frontiers in Psychiatry

TYPE Original Research
PUBLISHED 25 November 2026
DOI 10.3389/fpsyt.2026.1997260

Check for updates

OPEN ACCESS

EDITED BY
Mohammed Salah,
A'Sharqiyah University, Oman

REVIEWED BY
Yasmin Safi,
King Hussein Cancer Center, Jordan
Hüseyin Çapuk,
Sirnak University, Türkiye

*CORRESPONDENCE
Guohua Zhang
zghcnu@wmu.edu.cn
Yuya Song
syy@wmu.edu.cn

†These authors have contributed equally to this work

RECEIVED 13 September 2026
REVISED 02 November 2026
ACCEPTED 04 November 2026
PUBLISHED 25 November 2026

CITATION
Liu Y, Ge Z, Shi J, Li W, Zhang G and Song Y (2026) Factors associated with attitudes toward generative artificial intelligence among healthcare professionals: a cross-sectional survey using multi-group structural equation modeling. *Front. Psychiatry* 17:1997260. doi: 10.3389/fpsyt.2026.1997260

COPYRIGHT
© 2026 Liu, Ge, Shi, Li, Zhang and Song. This is an open-access article distributed under the terms of the Creative Commons Attribution License (CC BY). The use, distribution or reproduction in other forums is permitted, provided the original author(s) and the copyright owner(s) are credited and that the original publication in this journal is cited, in accordance with accepted academic practice. No use, distribution or reproduction is permitted which does not comply with these terms.

Factors associated with attitudes toward generative artificial intelligence among healthcare professionals: a cross-sectional survey using multi-group structural equation modeling

Yanyan Liu [1], Zhiqin Ge [2†], Jiaqi Shi [1], Wenjing Li [3], Guohua Zhang [4*] and Yuya Song [1*]

[1]The First Affiliated Hospital of Wenzhou Medical University, Wenzhou, China, [2]Renji College, Wenzhou Medical University, Wenzhou, China, [3]School of Nursing, Wenzhou Medical University, Wenzhou, China, [4]School of Mental Health, Wenzhou Medical University, Wenzhou, China

Background: Generative artificial intelligence (GenAI) is increasingly being integrated into health care for clinical decision support, knowledge retrieval, documentation, patient education, and professional learning. However, successful implementation depends not only on technological capability but also on health care professionals' attitudes toward and confidence in using these technologies. Although previous studies have identified factors associated with artificial intelligence (AI) acceptance, how AI literacy is associated with attitudes toward GenAI use through intervening psychological factors, and whether these associations differ between professional groups, remain insufficiently understood.

Objective: Drawing on Social Cognitive Theory and the Technology Acceptance Model, this cross-sectional study aimed to examine the associations between AI literacy and health care professionals' attitudes toward GenAI use via digital self-efficacy, perceived usefulness, and satisfaction, while accounting for perceived risk, and to determine whether these associations differ between physicians and nurses.

Methods: A cross-sectional online survey using convenience sampling was conducted among physicians and nurses working in three tertiary Grade A hospitals in Zhejiang Province, China, between January and August 2025. Of 575 questionnaires distributed, 558 were returned and analyzed (response rate 97.0%). The analyzed sample comprised 426 nurses and 132 physicians. AI literacy, digital self-efficacy, perceived usefulness, satisfaction, perceived risk, and attitudes toward GenAI use were measured using self-report scales. Confirmatory factor analysis was used to evaluate the measurement model, and structural equation modeling with maximum likelihood estimation was used to test the hypothesized associations. Indirect effects were estimated using bias-corrected bootstrapping with 5000 resamples. Measurement invariance across professions was tested before structural paths were compared using multigroup structural equation modeling. The study was approved by the Ethics Committee of Wenzhou Medical University (No. 2025073), and all participants provided electronic informed consent.

Results: The six-factor measurement model fit the data well (χ^2=459.53, df=390, CFI = 0.989, TLI = 0.987, RMSEA = 0.018, SRMR = 0.032), as did the structural model (χ^2=467.39, df=398, CFI = 0.989, TLI = 0.987, RMSEA = 0.018 [90% CI 0.009–0.024], SRMR = 0.036), which explained 34.6% of the variance in attitudes. AI literacy was positively associated with digital self-efficacy (β=0.47, P<.001), which was positively associated with perceived usefulness (β=0.47, P<.001). Perceived usefulness was positively associated with satisfaction (β=0.50, P<.001) and attitudes (β=0.23, P<.001), and satisfaction was positively associated with attitudes (β=0.43, P<.001). Perceived risk was negatively associated with attitudes (β=−0.12, P = .012). The serial indirect association of AI literacy with attitudes via digital self-efficacy, perceived usefulness, and satisfaction was statistically significant but small (β=0.047, 95% bias-corrected CI 0.030–0.070). Configural, metric, scalar, and strict invariance were supported across professions (|ΔCFI|≤0.003 for all steps). The AI literacy–digital self-efficacy association was stronger among physicians than nurses (β=0.67 vs 0.39; $\Delta\chi^2$[1]=7.73, P = .005), whereas the other paths did not differ significantly. The main findings were robust to adjustment for age, sex, clinical experience, profession, AI training, and GenAI use frequency.

Conclusions: In this cross-sectional sample, more favorable attitudes toward GenAI use were associated with a pattern consistent with a capability–belief–value–experience pathway, together with an inverse association with perceived risk. Because the data were cross-sectional and obtained from a convenience sample in one province, the indirect effects represent a statistical decomposition consistent with the proposed model rather than evidence of causal or temporal mediation, and the findings should be generalized with caution. The stronger AI literacy–self-efficacy association among physicians suggests that profession-sensitive approaches to GenAI training merit evaluation in longitudinal and intervention studies.

KEYWORDS

artificial intelligence literacy, attitude, cross-sectional study, digital self-efficacy, generative artificial intelligence, measurement invariance, nurses, physicians

1 Introduction

Generative artificial intelligence (GenAI) has rapidly transformed healthcare by providing new opportunities for clinical decision support, medical knowledge retrieval, documentation assistance, patient education, and professional learning (1). Compared with traditional artificial intelligence systems, GenAI demonstrates stronger capabilities in natural language processing, information integration, and interactive communication, enabling healthcare professionals to engage with digital technologies in more flexible and personalized ways (2, 3). However, successful implementation of GenAI in clinical practice depends not only on technological advancement but also on healthcare professionals' willingness and ability to adopt these technologies. As physicians and nurses are the primary users of healthcare technologies, their attitudes toward GenAI are an important precondition for whether these innovations can be effectively integrated into clinical workflows (4).

Despite the potential benefits of GenAI, its application in healthcare remains accompanied by substantial challenges (4). Healthcare professionals must balance the perceived benefits of improved efficiency and decision support against concerns regarding inaccurate information generation, algorithmic limitations, privacy protection, and professional responsibility (5, 6). Previous studies have mainly focused on the technical performance or general acceptance of artificial intelligence, whereas relatively limited attention has been paid to the psychological factors associated with healthcare professionals' attitudes toward GenAI (5). In particular, how AI literacy is related to favorable attitudes toward GenAI through individual cognitive factors remains insufficiently understood. Moreover, physicians and nurses differ considerably in their professional responsibilities, clinical decision-making, and patterns of GenAI use, suggesting that the factors associated with attitudes toward GenAI may vary across professional groups. Therefore, clarifying the psychological pathways associated with attitudes toward GenAI and examining potential professional differences are important for developing targeted strategies to facilitate the safe and effective integration of GenAI into healthcare practice.

Artificial intelligence literacy (AIL) refers to an individual's ability to understand fundamental artificial intelligence concepts, recognize the strengths and limitations of AI systems, critically evaluate AI-generated information, and apply AI technologies appropriately and safely to solve practical problems (1). In the

context of healthcare, the emergence of generative artificial intelligence (GenAI) has created new opportunities for improving clinical decision support, knowledge acquisition, documentation efficiency, and patient communication. However, the successful integration of GenAI into clinical practice requires more than technical availability (7); it depends largely on whether healthcare professionals possess sufficient competence and confidence to effectively utilize these technologies. Therefore, understanding how AI literacy is related to attitudes toward GenAI use is essential for promoting effective and responsible AI implementation in healthcare (8, 9).

To ensure consistent terminology, the following definitions are used throughout this article. AI literacy refers to the competencies defined above. GenAI refers to AI systems that generate text or other content in response to user prompts (e.g., large language model–based chatbots). Digital self-efficacy refers to confidence in one's ability to use AI tools effectively. Attitude toward GenAI use (the outcome of this study) refers to an individual's overall favorable or unfavorable evaluation of using GenAI in professional practice; it is a self-reported evaluative disposition rather than observed use. The broader terms acceptance and adoption are used only when referring to the wider technology acceptance literature.

Social Cognitive Theory (SCT) provides a theoretical framework for explaining how individual competence may relate to subsequent behaviors (10). According to SCT, knowledge and skills do not directly determine behavioral performance; rather, they are proposed to influence behavior through self-efficacy, which reflects individuals' beliefs about their capability to successfully perform specific tasks (11). In the context of GenAI adoption, healthcare professionals with higher AI literacy may better understand AI mechanisms, recognize appropriate application scenarios, and overcome difficulties encountered during technology use (4). These experiences can enhance their confidence in utilizing AI tools, thereby strengthening their digital self-efficacy (12). Individuals with higher digital self-efficacy are more likely to actively explore and engage with emerging technologies because they perceive themselves as capable of managing potential challenges during use (12, 13). Therefore, digital self-efficacy may represent a key psychological factor linking AI literacy with attitudes toward GenAI. Accordingly, we hypothesized: H1: AI literacy is positively associated with digital self-efficacy.

