Check for updates

European Journal of Education
SPECIAL ISSUE The Role of Artificial Intelligence in Education

WILEY

ORIGINAL ARTICLE OPEN ACCESS

Understanding Medical Students' Acceptance of Artificial Intelligence by Examining AI Literacy and an Extended UTAUT Model

Haiyang Li[1] | Ruoxi Gao[1,2] | Siyu Xing[1] | Haibo Xu[3,4]

[1]School of Public Health, Xuzhou Medical University, Xuzhou, China | [2]Institute for Advanced Studies (IAS), Universiti Malaya, Kuala Lumpur, Malaysia | [3]Smart Mental Health & Co-Innovation Lab, Xuzhou Medical University, Xuzhou, China | [4]Research Center for Psychological Crisis Prevention and Intervention of College Students in Jiangsu Province, Xuzhou Medical University, Xuzhou, China

Correspondence: Haibo Xu (xhb@xzhmu.edu.cn)

Received: 22 June 2026 | **Revised:** 27 October 2026 | **Accepted:** 29 October 2026

Keywords: AI literacy | generative artificial intelligence | medical higher education | PLS-SEM | UTAUT

ABSTRACT

As AI rapidly integrates into healthcare education, adoption among medical students has become a new concern. This study extended the Unified Theory of Acceptance and Use of Technology (UTAUT) by adding AI literacy as a key factor to clarify the psychological mechanisms underlying medical students' acceptance of AI. A large survey conducted from October 2024 to January 2025 included 1781 medical students and used validated scales for AI literacy, UTAUT constructs, AI usage and demographics. PLS-SEM analysis showed that AI literacy positively predicted performance expectancy, effort expectancy and social influence (all $p < 0.001$). UTAUT constructs significantly influenced behavioural intention, which strongly predicted actual AI use ($\beta = 0.603$, $p < 0.001$), more than facilitating conditions ($\beta = 0.234$, $p < 0.001$). Multiple mediating effects were identified. The study broadens UTAUT's scope in health education and emphasizes the importance of AI literacy.

1 | Introduction

With the rise of artificial intelligence (AI), technologies such as big data and virtual simulation are significantly reshaping teaching and learning. As a revolutionary technology, AI will fundamentally transform the medical sector (Al Kuwaiti et al. 2023) and greatly impact education (Maheshwari 2024), especially in medical training. This shift helps improve teaching quality, reduce costs and make better use of educational resources (Guan et al. 2025). As AI becomes more integrated into medicine and healthcare, AI literacy is increasingly crucial. It involves understanding AI concepts, using related tools and addressing ethical considerations (Shi and Mao 2024). Research indicates that medical students generally have basic AI literacy, but they need to develop skills to manage, apply and optimize AI. They also need to better understand and utilize AI tools to solve problems (Kang and Hao 2025). Therefore, improving AI literacy and related skills among medical students is essential for advancing medical education in disease prevention and for supporting intelligent healthcare within the 'New Medical Sciences' framework.

Research has incorporated digital competence, digital literacy and AI literacy into the Unified Theory of Acceptance and Use of Technology (UTAUT) to explain acceptance of emerging technologies (Qi et al. 2025; Luo and Day 2026). Yet evidence in medical education on how AI literacy and UTAUT beliefs shape behavioural intentions remains limited. This study adds AI literacy to UTAUT and examines its relationships with performance and effort expectations, social influence, facilitating conditions and behavioural intentions. It also compares a full mediation model with one including a direct path from AI literacy (AILit)

Haiyang Li, Ruoxi Gao and Siyu Xing contributed equally to this work (co-first author).

This is an open access article under the terms of the Creative Commons Attribution License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited.

© 2026 The Author(s). *European Journal of Education* published by John Wiley & Sons Ltd.

to behavioural intentions (BI), testing both direct and indirect associations. Thus, the study extends technology-acceptance research to medical education.

2 | Literature Review and Model Assumptions

2.1 | AI Literacy

AI literacy is a relatively recent concept that has emerged alongside the rapid growth of artificial intelligence (Ye et al. 2025). It encompasses a broad range of skills, including understanding, practical application and ethical considerations, enabling individuals to critically assess AI technologies, work effectively with machines and use AI tools appropriately across contexts (Long and Magerko 2020; Li 2021; Zhang et al. 2025). Importantly, AI literacy is not a fixed skill but a long-term ability that develops from primary education through higher education and into ongoing professional growth (Chee et al. 2025).

As AI becomes more embedded in medical education and clinical practice, improving medical students' AI literacy is essential (Shishehgar et al. 2025; Verghese et al. 2025). Despite this, studies indicate that students' AI knowledge still does not meet the requirements of medical practice. Most have only a shallow understanding and generally hold positive views on AI, but they lack systematic knowledge of core AI concepts and the practical skills to use clinical AI tools effectively (Li et al. 2026). Although students usually view AI positively in healthcare, their practical skills and professional understanding lag behind their attitudes, creating a gap between perception and ability (Amiri et al. 2024). As research and training in medical AI literacy continue to develop, future efforts should focus on strengthening students' theoretical understanding and practical skills, rather than simply encouraging passive acceptance of AI technology.

Beyond the general inadequacy of AI literacy development, current medical students show a noticeable internal imbalance in literacy levels (Laupichler et al. 2024). They demonstrate clear differences across literacy areas: excelling in AI-related medical ethics, clinical risk detection and willingness to adopt intelligent medical tools. However, they show significant gaps in core areas such as understanding AI principles, basic technical skills and the application of AI in complex clinical situations (Sobhanian et al. 2024). This structural imbalance underscores a common challenge: although students recognize AI's transformative role in medicine, they lack a deep understanding of how AI algorithms work and their limitations and they are unfamiliar with standard methods for integrating AI into clinical practice and optimizing intelligent medical products (Kang et al. 2024). This suggests that simply using AI tools regularly does not automatically improve AI literacy; targeted curricula and practical clinical training are essential to enhance students' AI skills.

The rising use of generative AI among university students underscores the urgent need for standardized AI literacy education for medical students. HEPI's Student Generative AI Survey shows AI tool use for academic tasks soared from 53% in 2024 to 88% in 2025, reflecting a clear trend toward AI-supported collaborative learning (HEPI 2025). Rapid AI advances are transforming higher education, emphasizing human-AI collaboration (Baig and Yadegaridehkordi 2024). In digital medical transformation, AI literacy now complements medical professionals' traditional skills (Xiao et al. 2026). With the widespread adoption of intelligent medical devices and AI diagnostic tools, students must learn core AI concepts, including big data and machine learning, while adhering to ethical standards to ensure safe AI healthcare. High-level AI literacy is now essential for success in modern medicine.

2.2 | UTAUT Model

The Unified Theory of Acceptance and Use of Technology (UTAUT) explains how individuals adopt technology by combining eight models, such as TAM and TPB. It emphasizes four key factors: performance expectancy, effort expectancy, social influence and facilitating conditions (Tang et al. 2025). Performance expectancy is the belief that technology enhances task performance or helps achieve goals, encouraging adoption (Baig and Yadegaridehkordi 2025; Ustun et al. 2024). Effort expectancy reflects ease of use; studies link it to intention to use (Raza et al. 2022). Social influence shows how others' opinions affect decisions, especially in higher education (Kolil and Achuthan 2023). Facilitating conditions include resources that support adoption and influence behavioural intentions and use (Strzelecki 2024a, 2024b).

