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Factors Influencing Clinical Nurses' Intention to Use and Actual Use of Generative Artificial Intelligence in China: A Multicentre Cross-sectional Study

Xiaoyan Gong
Sir Run Run Shaw Hospital
Lili Wu
Sir Run Run Shaw Hospital
Shan Li
Sir Run Run Shaw Hospital
Rongping Cha
Sir Run Run Shaw Hospital
Yijing Weng
Sir Run Run Shaw Hospital
Yeru Xia
Sir Run Run Shaw Hospital
Yunxia Shen
Sir Run Run Shaw Hospital
Jingbang Liu
liujb@srrsh.com

Sir Run Run Shaw Hospital

Research Article

Keywords: Generative artificial intelligence, Clinical nurses, Technology acceptance, UTAUT, Behavioural intention, Use behaviour

Posted Date: June 25th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-9357566/v1

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Additional Declarations: No competing interests reported.

Abstract

Background

Generative artificial intelligence is increasingly being integrated into healthcare and has the potential to transform nursing practice. However, empirical evidence on factors influencing clinical nurses' adoption of generative artificial intelligence remains limited.

Methods

A multicentre cross-sectional survey was conducted among clinical nurses in China between July and August 2025. A total of 1,921 valid responses were analysed using a structured questionnaire based on an extended Unified Theory of Acceptance and Use of Technology model. Structural equation modelling and multi-group analyses were performed to examine factors associated with behavioural intention and use behaviour.

Results

Performance expectancy (β = 0.302, p < 0.001), effort expectancy (β = 0.235, p < 0.001), social influence (β = 0.094, p = 0.004), and technology trust (β = 0.207, p < 0.001) were positively associated with behavioural intention, whereas perceived risk was negatively associated (β= −0.134, p < 0.001). Behavioural intention (β = 0.409, p < 0.001) and facilitating conditions (β = 0.289, p < 0.001) were associated with actual use. Differences across gender, age, and voluntariness of use were observed.

Conclusions

Clinical nurses'adoption of generative artificial intelligence is associated with perceived usefulness, ease of use, trust, and risk perception. Strategies to support AI integration in nursing practice should prioritise enhancing perceived value, strengthening trust, and addressing safety concerns. Further research using longitudinal and more representative designs is warranted.

Background

Rapid advancements in generative artificial intelligence (AI) and large language models present new opportunities and challenges for nursing practice. Applications such as ChatGPT and DeepSeek demonstrate powerful capabilities in natural language processing and content generation, offering potential to enhance nursing education, research, and clinical care[1–3]. Generative AI can lower adoption barriers for healthcare professionals and enable focus on higher-value activities[4], its applications in nursing range from documentation automation to clinical decision support and patient education[5–6].Nursing involves knowledge-intensive work with high communication demands. Generative AI offers pathways to optimize practice, reduce workload, and improve care quality. Previous studies have explored AI applications in nursing documentation[7], simulation-based teaching[8], clinical decision support[9], and patient health education[10–11]. However, generative AI also presents risks to patient safety and healthcare ethics, including information errors from hallucinations and bias[12–13].

Clinical nurses represent the largest professional group in healthcare, with their practice quality directly influencing patient outcomes[14]. In the generative AI era, nurses require AI literacy and higher-order cognitive skills to effectively use these technologies. However, many nurses demonstrate gaps in AI literacy, limiting their ability to leverage AI while maintaining independent clinical judgement[15–17].Successful technology implementation depends critically on user acceptance and adoption. As primary users, clinical nurses' attitudes and behavioral intentions will determine whether generative AI can be meaningfully integrated into practice[15–17]. Despite growing interest in artificial intelligence in healthcare, most existing studies have examined AI adoption in general contexts or among mixed populations of healthcare professionals and students[18–21]. Empirical, theory-driven research focusing specifically on clinical nurses' use of generative AI remains limited. Given that nurses represent the largest group of healthcare professionals and play a central role in patient care, understanding their acceptance and use of generative AI is critical for successful implementation.

