	Above college	Urban	Yes	30	15	17 / 14	10	20	Exploration of specific variables: PU is higher than PEOU. Explore the specific experiences of elderly people with high education who "recognize the value of AI but find it troublesome to operate".
P13	35	female	Under middle school	Rural	No	19	17	11 / 10	13	13	Exploration of specific variables: Low eHEALS leads to low PU/PEOU. Explore the cognitive blind spots of young people with low literacy regarding "not knowing what AI can help with".
P14	52	male	High school/Vocational	Urban	Yes	25	19	14 / 13	12	17	Typical moderate case: Explore the PU perception of middle-aged patients with chronic diseases towards the "understanding of discharge

Part A: Patient representatives (P01 - P20)											
											instructions" assisted by AI.
P15	71	female	Under middle school	Rural	Yes	13	23	8 / 7	14	11	Explain non-significant variables: High barriers + Low PU/PEOU + High Risk. Under the triple barriers, "would rather get lost than dare to/know how to use AI".
P16	28	male	Above college	Urban	No	37	11	19 / 19	5	23	Typical high scores: Both PU and PEOU are close to full marks. Explore their vision and boundaries of the "human - machine collaboration" nursing model.
P17	58	female	High school/Vocational	Urban	Yes	24	18	13 / 12	14	14	Exploration of Specific Variables: Moderate PU but Extremely High Risk. Explore how the perception of high risk "vetoes" the perception of moderate - level usefulness.
P18	42	male	Above college	Rural	No	32	13	17 / 16	7	21	Exploration of specific variables: Rural residents with high education have a relatively high PU. Explore how they expect AI to bridge the urban-rural medical information gap.
P19	68	female	High school/Vocational	Urban	Yes	22	17	11 / 10	13	14	Exploration of specific variables: Both PU and PEOU are relatively low. Explore the elderly's emotional dependence on the traditional "face-to-face communication with nurses".
P20	48	male	Under middle school	Urban	No	21	20	13 / 10	11	18	Exploration of specific variables: The PU is moderate but the PEOU is low. Explore the specific needs of the low - educated group for the simplified design of the AI interface

Part A: Patient representatives (P01 - P20)						
						(large - character version, voice interaction).
Part B: Stakeholders (M01 - M08)						
ID	Age	Gender	Title/Role	Working years	Educational background	Sampling Rationale / QUAN Link
M01	50	female	Director of the Nursing Department	25	Master	For Risk (β = − 0.22), explore how to standardize the AI usage process through nursing management policies and rebuild patients' trust.
M02	42	male	Head of the Information Department	15	undergraduate	For PEOU (β = 0.18), explore the technical feasibility of age - friendly design of AI interfaces and data privacy protection solutions.
M03	45	female	Outpatient Head Nurse	20	undergraduate	In view of the insignificant regression of Nav. Barriers (β = 0.02, ns), explore why it is necessary to retain the manual consultation desk to support groups with low literacy.
M04	55	male	Medical Affairs Office / Ethics Expert	28	Doctor	For Risk (β = − 0.22), explore the legal liability definition and exemption policy framework when AI misleads patients.
M05	38	female	Specialist Nurses for Chronic Disease Management	12	Master	Regarding eHEALS (β = 0.15) and PU (β = 0.25), explore how nurses can act as "translators" to help patients with low health literacy understand the value of AI and use it safely.
M06	48	female	Community Nursing Supervisor	22	undergraduate	Explore how to ensure the two - way safety of nurses and patients through policies and reduce patients' perceived risks when AI empowers the home - based care appointment.
M07	41	female	Head nurse for nursing quality control	16	Master	Explore how to establish an adverse event reporting and continuous quality improvement mechanism for AI nursing services to reduce risks institutionally.
M08	52	male	Deputy Dean in Charge of Nursing	30	Doctor	Explore the "Digital Inclusive Healthcare Policy" at a macro level to bridge the AI divide brought about by Age (β=-0.10) and eHEALS (β = 0.15).

3.2.2 Theme Extraction

Through Braun and Clarke's thematic analysis of the interview data, this study identified a total of 5 core themes and 15 subthemes (see **Supplementary Table S2**), covering perceived value, perceived risk, the healthcare navigation paradox, multiple vulnerabilities, and the reshaping of the nursing role.