Compared to traditional models, the UTAUT framework is more concise, comprehensive and adaptable, offering clear advantages across various settings. Many studies have validated its effectiveness in explaining behaviour in educational contexts, especially in linking students' intentions to use online learning platforms and virtual reality to their actual use (Raza et al. 2022; Ustun et al. 2024). As AI integrates into education, researchers have used UTAUT to assess acceptance of AI-driven platforms, smart tools and early-warning systems (Bayaga 2025). Mohadis et al. (2026) used the UTAUT2 model to study ChatGPT acceptance among 70 Malaysian medical students, showing that factors beyond technology, such as external support and social context, influence acceptance. Although existing research has examined the acceptance of AI-related technologies in various educational settings, studies still differ significantly in the technologies considered, the sample populations and the specific application contexts. In medical education in particular, systematic evidence on the relationship between AI literacy, UTAUT-related beliefs and behavioural intentions still needs to be accumulated.

2.3 | AI Literacy and the UTAUT Model

AI literacy is a cognitive trait that encompasses knowledge, skills and self-efficacy. Studies link it to UTAUT components such as performance and effort expectations and facilitating conditions. Changes in perceptions influence intentions, highlighting AI literacy's mediating role (Liu et al. 2025). In medical education, AI literacy helps students evaluate AI tools and form realistic expectations despite barriers. Incorporating AI literacy into UTAUT offers a comprehensive view of factors affecting AI adoption, including perceptions and skills and facilitates analysis of indirect effects, as shown in Figure 1.

14653435, 2026, 4, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/ejed.70940, Wiley Online Library on [25/11/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

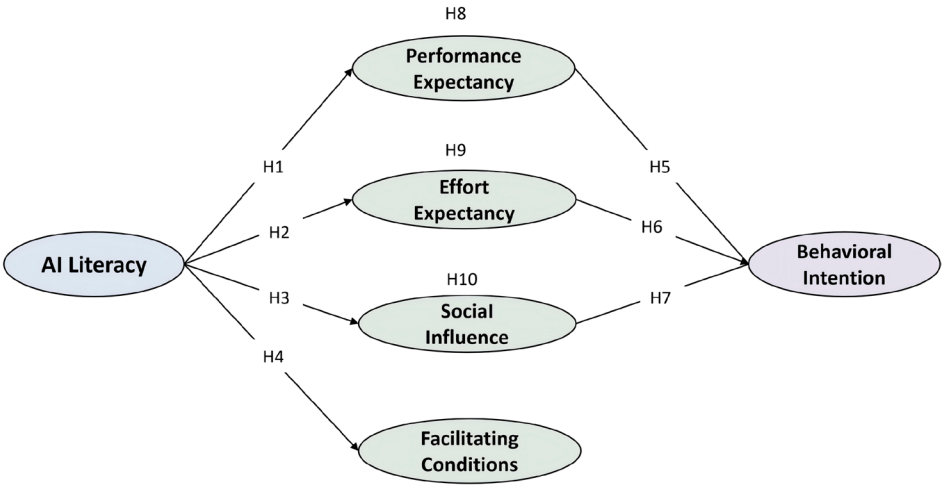

FIGURE 1 | An integrated model based on the UTAUT theory and its hypotheses.

Based on the above analysis, this paper proposes the following hypotheses:

H1. *AI literacy is positively associated with medical students' performance expectations.*

H2. *AI literacy is positively associated with medical students' effort expectations.*

H3. *AI literacy is positively associated with medical students' social influence.*

H4. *AI literacy is positively associated with medical students' perceived facilitating conditions.*

H5. *Performance expectations are positively associated with medical students' behavioural intention to use AI.*

H6. *Effort expectancy is positively associated with medical students' behavioural intention to use AI.*

H7. *Social influence is positively associated with medical students' behavioural intention to use AI.*

H8. *Performance expectancy significantly mediates the relationship between AI literacy and behavioural intention.*

H9. *Effort expectancy significantly mediates the relationship between AI literacy and behavioural intention.*

H10. *Social influence significantly mediates the relationship between AI literacy and behavioural intention.*

3 | Methods

3.1 | Participants and Procedure

This cross-sectional survey utilized convenience sampling and was conducted at a medical university in eastern China from October 2024 to January 2025. The questionnaire was distributed through the WenJuanXing online platform (https://www.wjx.cn) and the campus network platform provided students with direct access to the questionnaire link. The research team did not collect personally identifiable information, such as names, student ID numbers or IP addresses; it also did not access individual click or submission records from the platform and therefore cannot trace whether specific individuals participated, allowing respondents to complete it via a computer or mobile device. The study set no strict time limits, emphasizing authenticity over speed to reduce early respondent bias. Based on a pre-survey, we excluded questionnaires completed in less than 1 min. Ultimately, the analysis included 1781 valid questionnaires, representing a response rate of 91.6%. This study utilized G*Power 3.1.9.7 to conduct a prior power analysis. Using a fixed-effects model for linear multiple regression in the F-test (R^2 deviation from zero), with a small effect size of $f^2 = 0.02$, $\alpha = 0.05$, power $(1-\beta) = 0.95$ and four predictor variables, the minimum required sample size was calculated as 934. The actual sample size in this study was 1781, which exceeded this minimum requirement. Participants were informed of the study's purpose, content, duration, risks, ethical approval and data policy before signing informed consent, after which they could proceed. We recorded age using a categorical system (< 20 years, 20–25 years, 26–30 years, 31–35 years and > 35 years) and this study did not set age 18 as a mandatory inclusion criterion. The study was an anonymous, low-risk online survey that did not collect any personally identifiable information; after approval by the institutional ethics review committee, the committee waived the requirement for written informed consent from parents or guardians and for participants to sign informed consent forms. Participation was voluntary and participants could withdraw at any time and their data remained anonymous. The research complied with the Declaration of Helsinki and received approval from the Ethics Review Committee of Xuzhou Medical University (XZHMU-2024S071).

The demographic distribution of participants is shown in Table 1. There were 668 male and 1113 female participants, with females making up a larger proportion 66.3% of participants were under 20; the sample was mainly undergraduates (98.1%), with postgraduates accounting for a small proportion and spanning medicine-related disciplines, along with a small number of

14653435, 2026, 4, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/ejed.70940, Wiley Online Library on [25/11/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 1 | The demographic information of the samples ($N = 1781$).

Variables	Items	Frequency (%)
Age	Lower than 20 years	1180 (66.3%)
	21–25 years	578 (32.5%)
	26–30 years	11 (0.6%)
	31–35 years	3 (0.2%)
	More than 35 years	9 (0.5%)
Gender	Male	668 (37.5%)
	Female	1113 (62.5%)
Degree	Undergraduate Students	1748 (98.1%)
	Master's Students	23 (1.3%)
	Doctoral Students	10 (0.6%)
Major	Clinical Medicine	340 (19.1%)
	Anesthesiology	197 (11.1%)
	Stomatology	468 (26.3%)
	Nursing	167 (9.4%)
	Medical Imaging	113 (6.3%)
	Laboratory Medicine	36 (2.0%)
	Other Medical Specialties	275 (15.4%)
	Other Non-Medical Disciplines	185 (10.4%)

non-medical disciplines. The distribution across disciplines was relatively balanced, indicating a diverse academic background.