The Technology Acceptance Model (TAM) proposes that individuals' acceptance of new technologies is closely related to their perceptions of the technology's value, with perceived usefulness being one of the most important correlates of technology acceptance (14). However, perceived usefulness is not an inherent characteristic of technology itself; rather, it is shaped by users' experiences, capabilities, and cognitive evaluations (15). For healthcare professionals, confidence in their ability to use GenAI effectively may facilitate the exploration of its practical benefits in clinical decision support, nursing documentation, medical information retrieval, patient education, and research assistance (16, 17). Conversely, individuals with lower digital self-efficacy may experience greater uncertainty or difficulty during technology use, leading them to underestimate the potential value of GenAI (17). Thus, digital self-efficacy may be theoretically positioned as an antecedent of perceived usefulness. Furthermore, when healthcare professionals recognize that GenAI can improve work efficiency, enhance information processing, and support clinical tasks, they are more likely to develop favorable attitudes toward GenAI use. Therefore, we hypothesized: H2: Digital self-efficacy is positively associated with perceived usefulness; H3: Perceived usefulness is positively associated with attitudes toward GenAI use.

Beyond initial perceptions of technological value, users' subsequent experiences with technology may further shape their acceptance attitudes. Satisfaction reflects individuals' overall evaluation of their previous interaction with a technology and represents an important indicator of whether the technology has met their expectations and practical needs (18). In healthcare settings, when professionals continuously experience that GenAI contributes to improved efficiency, reduced workload, enhanced information management, or better clinical decision-making, they are more likely to develop positive evaluations and stronger intentions to continue using the technology (18, 19). Previous technology acceptance research has suggested that perceived usefulness is not only directly related to acceptance but may also be related to satisfaction by reinforcing positive user experiences (20). Therefore, satisfaction may represent a subsequent psychological pathway through which perceived usefulness is linked to attitudes toward GenAI use. Accordingly, we hypothesized: H4: Perceived usefulness is positively associated with satisfaction; H5: Satisfaction is positively associated with attitudes toward GenAI use.

Although GenAI provides substantial opportunities for healthcare improvement, its adoption is not solely determined by perceived benefits. Healthcare is a high-stakes environment in which inaccurate information, algorithmic bias, privacy concerns, and unclear accountability may influence professionals' willingness to rely on AI-generated outputs (21). Risk perception represents individuals' concerns regarding potential negative consequences associated with technology use and may act as an inhibitory factor in technology acceptance. Healthcare professionals who perceive greater risks associated with GenAI may be more cautious about integrating AI into clinical practice, even when recognizing its potential usefulness (22). Therefore, we hypothesized: H6: Perceived risk is negatively associated with attitudes toward GenAI use.

Meanwhile, integrating SCT and TAM suggests that attitudes toward GenAI may be organized along a theoretically ordered sequence in which AI literacy is linked to digital self-efficacy, digital self-efficacy to perceived usefulness, perceived usefulness to satisfaction, and satisfaction to attitudes toward GenAI use (23, 24). This capability-related pathway may coexist with a risk-related pathway, reflecting the dual influence of perceived benefits and perceived concerns in healthcare professionals' technology acceptance (21). Therefore, we hypothesized: H7: Digital self-efficacy, perceived usefulness, and satisfaction serially account for (i.e., statistically mediate) the association between AI literacy and attitudes toward GenAI use.

Although previous studies have identified several factors associated with AI acceptance, most have focused on the average relationships among psychological constructs, with limited

attention to whether these relationships differ across professional groups (25, 26). Physicians and nurses differ substantially in their professional responsibilities, clinical decision-making processes, and typical applications of generative artificial intelligence, which may influence how AI literacy relates to attitudes toward GenAI (25, 27, 28). Examining these potential differences may provide a more nuanced understanding of the psychological pathways associated with attitudes toward GenAI and facilitate the development of profession-specific implementation strategies. Therefore, this study employed multi-group structural equation modeling to examine whether the proposed associations differed between physicians and nurses, after first testing measurement invariance (27, 28). Accordingly, we hypothesized: H8: The associations among AI literacy, digital self-efficacy, perceived usefulness, satisfaction, perceived risk, and attitudes toward GenAI use differ between physicians and nurses.

2 Methods

2.1 The aim

This study aimed to examine whether AI literacy is associated with healthcare professionals' attitudes toward GenAI use directly and indirectly through digital self-efficacy, perceived usefulness, and satisfaction, while accounting for perceived risk, and to compare these associations between physicians and nurses.Because the present study used a cross-sectional design, H1–H8 are specified as theory-derived directional associations. The analyses test whether the data are consistent with the proposed ordering of constructs; they cannot establish temporal precedence or causality.

2.2 Study design, setting, and participants

A cross-sectional online survey was conducted in Zhejiang Province, China, between January and August 2025. The target population comprised physicians and registered nurses currently engaged in clinical practice in hospitals in Zhejiang Province. The analyzed sample comprised respondents from three tertiary Grade A hospitals; recruitment was limited to tertiary hospitals, and secondary and primary care institutions were not included. Respondents met the eligibility criteria and passed quality control. Because participants were recruited by convenience sampling, the analyzed sample should be regarded as a sample of accessible healthcare professionals rather than a probability sample of the target population. Multiple participants were recruited from each institution: Hospital A contributed 238 participants (42.7%; 156 nurses and 82 physicians), Hospital B 167 (29.9%; 142 nurses and 25 physicians), and Hospital C 153 (27.4%; 128 nurses and 25 physicians).

Eligible participants were required to (1) be currently working as a physician or nurse in a clinical setting; (2) have direct experience with clinical practice and exposure to digital healthcare environments; and (3) voluntarily provide informed consent. Healthcare students, interns, and retired healthcare professionals were excluded.

2.3 Recruitment, data collection, and quality control

Data were collected using an online questionnaire developed and distributed via the Wenjuanxing platform (https://www.wjx.cn), a widely used electronic survey platform in China. The questionnaire link was distributed to physicians and nurses of the three participating hospitals through hospital-based communication channels (e.g., departmental WeChat groups) and professional networks. A total of 575 questionnaires were distributed, and 558 were returned (response rate 97.0%). All questionnaires were completed independently without researcher intervention.

Returned questionnaires were screened against prespecified quality-control criteria, under which a questionnaire was to be classified as invalid if the respondent did not meet the eligibility criteria (e.g., students or interns), if it was incomplete, if it failed the embedded attention-check item, if the completion time was implausibly short, or if it showed patterned responding (e.g., identical responses across consecutive items). All 558 returned questionnaires passed these checks and were included in the analysis; the remaining 17 distributed questionnaires were not returned. No missing item responses were present in the retained dataset; therefore, no imputation was required. The survey system was configured to restrict repeated submissions from the same device. This procedure reduces, but does not guarantee, unique participation, and it may have prevented eligible individuals who shared a device from participating; this is acknowledged as a limitation.

2.4 Measurement instruments

2.4.1 General information

Demographic and professional characteristics were collected using a self-designed questionnaire, including age, sex, educational level, professional category (physician or nurse), years of clinical experience, professional title, previous AI-related training, and frequency of GenAI use. Frequency of GenAI use was assessed with a single item (daily, weekly, monthly, or rarely) and was used as an indicator of prior direct experience with GenAI.

2.4.2 Instrument adaptation

Items adapted from English-language instruments (digital self-efficacy, perceived usefulness, satisfaction, perceived risk, and attitude toward GenAI use) were translated into Chinese by the research team, and their wording was contextualized to GenAI use in clinical practice. The AI literacy items were developed in Chinese by the research team. All items of each scale were specified before data collection, and no items were removed or modified after inspection of the study data.

2.4.3 Artificial intelligence literacy

AI literacy was assessed using a 9-item scale developed by the research team on the basis of previous research on healthcare professionals' and students' understanding of, confidence in, and critical use of AI (29). The scale evaluates individuals' understanding

10.3389/fpsyt.2026.1997260

of AI, the ability to critically evaluate AI-generated information, and confidence in using AI tools appropriately. Items were rated on a 4-point Likert scale ranging from 1 (strongly disagree) to 4 (strongly agree). Because the items were negatively worded, all items were reverse-scored before analysis so that higher scores indicate greater AI literacy (score range 9–36; item-mean range 1–4). As the scale had not been validated previously, its psychometric properties were examined in the present sample: all nine items loaded significantly on a single factor in the CFA (standardized loadings 0.57–0.73; Table 1), composite reliability was 0.879, and discriminant validity from the other constructs was supported (Table 2). In the present study, Cronbach's α was 0.878.

TABLE 1 Confirmatory factor analysis: standardized factor loadings, reliability, and convergent validity (N = 558).