The Unified Theory of Acceptance and Use of Technology (UTAUT) framework identifies four key determinants of technology adoption: performance expectancy, effort expectancy, social influence, and facilitating conditions[22–24]. These constructs predict user behavioral intention and usage behaviour, with age, gender, experience, and voluntariness serving as moderating factors[23]. As a mainstream framework explaining technology adoption, UTAUT has been used to identify and predict factors affecting healthcare professionals' AI adoption[25–26]. Previous UTAUT-based studies have examined factors affecting healthcare professionals' AI adoption through meta-analyses and surveys[27–29]. Dai et al.[20]found that perceived risk negatively influenced nurses' AI adoption, while Bhuyan et al.[29]demonstrated generative AI's potential to reduce healthcare professionals' workload through documentation automation. Zhi et al.and El Arab et al.[18, 30]emphasized the importance of institutional support and organizational culture, respectively. However, theory-driven investigations examining determinants of clinical nurses' generative AI adoption remain scarce.

Therefore,we specifically targets clinical nurses, integrating nursing professional characteristics with generative AI's technological attributes. The UTAUT framework serves as the primary theoretical foundation, it has strong extensibility, and many scholars have expanded the original model by introducing additional variables in accordance with specific research contexts and technological characteristics[22–23, 28]. Previous studies have incorporated safety-related and privacy-related risks into UTAUT, and others have introduced individual innovativeness and perceived risk within a

UTAUT-based framework for mobile health education[31–32]. Dai et al.[20] emphasized nurses' roles as AI users and highlighted that perceived risk and technology trust are critical for bridging the technological gap. Moreover, evidence suggests that healthcare professionals' hesitation to use AI is also reflected in dimensions such as technology trust and perceived risk[33–35]. Consequently, this investigation expanded the UTAUT framework by incorporating perceived risk and technology trust as supplementary constructs and formulated the following hypotheses (see Fig. 1):

H1: Performance expectancy (PE) exerts a significant positive influence on clinical nurses' behavioral intention (BI) to utilize generative AI.

H2: Effort expectancy (EE) exerts a significant positive influence on clinical nurses' behavioral intention (BI) to utilize generative AI.

H3: Social influence (SI) exerts a significant positive influence on clinical nurses' behavioral intention (BI) to utilize generative AI.

H4: Facilitating conditions (FC) exert a significant positive influence on clinical nurses' actual use behaviour (UB) of generative AI.

H5: Technology trust (TR) exerts a significant positive influence on clinical nurses' behavioral intention (BI) to utilize generative AI.

H6: Perceived risk (PR) exerts a significant negative influence on clinical nurses' behavioral intention(BI) to utilize generative AI .

H7: Clinical nurses' behavioral intention(BI) to utilize generative AI exerts a significant positive influence on their actual use behaviour (UB).

H8: Gender serves as a moderator for the effects of performance expectancy, effort expectancy, and social influence on behavioral intention.

H9: Age serves as a moderator for the effects of performance expectancy, effort expectancy, social influence, and facilitating conditions on behavioral intention.

H10: Voluntariness of use serves as a moderator for the effect of social influence on behavioral intention.

Methods

Study design

A multicentre cross-sectional survey was conducted between July and August 2025. The study was reported in accordance with the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) guidelines.

Participants and setting

Clinical nurses were recruited from multiple healthcare institutions across different regions of China using a convenience sampling approach. Hospitals of varying levels were included to enhance sample diversity.Eligible participants were registered nurses who were currently employed in a healthcare institution and able to provide informed consent. Questionnaires were excluded if they were incomplete, contained logically inconsistent responses, or showed evidence of patterned answering.A total of 1,921 valid questionnaires were included in the final analysis.

Sample size

The minimum sample size was estimated using Kendall's principle (10–20 participants per variable). Based on 21 observed variables and allowing for a 20% attrition rate, the required sample size ranged from 263 to 525. The final sample size exceeded this requirement, supporting the robustness of subsequent analyses.