3.3 Integration of Mixed-Methods Results

This study employed a merging strategy to present the quantitative predictors from Phase 1 and the qualitative themes from Phase 2 in a joint display, thereby deriving macro-level nursing policy implications. See Table 4 for details.

Table 4

Joint Display Integrating Quantitative Findings, Qualitative Themes, and Nursing Policy Implications

Dimension 1:Perceived Value of AI & Health Literacy Divide		
QUAN Anchor	QUAL Themes & Illustrative Quotes	Nursing Policy Implications
Both PU (β = 0.25***) and eHEALS (β = 0.15**) significantly and positively predict AI acceptance; the AI acceptance of the low - education group is significantly lower than that of the high - education group.	**Theme**: "Not knowing what AI can help with" vs. "AI is my translator" P13: "AI? What's that? Even the health code on my phone was set up for me by my child." P03: "Every time I get the test report, I don't understand whether the arrows on it point up or down. I just wait for the doctor to say 'It's nothing serious'. You mean there's something that can translate it into plain language? I've never seen that." P01: "I'm using ChatGPT to read my medical report now. It's much better than the doctor dismissing you in 30 seconds in the consulting room." P16: "The greatest value of AI is to translate medical language into plain language." M05: "Patients with low health literacy don't reject AI. No one has ever told them that AI can help them. Nurses should become the 'prescribers' of AI." **Inference**: Patients with low literacy have cognitive blind spots rather than actively rejecting it, which is consistent with Norman & Skinner's (2006) eHealth literacy framework.	Establish a "nurse-led AI literacy assessment and graded recommendation system": Upon admission, the responsible nurse uses eHEALS to assess digital literacy and recommend AI tools at different levels (high → independent use; medium → nurse-assisted; low → retain traditional face-to-face education), referring to the UK NHS Digital Inclusion Framework.
Dimension 2:Perceived Risk as the Primary Barrier		
QUAN Anchor	QUAL Themes & Illustrative Quotes	Nursing Policy Implications
Perceived Risk is the strongest negative predictor (β=-0.22***); Case P04: PU/PEOU is above average but Risk is extremely high (14/15), and the total AI score is only 44.	**Theme**: "Knowing it's useful, but afraid to use it" P04: "What if it interprets the indicators of a malignant tumor as 'normally high'? If I believe it and it delays treatment, what then? Who will be responsible?" P17: "Sometimes AI 'talks nonsense with a straight face'. In medical matters, even the slightest mistake is unacceptable." P08: "You want me to upload my examination report to some AI? Won't the whole world know about my illness then?" P19: "No matter how smart the machine is, it won't care if you're uncomfortable or not. When you're sick, what you need is the warmth of a human being." M04: "Currently, the legal positioning of AI medical assistance tools in China is ambiguous, and the liability chain is broken." M01: "If the home care advice given by AI to a patient is inaccurate, whose responsibility is it? The policy must clarify this first." **Inference**: Risk perception consists of three layers: technology, privacy, and emotion. The institutional vacuum further amplifies risk perception, which is consistent with Lupton's (2018) sociological analysis of digital health risks.	(a) Develop the "Clinical Use Specification for AI - Assisted Patient Health Education and Nursing Navigation", clarify that the position of AI is an "auxiliary information tool", attach a standardized disclaimer to all outputs, and establish a dual - verification mechanism of "nurse review → patient use"; (b) Incorporate "Informed Consent for AI Use" into the nursing informed consent process.
Dimension 3:The Navigation Barriers Paradox		
QUAN Anchor	QUAL Themes & Illustrative Quotes	Nursing Policy Implications