Construct/item	B (SE)	λ	95% CI of λ	α	CR	AVE
AI literacy (AIL)				0.878	0.879	0.448
AIL1	1.000 (fixed)	0.663	0.607–0.712			
AIL2	1.049 (0.071)	0.729	0.674–0.774			
AIL3	0.878 (0.069)	0.606	0.538–0.665			
AIL4	1.065 (0.074)	0.706	0.651–0.753			
AIL5	0.817 (0.069)	0.566	0.488–0.630			
AIL6	1.023 (0.072)	0.688	0.622–0.740			
AIL7	1.051 (0.070)	0.730	0.675–0.772			
AIL8	0.942 (0.073)	0.617	0.551–0.676			
AIL9	1.057 (0.073)	0.700	0.646–0.744			
Digital self-efficacy (DSE)				0.753	0.753	0.433
DSE1	1.000 (fixed)	0.622	0.550–0.691			
DSE2	1.151 (0.097)	0.726	0.664–0.782			
DSE3	0.973 (0.087)	0.621	0.547–0.685			
DSE4	1.026 (0.089)	0.659	0.588–0.722			
Perceived usefulness (PU)				0.872	0.873	0.578
PU1	1.000 (fixed)	0.745	0.698–0.787			
PU2	0.960 (0.056)	0.756	0.708–0.798			
PU3	1.007 (0.057)	0.782	0.738–0.822			
PU4	0.992 (0.059)	0.743	0.692–0.786			
PU5	1.026 (0.058)	0.775	0.729–0.815			
Satisfaction (SAT)				0.763	0.764	0.448
SAT1	1.000 (fixed)	0.723	0.664–0.775			
SAT2	0.853 (0.070)	0.640	0.574–0.703			
SAT3	0.905 (0.073)	0.649	0.580–0.708			
SAT4	0.889 (0.066)	0.662	0.590–0.725			
Perceived risk (PR)				0.761	0.763	0.518
PR1	1.000 (fixed)	0.708	0.635–0.771			
PR2	0.975 (0.079)	0.690	0.626–0.752			
PR3	1.005 (0.081)	0.758	0.694–0.822			
Attitude toward GenAI use (ATT)				0.850	0.851	0.534
ATT1	1.000 (fixed)	0.691	0.637–0.739			
ATT2	0.963 (0.065)	0.714	0.658–0.763			
ATT3	1.114 (0.067)	0.807	0.760–0.846			
ATT4	1.077 (0.069)	0.760	0.714–0.802			
ATT5	0.904 (0.064)	0.673	0.611–0.726			

B, unstandardized loading; λ, standardized loading; 95% CI, percentile bootstrap confidence interval of λ (2000 resamples); α, Cronbach's α; CR, composite reliability; AVE, average variance extracted. The first loading of each factor was fixed to 1 for identification. All freely estimated loadings were significant at $P < 0.001$. Item residuals were uncorrelated; no correlated residuals were specified. Model fit: $\chi^2 = 459.53$, df = 390, CFI = 0.989, TLI = 0.987, RMSEA = 0.018, SRMR = 0.032.

TABLE 2 Descriptive statistics, correlations, and discriminant validity.

Variable	Mean ± SD	1	2	3	4	5	6
1. AI literacy	2.50 ± 0.72	**0.67**	*0.45*	*0.28*	*0.18*	*0.03*	*0.15*
2. Digital self-efficacy	3.17 ± 0.86	0.37***	**0.66**	*0.45*	*0.24*	*0.03*	*0.23*
3. Perceived usefulness	3.20 ± 0.93	0.24***	0.36***	**0.76**	*0.50*	*0.05*	*0.45*
4. Satisfaction	3.15 ± 0.88	0.14***	0.18***	0.41***	**0.67**	*0.03*	*0.54*
5. Perceived risk	2.87 ± 0.95	0.03	0.03	−0.04	0.02	**0.72**	*0.11*
6. Attitude toward GenAI use	3.18 ± 0.90	0.13**	0.18***	0.39***	0.43***	−0.09*	**0.73**

Lower triangle: Pearson correlations between composite (item-mean) scores; diagonal (bold): square root of AVE; upper triangle (italics): heterotrait–monotrait (HTMT) ratios. Latent correlations from the CFA ranged from −0.12 to 0.54 and were all smaller than the square roots of the AVEs of the respective constructs (Fornell–Larcker criterion). Scores are item means (AI literacy, range 1–4; other constructs, range 1–5). *P < 0.05; **P < 0.01; ***P < 0.001.

2.4.4 Digital self-efficacy

Digital self-efficacy was assessed using four items adapted from the computer self-efficacy measure developed by Compeau and Higgins (30) and contextualized to the use of AI tools. The construct reflects individuals' confidence in their capability to use AI technologies effectively to obtain valuable information, overcome potential limitations, and achieve desired outcomes. Items were rated on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), with higher scores indicating greater confidence. In the present study, Cronbach's α was 0.753.

2.4.5 Perceived usefulness

Perceived usefulness was assessed using five items adapted from the TAM-based perceived usefulness items of Liu and Ma (31), with item wording contextualized to GenAI use in clinical practice. The construct reflects the extent to which individuals believe that using GenAI can improve their work performance and effectiveness. Items were rated on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). In the present study, Cronbach's α was 0.872.

2.4.6 Satisfaction

Satisfaction was assessed using four items adapted from the satisfaction construct of Bhattacherjee's Expectation–Confirmation Model (32) and contextualized to participants' experiences with GenAI. Items were rated on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), with higher scores indicating greater satisfaction. In the present study, Cronbach's α was 0.763.

2.4.7 Perceived risk

Perceived risk was assessed using three items adapted from the perceived risk subscale of the Technology Acceptance Model Edited to Assess ChatGPT Adoption (TAME-ChatGPT) instrument developed and validated by Sallam et al. (33), with item wording contextualized to GenAI use in clinical practice. The items address the main risk domains of the original subscale, namely the reliability of generated information and privacy or data-security risks. In the original instrument, the items are phrased as concerns, so that agreement indicates greater perceived risk. In the adapted version, the three items were phrased as positive statements about the reliability and safety of GenAI use in clinical practice; agreement therefore indicated lower perceived risk. Items were rated on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree) and were reverse-scored before analysis (6 – raw score) so that, as in the original subscale, higher scores indicate greater perceived risk. In the present study, Cronbach's α was 0.761.

2.4.8 Attitude toward GenAI use

Attitude toward GenAI use was measured using five items adapted by the research team from the attitude section of the questionnaire developed by Cherrez-Ojeda et al. to assess healthcare students' attitudes toward AI-powered language models (34); item wording was adjusted to refer to GenAI use in the clinical practice of physicians and nurses. The construct reflects individuals' overall evaluation of using GenAI in professional practice and is not a measure of observed use. Items were rated on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). In the adapted version, all five items were negatively worded; they were therefore reverse-scored before analysis so that higher scores indicate more favorable attitudes. In the present study, Cronbach's α was 0.850.

2.5 Data analysis

2.5.1 Software and preliminary analyses

Descriptive analyses were performed using SPSS version 26.0 (IBM Corp., Armonk, NY, USA), and structural equation models were estimated by maximum likelihood using AMOS version 26.0 (IBM Corp.). The models were also re-estimated with custom Python scripts, which reproduced the AMOS solution exactly and were used for the sensitivity analyses. A two-tailed $P < 0.05$ was considered statistically significant. Continuous variables are presented as means and standard deviations (SDs), and categorical variables as frequencies and percentages. Differences between physicians and nurses were examined using t-tests and χ^2 tests, and associations among composite scores using Pearson correlations.

Before model estimation, item skewness and kurtosis, multivariate normality (Mardia's coefficient), and multivariate outliers (Mahalanobis distance, $P < 0.001$) were examined. Because the

indicators were ordinal items treated as continuous, bias-corrected bootstrap confidence intervals (5000 resamples) were used for the structural paths and indirect effects.

2.5.2 Measurement model

A six-factor confirmatory factor analysis (CFA) was specified, with the first loading of each factor fixed to 1 for identification. Item residuals were uncorrelated, and no correlated residuals or modification-index–based respecifications were introduced. Items were retained if their standardized loadings were ≥ 0.50 and statistically significant. Good fit was defined as CFI and TLI ≥ 0.95, RMSEA ≤ 0.06, and SRMR ≤ 0.08; χ^2/df and other indices are reported for completeness. Reliability was assessed using Cronbach's α and composite reliability (CR ≥ 0.70), and convergent validity using average variance extracted (AVE ≥ 0.50, with 0.40–0.50 considered acceptable when CR exceeded 0.60). Discriminant validity was assessed using the Fornell–Larcker criterion and the heterotrait–monotrait ratio (HTMT < 0.85). The six-factor model was compared with alternative models merging conceptually adjacent constructs and with a single-factor model using χ^2 difference tests. Common method bias was examined using Harman's single-factor test and the single-factor CFA comparison (35).

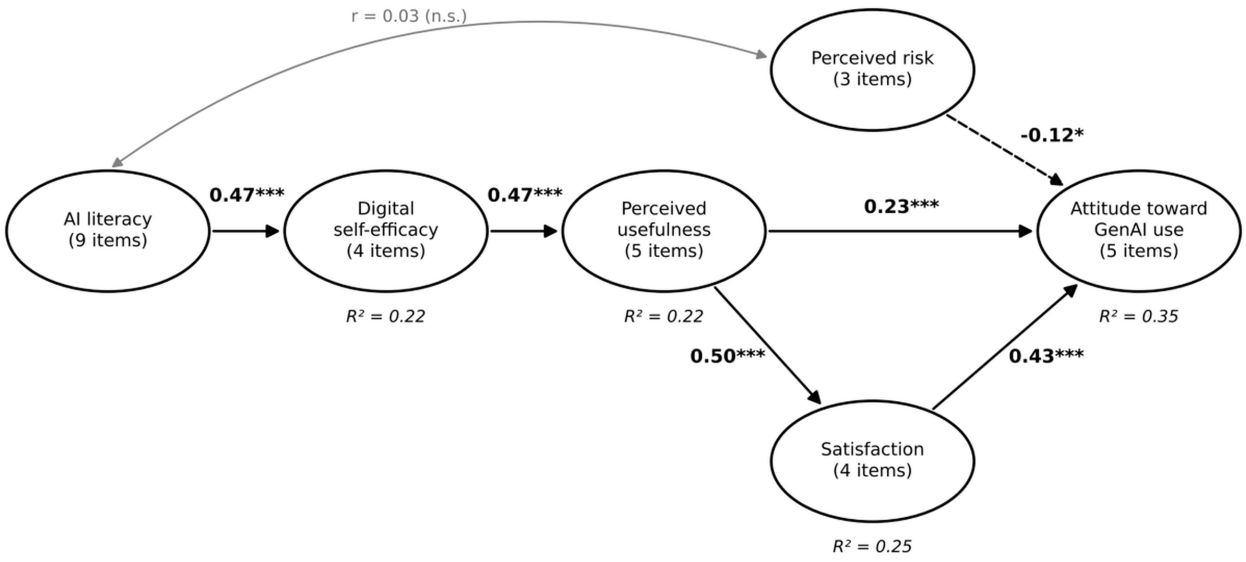
2.5.3 Structural model and indirect effects