Measures

Data were collected using a structured questionnaire that we specifically developed for this research based on the UTAUT framework and relevant literature on artificial intelligence adoption (see in Supplementary file 1). Items for each dimension were adapted from previously validated UTAUT-based instruments and modified to reflect the context of generative AI in nursing practice. Minor wording adjustments were made to ensure clarity and contextual relevance.The questionnaire included the following dimensions: performance expectancy (5 items), effort expectancy (3 items), social influence (4 items), facilitating conditions (3 items), technology trust (2 items), perceived risk (2 items), behavioural intention (2 items). In addition to the content of this questionnaire, we also collected data on use behavior, which was measured by self-reported frequency of generative AI use in clinical practice. Participants were asked how often and how long they used generative AI in their daily work on a five-point scale, and scope of use in clinical tasks. Participants who reported no prior use of generative AI were assigned the lowest score on the use behaviour scale. All items were rated on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Items were reverse-coded where necessary so that higher scores consistently indicated stronger agreement with each construct.

Instrument development and pilot testing

The questionnaire was refined through a two-round Delphi consultation involving 15 nursing experts from six provinces in China. The panel included clinical nurses, nursing educators, and researchers with extensive professional experience.Authority coefficients were 0.85 and 0.89 for the two rounds, with response rates of 93.3% and 100%, respectively. Items with mean importance ratings < 4.0 or coefficients of variation > 0.25 were revised or removed. After two rounds of feedback, the final questionnaire contained 21 items across 7 dimensions. A pilot study was conducted with 56 nurses to assess the clarity and feasibility of the instrument. Internal consistency and preliminary validity were examined, and no major modifications were required prior to the main survey (see in Supplementary file 2).

Data collection

Data were collected using an anonymous online survey platform. Participation was voluntary, and informed consent was obtained electronically prior to survey completion. To minimise common method bias, participants were assured of anonymity and confidentiality, and the questionnaire was structured to reduce response patterns.

Statistical analysis

Descriptive statistics were used to summarise participant characteristics. Reliability was assessed using Cronbach's alpha and composite reliability (CR).Convergent validity was evaluated using average variance extracted (AVE), and discriminant validity was assessed using both the Fornell–Larcker criterion and heterotrait–monotrait ratio (HTMT) [36–37]. .Structural equation modelling (SEM) was conducted to examine relationships between constructs. Model fit was evaluated using established indices, including χ^2/df, comparative fit index (CFI), Tucker–Lewis index (TLI), root mean square error of approximation (RMSEA), and standardised root mean square residual (SRMR).Standardised path coefficients, 95% confidence intervals, and p-values were reported. The explanatory power of the model was assessed using the coefficient of determination (R^2).Multi-group analyses were performed to explore potential moderating effects of gender, age, and voluntariness of use. Measurement invariance was assessed prior to group comparisons, and differences between groups were evaluated using pairwise comparisons of path coefficients.All analyses were conducted using SPSS version 26.0 and R software. A two-sided p-value < 0.05 was considered statistically significant.

Ethical considerations

This study was approved by the Ethics Committee of Sir Run Run Shaw Hospital on July 10, 2024 (Ethics Approval No: 2025 – 0526). All participants provided informed consent and voluntarily participated in the study. All procedures were conducted in accordance with the Declaration of Helsinki and other relevant guidelines and regulations concerning research involving human participants. Responses were anonymous and confidential, and participants could withdraw at any time. De-identified data were securely stored.

Results

Participant characteristics

A total of 1,921 valid questionnaires were included in the final analysis. Among all participants, 1,689 reported prior use of generative AI, accounting for 87.9% of the study sample. Within this subgroup, 91.2% were female and 8.8% were male. In terms of age, 49.9% were aged 20–30 years, 38.1% were aged 31–40 years, and 12.1% were aged 41 years or older. Regarding voluntariness of use, 93.8% reported being willing to use generative AI, 3.3% reported a neutral attitude, and 2.9% reported being unwilling to use it.

Assessment of common method bias

Because all study variables were collected by self-report questionnaires, common method bias was assessed using Harman's single-factor test. Unrotated principal component analysis identified six factors with eigenvalues greater than 1, and the first factor accounted for 29.98% of the total variance, which was below the commonly used threshold of 50%. These findings suggest that common method bias was unlikely to pose a serious threat to the interpretation of the results.