Dimension 1:Perceived Value of AI & Health Literacy Divide		
Nav. Barriers was not significant in the regression (β = 0.02, ns), but patients with the highest navigation barriers (P03 = 23, P10 = 24, P15 = 23) had the lowest levels of AI acceptance (30–37).	**Theme**: "Those who need the most help are the least likely to use AI for help." P10: "Every time I go to the hospital, I get lost and wander around the building for half an hour. You say use the mobile phone navigation? I don't even know how to use the mobile phone map." P15: "It's hard to register, the queues are long, and I can't find my way. I'm used to all these. Every time, my son takes time off to accompany me." P05: "If the mobile phone could tell me where to go first and then where to go, it would save me a lot of walking. But the premise is that the characters should be big, and it would be best if it could tell me by voice." M03: "It's precisely the elderly who don't know how to use mobile phones who come to ask for directions. AI navigation can't replace the information desk, it can only be a supplement." **Inference**: The insignificance of Nav. Barriers is due to its being moderated by the eHEALS and TAM variables - the group that needs AI the most can't use AI due to the digital divide, which is consistent with the WHO (2021) warning on digital health equity.	(a) Implement the "dual-channel parallel" mandatory policy: Institutions that introduce AI navigation must also retain the manual consultation positions and shall not cut staff on the grounds of deploying AI; (b) Promote the design standards for "aging-friendly AI nursing tools": Mandatorily require large fonts, voice interaction, and dialect support, and nurses shall provide "one-on-one digital companionship" guidance for the first use.
Dimension 4:Age × Chronic Disease: Compounded Vulnerability		
QUAN Anchor	QUAL Themes & Illustrative Quotes	Nursing Policy Implications
Age (β=-0.10*) and chronic diseases (β=-0.07*) were both independently significant in the final model; the acceptance of AI in the group aged ≥ 60 years was significantly lower than that in the 18–35 - year - old group.	**Theme**: The Sense of Powerlessness of "Being Left Behind by the Times" P02: "You need a mobile phone to register, pay, and now they say you need to use AI for medical treatment. I can't do any of these and always have to trouble my children. Sometimes I wonder if people like me shouldn't go to big hospitals for medical treatment." P10: "There used to be windows for queuing to register, but now it's all machines. I feel that hospitals are becoming less and less welcoming to us elderly people." P12: "I don't reject new technologies, but the hospital APP is too complicated. If AI can be in the form of voice dialogue, just like talking to a person, I'm definitely willing to use it." M08: "The population aged 60 and above has exceeded 280 million, which is precisely the largest user group of medical services. Any AI care policy that doesn't put the elderly at the core is a failed policy." M06: "Many elderly people living alone don't even have smartphones. The entrance to the AI system can't just be on mobile phones. There should be a telephone voice entrance and even a touch - screen terminal at the community service station." **Inference**: Elderly patients with chronic diseases bear the triple burden of high medical visit frequency, low digital literacy, and high risk perception. The digital transformation is systematically excluding its largest service target, which is consistent with the digital exclusion research of Seifert et al. (2021).	(a) Establish the "Nurse-led Digital Health Companion" project, set up a "Digital Health Service Station" in the outpatient department and incorporate it into the nursing quality assessment; (b) Mandate that the AI home nursing system provides "multimodal access" (APP + telephone voice + community touch - screen terminal)
Dimension 5:Redefining Nursing Roles		
QUAN Anchor	QUAL Themes & Illustrative Quotes	Nursing Policy Implications

Dimension 1:Perceived Value of AI & Health Literacy Divide		
eHEALS remains significant in the final model (β = 0.15**), and the ΔR² of Model 3 is 0.157 (p < 0.001), indicating that technological perception is the most crucial factor group. However, the "human factor" cannot be completely replaced by technology.	**Theme**: "We won't be replaced, but the way we work must change." M05: "If AI can do a round of basic interpretation first, I can spend my time on things that AI can't do, such as assessing the patient's psychological state and family support system." M01: "In the future, nurses will need three new capabilities: assessing patients' digital literacy, 'prescribing' appropriate AI tools, and supervising and correcting AI outputs." M07: "What I'm most worried about is that no one will notice if AI makes mistakes. We need to establish an adverse event reporting mechanism for AI nursing services, and nurses should be the 'last line of defense' for AI outputs." P16: "Let AI help me review reports, register for appointments, and plan routes first, but nurses and doctors should still be in charge of key decisions. Humans and machines should cooperate and each perform their own duties." **Inference**: The continuous significance of eHEALS statistically proves that the 'human factor' is irreplaceable. The role of nurses will transform into evaluators, prescribers, supervisors, and emotional supporters of AI, which is consistent with the view in Topol (2019) Deep Medicine.	(a) Incorporate the "AI Nursing Informatics Competency" into the compulsory modules for nurses' continuing education and professional title promotion; (b) Establish the "AI Nursing Service Adverse Event Monitoring and Continuous Quality Improvement Mechanism", add AI - related categories referring to the existing nursing adverse event reporting system, and form a PDCA cycle.