3.2 | Measurements

3.2.1 | AI Literacy Scale

The Artificial Intelligence Literacy Scale (AILS), created by Wang et al. (2023), was used to measure participants' AI literacy. It includes four dimensions—cognitive, usage, evaluation and ethics—and contains 12 items rated on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). This study treats the four dimensions as lower-order constructs and artificial intelligence literacy as a higher-order construct. The scale shows strong reliability and validity: the overall Cronbach's α is 0.83 and confirmatory factor analysis indicates a robust four-factor structure with a CFI of 0.99, TLI of 0.99 and RMSEA of 0.01 (Wang et al. 2023). Researchers have used or adapted it in numerous subsequent studies, including validating the Turkish version (Topal et al. 2025) and testing its suitability among Chinese university students, confirming its strong cross-cultural applicability.

3.2.2 | UTAUT Scale

This study used a modified Unified Theory of Acceptance and Use of Technology (UTAUT) scale originally developed by Venkatesh et al. (2003), to assess factors affecting medical students' acceptance of AI technologies in academic environments. The scale includes four main dimensions: performance expectancy, effort expectancy, social influence and facilitating conditions and comprises 15 items. Responses are rated on a seven-point Likert scale (1 = strongly disagree, 5 = strongly agree). The original scale shows high internal consistency, with Cronbach's α values of 0.91 for performance expectancy, 0.91 for effort expectancy, 0.87 for social influence and 0.82 for facilitating conditions. These four factors account for up to 70% of the variance in technology use behaviours. The UTAUT scale has been extensively used in acceptance research across various technological fields and has proven adaptable across cultures (Venkatesh et al. 2003). In this research, we calculate each dimension's score as the mean of its items and the overall scale score as either the average of the dimension scores or their total; higher scores reflect greater acceptance of the technology by participants.

In the UTAUT model, 'Facilitating Conditions' (FC) measures the extent to which individuals perceive the organizational and technical infrastructure that supports system use (Venkatesh et al. 2003). The items in this study reflect students' subjective judgements about the adequacy of available resources, support and conditions, rather than the school's objective resources. Furthermore, because the questionnaire broadly defines the technological reference as 'AI technology/related applications' and does not limit it to any specific AI system or generative AI tool, we renamed the concept 'Perceived Facilitating Conditions' (PFC). This renaming does not alter the theoretical connotation of FC; instead, it explicitly reflects the perceptual nature already inherent in the original definition and ensures the conceptual label aligns with the questionnaire's operational focus.

3.3 | Data Analysis

This study uses partial least squares structural equation modelling (PLS-SEM) to examine relationships among AI literacy, the UTAUT constructs and AI usage behaviour. Data analysis was conducted using SPSS 26.0 and SmartPLS 4.1.1.8, following a systematic process to ensure reliable results.

Initially, this study employed a two-stage, separate approach to analyse higher-order constructs. In the first stage, four reflective lower-order constructs—AW (items 1–3), US (items 4–6), EV (items 7–9) and ET (items 10–12)—were established and latent variable scores were obtained for each lower-order construct; in the second stage, the first-stage construct scores for AW, US, EV and ET were used as indicators of higher-order AI literacy (AILit). This is because Wang et al. (2023) did not define AILS as a validated, reflective higher-order construct. Given its four-dimensional structure, this study models artificial intelligence literacy as a higher-order construct to capture shared higher-order variance while maintaining model parsimony. This approach aligns with the methodological view that higher-order models can provide a more parsimonious representation when certain conditions are met (Wen et al. 2019).

We computed descriptive statistics in SPSS 26 to characterize the sample's demographics and key variables. To assess potential common method bias, we conducted Harman's one-factor

14653435, 2026, 4, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/ejed.70940, Wiley Online Library on [25/11/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

test following established protocols (Hair Jr et al. 2021). The first principal component explained 49.565% of the variance. Given the Harman test's limitations, we also used the variance inflation factor (VIF) as a diagnostic measure. The VIF values for the latent variables ranged from 1.386 to 3.012, all below Kock's (2015) reference threshold of 3.3. We observed no diagnostic evidence of significant common-method bias.

Subsequently, we evaluated the measurement model for factor loadings, convergent reliability and convergent validity. We assessed internal consistency using Cronbach's alpha, the rho_A reliability coefficient and composite reliability (CR), all of which exceeded 0.70. We established construct validity by ensuring that the average variance extracted (AVE) for each construct exceeded 0.50 (Fornell and Larcker 1981).

We evaluated discriminant validity using two approaches: the Fornell-Larcker criterion and the heterogeneity-to-homogeneity (HTMT) ratio. The Fornell-Larcker criterion requires that the square root of each latent variable's AVE (the diagonal elements) exceed its correlations with all other variables. Additionally, the study consistently applied a stricter HTMT threshold of <0.85 (Henseler et al. 2015); HTMT values below this threshold indicate adequate discriminant validity among the constructs.

The structural model evaluation included path coefficients, R^2, f^2, SRMR and BIC. We used the effect size f^2 to classify effects as small, medium or large, following Cohen's thresholds of approximately 0.02, 0.15 and 0.35, respectively. We tested mediation and direct effects using 5000 bootstrap repetitions, two-tailed tests, $\alpha = 0.05$ and a fixed random seed; we reported the bias-corrected 95% confidence intervals generated by SmartPLS. Following the mediation framework proposed by Zhao et al. (2010), we interpret significant, directionally consistent direct and indirect effects as complementary mediation.

To assess the validity of the full mediation assumption, this study compared two competing models: Model 1 omitted the direct path and retained only the indirect mechanisms from PE, EE and SI to BI; Model 2 retained these three indirect mechanisms and added a direct path from AILit to BI. We then conducted predictive analysis using the PLSpredict program, employing 10-fold cross-validation and repeated partitioning. We assessed the models' predictive correlation relative to a simple predictive benchmark using Q^2_predict and we compared PLS-SEM's predictive errors with those of the linear model (LM). We also used CVPAT to compare predictive losses across benchmarks, providing a supplementary assessment of the models' out-of-sample predictive performance.

Furthermore, this study analysed supplementary control variables, incorporating gender, degree level and discipline category into the model as controls for BI to examine whether differences in sample composition influenced the main model's estimates.

4 | Results

4.1 | Descriptive Statistics

Descriptive statistics for the UTAUT model show that performance expectancy scored the highest ($M = 5.914$, SD = 1.069), followed by behavioural intention ($M = 5.340$, SD = 1.150), effort expectancy ($M = 5.083$, SD = 1.250), social influence ($M = 5.074$, SD = 1.351) and perceived facilitating conditions ($M = 5.040$, SD = 1.270), all of which were slightly above average. These findings highlight the medical students' recognition of the practical utility of AI tools for their academic tasks. Meanwhile, the overall mean AI literacy score was moderate ($M = 3.878$, SD = 0.762).