Reliability and validity of the measurement model

Internal consistency was acceptable for most constructs. Cronbach's alpha coefficients exceeded 0.70 for all dimensions except technology trust. Corrected item–total correlations for all items were greater than 0.50, supporting item homogeneity. No items were removed following item analysis. Item-level statistics are shown in Table 1.

Confirmatory factor analysis supported the adequacy of the measurement model. Model fit indices indicated excellent fit to the data ($\chi^2/df = 1.32$, CFI = 0.996, TLI = 0.995, RMSEA = 0.014, SRMR = 0.017). Composite reliability and average variance extracted met recommended thresholds for all constructs except technology trust, for which composite reliability was slightly below 0.70 (CR = 0.693). Discriminant validity was supported by the Fornell–Larcker criterion, with the square root of the average variance extracted for each construct exceeding the corresponding inter-construct correlations (see Table 2). Taken together, these results support the overall reliability and validity of the measurement model, while suggesting that the technology trust construct should be interpreted with some caution.

Table 1
Item-Total Statistics

Factor	Item	CITC	Alpha if Item Deleted
PE	PE1	0.620	0.811
	PE2	0.646	0.799
	PE3	0.652	0.797
	PE4	0.644	0.800
	PE5	0.637	0.802
EE	EE1	0.654	0.746
	EE2	0.662	0.726
	EE3	0.662	0.728
SI	SI1	0.652	0.814
	SI2	0.692	0.791
	SI3	0.679	0.798
	SI4	0.697	0.789
FC	FC1	0.745	0.807
	FC2	0.737	0.812
	FC3	0.744	0.806
TR	TR1	0.528	0.419
	TR2	0.528	0.664
PR	PR1	0.706	0.602
	PR2	0.706	0.829
BI	BI1	0.602	0.606
	BI2	0.602	0.597

Table 2
Discriminant Validity Analysis (Fornell-Larcker Criterion)

Factor	PE	EE	SI	FC	TR	PR	BI	UB
PE	0.713							
EE	0.383	0.767						
SI	0.350	0.347	0.871					
FC	0.363	0.376	0.352	0.825				
TR	0.355	0.333	0.416	0.329	0.729			
PR	-0.324	-0.346	-0.328	-0.294	-0.322	0.859		
BI	0.531	0.494	0.410	0.501	0.464	-0.414	0.776	
UB	0.353	0.281	0.252	0.467	0.276	-0.230	0.544	0.847

Note: The diagonal elements (bold) represent the square root of the AVE; off-diagonal elements represent the correlations between constructs.

Structural model results

The structural model also demonstrated a good fit to the data ($\chi^2/df = 1.58$, CFI = 0.992, RMSEA = 0.019), indicating that the hypothesised model was broadly consistent with the observed data. Path analysis showed that performance expectancy, effort expectancy, social influence, and technology trust were positively associated with behavioural intention, whereas perceived risk was negatively associated with behavioural intention. In addition, behavioural intention and facilitating conditions were both positively associated with use behaviour.

More specifically, performance expectancy showed the strongest positive association with behavioural intention ($\beta = 0.302$, $p < 0.001$), followed by effort expectancy ($\beta = 0.235$, $p < 0.001$) and technology trust ($\beta = 0.207$, $p < 0.001$). Social influence was also positively associated with behavioural intention, although the magnitude of this association was comparatively smaller ($\beta = 0.094$, $p = 0.004$). Perceived risk showed a negative association with

behavioural intention (β = −0.134, p < 0.001). Behavioural intention was positively associated with use behaviour (β = 0.409, p < 0.001), and facilitating conditions were also positively associated with use behaviour (β = 0.289, p < 0.001). Full path coefficients are presented in Table 3 and Fig. 2.

Table 3
Path Analysis Results

Hypothesis	Path	Std. Beta	P-value	Result
H1	PE ---->BI	0.302	< 0.001	Supported
H2	EE ---->BI	0.235	< 0.001	Supported
H3	SI ---->BI	0.094	0.004	Supported
H4	FC ---->UB	0.289	< 0.001	Supported
H5	TR ---->BI	0.207	< 0.001	Supported
H6	PR ---->BI	-0.134	< 0.001	Supported
H7	BI ---->UB	0.409	< 0.001	Supported

Multi-group analysis

Multi-group analysis was conducted to examine whether the structural relationships differed by gender, age, and voluntariness of use. Measurement invariance was assessed before between-group comparisons, and the results supported the comparability of the groups analysed.