The structural model specified the six hypothesized paths (AI literacy → digital self-efficacy → perceived usefulness → satisfaction → attitude, perceived usefulness → attitude, and perceived risk → attitude). AI literacy and perceived risk were treated as exogenous latent variables and were allowed to covary; the disturbances of the four endogenous latent variables were specified as uncorrelated. With 30 observed indicators (465 sample moments) and 67 free parameters, the model was over-identified with 398 degrees of freedom (Figure 1). No *post hoc* modifications were made. Specific and total indirect effects were estimated as products of standardized coefficients, and their 95% bias-corrected bootstrap CIs (5000 resamples) were computed; an indirect effect was considered statistically significant if its CI excluded zero. Because all constructs were measured at a single time point, indirect effects were interpreted as a statistical decomposition of covariances consistent with the proposed model, not as evidence of temporal or causal mediation. A model adding a direct path from AI literacy to attitude was also compared with the hypothesized model using a χ^2 difference test.

Physicians and nurses differed in age, sex, and clinical experience. The primary model was specified without covariates to test the theory-derived structure parsimoniously. To evaluate whether these differences could account for the findings, three covariate-adjusted sensitivity models were estimated in which age, sex, and years of clinical experience (Model S1); additionally profession (Model S2); and additionally AI-related training and GenAI use frequency (Model S3) were entered as observed covariates predicting all four endogenous constructs. Because age and clinical experience were highly correlated (r = 0.97), the coefficients of individual covariates were not interpreted.

2.5.4 Measurement invariance and multigroup analysis

Measurement invariance across physicians and nurses was tested using multigroup CFA through a sequence of increasingly constrained models: configural, metric, scalar, and strict invariance. Invariance at each step was supported if ΔCFI ≥ −0.010 together



χ^2 = 467.39, df = 398, χ^2/df = 1.174; CFI = 0.989; TLI = 0.987; RMSEA = 0.018 (90% CI 0.009–0.024); SRMR = 0.036
Standardized estimates (maximum likelihood, N = 558). Indicators and residual terms are omitted for clarity. Solid line = positive path; dashed line = negative path.
*P < .05, **P < .01, ***P < .001.

FIGURE 1
Structural equation model of the associations between AI literacy and attitude toward GenAI use (standardized estimates, N = 558). The model includes 30 observed indicators, six latent variables, and 67 free parameters (df = 398).

with ΔRMSEA ≤ 0.015 and ΔSRMR ≤ 0.030 for metric invariance (≤ 0.015 for scalar and strict invariance). Latent mean differences were estimated under scalar invariance, with nurses as the reference group. Structural paths were then compared in a multigroup structural equation model in which factor loadings were constrained to be equal; each path was tested by constraining it to equality across groups ($\Delta\chi^2$ with 1 df). To examine whether the professional difference in the AI literacy–digital self-efficacy path was attributable to demographic differences between the groups, the multigroup structural model was re-estimated with clinical experience and sex (Model S4a), age and sex (Model S4b), or clinical experience, sex, and educational level (Model S4c) as observed covariates predicting all four endogenous constructs, with covariate effects estimated freely in each group; age and clinical experience were not entered together because of their high correlation (r = 0.97). The equality of the path across groups was then retested ($\Delta\chi^2$ with 1 df). In addition, a pooled regression of digital self-efficacy on AI literacy, with AI literacy × profession, AI literacy × sex, and AI literacy × clinical experience interactions entered simultaneously (Model S5; mean-centered composite scores, HC3 robust standard errors), examined whether the moderation was specific to profession; educational level was examined in a further step.

2.5.5 Sample-size and power considerations

No *a priori* power analysis was conducted; therefore, the adequacy of the sample was evaluated *post hoc* against the specified model. The pooled structural model contains 30 indicators, six latent variables, and 67 free parameters (N:q = 8.3:1). A Monte Carlo simulation (500 replications) based on the estimated model and the observed group sizes (426 nurses and 132 physicians) was used to estimate the power to detect each path and between-group differences in paths.

2.6 Ethical considerations

This study involved human participants. It was approved by the Ethics Committee of Wenzhou Medical University (Approval No. 2025073) before data collection began and was conducted in accordance with the principles of the Declaration of Helsinki. Before completing the online questionnaire, all participants were presented with an electronic informed consent page describing the study objectives, procedures, the voluntary nature of participation, the right to withdraw at any time without consequences, and how their data would be stored and used. Participants could proceed to the survey only after indicating their consent electronically. The questionnaire was anonymous: no directly identifying information (e.g., name, employee ID, or telephone number) was collected. Data were exported from the survey platform to a password-protected computer accessible only to the research team, and were used solely for the purposes of the approved study. Because participants consented to the use of their data for the approved study only, the dataset is not publicly available; deidentified data are available upon reasonable request, as described in the Availability of data and materials section.

3 Results

3.1 Participant characteristics

A total of 558 healthcare professionals were included in the final analysis, comprising 426 nurses (76.3%) and 132 physicians (23.7%) (Table 3). Participants had a mean age of 32.28 ± 6.27 years and a mean of 8.56 ± 5.96 years of clinical experience. Compared with nurses, physicians were older (35.73 ± 6.32 vs 31.21 ± 5.86 years), had longer clinical experience (11.77 ± 6.37 vs 7.57 ± 5.47 years), and were more often male (60.6% vs 20.2%) (all P < 0.001). No significant differences were observed between the two groups in AI-related training (P = 0.423) or GenAI use frequency (P = 0.161). All participants reported at least some prior direct use of GenAI: 119 (21.3%) used it daily, 221 (39.6%) weekly, 160 (28.7%) monthly, and 58 (10.4%) rarely. Satisfaction and attitudes therefore reflect evaluations by respondents with some first-hand experience of GenAI.

3.2 Preliminary analyses and common method bias

Item skewness (−0.14 to 0.19) and kurtosis (−1.20 to −0.68) were within acceptable ranges, Mardia's coefficient indicated no excess multivariate kurtosis, and no multivariate outliers were identified; therefore, all 558 cases were retained. Harman's single-factor test showed that the first unrotated factor accounted for 22.69% of the total variance, below the 40% threshold (35), and the single-factor CFA fit the data poorly (Table 4). Although these tests cannot rule out common method bias (35), they suggest that a single method factor did not account for most of the covariance among items.

3.3 Measurement model

The six-factor CFA showed good fit (χ^2 = 459.53, df = 390, χ^2/df = 1.178, CFI = 0.989, TLI = 0.987, IFI = 0.989, GFI = 0.948, RMSEA = 0.018 [90% CI 0.010–0.024], SRMR = 0.032) (Table 4). All standardized factor loadings were statistically significant (P < 0.001) and ranged from 0.57 to 0.81, exceeding the retention criterion of 0.50; therefore, no items were removed (Table 1). Cronbach's α (0.753–0.878) and CR (0.753–0.879) exceeded 0.70 for all constructs. AVE exceeded 0.50 for perceived usefulness (0.578), perceived risk (0.518), and attitude toward GenAI use (0.534), and ranged from 0.433 to 0.448 for AI literacy, digital self-efficacy, and satisfaction. Because CR exceeded 0.75 for these three constructs, convergent validity was considered acceptable, although these AVE values indicate that a substantial proportion of item variance was not explained by the respective constructs.

Discriminant validity was supported by both criteria (Table 2). The square root of the AVE of each construct (0.658–0.760) exceeded its correlations with all other constructs, both for the latent correlations (maximum r = 0.539, between satisfaction and attitude) and for the composite-score correlations, and all HTMT ratios (0.029–0.538) were well below 0.85. The hypothesized six-factor model fitted significantly better than all alternative models in which conceptually adjacent constructs were merged (all $\Delta\chi^2$ ≥

10.3389/fpsyt.2026.1997260

TABLE 3 Demographic and professional characteristics of participants by profession.