4.2 | Measurement Model

We assessed the model's reliability and validity. The results of the two-stage high-order construct modelling of AI literacy indicate that, in the first stage, the factor loadings for the four lower-order constructs—AW (0.917–0.942), US (0.916–0.937), EV (0.932–0.944) and ET (0.872–0.935)—all exceeded 0.70, reaching an acceptable level. The composite reliability (rho-c) ranged from 0.935 to 0.956, whilst the average variance extracted (AVE) ranged from 0.828 to 0.897, supporting its internal consistency and convergent validity. In the second stage, the four lower-order constructs loaded onto the higher-order AI literacy (AILit) with loadings of 0.946, 0.955, 0.949 and 0.832, respectively, indicating that the four dimensions effectively reflect the overall concept of AI literacy.

In the final measurement model, each construct's loadings ranged from 0.832 to 0.964. Cronbach's α ranged from 0.902 to 0.965; composite reliability (rho_c) ranged from 0.939 to 0.975; and rho_a ranged from 0.906 to 0.966, all above 0.70, indicating strong internal consistency (Hair Jr et al. 2017). Average Variance Extracted (AVE) ranged from 0.837 to 0.917, exceeding 0.50, indicating that each construct explains more than 50% of the variance and supporting adequate convergent validity (Fornell and Larcker 1981). The results are summarized in Table 2.

Discriminant validity was further assessed using the HTMT and Fornell–Larcker criteria. The results showed that the HTMT values for all constructs ranged from 0.524 to 0.791, with the highest value (0.791) between PFC and EE; all values were below 0.85, indicating that these constructs are independent and do not overlap (Henseler et al. 2015). Furthermore, the square roots of the AVE for each construct exceeded the correlation coefficients between that construct and the others, further supporting discriminant validity among the constructs. Table 3 presents the complete HTMT matrix.

4.3 | Structural Model

We employed a Partial Least Squares Structural Equation Model (PLS-SEM) to further evaluate the structural model. First, we compared the full mediation model (Model 1) with a model that included a direct path from AILit to BI (Model 2). Compared with Model 1, Model 2 increased the explanatory power for behavioural intention from 0.621 to 0.658 and the adjusted R^2 rose from 0.620 to 0.657; simultaneously, the estimated-model SRMR decreased from 0.150 to 0.137 and the BIC for BI decreased from −1697.831 to −1872.333. Based on these indicators, we retained Model 2 as the final structural model.

14653435, 2026, 4, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/ejed.70940, Wiley Online Library on [25/11/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 2 | Measurement model results.

Construct	Items	Factor loadings	Cronbach's α	rho_A	CR	AVE
AILit	AW	0.946	0.940	0.952	0.958	0.850
	US	0.955				
	EV	0.949				
	ET	0.832				
PE	PE1	0.955	0.965	0.966	0.975	0.906
	PE2	0.946				
	PE3	0.960				
	PE4	0.946				
EE	EE1	0.906	0.902	0.906	0.939	0.837
	EE2	0.904				
	EE3	0.934				
SI	SI1	0.954	0.955	0.956	0.971	0.917
	SI2	0.964				
	SI3	0.955				
PFC	FC1	0.934	0.953	0.953	0.966	0.877
	FC2	0.950				
	FC3	0.954				
	FC4	0.908				
BI	BI1	0.923	0.914	0.916	0.946	0.853
	BI2	0.950				
	BI3	0.897				

Abbreviations: AILit, AI Literacy; BI, Behavioural Intention; EE, Effort Expectancy; PFC, Perceived Facilitating Conditions; PE, Performance Expectancy; SI, Social Influence.

TABLE 3 | Discriminant validity (HTMT values).

	AILit	BI	EE	PFC	PE	SI
AILit						
BI	0.730					
EE	0.682	0.701				
PE	0.596	0.730	0.583			
PFC	0.701	0.759	0.791	0.524		
SI	0.624	0.732	0.735	0.590	0.706	

Abbreviations: AILit, AI Literacy; BI, Behavioural Intention; EE, Effort Expectancy; PE, Performance Expectancy; PFC, Perceived Facilitating Conditions; SI, Social Influence.

In the final model, BI explained 65.8% of the variance ($R^2 = 0.658$). The R^2 values for EE, PE, PFC and SI were 0.404, 0.323, 0.449 and 0.354, respectively. The corresponding adjusted R^2 values were 0.403, 0.323, 0.449 and 0.354. The structural relationships among the constructs are illustrated in Figure 2.

We further assessed the effect sizes of each structural path using f^2. The effect sizes of AILit on PFC, EE, SI and PE were 0.816, 0.677, 0.549 and 0.477, respectively, all indicating large effects; the effect size of AILit on BI was 0.107. For the three UTAUT predictors of BI, the effect sizes were 0.180 for PE, 0.095 for SI and 0.015 for EE. Overall, PE explained BI more than SI and EE, while AILit showed a strong explanatory role for each UTAUT antecedent construct.

Furthermore, the PLS-SEM prediction results show that the Q^2_predict values for the three observed measures of BI are all greater than 0, with BI1, BI2 and BI3 at 0.433, 0.403 and 0.344, respectively, indicating that the model has out-of-sample predictive validity for behavioural intention. The RMSEs for BI1, BI2 and BI3 in the PLS-SEM model were 0.878, 0.957 and 1.081, respectively, all slightly higher than the corresponding values for the linear model (LM) (0.874, 0.949 and 1.065). The CVPAT results showed that the PLS-SEM model outperformed the simple average benchmark but did not outperform the LM.

4.4 | Direct Effects and Mediating Effects

The results of 5000 bootstrap simulations showed a significant positive association between AILit and BI ($\beta = 0.269$, $t = 9.502$, $p < 0.001$, 95% CI [0.215, 0.327]). Furthermore, AILit

14653435, 2026, 4, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/ejed.70940, Wiley Online Library on [25/11/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