Gender differences

Measurement invariance across gender groups was supported at the configural, metric, and scalar levels. The pattern of associations differed between female and male nurses. Among female nurses, performance expectancy (β = 0.314, p < 0.001), effort expectancy (β = 0.230, p < 0.001), social influence (β = 0.106, p = 0.002), and technology trust (β = 0.185, p < 0.001) were positively associated with behavioural intention, whereas perceived risk was negatively associated with behavioural intention (β = −0.137, p < 0.001). Behavioural intention (β = 0.417, p < 0.001) and facilitating conditions (β = 0.277, p < 0.001) were positively associated with use behaviour.

Among male nurses, effort expectancy (β = 0.270, p = 0.026) and technology trust (β = 0.424, p = 0.004) were positively associated with behavioural intention, whereas performance expectancy, social influence, and perceived risk were not statistically significant in this group. Behavioural intention (β = 0.324, p = 0.017) and facilitating conditions (β = 0.415, p < 0.001) remained positively associated with use behaviour. Overall, these results suggest that technology trust may play a comparatively stronger role among male nurses, whereas performance expectancy and social influence appeared more salient among female nurses. See in Table 4.

Table 4
Path Coefficients Comparison: Gender

Path	Female (β)	Male (β)	Female (P)	Male (P)
PE ---->BI	0.314	0.185	< 0.001	0.115
EE ---->BI	0.230	0.270	< 0.001	0.026
SI ---->BI	0.106	0.014	0.002	0.883
TR ---->BI	0.185	0.424	< 0.001	0.004
PR ---->BI	-0.137	-0.075	< 0.001	0.470
BI ---->UB	0.417	0.324	< 0.001	0.017
FC ---->UB	0.277	0.415	< 0.001	< 0.001

Age differences

Scalar invariance was supported across age groups, with variations in association patterns. Among nurses aged 20–30 years, behavioural intention was positively associated with performance expectancy, effort expectancy, and technology trust, while perceived risk showed a marginal negative association. In the 31–40 years group, performance expectancy, effort expectancy, and technology trust remained positively associated with behavioural intention, whereas perceived risk showed a stronger negative association. Among nurses aged ≥ 41 years, only effort expectancy was significantly associated with behavioural intention, while perceived risk remained negatively associated. Behavioural intention and facilitating conditions were consistently positively associated with use behaviour across all age groups. Overall, perceived risk appeared more influential with increasing age, whereas the role of technology trust weakened among older nurses.See in Table 5.

Table 5
Path Coefficients Comparison: Age

Path	20–30 (β)	31–40 (β)	> 41 (β)	20–30 (P)	31–40 (P)	> 41 (P)
PE ---->BI	0.317	0.321	0.163	< 0.001	< 0.001	0.146
EE ---->BI	0.261	0.191	0.254	< 0.001	0.000	< 0.001
SI ---->BI	0.079	0.094	0.158	0.087	0.069	0.254
TR ---->BI	0.277	0.159	0.039	< 0.001	0.049	0.749
PR ---->BI	-0.074	-0.188	-0.191	0.062	< 0.001	0.023
BI ---->UB	0.375	0.458	0.390	< 0.001	< 0.001	< 0.001
FC ---->UB	0.276	0.281	0.388	< 0.001	< 0.001	< 0.001

Voluntariness of use

Scalar invariance was also supported across voluntariness-of-use groups (p = 0.677). The pattern of associations varied substantially across these groups. In the willing group, all hypothesised paths were statistically significant and in the expected directions. In the neutral group, facilitating conditions showed a positive association with use behaviour (β = 0.593, p = 0.010), whereas the remaining paths were not statistically significant. In the unwilling group, most antecedent variables, including performance expectancy, effort expectancy, social influence, and technology trust, were not significantly associated with behavioural intention. In this group, only behavioural intention showed a significant positive association with use behaviour (β = 0.410, p = 0.018).