Characteristic	Total (n = 558)	Nurses (n = 426)	Physicians (n = 132)	t/χ^2	P
Age, years, mean ± SD	32.28 ± 6.27	31.21 ± 5.86	35.73 ± 6.32	t = 7.32	<0.001
Clinical experience, years, mean ± SD	8.56 ± 5.96	7.57 ± 5.47	11.77 ± 6.37	t = 6.82	<0.001
Sex, n (%)				χ^2 = 78.77	<0.001
Female	392 (70.3)	340 (79.8)	52 (39.4)		
Male	166 (29.7)	86 (20.2)	80 (60.6)		
Educational level, n (%)				χ^2 = 293.04	<0.001
College diploma	35 (6.3)	35 (8.2)	0 (0.0)		
Bachelor	372 (66.7)	352 (82.6)	20 (15.2)		
Master or above	151 (27.1)	39 (9.2)	112 (84.8)		
Professional title, n (%)[a]				—	—
Nurse	109 (19.5)	109 (25.6)	—		
Senior nurse	156 (28.0)	156 (36.6)	—		
Supervisor nurse	144 (25.8)	144 (33.8)	—		
Associate chief nurse or above	17 (3.0)	17 (4.0)	—		
Resident physician	15 (2.7)	—	15 (11.4)		
Attending physician	46 (8.2)	—	46 (34.8)		
Associate chief physician	59 (10.6)	—	59 (44.7)		
Chief physician	12 (2.2)	—	12 (9.1)		
AI-related training, n (%)				χ^2 = 0.64	0.423
Yes	191 (34.2)	142 (33.3)	49 (37.1)		
No	367 (65.8)	284 (66.7)	83 (62.9)		
GenAI use frequency, n (%)				χ^2 = 5.15	0.161
Daily	119 (21.3)	83 (19.5)	36 (27.3)		
Weekly	221 (39.6)	170 (39.9)	51 (38.6)		
Monthly	160 (28.7)	124 (29.1)	36 (27.3)		
Rarely	58 (10.4)	49 (11.5)	9 (6.8)		

Percentages are column percentages. Group comparisons used Welch's t-tests for continuous variables and Pearson χ^2 tests for categorical variables. [a]Professional title categories are profession-specific; therefore, no statistical test was performed. AI, artificial intelligence; GenAI, generative artificial intelligence.

389.35, P < 0.001) and the single-factor model (Table 4). Composite-score correlations showed that AI literacy, digital self-efficacy, perceived usefulness, satisfaction, and attitude toward GenAI use were positively correlated with one another (r = 0.13–0.43), whereas perceived risk was weakly and negatively correlated with attitude (r = −0.09, P = 0.029) and was not significantly correlated with the other constructs. No correlation exceeded 0.80.

3.4 Structural model and indirect effects

The hypothesized structural model (Figure 1) showed good fit: χ^2 = 467.39, df = 398, χ^2/df = 1.174, CFI = 0.989, TLI = 0.987, IFI = 0.989, GFI = 0.948, RMSEA = 0.018 (90% CI 0.009–0.024), and SRMR = 0.036. Its fit was close to that of the measurement model (Table 4), indicating that the fit of the full model was not attributable solely to the measurement component. These indices should nevertheless be interpreted together with the measurement-model results, and good fit does not exclude statistically equivalent models with different directional orderings.

As shown in Table 5, all six hypothesized paths were statistically significant. AI literacy was positively associated with digital self-efficacy (β = 0.47, P < 0.001), which was positively associated with perceived usefulness (β = 0.47, P < 0.001). Perceived usefulness was positively associated with satisfaction (β = 0.50, P < 0.001) and with attitude toward GenAI use (β = 0.23, P < 0.001), and satisfaction was positively associated with attitude (β = 0.43, P < 0.001). Perceived risk was negatively associated with attitude (β = −0.12, P = 0.012). Bootstrap standard errors were nearly identical to the maximum likelihood standard errors (Table 5), supporting the robustness of the inferences to the ordinal nature of the indicators. The model explained 22.4%, 22.1%, 24.6%, and 34.6% of the variance in digital self-efficacy, perceived usefulness, satisfaction, and attitude, respectively.

Bootstrap analysis (Table 6) showed that AI literacy had a statistically significant indirect association with attitude through digital self-efficacy and perceived usefulness (β = 0.052, 95% BC CI 0.029–0.081) and through digital self-efficacy, perceived usefulness, and satisfaction (β = 0.047, 95% BC CI 0.030–0.070); the total

10.3389/fpsyt.2026.1997260

TABLE 4 Fit indices of the measurement, alternative, and structural models.

Model	χ^2	df	χ^2/df	CFI	TLI	RMSEA (90% CI)	SRMR	$\Delta\chi^2$ (Δdf)[a]
M0: Six-factor CFA (hypothesized)	459.53	390	1.18	0.989	0.987	0.018 (0.010–0.024)	0.032	—
M1: Five-factor (PU + SAT merged)	848.87	395	2.15	0.925	0.917	0.045 (0.041–0.050)	0.052	389.35 (5)***
M2: Five-factor (AIL + DSE merged)	852.81	395	2.16	0.924	0.917	0.046 (0.041–0.050)	0.058	393.28 (5)***
M3: Five-factor (SAT + ATT merged)	1010.97	395	2.56	0.898	0.888	0.053 (0.049–0.057)	0.059	551.44 (5)***
M4: Four-factor (PU + SAT + ATT merged)	1726.52	399	4.33	0.781	0.761	0.077 (0.074–0.081)	0.080	1266.99 (9)***
M5: Single-factor	3827.86	405	9.45	0.434	0.393	0.123 (0.120–0.127)	0.132	3368.33 (15)***
Structural model (hypothesized)	467.39	398	1.17	0.989	0.987	0.018 (0.009–0.024)	0.036	7.86 (8)[b]

[a]Compared with M0. [b]The structural model is nested within M0 (it constrains the eight construct covariances not implied by the six hypothesized paths); $\Delta\chi^2(8) = 7.86$, P = 0.447. Structural model: IFI = 0.989, GFI = 0.948. AIL, AI literacy; DSE, digital self-efficacy; PU, perceived usefulness; SAT, satisfaction; ATT, attitude toward GenAI use; CFI, comparative fit index; TLI, Tucker–Lewis index; RMSEA, root mean square error of approximation; SRMR, standardized root mean square residual. ***P < 0.001.

indirect association was 0.099 (95% BC CI 0.068–0.134). These indirect associations were small in magnitude. Adding a direct path from AI literacy to attitude did not improve model fit ($\Delta\chi^2(1)$ = 0.41, P = 0.523), and the direct path was not significant (β = 0.028, P = 0.523). Thus, the data were consistent with the proposed model, in which the association between AI literacy and attitude was fully accounted for by the specified intervening constructs. Because all variables were measured concurrently, this decomposition does not establish that AI literacy temporally precedes or causes the intervening variables.

In the covariate-adjusted sensitivity analyses (Supplementary Table S1), the six structural paths remained statistically significant and virtually unchanged after adjustment for age, sex, and clinical experience (Model S1), additionally for profession (Model S2), and additionally for AI-related training and GenAI use frequency (Model S3). Across models, the standardized coefficients changed by at most 0.02, and the two serial indirect associations remained between 0.046 and 0.052. Profession was not significantly associated with any endogenous construct after adjustment for the other variables in the model (all P > 0.05).

3.5 Measurement invariance across professions

The six-factor CFA fitted well in both nurses (CFI = 0.989, RMSEA = 0.017, SRMR = 0.035) and physicians (CFI = 0.994, RMSEA = 0.013, SRMR = 0.061). As shown in Table 7, the configural model showed good fit, and imposing equality constraints on factor loadings (metric invariance), item intercepts (scalar invariance), and residual variances (strict invariance) did not meaningfully reduce fit (all ΔCFI ≥ 0, ΔRMSEA ≤ 0, ΔSRMR ≤ 0.001; all $\Delta\chi^2$ P > 0.05). Full strict invariance was therefore supported, indicating that the constructs were measured equivalently in physicians and nurses and that comparisons of structural paths and latent means are interpretable. Under scalar invariance, physicians had higher latent means than nurses for AI literacy (difference = 0.21, P = 0.007; d = 0.31) and digital self-efficacy (difference = 0.24, P = 0.006; d = 0.34), whereas no significant differences were observed for perceived usefulness, satisfaction, perceived risk, or attitude toward GenAI use (all P > 0.15).

3.6 Multigroup structural equation modeling

The multigroup structural model with invariant factor loadings showed good fit (χ^2 = 873.66, df = 820, CFI = 0.991, TLI = 0.990, RMSEA = 0.015, SRMR = 0.047). As shown in Table 8, the association between AI literacy and digital self-efficacy was stronger among physicians (β = 0.67) than among nurses (β = 0.39; $\Delta\chi^2(1)$ = 7.73, P = 0.005), and this difference remained significant after Bonferroni correction for six comparisons (P < 0.0083). The other five paths did not differ significantly between groups (all P > 0.05); for example, the association between satisfaction and attitude was virtually identical in nurses and physicians (β = 0.43 vs 0.43). Perceived risk was significantly associated with attitude among nurses (β = −0.14, P = 0.006) but not among physicians (β = −0.02, P = 0.803), although the between-group difference was not significant (P = 0.236).

TABLE 5 Structural path estimates of the hypothesized model (N = 558).

Hypothesis	Path	B	SE	CR	P	β	95% BC CI of β	Supported
H1	AIL → DSE	0.494	0.062	7.95	<0.001	0.473	0.385 to 0.553	Yes
H2	DSE → PU	0.572	0.071	8.03	<0.001	0.470	0.378 to 0.554	Yes
H3	PU → ATT	0.218	0.051	4.28	<0.001	0.232	0.129 to 0.330	Yes
H4	PU → SAT	0.477	0.053	9.04	<0.001	0.496	0.415 to 0.568	Yes
H5	SAT → ATT	0.417	0.061	6.81	<0.001	0.427	0.313 to 0.531	Yes
H6	PR → ATT	−0.114	0.045	−2.50	0.012	−0.115	−0.203 to −0.025	Yes

B, unstandardized coefficient; SE, maximum likelihood standard error (bootstrap SEs differed by ≤ 0.003); CR, critical ratio; β, standardized coefficient; BC CI, bias-corrected bootstrap confidence interval (5000 resamples). AIL, AI literacy; DSE, digital self-efficacy; PU, perceived usefulness; SAT, satisfaction; PR, perceived risk; ATT, attitude toward GenAI use. The covariance between AIL and PR was r = 0.03 (not significant).