3.3.1 Dimension 1: Perceived Value of AI & Health Literacy Divide

The quantitative regression model shows that perceived usefulness ($\beta = 0.25$) and e-health literacy ($\beta = 0.15$) are the core drivers of positive use intention of AI, and that individuals with lower educational attainment score significantly lower. Qualitative interviews explained this phenomenon: low-literacy groups do not actively reject AI but rather have cognitive blind spots (e.g., P13: “Even my health code was set up by my child”). They are unclear about what kind of assistance AI can provide. In contrast, high-literacy groups view AI as an interpreter of medical reports (P01, P16).

3.3.2 Dimension Two: Perceived Risk as the Primary Barrier

In the regression model, perceived risk is negative predictor ($\beta = -0.22$). Case studies of extreme cases revealed that even when patients (e.g., P04) have a high perception of AI’s utility, their extremely high perception of risk leads to a significant decline in overall use intention. Interviews indicated that patients’ risk anxiety stemmed from fears that AI hallucinations might lead to misdiagnoses or missed diagnoses (P17) and concerns about the leakage of personal medical privacy (P08). Additionally, patients worried that machine algorithms were too impersonal to empathize with their feelings (P19).

3.3.3 Dimension Three: The Navigation Barriers Paradox

The quantitative results reveal a somewhat anomalous phenomenon: barriers to healthcare access did not exhibit a significant predictive effect in the regression model ($\beta = 0.02$, $P > 0.05$). Qualitative interviews may offer some explanation: the groups that are most likely to get lost in real life and face the greatest difficulty in making appointments (e.g., P10, P15, who scored extremely high on navigation barriers) are precisely those who, due to the digital divide, lack the ability to use mobile AI navigation. This results in their extremely low AI use intention rates in the quantitative survey. This suggests that for digitally disadvantaged groups, high technical barriers block the pathway from care needs to willingness to use AI.

3.3.4 Dimension Four: Age × Chronic Disease: Compounded Vulnerability

The quantitative model shows that advanced age ($\beta = -0.10$) and chronic disease ($\beta = -0.07$) both independently and significantly reduce patients’ use intention of AI, and the total scores for the ≥ 60 age group are significantly lower than those of the younger group. Qualitative interviews captured the deep psychological experiences of this group when facing healthcare digitization. As frequent users of healthcare resources, elderly patients with chronic diseases generally feel a sense of helplessness and abandonment by the times when faced with increasingly complex digital healthcare processes (P02). They rely heavily on compensatory assistance from family members and even feel panic and rejection toward the further introduction of AI systems (P10).

3.3.5 Dimension Five: Redefining Nursing Roles

Although the TAM technical variables (Model 3) significantly improved the model’s explanatory power ($\Delta R^2 = 0.157$), e-health literacy—representing human intrinsic capabilities—remained significant in the final model. Qualitative findings provide a reasonable explanation for this statistical retention: neither patients nor stakeholders believe that machines can replace humans. Patients believe that even if AI can efficiently interpret reports or plan

routes, the oversight provided by nurses and doctors in critical decision-making, as well as the emotional support they offer, is irreplaceable (P16, P19). Nursing managers also pointed out that during the implementation of AI systems, human supervision serves as the final line of defense for ensuring patient safety (M05, M07).

4 Discussion

This study employed an explanatory mixed-methods design to systematically examine patients' use intention of AI-assisted nursing services and the underlying multidimensional factors. Integrating quantitative predictive models with qualitative in-depth interviews revealed that, while AI has application potential in areas such as healthcare navigation, medical report interpretation, and continuity of care, patient acceptance is not solely determined by the AI's technological sophistication. Instead, it is subject to multiple constraints, including e-health literacy, perceived risk, and demographic vulnerability.