Discussion

Principal findings

This study examined factors associated with clinical nurses' behavioural intention to use and actual use of generative artificial intelligence based on an extended UTAUT model. The findings indicate that performance expectancy, effort expectancy, social influence, and technology trust were positively associated with behavioural intention, whereas perceived risk showed a negative association. In addition, behavioural intention and facilitating conditions were both associated with actual use.Among these factors, performance expectancy showed the strongest association with behavioural intention, suggesting that perceived usefulness remains a central driver of technology adoption among clinical nurses. Effort expectancy also played an important role, indicating that ease of use continues to influence adoption decisions even in the context of advanced technologies such as generative AI. These findings are consistent with prior UTAUT-based research in healthcare settings and reinforce the relevance of core UTAUT constructs in explaining technology acceptance among nurses [22–24, 28].

Technology trust emerged as an important factor associated with behavioural intention, highlighting the role of perceived reliability and safety in shaping nurses' willingness to use generative AI. Given the potential risks associated with AI-generated outputs, including inaccuracies and bias, trust in the technology may be particularly important in clinical contexts [33–35]. Conversely, perceived risk was negatively associated with behavioural intention, suggesting that concerns related to privacy, data security, and clinical reliability may hinder adoption [20, 33].The positive association between behavioural intention and use behaviour supports the theoretical assumptions of technology acceptance models [23, 28]. Facilitating conditions were also associated with use behaviour, indicating that organisational support, resources, and infrastructure are important in translating intention into actual use [18, 30].

Interpretation of subgroup differences

The findings suggest variability in the pattern of associations across demographic groups. Differences by gender, age, and voluntariness of use indicate that technology acceptance is not uniform among clinical nurses.Gender differences were observed in the relative importance of different factors. Performance expectancy and social influence appeared more salient among female nurses, whereas technology trust showed a stronger association among male nurses. These differences may reflect variations in how nurses evaluate the usefulness and reliability of emerging technologies, although these interpretations should be treated with caution given the relatively small proportion of male participants in the sample[24].

Age-related differences were also identified. The association between perceived risk and behavioural intention appeared more pronounced in older age groups, whereas technology trust showed weaker associations among nurses aged 41 years or older. These findings may suggest that risk perception becomes increasingly important with age, while trust in new technologies may be more difficult to establish among more experienced practitioners[38].Substantial variation was also observed across voluntariness-of-use groups. In the willing group, all hypothesised relationships were supported, whereas in the neutral and unwilling groups, most associations were not statistically significant. This pattern suggests that traditional determinants of technology acceptance may be less influential among individuals with lower intrinsic motivation to use generative AI. However, these findings should be interpreted cautiously due to the relatively small sample sizes in the neutral and unwilling groups.

Implications for policy and practice

The findings have several implications for the implementation of generative AI in nursing practice. First, enhancing perceived usefulness should be a key priority. Demonstrating clear benefits in terms of workload reduction, efficiency, and quality of care may help increase nurses' willingness to adopt generative AI tools[9, 39]. Second, building technology trust is critical. Healthcare organisations and developers should focus on improving transparency, reliability, and explainability of AI systems, particularly in clinical applications where patient safety is a primary concern[40]. Providing training on the appropriate use and limitations of generative AI may also help strengthen trust.Third, perceived risk should be actively addressed. Clear policies on data protection, privacy, and ethical use of AI are essential to reduce concerns and promote acceptance. In addition, organisational support, including access to resources, technical assistance, and training opportunities, appears important in facilitating actual use[41].Finally, the observed subgroup differences suggest that implementation strategies should be tailored to different nurse populations. Interventions targeting older nurses may need to place greater emphasis on risk management and safety, whereas strategies for younger nurses may focus more on enhancing perceived benefits and usability.