TABLE 6 Standardized indirect associations estimated using bootstrapping.

Indirect pathway	β	Boot SE	95% BC CI
AIL → DSE → PU → ATT	0.052	0.013	0.029–0.081
AIL → DSE → PU → SAT → ATT	0.047	0.010	0.030–0.070
Total indirect association (AIL → ATT)	0.099	0.017	0.068–0.134

Indirect associations are products of standardized path coefficients. Boot SE = bootstrap standard error; BC CI, bias-corrected bootstrap confidence interval (5000 resamples). Because the hypothesized model contains no direct AIL → ATT path, the total indirect association equals the total standardized association. Abbreviations as in Table 5.

In the sensitivity analyses (Supplementary Table S2), the difference in the AI literacy–digital self-efficacy association persisted after adjustment for clinical experience and sex (Model S4a: β = 0.38 in nurses vs 0.66 in physicians; $\Delta\chi^2(1) = 7.56$, P = 0.006), age and sex (Model S4b: β = 0.38 vs 0.67; $\Delta\chi^2(1) = 7.65$, P = 0.006), and clinical experience, sex, and educational level (Model S4c: β = 0.38 vs 0.66; $\Delta\chi^2(1) = 7.23$, P = 0.007). None of the covariates was significantly associated with digital self-efficacy in either group (all P > 0.11). In the pooled interaction model (Model S5), the AI literacy × profession interaction remained significant (B = 0.34, 95% CI 0.08 to 0.60, P = 0.010), whereas the interactions with sex (B = 0.01, P = 0.93) and clinical experience (B = −0.01, P = 0.22) were not. When an AI literacy × educational level interaction was added, neither the profession interaction (B = 0.17, P = 0.32) nor the education interaction (B = 0.20, P = 0.18) was significant, reflecting the near-complete overlap between profession and educational level (84.8% of physicians vs 9.2% of nurses held a master's degree or higher).

3.7 Sample-size and power analysis

The participant-to-parameter ratio was 8.3:1. In the Monte Carlo simulation, power to detect each hypothesized path in the pooled sample was ≥ 0.99, except for perceived risk → attitude (0.72), and power to detect the observed group difference in the AI literacy–digital self-efficacy path was 0.82. However, only moderate-to-large between-group differences could be detected reliably (minimum detectable difference in standardized coefficients ≈ 0.27–0.45); smaller differences may have remained undetected, and non-significant group differences should not be interpreted as evidence of equivalence.

4 Discussion

This study examined the factors associated with healthcare professionals' attitudes toward GenAI use by integrating Social Cognitive Theory (SCT) and the Technology Acceptance Model (TAM). Using cross-sectional survey data, structural equation modeling was used to examine a theoretically ordered set of associations linking AI literacy, digital self-efficacy, perceived usefulness, satisfaction, and attitude toward GenAI use, with perceived risk included as a factor associated with less favorable attitudes. After establishing measurement invariance, multigroup analysis examined whether these associations differed between physicians and nurses. Overall, the data were consistent with the proposed framework: the hypothesized paths were supported, and the association between AI literacy and attitude was statistically accounted for by digital self-efficacy, perceived usefulness, and satisfaction. Only one path, the association between AI literacy and digital self-efficacy, differed significantly between professions. Because all constructs were measured concurrently, these results describe a pattern of associations compatible with the proposed model rather than a demonstrated causal or developmental process.

A central finding was the serial indirect association linking AI literacy to attitudes toward GenAI use through digital self-efficacy, perceived usefulness, and satisfaction. From an SCT perspective, AI-related knowledge and skills may become behaviorally meaningful when they are internalized as confidence in one's ability to perform AI-related tasks (36). Healthcare professionals who understand the capabilities and limitations of GenAI may be better positioned to formulate appropriate queries, critically evaluate generated information, and recognize erroneous outputs; however, such competence may not necessarily translate into favorable technology evaluations unless users also believe that they can apply it effectively (37). Digital self-efficacy may therefore represent an important psychological link between competence and actionable confidence, although the present cross-sectional data cannot establish this ordering. This pattern is also consistent with TAM in suggesting that perceived usefulness may depend partly on users' perceived capacity to extract value from a technology rather than solely on its technical functionality (18). The association of satisfaction with attitudes further suggests that recognition of utility may be consolidated through experience: a tool may appear useful in principle, yet repeated verification burden, workflow disruption, or poor contextual relevance can prevent this value from developing into a favorable attitude. Taken together, the serial pattern is consistent with a capability–belief–value–experience process, thereby connecting SCT and TAM and moving beyond models that treat AI literacy or usefulness as isolated predictors (20). If confirmed in longitudinal or intervention studies, this would suggest that GenAI implementation should progress beyond knowledge-oriented education. Training should combine foundational AI

TABLE 7 Measurement invariance of the six-factor model across nurses (n = 426) and physicians (n = 132).

Model	χ^2 (df)	CFI	TLI	RMSEA (90% CI)	SRMR	$\Delta\chi^2$ (Δdf)	P	ΔCFI	ΔRMSEA	ΔSRMR
Configural	836.62 (780)	0.991	0.989	0.016 (0.000–0.025)	0.041	—	—	—	—	—
Metric	856.93 (804)	0.991	0.990	0.015 (0.000–0.024)	0.042	20.31 (24)	0.679	+0.001	−0.001	+0.001
Scalar	865.20 (828)	0.994	0.993	0.013 (0.000–0.022)	0.042	8.27 (24)	0.999	+0.003	−0.003	+0.000
Strict	884.18 (858)	0.996	0.996	0.010 (0.000–0.021)	0.043	18.98 (30)	0.940	+0.002	−0.002	+0.000

Each model is compared with the preceding, less constrained model; all invariance steps were supported. Metric, equal factor loadings; scalar, equal loadings and intercepts (latent means free in physicians); strict, equal loadings, intercepts, and residual variances. Criteria: ΔCFI ≥ −0.010 with ΔRMSEA ≤ 0.015 and ΔSRMR ≤ 0.030 (metric) or ≤ 0.015 (scalar and strict).

TABLE 8 Multigroup comparison of structural paths between nurses (n = 426) and physicians (n = 132).

Path	Nurses β (B, SE)	Physicians β (B, SE)	$\Delta\chi^2$ (1)	P	Interpretation
AIL → DSE	0.389*** (0.402, 0.066)	0.673*** (0.707, 0.105)	7.73	0.005	Physicians > nurses
DSE → PU	0.487*** (0.603, 0.082)	0.423*** (0.518, 0.125)	0.37	0.543	Comparable
PU → ATT	0.238*** (0.228, 0.060)	0.206 (0.181, 0.094)	0.19	0.663	Comparable
PU → SAT	0.515*** (0.520, 0.061)	0.427*** (0.333, 0.083)	3.66	0.056	Comparable
SAT → ATT	0.429*** (0.408, 0.066)	0.433*** (0.489, 0.143)	0.29	0.589	Comparable
PR → ATT	−0.143** (−0.143, 0.053)	−0.024 (−0.022, 0.088)	1.40	0.236	Comparable

Estimates are from the multigroup structural model with factor loadings constrained to be equal across groups. β = standardized coefficient; B = unstandardized coefficient; $\Delta\chi^2(1)$ = increase in χ^2 when the path is constrained to be equal across groups. *P < 0.05; **P < 0.01; ***P < 0.001. Abbreviations as in Table 5.

literacy with scenario-based practice, opportunities to verify and correct generated outputs, and clinically relevant tasks that allow users to experience observable value. Healthcare organizations should also optimize workflow integration and routinely collect user feedback, because increasing knowledge without efficacy, or providing technically useful systems without satisfactory use experiences, may be insufficient to foster sustained acceptance (38, 39).

Two qualifications are important when interpreting this serial pattern. First, the indirect associations were small ($\beta \approx 0.05$ for each specific pathway and 0.10 in total), indicating that AI literacy explains only a modest share of the variance in attitudes through these routes. Second, reverse and reciprocal relationships are plausible. For example, professionals who already hold favorable attitudes toward GenAI may use it more often, which may in turn increase their satisfaction, perceived usefulness, self-efficacy, and AI literacy. Statistically equivalent models with different directional orderings may fit the data equally well, and cross-sectional estimates of mediation can differ substantially from longitudinal effects. The serial indirect association should therefore be regarded as a statistical decomposition consistent with the proposed theoretical ordering, and its temporal sequence needs to be tested in longitudinal (e.g., cross-lagged panel) or experimental designs.

In parallel with this benefit-oriented pathway, perceived risk was negatively associated with attitudes toward GenAI, indicating that attitudes toward GenAI in healthcare cannot be understood solely through perceived benefits. This association was modest ($\beta = -0.12$), and perceived risk was essentially uncorrelated with AI literacy, digital self-efficacy, perceived usefulness, and satisfaction ($|r| \leq 0.04$), suggesting that risk appraisals may operate largely independently of capability- and value-related beliefs rather than being offset by them. GenAI can produce plausible but inaccurate information, reproduce bias, raise privacy concerns, and create uncertainty regarding professional accountability. Healthcare professionals may therefore recognize substantial utility while remaining cautious about relying on GenAI in clinical practice (21). This coexistence supports a benefit–risk co-evaluation perspective in which favorable attitudes reflect not simply technological enthusiasm, but a balance between anticipated clinical value and perceived professional risk (12). Importantly, risk perception should not automatically be interpreted as resistance to innovation. In high-stakes healthcare environments, appropriate caution may represent professional vigilance and may be necessary for safe adoption (24). Implementation efforts should therefore aim to calibrate rather than simply suppress risk perceptions. Clear boundaries for appropriate GenAI use, standardized output-verification procedures, privacy safeguards, explicit accountability arrangements, and stronger human oversight for higher-risk tasks may help professionals distinguish manageable risks from unacceptable ones. Training should consequently address not only how to use GenAI, but also when not to rely on it and when independent clinical verification is required, supporting responsible rather than indiscriminate use.