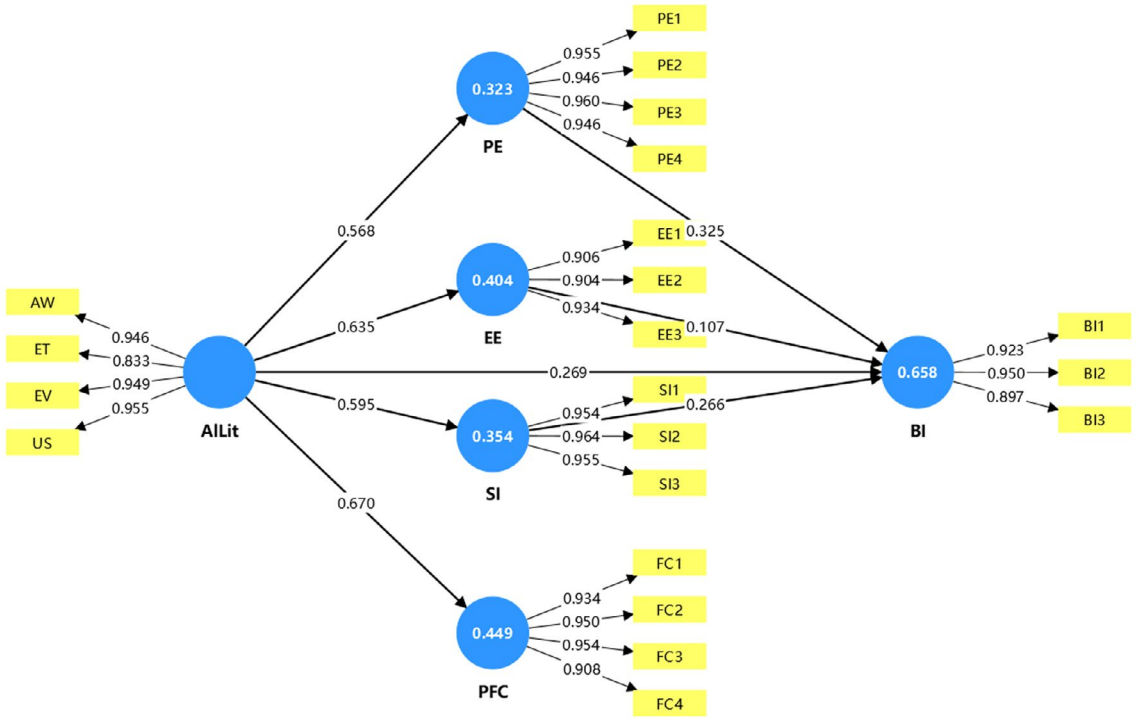

FIGURE 2 | The model tests hypotheses about the path influence among variables. AILit, AI Literacy; BI, Behavioural Intention; PE, Performance Expectancy; EE, Effort Expectancy; SI, Social Influence; FC, Facilitating Conditions; UB, Use Behaviour.

was significantly positively correlated with EE ($\beta = 0.635$), PE ($\beta = 0.568$), PFC ($\beta = 0.670$) and SI ($\beta = 0.595$) (all $p < 0.001$).

Among the UTAUT constructs and behavioural intentions, the association between PE and BI was the strongest ($\beta = 0.325$, $t = 12.957$, $p < 0.001$, 95% CI [0.275, 0.374]), followed by SI ($\beta = 0.266$, $t = 8.327$, $p < 0.001$, 95% CI [0.204, 0.327]). The association between EE and BI was weaker but still statistically significant ($\beta = 0.107$, $t = 3.509$, $p < 0.001$, 95% CI [0.046, 0.166]).

Furthermore, AILit had a significant total indirect effect on BI ($\beta = 0.411$, $t = 17.648$, $p < 0.001$, 95% CI [0.363, 0.455]). All three specific indirect pathways were statistically significant, with the indirect effect via PE being the largest ($\beta = 0.185$, 95% CI [0.154, 0.216]), followed by SI ($\beta = 0.158$, 95% bias-corrected CI [0.122, 0.196]) and EE ($\beta = 0.068$, 95% bias-corrected CI [0.029, 0.106]). The total effect of AILit on BI was 0.681 ($p < 0.001$). The results are presented in Table 4.

Because both the direct effect of AILit→BI and the total indirect effect were significant and in the same direction, this result aligns with the characteristics of complementary mediation. In other words, the relationship between AI literacy and behavioural intention includes both a direct association and partial mediation through performance expectations, social influence and effort expectations.

TABLE 4 | Analysis of the influence effect between paths in the structural equation model.

Paths	β	f^2	T value	p
Direct effects				
AILit → BI	0.269	0.107	9.502	< 0.001
AILit → EE	0.635	0.677	36.157	< 0.001
AILit → PE	0.568	0.477	29.863	< 0.001
AILit → PFC	0.670	0.816	38.369	< 0.001
AILit → SI	0.595	0.549	28.101	< 0.001
EE → BI	0.107	0.015	3.509	< 0.001
PE → BI	0.325	0.180	12.957	< 0.001
SI → BI	0.266	0.095	8.327	< 0.001
Mediation effects				
AILit → BI	0.411	—	17.648	< 0.001
AILit → PE → BI	0.185	—	11.641	< 0.001
AILit → SI → BI	0.158	—	8.241	< 0.001
AILit → EE → BI	0.068	—	3.478	< 0.001
Total effect				
AILit → BI	0.681	—	38.572	< 0.001

Abbreviations: AILit, AI Literacy; BI, Behavioural Intention; EE, Effort Expectancy; PE, Performance Expectancy; PFC, Perceived Facilitating Conditions; SI, Social Influence.

5 | Discussion

Drawing on the extended UTAUT framework, this study examined the relationship between AI literacy and medical students' acceptance of artificial intelligence, presenting a developmental process characterized by 'competence—cognitive evaluation—willingness'. Overall, AI literacy is closely associated with medical students' performance expectations,

14653435, 2026, 4, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/ejed.70940, Wiley Online Library on [25/11/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

effort expectations, social influence and perceived facilitating conditions and it is also independently associated with behavioural intention; meanwhile, performance expectations, social influence and effort expectations mediate the relationship between AI literacy and behavioural intention. These findings suggest that AI literacy may play a broader role in AI acceptance than merely shaping technological beliefs. Consequently, medical students with higher AI literacy are more likely to form positive judgements about AI's utility, usability and social acceptance and may also be more confident in incorporating AI into their learning activities and future medical practice.

5.1 | The 'Pioneering Role' of AI Technological Literacy

AI literacy is vital in shaping how medical students view, engage with and use AI technologies. Research shows that AI literacy consistently affects performance and effort expectations, social influences and enabling conditions, which in turn shape both behavioural intentions and actual AI use. It also facilitates the 'learning–use–benefit' cycle. Previous studies (Caner-Yıldırım 2025) suggest that AI literacy, combined with cognitive ability, shapes students' problem-solving with AI, their confidence in its benefits and their perception of reduced effort (Jing et al. 2024; Wang et al. 2025). Recent research in Chinese higher education also finds that AI literacy correlates significantly with students' intention to adopt generative AI; for students, this competency matters more than certain general technological experience factors (Yu et al. 2026). This result echoes the present study's findings, suggesting that, as AI rapidly integrates into learning environments, students' ability to understand and evaluate AI may provide a crucial foundation for stable acceptance intentions. This study further indicates that traditional UTAUT beliefs cannot fully explain the relationship between AI literacy and behavioural intention.

Although performance expectations, effort expectations and perceived ease of use mediate the relationship between AI literacy and behavioural intentions, this pattern suggests that students' AI literacy is strongly linked to a favourable attitude toward AI (Laupichler et al. 2024). However, AI literacy remains independently associated. This suggests that AI literacy may represent a category of individual competence factors not yet fully encompassed within the classical construct of technology acceptance. This role is particularly important for medical students. Medical education involves information authenticity, clinical judgement, patient safety and ethical responsibility; whether students understand the fundamental mechanisms, limits of evidence and potential risks of AI may directly influence their willingness to adopt relevant technologies in their studies and future professional practice (Lee et al. 2026). Therefore, rather than viewing AI literacy as a general 'digital skill', it is more appropriate to understand it as a foundational competence that underpins students' ability to form informed, prudent judgements about technology. This finding also expands existing research on AI acceptance in higher education. Yu et al. (2026) found that, among faculty and students at Chinese business schools, technology acceptance depends not only on whether the tool is useful or easy to operate, but also on whether users have sufficient competence to understand and manage the uncertainties posed by artificial intelligence. In medical education, this issue may be even more pronounced, as students must not only learn how to use artificial intelligence but also know when to trust it, when to verify it and when not to rely on it. Overall, AI literacy is essential for shaping perceptions and acceptance of AI.