Strengths and limitations

This study has several strengths. It used a large, multicentre sample of clinical nurses and applied a theory-driven analytical framework to examine factors associated with generative AI adoption. The inclusion of technology trust and perceived risk extends the traditional UTAUT model and provides additional insights into AI adoption in clinical settings. However, several limitations should be acknowledged. First, the cross-sectional design limits the ability to draw causal inferences, and the findings should be interpreted as associations rather than causal relationships. Second, the use of convenience sampling may introduce selection bias, as participants with greater interest in AI may have been more likely to participate. Third, all data were self-reported, which may increase the risk of common method bias despite the steps taken to mitigate this issue[42]. Fourth, the sample was drawn from a single national context, which may limit the generalisability of the findings to other healthcare systems.

Future research

Future research should consider longitudinal designs to examine changes in generative AI adoption over time and to better understand causal relationships. Studies using more representative sampling strategies and diverse international settings are also needed to enhance generalisability. In addition, further research could explore the impact of specific training interventions or organizational strategies on nurses' adoption of generative AI in clinical practice. Finally, qualitative studies may provide deeper insights into how nurses perceive and interact with generative AI, particularly in relation to trust, risk, and ethical considerations.

Conclusions

This study examined factors associated with clinical nurses' intention to use and actual use of generative AI based on an extended UTAUT model. The findings indicate that performance expectancy, effort expectancy, and technology trust were positively associated with behavioural intention, whereas perceived risk was negatively associated. Behavioural intention and facilitating conditions were further associated with actual use.These findings highlight the importance of perceived usefulness, ease of use, trust, and risk perception in shaping nurses' engagement with generative AI. Organisational support and resource availability also appear to play a key role in translating intention into practice.From a practical perspective, strategies to support the implementation of generative AI in nursing should prioritise enhancing perceived value, strengthening technology trust, and addressing safety and privacy concerns. Tailored approaches may be needed to account for differences across nurse subgroups. Given the cross-sectional design and sampling approach, the findings should be interpreted with caution. Further research using longitudinal designs and more diverse samples is needed to better understand the adoption of generative AI in nursing practice.

Abbreviations

AI
Artificial Intelligence
UTAUT
Unified Theory of Acceptance and Use of Technology
CR
composite reliability
AVE
average variance extracted
HTMT
heterotrait–monotrait ratio
SEM
structural equation modelling
CFI
comparative fit index
TLI
Tucker–Lewis index
RMSEA
root mean square error of approximation

SRMR
standardised root mean square residual

Declarations

Ethics approval and consent to participate

This study was approved by the Ethics Committee of Sir Run Run Shaw Hospital on July 10, 2024 (Ethics Approval No: 2025-0526). All participants provided informed consent and voluntarily participated in the study. All procedures were conducted in accordance with the Declaration of Helsinki and other relevant guidelines and regulations concerning research involving human participants.

Consent for publication: All authors have read and approved the final version of the manuscript and agree to its submission to BMC Nursing.

Availability of data and materials: The data that support the findings of this study are available from the corresponding author upon reasonable request.

Competing interests: No conflict of interest has been declared by the authors.

Funding: The study was funded by Zhejiang Provincial Health Industry Science and Technology Plan (2025HY0442; 2025HY0459).

Authors' contributions:

S. Li, R. Cha, and Y. Xia conducted data collection and processing tasks.

Y. Shen and Y. Weng were responsible for conceptualization and design, data acquisition, as well as data analysis and interpretation.

X. Gong and L. Wu were responsible for in manuscript drafting.

J. Liu was responsible for revision and final approval of the manuscript for publication.

Acknowledgements

We acknowledge all the research participants for their time and valuable contributions to this study.This study would not have been possible without the support of Sir Run Run Shaw Hospital,and We are grateful to thank all staff involved sincerely.