After controlling for confounding factors, this study found that patients' objective barriers to navigating the healthcare system did not significantly predict their willingness to use AI. However, an in-depth analysis during the qualitative phase provided a reasonable explanation for this statistical finding. In reality, elderly patients and those with chronic conditions face the most severe barriers to accessing healthcare; yet, precisely because of their extremely low e-health literacy and unfamiliarity with smart devices, this group is unable to translate their desire for navigation assistance into a willingness to use AI tools. From a statistical perspective, this may reflect a suppression effect[23], wherein eHEALS and perceived risk act as moderating variables that mask the direct effect of healthcare navigation barriers on willingness to use AI. From a sociological perspective, this phenomenon can be viewed as an extension of Tudor Hart's (1971) Inverse Care Law into the digital age[24, 25]. In this law[24], the groups most in need of healthcare assistance often have the least access to relevant technologies. Seifert et al. (2020) reported similar findings in their study on digital exclusion among older adults in Europe[26]. They noted that digital transformation is systematically excluding its primary target population. In this study, age and a history of chronic illness emerged as significant negative predictors. Older adults with chronic conditions bear a triple burden of high healthcare utilization, low digital literacy, and high perceived risk. Furthermore, while coping with the burden of illness, they experience a sense of abandonment due to technological obsolescence. These findings suggest that adopting a technodeterministic perspective when introducing AI-based care tools may exacerbate existing healthcare service inequities

Based on the Technology Acceptance Model (TAM), regression analysis indicates that perceived risk is negative factor hindering patients' use intention of AI-assisted nursing services. This finding aligns with Esmaeilzadeh's (2020) conclusion that patients have lower tolerance for technological errors in high-risk areas involving life and health than in everyday consumer contexts[27]. Qualitative data further reveals that patients' risk perception is not single-dimensional but rather multi-layered and complex, comprising technological distrust (e.g., concerns about receiving incorrect medical advice[28]), privacy anxiety (e.g., fears of data breaches[29]), and emotional alienation (e.g., rejection of machine indifference[30]). Interestingly, even among patients with higher education levels and a strong perception of utility, such as Case P04, an extremely high perception of risk can suppress their willingness to use these technologies. This suggests that risk perception may play a moderating role between perceived utility and willingness to use rather than having an additive effect. Kritika (2024) noted in his sociological analysis of digital health risks that patients' trust in technology often requires a foundation of institutional trust[31]. Currently, gray areas remain regarding the legal status and delineation of responsibility for AI-based medical assistance tools. This institutional vacuum amplifies patients' anxiety to some extent. Therefore, it is as important as—if not more urgent than—optimizing AI algorithms to determine how to reduce patients' risk perception through nursing management policies.

The findings of this study reaffirm the important role of the "human factor" in the digital healthcare era. Electronic health literacy (eHEALS), representing intrinsic cognitive abilities, demonstrated independent predictive power in the final model. These results provide statistical evidence that technological awareness alone cannot replace the role of human cognitive abilities. Qualitative findings suggest that the low acceptance of AI among groups with low literacy skills largely stems from cognitive blind spots rather than active resistance. As noted in M05, "No one has ever told them how AI can help." This is consistent with the e-health literacy framework of Norman and Skinner (2006)[32], which states that technological accessibility depends on both the tool itself and whether users have the cognitive prerequisites to identify and use it. At the same time, respondents universally called for a nursing model of "human-machine collaboration" rather than "machine substitution." Topol et al. argue that AI's greatest value lies in freeing clinical practitioners from repetitive tasks so they can focus on the essence of humanistic care[33]. The qualitative findings of this study provide empirical support for this argument in the Chinese nursing context. Nursing administrators believe that nurses' roles are shifting—from providing basic, repetitive health education to becoming "prescribers" of AI tools, "assessors" of patients' digital literacy, and "final supervisors" of AI outputs[34, 35]. In clinical settings where patients rely heavily on emotional support, current algorithms still struggle to fully replicate the empathy and humanistic care provided by nurses.