The multigroup findings add a professional-context perspective to these associations. Because full measurement invariance was supported, the constructs appear to have been measured equivalently among physicians and nurses, and the observed differences in structural coefficients are unlikely to reflect differential item functioning. Against this background, the pattern of associations was largely similar across professions. The association between AI literacy and digital self-efficacy was the only path that differed significantly, being stronger among physicians than among nurses (40), and this difference remained significant after correction for multiple comparisons. Physicians also reported higher latent levels of AI literacy and digital self-efficacy, whereas the groups did not differ in perceived usefulness, satisfaction, perceived risk, or attitude. One possible explanation is that physicians' work involves substantial diagnostic reasoning, information synthesis, and autonomous clinical decision-making; consequently, conceptual understanding of AI may more readily be associated with confidence in evaluating and applying GenAI-supported information (41). For nurses, the weaker coupling between AI literacy and digital self-efficacy may indicate that confidence in using GenAI depends to a greater extent on factors beyond conceptual knowledge, such as workflow integration, organizational support, and opportunities for hands-on practice embedded in continuous care, communication, and documentation processes (42, 43). These interpretations remain speculative, because professional-context mechanisms were not measured, the physician subgroup was relatively small, and physicians and nurses differed in age, sex, and clinical experience. In sensitivity analyses, the professional difference persisted after adjustment for age, sex, clinical experience, and educational level within each group, and it was not explained by moderation by sex or clinical experience. However, profession and educational level were almost completely confounded in this sample, and their moderating roles could not be separated; the stronger association among physicians may therefore partly reflect more advanced academic training, including greater exposure to research methods and critical appraisal. The group difference was observed in a cross-sectional convenience sample and should be regarded as

hypothesis-generating. In addition, the power analysis indicated that only moderate-to-large differences could be detected reliably; the absence of significant differences in the remaining paths, including the satisfaction–attitude path, therefore does not demonstrate that these associations are equivalent across professions. With these caveats, the findings suggest that a uniform implementation strategy may not be optimal. Physician-oriented programs might build on AI literacy through critical appraisal and clinically complex decision-support scenarios, whereas nurse-oriented programs may benefit from combining AI literacy education with practice-based confidence building and attention to workflow compatibility in routine care (43, 44). Whether such profession-sensitive approaches improve attitudes or actual use should be evaluated in intervention studies.

Several limitations should be considered. First, the cross-sectional design precludes causal inference. The hypothesized ordering of constructs was derived from theory, but reverse causation (e.g., favorable attitudes leading to more use and, consequently, higher reported AI literacy, self-efficacy, usefulness, and satisfaction) and reciprocal relationships cannot be excluded. The indirect associations represent a statistical decomposition rather than evidence of temporal mediation; longitudinal or experimental studies are required to test causal and sequential processes. Second, participants were recruited by convenience sampling in three tertiary Grade A hospitals in Zhejiang Province, an economically developed region with relatively advanced digital infrastructure. Secondary and primary care institutions were not included. Although the response rate was high (97.0%), professionals who were more interested in technology, more digitally engaged, or more favorable toward GenAI may have been more likely to participate. All respondents reported at least some prior use of GenAI, so the findings may not apply to non-users. Accordingly, the results describe the analyzed sample and may not generalize to the broader population of healthcare professionals in Zhejiang Province, to non-tertiary hospitals, other regions of China, or other healthcare systems. Third, the sample was unbalanced, with nurses accounting for 76.3% of participants; the pooled estimates are therefore weighted toward nurses, the physician-specific estimates were less precise, and the power to detect small professional differences was limited. In addition, professional group was almost completely confounded with educational level, so differences attributed to profession may partly reflect educational background. Fourth, participants were nested within hospitals and departments, but this clustering was not modeled because three hospitals are too few for multilevel analysis, which may have led to underestimated standard errors; the distribution of participants across specialties was also not considered in the analysis. Fifth, all constructs were assessed using self-report measures at a single time point, which may be affected by social desirability and common method bias; Harman's test and the single-factor CFA comparison have limited sensitivity in this respect (35). Sixth, restricting repeated submissions by device does not guarantee unique participation and may have excluded eligible professionals who shared devices. Seventh, the AVE values of AI literacy, digital self-efficacy, and satisfaction were below 0.50, the AI literacy scale was developed by the research team and had not been validated in previous studies, the other instruments were adapted and contextualized for GenAI, and ordinal items were analyzed as continuous variables; the psychometric properties of the adapted scales should be confirmed in independent samples. Finally, the outcome was a self-reported attitude rather than observed GenAI use, and favorable attitudes may not translate into actual or appropriate use in clinical practice. The contextual factors proposed to explain professional differences, such as clinical autonomy, task structure, and workflow dependence, were also not measured; future studies should incorporate these variables, include objective usage data, and examine whether the observed differences persist across specialties, regions, and stages of GenAI implementation.

5 Conclusion

This cross-sectional study provides an association-based understanding of healthcare professionals' attitudes toward GenAI use by integrating SCT and TAM. In this sample, AI literacy was associated with more favorable attitudes through a serial pattern involving digital self-efficacy, perceived usefulness, and satisfaction, whereas perceived risk was independently associated with less favorable attitudes. The measurement model was invariant across physicians and nurses, and the associations were largely similar across professions, except for a stronger association between AI literacy and digital self-efficacy among physicians. Because the design was cross-sectional and based on a convenience sample from one province, these findings do not establish causal or temporal mechanisms and should be generalized with caution. Nevertheless, they suggest that strategies combining AI literacy education with confidence building, demonstration of clinical value, attention to user experience, and appropriate risk governance—possibly tailored to professional roles—merit evaluation in longitudinal and intervention studies.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

The studies involving humans were approved by Ethics Committee of Wenzhou Medical University. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

Author contributions

YL: Writing – original draft. ZG: Writing – original draft. JS: Writing – original draft. WL: Writing – original draft. GZ: Writing – review & editing. YS: Writing – review & editing.

Funding

The author(s) declared that financial support was received for this work and/or its publication. This study was supported by The Wenzhou Science and Technology Project (Grant No. RC20250251); National Innovation and Entrepreneurship Training Program for College Students (S202513284022) and The Summit Advancement Disciplines of Zhejiang Province (Wenzhou Medical University-Pharmaceutics). This study was also supported by the Wenzhou Key Research Base for Philosophy and Social Sciences (Social Psychological Service Research Institute, Wenzhou Medical University).

Acknowledgments

The authors would like to thank all physicians and nurses who participated in this study and the colleagues who assisted with participant recruitment and data collection.

Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declared that generative AI was used in the creation of this manuscript. The authors used Claude Opus 5.5 (Anthropic) to assist with the code for the sensitivity analyses and with language editing during revision; all AI-assisted content was verified by the authors, who take full responsibility for the article.

Any alternative text (alt text) provided alongside figures in this article has been generated by Frontiers with the support of artificial intelligence and reasonable efforts have been made to ensure accuracy, including review by the authors wherever possible. If you identify any issues, please contact us.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyt.2026.1997260/full#supplementary-material

SUPPLEMENTARY TABLE 1
Standardized structural coefficients before and after covariate adjustment.

SUPPLEMENTARY TABLE 2
Multigroup comparison of the AI literacy → digital self-efficacy path between nurses (n = 426) and physicians (n = 132) after covariate adjustment.

References

1. Teo ZL, Thirunavukarasu AJ, Elangovan K, Cheng H, Moova P, Soetikno B, et al. Generative artificial intelligence in medicine. *Nat Med*. (2025) 31:3270–82. doi: 10.1038/s41591-025-03983-2

2. Shanmugam D, Agrawal M, Movva R, Chen IY, Ghassemi M, Jacobs M, et al. Generative artificial intelligence in medicine. *Annu Rev BioMed Data Sci*. (2025) 8:199–226. doi: 10.1146/annurev-biodatasci-103123-095332

3. Bhuyan SS, Sateesh V, Mukul N, Galvankar A, Mahmood A, Nauman M, et al. Generative artificial intelligence use in healthcare: Opportunities for clinical excellence and administrative efficiency. *J Med Syst*. (2025) 49:10. doi: 10.1007/s10916-024-02136-1

4. Oleribe OO, Brash M, Tarfa A, Izurieta R, Taylor-Robinson SD. Healthcare providers' perspectives on generative artificial intelligence (GenAI) adoption, adaptation, assimilation, and use in the United States. *Healthcare (Basel)*. (2026) 14:775. doi: 10.3390/healthcare14060775

5. Roberts LJ, Jayasena R, Khanna S, Arnott L, Lane P, Bain C, et al. Challenges for implementing generative artificial intelligence (GenAI) into clinical healthcare. *Intern Med J*. (2025) 55:1063–9. doi: 10.1111/imj.70035

6. Wah JNK. Revolutionizing e-health: The transformative role of AI-powered hybrid chatbots in healthcare solutions. *Front Public Health*. (2025) 13:1530799. doi: 10.3389/fpubh.2025.1530799

7. Zhao Y, Yuan Y, Wen Z, Leng L, Shi L, Hu X, et al. The current status, knowledge, attitudes, and challenges of generative artificial intelligence use among undergraduate nursing students: A single-center cross-sectional survey of western China. *Front Public Health*. (2025) 13:1648416. doi: 10.3389/fpubh.2025.1648416