This research finds a strong link between AI literacy and social influence (SI). This suggests that students' understanding of and judgements regarding artificial intelligence may be closely linked to the social norms and support available within their learning environment. Existing research also indicates that peers', teachers' and other significant others' attitudes can influence students' acceptance of and intention to use new technologies. When students see positive role models and norms among tutors and peers, AI acceptance and use increase (Ren and Wu 2024). In medical education, teacher demonstrations, peer interactions and curriculum-embedded norms about technology use may collectively shape students' understanding of and evaluation of artificial intelligence. Furthermore, the social information processing perspective may explain this relationship: individuals base their judgements of social situations on encoding and interpreting external social cues, while prior knowledge, experience and social norms shape this processing (Ziv and Hadad 2021). Consequently, students with higher AI literacy may better recognize and understand AI-related information and norms conveyed by teachers, peers and other significant others in the learning environment, thereby strengthening the link between AI literacy and social influence.

Furthermore, the correlation between AI literacy and the conditions that foster its perception suggests that students' assessment of technology-supported learning environments may depend not only on the availability of objective resources but also on their ability to identify, understand and make effective use of these resources. Higher AI literacy may enable students to identify available technical support and more readily turn it into learning opportunities. Existing research also indicates that digital competence is closely linked to learners' effective use of technological environments, while providing technical platforms or resources alone is insufficient to guarantee an effective learning experience (Zhao et al. 2021; Olszewski and Crompton 2020). Consequently, AI infrastructure development in medical education should proceed alongside cultivating students' AI literacy.

AI literacy is vital for guiding medical students in using AI tools effectively. It involves more than just cognitive skills; it influences behaviours, perceptions of value, operational experiences and social expectations (Börekci and Çelik 2024). Focusing on literacy through educational strategies is more effective for sustainable change than simply requiring use or changing attitudes at the behavioural level. Hence, AI education should extend beyond tool demonstrations and skills training; it should be a fundamental part of medical curricula. Evidence indicates that students generally view AI favourably, yet their technical knowledge remains behind their perceived ability to operate it (Laupichler et al. 2024). Structured AI literacy education helps students recognize AI's potential value while gaining a more accurate understanding of its limitations

14653435, 2026, 4, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/ejed.70940, Wiley Online Library on [25/11/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

and risks, fostering a more prudent, balanced attitude toward adopting technology.

5.2 | UTAUT Model

In this study, within the UTAUT framework, performance expectancy consistently had the strongest impact on behavioural intention. This suggests that when medical students decide whether to embrace artificial intelligence, their primary concern remains whether the technology can deliver practical educational value. This highlights the role of perceived benefits in encouraging Chinese medical students to adopt AI technology. A prior study on higher-education students also showed a significant positive link between performance expectancy (PE) and behavioural intention (BI) to use AI (Strzelecki and ElArabawy 2024). A cross-national study by Budhathoki et al. (2024) involving students in the UK and Nepal similarly found that performance expectations are a key factor in the intention to adopt AI. Our results reinforce this, suggesting that medical students are more inclined to reuse AI tools when they believe these tools can effectively assist with academic tasks and enhance learning efficiency.

Second, social influence significantly shapes behavioural intentions, suggesting that medical students' acceptance of artificial intelligence is not entirely an individual decision. Lecturers', peers' and the institution's attitudes toward artificial intelligence may collectively shape the social environment in which students assess whether a particular use is reasonable, appropriate and acceptable. This aligns with Zhao et al. (2024) and Moradi (2025), highlighting that peers and educators heavily shape perceptions and intentions regarding technology. In the demanding context of medical education, teachers' and peers' actions and endorsements have a lasting impact. This is because medical training relies heavily on tutor demonstrations, peer interaction and professional standards. When tutors can clearly demonstrate learning scenarios where artificial intelligence can be used, how to verify results and which applications pose ethical risks, students can set clear, consistent boundaries for its use. Consequently, social influence not only fosters acceptance of artificial intelligence but also reinforces the intention to use it by establishing shared norms for its application.

By contrast, whilst effort expectancy remains associated with behavioural intention, its effect is relatively limited. This supports the UTAUT model (Venkatesh et al. 2012) and aligns with findings from research on higher-education learners (Strzelecki 2024a, 2024b). For medical students with basic digital skills, usability isn't a major barrier. When students view technology positively, effort expectancy has less influence on BI (Vasuthevan et al. 2024). Medical students are willing to exert effort if it improves their performance. This further illustrates that, in a mature digital environment, acceptance of artificial intelligence may gradually shift from making the tools easier to use to ensuring students understand how to use them effectively, reliably and responsibly.

Finally, this model identifies three parallel indirect paths between AI literacy and acceptance intention, indicating that a single mechanism does not drive their relationship. Specifically, performance expectations reflect students' assessment of AI's educational value, social influence reflects norms and support within the learning environment and effort expectations relate to the effort required to use AI. A study by Duong et al. (2023) on ChatGPT acceptance found that students' intention to use the technology is not determined solely by a single technological judgement; factors such as performance expectations play an important mediating role in the technology acceptance process. For medical students, the learning environment, resources and support also significantly shape AI adoption (Xu et al. 2026). Adequate training and technical help develop skills and simulate clinical settings, boosting practical competence. Greater accessibility helps students become proficient AI users, increasing their competitiveness in healthcare (Pham et al. 2025). Consequently, this study does not propose a new mechanism to replace UTAUT; instead, it positions AI literacy as a key antecedent of UTAUT-related beliefs and further explains how students' intentions to adopt AI form differently in the context of medical education.

5.3 | Recommendations for the Future

First, medical schools should make AI literacy a core component of the curriculum, integrating principles, data, algorithms, applications and ethics into medical courses. Teaching should not be limited to the practical application of tools; it should also help students understand the practical value, evidence base and potential limitations of AI in tasks such as case discussions, literature searches and clinical reasoning, thereby enabling them to form more accurate expectations of its performance and develop a prudent approach to its use.

Second, attention should be paid to the social norms teachers and the learning environment establish. Teachers can model appropriate, transparent and critical AI use, clarify boundaries for acceptable use across different learning activities and guide students in verifying AI-generated content, thereby mitigating risks such as over-reliance, declining critical thinking and academic misconduct. Affiliated hospitals and clinical teaching centers can also design AI-based learning activities aligned with clinical tasks while providing necessary feedback and guidance.

Third, education authorities should embed medical AI literacy into undergraduate and residency curricula to build an institutional foundation for reform. Resources should support literacy courses, simulated environments and educator training. Multicenter research can evaluate and improve literacy initiatives by gathering local evidence to inform policy.