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Figures

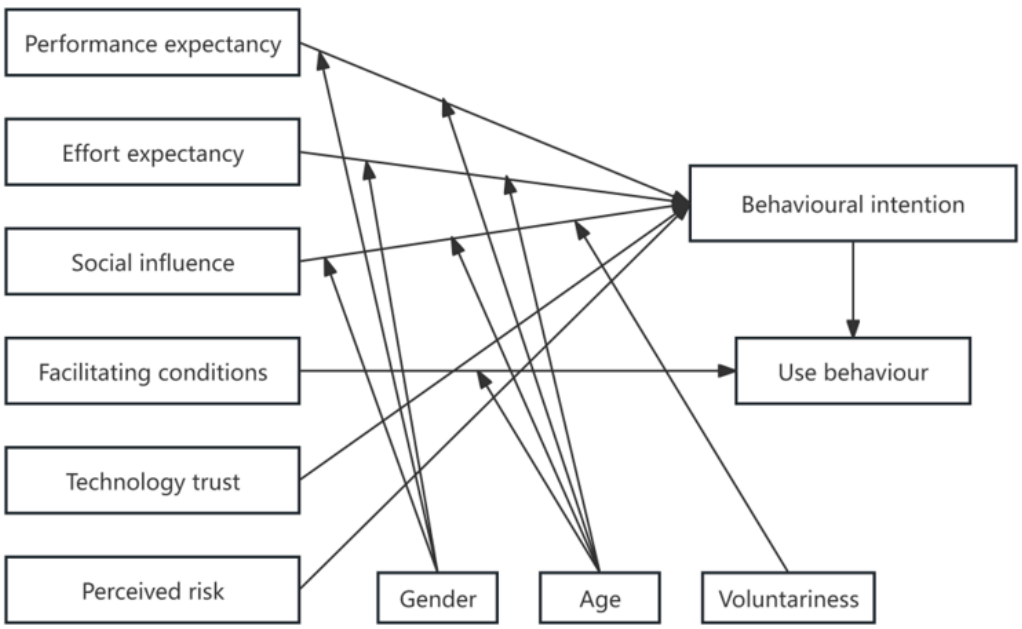


Figure 1

Hypothesized model based on UTAUT.

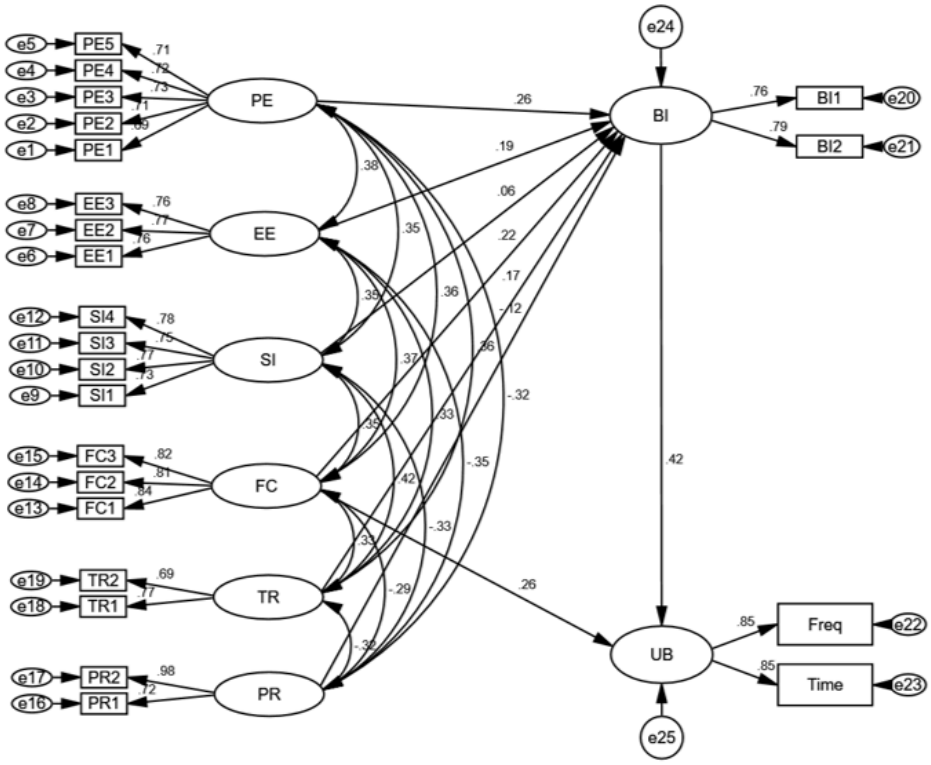


Figure 2

Results of measurement and structural models.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- Supplementaryfile1Englishversionofthestructuredquestionnaire.docx
- Supplementaryfile2PilotSurveyResultsAnalysis.docx