8. Haque MA, Siddique HR. Generative artificial intelligence and large language models in smart healthcare applications: Current status and future perspectives. *Comput Biol Chem*. (2026) 120:108611. doi: 10.1016/j.compbiolchem.2025.108611

9. Karppinen SL, Tripathi N. Generative AI in healthcare solutions: A review of opportunities and challenges. *Stud Health Technol Inform*. (2026) 336:909–13. doi: 10.3233/shti260311

10. Islam KF, Awal A, Mazumder H, Munni UR, Majumder K, Afroz K, et al. Social cognitive theory-based health promotion in primary care practice: A scoping review. *Heliyon*. (2023) 9:e14889. doi: 10.1016/j.heliyon.2023.e14889

11. Bandura A. Health promotion by social cognitive means. *Health Educ Behav*. (2004) 31:143–64. doi: 10.1177/1090198104263660

12. Zhao H, Wu P. Artificial intelligence job substitution risks, digital self-efficacy, and mental health among employees. *J Occup Environ Med*. (2025) 67:e302–e10. doi: 10.1097/jom.0000000000003335

13. Conte G, Arrigoni C, Magon A, De Angeli G, Paglione G, Baroni I, et al. Unlocking the determinants of digital and technological self-efficacy: Insights from a cross-sectional study among nurses and nursing students. *Healthcare (Basel)*. (2025) 13:2208. doi: 10.3390/healthcare13172208

14. Holden RJ, Karsh BT. The technology acceptance model: Its past and its future in health care. *J BioMed Inform*. (2010) 43:159–72. doi: 10.1016/j.jbi.2009.07.002

15. Lee JWY, Tan JY, Bello F. Technology acceptance model in medical education: Systematic review. *JMIR Med Educ*. (2025) 11:e67873. doi: 10.2196/67873

16. Chan KS, Zary N. Applications and challenges of implementing artificial intelligence in medical education: Integrative review. *JMIR Med Educ*. (2019) 5:e13930. doi: 10.2196/13930

17. Reddy S. Generative AI in healthcare: An implementation science informed translational path on application, integration and governance. *Implement Sci*. (2024) 19:27. doi: 10.1186/s13012-024-01357-9

18. Shen Y, Cui W. Perceived support and AI literacy: The mediating role of psychological needs satisfaction. *Front Psychol*. (2024) 15:1415248. doi: 10.3389/fpsyg.2024.1415248

19. Hassan H, Zipursky AR, Rabbani N, You JG, Tse G, Orenstein E, et al. Clinical implementation of artificial intelligence scribes in health care: A systematic review. *Appl Clin Inform*. (2025) 16:1121–35. doi: 10.1055/a-2597-2017

20. Hämäläinen T, Kaipainen K, Lappalainen P, Puolakanaho A, Keinonen K, Lappalainen R, et al. Usage activity, perceived usefulness, and satisfaction in a web-based acceptance and commitment therapy program among Finnish ninth-grade adolescents. *Internet Interv*. (2021) 25:100421. doi: 10.1016/j.invent.2021.100421

21. Dai Q, Li M, Yang M, Shi S, Wang Z, Liao J, et al. Attitudes, perceptions, and factors influencing the adoption of AI in health care among medical staff: Nationwide cross-sectional survey study. *J Med Internet Res*. (2025) 27:e75343. doi: 10.2196/75343

22. Tun HM, Rahman HA, Naing L, Malik OA. Trust in artificial intelligence-based clinical decision support systems among health care workers: Systematic review. *J Med Internet Res*. (2025) 27:e69678. doi: 10.2196/69678

23. Wang A, Zhou Y, Ma H, Tang X, Li S, Pei R, et al. Preparing for aging: Understanding middle-aged user acceptance of AI chatbots through the technology acceptance model. *Digital Health*. (2024) 10:20552076241284903. doi: 10.1177/20552076241284903

24. Nofal HA, Mohamed AE, Almadani N, Mahfouz R, Bahri HA, Ali HT, et al. The impact of an artificial intelligence enhancement program on healthcare providers' knowledge, attitudes, and workplace flourishing. *Front Public Health*. (2025) 13:1639333. doi: 10.3389/fpubh.2025.1639333

25. Sorrentino M, Fiorilla C, Mercogliano M, Esposito F, Stilo I, Affinito G, et al. Technological interventions in European dementia care: A systematic review of acceptance and attitudes among people living with dementia, caregivers, and healthcare workers. *Front Neurol*. (2024) 15:1474336. doi: 10.3389/fneur.2024.1474336

26. Jain A, Way D, Gupta V, Gao Y, de Oliveira Marinho G, Hartford J, et al. Development and assessment of an artificial intelligence-based tool for skin condition diagnosis by primary care physicians and nurse practitioners in teledermatology practices. *JAMA Netw Open*. (2021) 4:e217249. doi: 10.1001/jamanetworkopen.2021.7249

27. Lee AT, Ramasamy RK, Subbarao A. Understanding psychosocial barriers to healthcare technology adoption: A review of TAM technology acceptance model and unified theory of acceptance and use of technology and UTAUT frameworks. *Healthcare*. (2025) 13:250. doi: 10.3390/healthcare13030250

28. Scipion CEA, Manchester MA, Federman A, Wang Y, Arias JJ. Barriers to and facilitators of clinician acceptance and use of artificial intelligence in healthcare settings: A scoping review. *BMJ Open*. (2025) 15:e092624. doi: 10.1136/bmjopen-2024-092624

29. Sit C, Srinivasan R, Amlani A, Muthuswamy K, Azam A, Monzon L, et al. Attitudes and perceptions of UK medical students towards artificial intelligence and radiology: A multicentre survey. *Insights into Imaging*. (2020) 11:14. doi: 10.1186/s13244-019-0830-7

30. Compeau DR, Higgins CA. Computer self-efficacy: Development of a measure and initial test. *Mis Q*. (1995) 19:189–211. doi: 10.2307/249688

31. Liu GX, Ma CJ. Measuring EFL learners' use of ChatGPT in informal digital learning of English based on the technology acceptance model. *Innovation Lang Learn Teach*. (2024) 18:125–38. doi: 10.1080/17501229.2023.2240316

32. Bhattacherjee A. Understanding information systems continuance: An expectation-confirmation model. *MIS Q*. (2001) 25:351–70. doi: 10.2307/3250921

33. Sallam M, Salim NA, Barakat M, Al-Mahzoum K, Al-Tammemi AB, Malaeb D, et al. Assessing health students' attitudes and usage of ChatGPT in Jordan: Validation study. *JMIR Med Educ*. (2023) 9:e48254. doi: 10.2196/48254

34. Cherrez-Ojeda I, Gallardo-Bastidas JC, Robles-Velasco K, Osorio MF, Velez Leon EM, Leon Velastegui M, et al. Understanding health care students' perceptions, beliefs, and attitudes toward AI-powered language models: Cross-sectional study. *JMIR Med Educ*. (2024) 10:e51757. doi: 10.2196/51757

35. Howard MC, Boudreaux M, Oglesby M. Can Harman's single-factor test reliably distinguish between research designs? Not in published management studies. *Eur J Work Organizational Psychol*. (2024) 33:790–804. doi: 10.1080/1359432x.2024.2393462

36. Sun QY. Exploring Chinese music students' AI familiarity and AI self-efficacy: A mixed-methods study based on social cognitive theory (SCT). *Eur J Educ*. (2026) 61:e70446. doi: 10.1111/ejed.70446

37. Yunis M, Jamali D, Umar M. The illusion of AI mastery: "Skill inflation" in the age of accessible AI tools. *J Innovation Knowl*. (2026) 18:101084. doi: 10.1016/j.jik.2026.101084

38. Scheibenzuber C, Chernikova O, Vejvoda J, Sailer M, Fischer F. Scenario-based AI literacy scale (SAILS): Evidence for distinct instrumental and critical-reflective AI skills and their difference from traditional digital skills. *Br J Educ Technol*. (2026). doi: 10.1111/bjet.70065

39. Shapiro H, Souto-Otero M, Watermeyer R. Metacognitive AI literacy: Going beyond the AI skills gap agenda. *Learn Media Technol*. (2026) 1–15. doi: 10.1080/17439884.2026.2652638

40. Tüshaus L, Keuth R, Heinrich M, Dukart J. Methodology of artificial intelligence. Basis for AI literacy in pediatrics. *Monatsschrift Kinderheilkunde*. (2025) 173:282–9. doi: 10.1007/s00112-025-02156-2

41. Mehta N, Mehta S, Rubenstein A, Wood SK. Not replaced, but reinvented: AI education pathways to prepare future physicians to lead healthcare transformation. *Perspect Med Educ*. (2025) 14:849–59. doi: 10.5334/pme.2233

42. Liu S, Xiao Y, Nie M, Yuan X, Wang L, Wang M, et al. Nurses' attitudes toward artificial intelligence: AI literacy as a predictor and the mediating effect of AI anxiety. *BMC Nurs*. (2025) 24:1511. doi: 10.1186/s12912-025-04142-1

43. Kotp MH, Ismail HA, Basyouny HAA, Aly MA, Hendy A, Nashwan AJ, et al. Empowering nurse leaders: Readiness for AI integration and the perceived benefits of predictive analytics. *BMC Nurs*. (2025) 24:56. doi: 10.1186/s12912-024-02653-x

44. Gerlach M, Renggli FJ, Bieri JS, Sariyar M, Golz C. Exploring nurse perspectives on AI-based shift scheduling for fairness, transparency, and work-life balance. *BMC Nurs*. (2025) 24:1161. doi: 10.1186/s12912-025-03808-0