5.4 | Limitations and Future Research Directions

Although this study sheds light on the factors influencing medical students' adoption of artificial intelligence, it has several notable limitations. First, relying on cross-sectional data from a single survey limits the ability to determine causality. Structural equation modelling (SEM) can identify correlations among variables, but it cannot establish cause-and-effect relationships. For complex concepts such as AI literacy and behavioural intentions, future research should use longitudinal methods to provide stronger causal evidence and better track

14653435, 2026, 4, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/ejed.70940, Wiley Online Library on [25/11/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

how students' intentions to adopt AI change as they gain experience with AI technologies. Second, the sample came from a single medical university and used convenience sampling, so the findings should not be generalized directly to students at other institutions or in other regions. Sensitivity analyses controlling for demographic factors indicated that gender, degree level and enrollment in medical or non-medical programs did not substantially alter the core structural relationships. However, the uneven sample distribution limited more detailed subgroup and multi-group comparisons. Finally, although the study focused on AI literacy and the UTAUT model, it did not examine other potentially influential factors. Attitudes toward technology, anxiety and perceived risks may also play important roles in AI adoption, particularly given the rapid pace of AI development. Including these factors in future research would provide a more comprehensive understanding of AI adoption in higher education.

6 | Conclusion

Based on the UTAUT framework, this study examined the relationship between AI literacy and Chinese medical students' acceptance of artificial intelligence and their behavioural intentions. The findings indicate that AI literacy is significantly and positively associated with performance expectations, effort expectations, social influence and perceived facilitating conditions and is directly linked to behavioural intentions. At the same time, performance expectations, social influence and effort expectations played significant indirect roles in the relationship between AI literacy and behavioural intentions, with performance expectations exhibiting a relatively stronger effect. The findings reveal that AI literacy is a key factor in understanding medical students' acceptance of AI, whilst students' assessments of the practical benefits of AI, the difficulty of its use and the social environment are also closely related to their behavioural intentions. As AI-related curriculum and teaching reforms advance, medical education should simultaneously cultivate students' AI literacy, demonstrate the technology's educational value and establish a supportive learning environment.

Author Contributions

Haiyang Li: writing – original draft, data curation, methodology, validation, project administration, resources, funding acquisition, writing – review and editing. **Ruoxi Gao:** methodology, software, data curation, formal analysis, writing – original draft, investigation, validation, writing – review and editing. **Siyu Xing:** writing – original draft, data curation, investigation, methodology. **Haibo Xu:** conceptualization, validation, visualization, supervision, writing – review and editing, funding acquisition.

Acknowledgements

The authors express gratitude to all participants in this study.

Funding

This study is supported by Jiangsu Provincial University's Philosophy and Social Sciences Foundation Project (2021SJA1073) and the Comprehensive Reform and Quality Enhancement Project for Ideological and Political Work in Higher Education Institutions of the Ministry of Education (2025No.35).

Ethics Statement

Research was conducted in accordance with the Declaration of Helsinki guidelines and was approved by the Ethics Committee of Xuzhou Medical University (approval number: XZHMU-2024S071).

Consent

Informed consent was obtained from all individual participants included in the study.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data used in this study are available on request from the corresponding author.

References

Al Kuwaiti, A., K. Nazer, A. Al-Reedy, et al. 2023. "A Review of the Role of Artificial Intelligence in Healthcare." *Journal of Personalized Medicine* 13, no. 6: 951. https://doi.org/10.3390/jpm13060951.

Amiri, H., S. Peiravi, S. S. Rezazadeh Shojaee, et al. 2024. "Medical, Dental, and Nursing Students' Attitudes and Knowledge Towards Artificial Intelligence: A Systematic Review and Meta-Analysis." *BMC Medical Education* 24, no. 1: 412. https://doi.org/10.1186/s12909-024-05406-1.

Baig, M. I., and E. Yadegaridehkordi. 2024. "ChatGPT in the Higher Education: A Systematic Literature Review and Research Challenges." *International Journal of Educational Research* 127: 102411. https://doi.org/10.1016/j.ijer.2024.102411.

Baig, M. I., and E. Yadegaridehkordi. 2025. "Factors Influencing Academic Staff Satisfaction and Continuous Usage of Generative Artificial Intelligence (GenAI) in Higher Education." *International Journal of Educational Technology in Higher Education* 22, no. 1: 5. https://doi.org/10.1186/s41239-025-00506-4.

Bayaga, A. 2025. "Leveraging AI-Enhanced and Emerging Technologies for Pedagogical Innovations in Higher Education." *Education and Information Technologies* 30, no. 1: 1045–1072. https://doi.org/10.1007/s10639-024-13122-y.

Börekci, C., and Ö. Çelik. 2024. "Exploring the Role of Digital Literacy in University Students' Engagement With AI Through the Technology Acceptance Model." *Sakarya University Journal of Education* 14, no. Special Issue-AI in Education: 228–249. https://doi.org/10.19126/suje.1468866.

Budhathoki, T., A. Zirar, E. Tchouamou Njoya, and A. Timsina. 2024. "ChatGPT Adoption and Anxiety: A Cross-Country Analysis Utilising the Unified Theory of Acceptance and Use of Technology (UTAUT)." *Studies in Higher Education* 49, no. 5: 831–846. https://doi.org/10.1080/03075079.2024.2333937.

Caner-Yıldırım, S. 2025. "Modeling ChatGPT Adoption Among Undergraduates: An Integrated UTAUT2 and Digital Competence Framework." *SAGE Open* 15, no. 2: 21582440251343340. https://doi.org/10.1177/21582440251343340.

Chee, H., S. Ahn, and J. Lee. 2025. "A Competency Framework for AI Literacy: Variations by Different Learner Groups and an Implied Learning Pathway." *British Journal of Educational Technology* 56, no. 5: 2146–2182. https://doi.org/10.1111/bjet.13556.

Duong, C. D., T. N. Vu, and T. V. N. Ngo. 2023. "Applying a Modified Technology Acceptance Model to Explain Higher Education Students' Usage of ChatGPT: A Serial Multiple Mediation Model With Knowledge Sharing as a Moderator." *International Journal of*

14653435, 2026, 4, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/ejed.70940, Wiley Online Library on [25/11/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Management Education 21, no. 3: 100883. https://doi.org/10.1016/j.ijme.2023.100883.

Fornell, C., and D. F. Larcker. 1981. "Evaluating Structural Equation Models With Unobservable Variables and Measurement Error." *Journal of Marketing Research* 18, no. 1: 39–50. https://doi.org/10.1177/002224378101800104.

Guan, Q., P. Lu, X. Han, and T. Li. 2025. "Research on Generative Artificial Intelligence Empowering Medical Immunology Teaching Practice." *Chinese Journal of Immunology* 41, no. 6: 1306–1309, 1314 [Article in Chinese.].

Hair, J. F., Jr., G. T. M. Hult, C. M. Ringle, M. Sarstedt, N. P. Danks, and S. Ray. 2021. *Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R: A Workbook*. Springer Nature.

Hair, J. F., Jr., L. M. Matthews, R. L. Matthews, and M. Sarstedt. 2017. "PLS-SEM or CB-SEM: Updated Guidelines on Which Method to Use." *International Journal of Multivariate Data Analysis* 1, no. 2: 107. https://doi.org/10.1504/IJMDA.2017.087624.