5 Implications for Nursing Policy

By integrating quantitative predictors with qualitative core themes, this study—based on a mixed-methods integration matrix (Table 4)—offers the following policy recommendations for health administration departments and hospital nursing managers. For digitally underserved populations, policies should mandate the widespread deployment of AI-powered wayfinding and triage systems in outpatient clinics and inpatient wards; however, hospitals should retain manual patient guidance and nursing service counters to avoid reducing basic nursing positions under the pretext of technological upgrades. Furthermore, efforts should be accelerated to establish design and access standards for age-friendly AI nursing tools (e.g., providing voice interaction, large-print versions, and dialect support). Additionally, nurse-led digital health stations should be established at the community level, utilizing multimodal access methods (apps, telephone voice services, and community touchscreen terminals) to ensure healthcare accessibility for elderly patients with chronic conditions.

Furthermore, in response to patients' heightened perception of risk, it is recommended that the *Clinical Guidelines for AI-Assisted Patient Health Education and Navigation* be established to clearly define AI's role solely as an auxiliary information tool. For scenarios such as home care appointments and the interpretation of medical reports, a quality control mechanism should be implemented involving AI-generated preliminary results, nurse review and confirmation, and informed patient use. At the same time, AI-assisted adverse nursing events should be formally incorporated into existing hospital adverse nursing event reporting systems.

Health administration departments and academic institutions should proactively incorporate "AI and Nursing Informatics Literacy" into the foundational curriculum of nursing programs and the continuing education credit system for clinical nurses. Nurses should be trained to assess patients' e-health literacy, enabling them to "prescribe" AI-assisted tools of varying levels of complexity based on patients' cognitive abilities, thereby building a bridge of trust between patients and cutting-edge technology on the front lines of clinical care.

6 Limitation

This study has certain limitations. First, the quantitative phase employed a cross-sectional design; while the stratified regression model revealed the predictive power of various variables on the willingness to use AI, it could not establish a strict causal relationship. Second, the data in this study were primarily based on patient self-reports, and since some patients lacked in-depth practical experience with AI medical tools, there may be hypothetical bias or social desirability bias. Third, the interviews in the qualitative phase were conducted in a hospital setting. Although the researchers employed differentiated environmental strategies to mitigate power imbalances, they could not completely rule out the influence of the social desirability effect—where patients may have held back their true expressions due to being in a medical institution—on their responses. Fourth, the study sample was drawn from a large Grade A tertiary hospital in northern China. Given the regional variations in economic conditions and the distribution of medical resources, caution is warranted when extrapolating the findings to primary care facilities or populations with different cultural backgrounds. Furthermore, current AI technology is evolving rapidly, and patients' perceptions and attitudes may change dynamically as the technology advances. This study adopted a broad, cross-departmental inclusion strategy, which, while helpful for identifying common influencing factors at a macro level, did not delve deeply into the differential impacts of different disease types or stages of diagnosis and treatment (such as initial versus follow-up visits, or acute versus chronic management phases) on AI acceptance. Future research should include multicenter, longitudinal studies incorporating samples from primary care settings. These studies should conduct more targeted surveys of specific patient populations (such as cancer patients and those with chronic conditions) and integrate feedback on the actual user experience of AI tools to dynamically assess the evolution of patient willingness to use AI and the changing trajectory of nursing policy needs.

7 Conclusion

This study, designed using an explanatory time-series mixed-methods approach, demonstrates that AI technology has the potential to optimize nursing service models by empowering patients with healthcare navigation and enhancing health literacy. However, its practical implementation faces challenges, notably perceived risks and the digital divide. Due to multiple vulnerabilities—including age, the burden of chronic diseases, and low e-health literacy—some patients may face the risk of marginalization amid the digital transformation. Therefore, the introduction of AI systems in healthcare institutions should not merely constitute a technological upgrade; it must be accompanied by corresponding enhancements to macro-level nursing policies. By establishing a clear ethical framework for accountability, implementing parallel service mechanisms that promote digital inclusion, and actively empowering nurses to transition into supervisors of "human-machine collaboration," it is expected that a leap from "technology-centered" to "patient-centered" smart nursing can be achieved.

Abbreviations

1. AI: Artificial Intelligence
2. eHEALS: e-Health Literacy Scale
3. TAM: Technology Acceptance Model
4. UTAUT: Unified Theory of Acceptance and Use of Technology
5. GRAMMS: Guidelines for Reporting Mixed Methods Studies
6. COREQ: Common Reporting Standards for Qualitative Research
7. TBQ: Treatment Burden Questionnaire
8. S-CVI: Scale-level Content Validity Index
9. I-CVI: Item-level Content Validity Index
10. SPSS: Statistical Package for the Social Sciences
11. ANOVA: Analysis of Variance
12. VIF: Variance Inflation Factor
13. NVivo: Non-linear Visual Interactive Organizer
14. β: Beta coefficient
15. ΔR^2: Change in R-squared

16. P: P-value
17. r: Pearson correlation coefficient
18. N: Sample size

Declarations

The statistics were checked prior to submission by an expert statistician.(XingHua Bai: *E-mail address:*2541560156@qq.com)

Ethics approval and consent to participate

This study was approved by the Ethics Committee of The First Hospital of China Medical University (approval number: [2025] 2025-805-2). The procedures were conducted in accordance with the Declaration of Helsinki, and written informed consent was obtained from all participants.

Consent for publication

Not applicable. This manuscript does not contain any individual person's data in any form.

Availability of data and materials

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Competing interests

The authors declare that they have no competing interests

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CRediT authorship contribution statement:

Yike Wang: Conceptualization, Data curation, Investigation, Methodology, Project administration, Formal analysis, Software, Writing - original draft, Writing - review & editing.

Xing-Hua Bai: Conceptualization, Funding acquisition, Supervision,Validation, Writing - review & editing.

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Patient or Public Contribution

This study did not include patient or public involvement in its design, conduct, or reporting.

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Figures

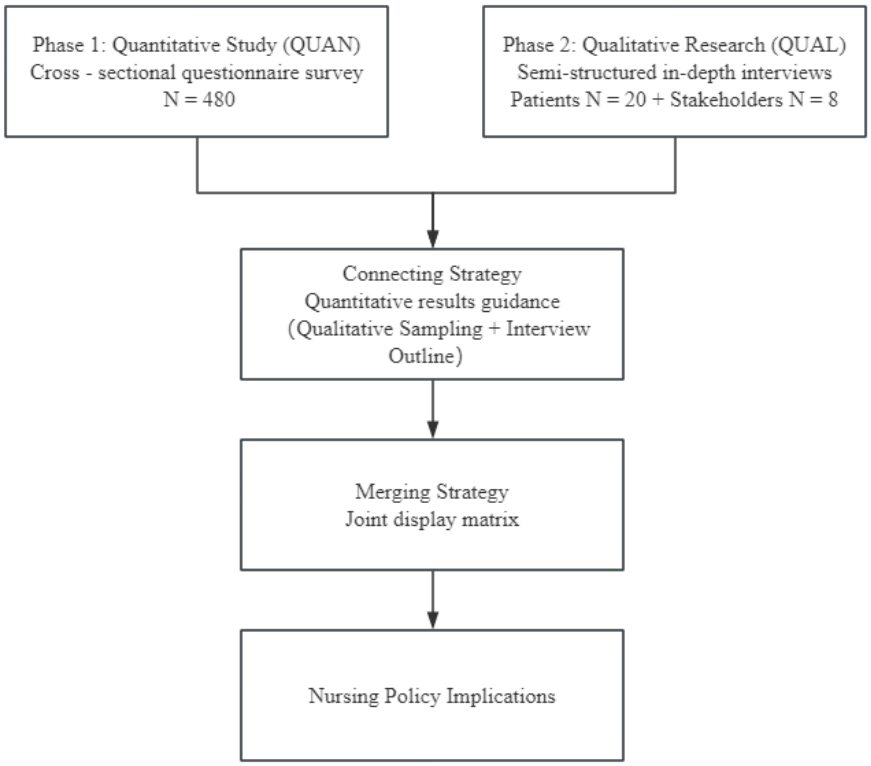


Figure 1

Flowchart of the Explanatory Sequential Mixed-Methods Design.

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