Henseler, J., C. M. Ringle, and M. Sarstedt. 2015. "A New Criterion for Assessing Discriminant Validity in Variance-Based Structural Equation Modeling." *Journal of the Academy of Marketing Science* 43, no. 1: 115–135. https://doi.org/10.1007/s11747-014-0403-8.

HEPI. 2025. *Student Generative AI Survey 2025*. Higher Education Policy Institute UK.

Jing, Y., H. Wang, X. Chen, and C. Wang. 2024. "What Factors Will Affect the Effectiveness of Using ChatGPT to Solve Programming Problems? A Quasi-Experimental Study." *Humanities & Social Sciences Communications* 11, no. 1: 1–12. https://doi.org/10.1057/s41599-024-02751-w.

Kang, N., and Y. Hao. 2025. "Analysis of the Status and Influencing Factors of AI Literacy and Ability Among Medical Students." *Technology Intelligence Engineering* 11, no. 3: 114–127 [Article in Chinese.].

Kang, N., Y. Hao, F. Li, J. Liu, and Y. Wu. 2024. "Constructing an AI Literacy Competency Framework for Medical Students." *Journal of Academic Library and Information Science* 42, no. 3: 46–51 [Article in Chinese.].

Kock, N. 2015. "Common Method Bias in PLS-SEM: A Full Collinearity Assessment Approach." *International Journal of e-CollaborationInternational Journal of E-Collaboration* 11, no. 4: 1–10. https://doi.org/10.4018/ijec.2015100101.

Kolil, V. K., and K. Achuthan. 2023. "Longitudinal Study of Teacher Acceptance of Mobile Virtual Labs." *Education and Information Technologies* 28, no. 7: 7763–7796. https://doi.org/10.1007/s10639-022-11499-2.

Laupichler, M. C., A. Aster, M. Meyerheim, T. Raupach, and M. Mergen. 2024. "Medical Students' AI Literacy and Attitudes Towards AI: A Cross-Sectional Two-Center Study Using Pre-Validated Assessment Instruments." *BMC Medical Education* 24, no. 1: 401. https://doi.org/10.1186/s12909-024-05400-7.

Lee, B., G. Bang, and S. J. Chae. 2026. "Medical AI Use Intention Among Medical Students and Faculty and Its Associations With AI Literacy, Perceived Benefits, and Risks: Cross-Sectional Survey Study." *JMIR Medical Education* 12: e105032. https://doi.org/10.2196/105032.

Li, C., S. Hsiang-Te Tsuei, and H. Wu. 2026. "AI Literacy Among Chinese Medical Students: Cross-Sectional Examination of Individual and Environmental Factors." *JMIR Medical Education* 12, no. 1: e80604.

Li, X. 2021. "The Connotation Formation and Cultivation Path of Normal School Students' Intelligent Education Literacy." *Modern Educational Technology* 31, no. 9: 5–12 [Article in Chinese.].

Liu, C., L. Yang, X. Dong, and X. Li. 2025. "Factors Influencing Generative AI Usage Intention in China: Extending the Acceptance–Avoidance Framework With Perceived AI Literacy." *System* 13, no. 8: 639. https://doi.org/10.3390/systems13080639.

Long, D., and B. Magerko. 2020. "What Is AI Literacy? Competencies and Design Considerations." In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, 1–16. Association for Computing Machinery. https://doi.org/10.1145/3313831.3376727.

Luo, Y., and M. J. Day. 2026. "Determinants of Lecturer Readiness to Adopt Generative AI in Higher Education: Survey Evidence From UTAUT and Self-Determination Theory." *Education and Information Technologies* 31: 3399–3430. https://doi.org/10.1007/s10639-026-13931-3.

Maheshwari, G. 2024. "Factors Influencing Students' Intention to Adopt and Use ChatGPT in Higher Education: A Study in the Vietnamese Context." *Education and Information Technologies* 29, no. 10: 12167–12195. https://doi.org/10.1007/s10639-023-12333-z.

Mohadis, H. M., I. Ismail, I. Ibrahim, Z. A. Maher, S. Yaacob, and A. M. C. Azmi. 2026. "Integrating AI Chatbot in Medical Education: A Technology Acceptance Study of ChatGPT Using UTAUT2." *Journal of Advanced Research in Applied Sciences and Engineering Technology* 56, no. 1: 215–239. https://doi.org/10.37934/araset.56.1.215239.

Moradi, H. 2025. "Integrating AI in Higher Education: Factors Influencing ChatGPT Acceptance Among Chinese University EFL Students." *International Journal of Educational Technology in Higher Education* 22, no. 1: 30. https://doi.org/10.1186/s41239-025-00530-4.

Olszewski, B., and H. Crompton. 2020. "Educational Technology Conditions to Support the Development of Digital Age Skills." *Computers & Education* 150: 103849. https://doi.org/10.1016/j.compedu.2020.103849.

Pham, T. D., N. Karunaratne, B. Exintaris, et al. 2025. "The Impact of Generative AI on Health Professional Education: A Systematic Review in the Context of Student Learning." *Medical Education* 59, no. 12: 1280–1289. https://doi.org/10.1111/medu.15746.

Qi, K., Y. Gong, and C. Ke. 2025. "Bridging AI Literacy and UTAUT Constructs: Structural Equation Modeling of AI Adoption Among Chinese University Students." *Humanities & Social Sciences Communications* 12: 1452. https://doi.org/10.1057/s41599-025-05775-y.

Raza, S. A., Z. Qazi, W. Qazi, and M. Ahmed. 2022. "E-Learning in Higher Education During COVID-19: Evidence From Blackboard Learning System." *Journal of Applied Research in Higher Education* 14, no. 4: 1603–1622. https://doi.org/10.1108/JARHE-02-2021-0054.

Ren, H., and Y. Wu. 2024. "A Study of Generative Information Search Behaviour of Scientific Research User: ChatGPT as an Example." *Journal of Academic Library and Information Science* 42, no. 1: 3–14. [Article in Chinese.].

Shi, Y., and Y. Mao. 2024. "Concepts, Frameworks and Education for Artificial Intelligence Literacy." *Library Tribune* 44, no. 11: 90–100 [Article in Chinese.].

Shishehgar, S., P. Murray-Parahi, E. Alsharaydeh, S. Mills, and X. Liu. 2025. "Artificial Intelligence in Health Education and Practice: A Systematic Review of Health Students' and Academics' Knowledge, Perceptions and Experiences." *International Nursing Review* 72, no. 2: e70045. https://doi.org/10.1111/inr.70045.

Sobhanian, P., S. Eslami, and M. A. Ghezel. 2024. "Attitudes and Readiness of Iranian Medical Science Students Toward Artificial Intelligence: A Cross-Sectional Study." *Iranian Biomedical Journal* 28: 115.

Strzelecki, A. 2024a. "Students' Acceptance of ChatGPT in Higher Education: An Extended Unified Theory of Acceptance and Use of Technology." *Innovative Higher Education* 49, no. 2: 223–245. https://doi.org/10.1007/s10755-023-09686-1.

Strzelecki, A. 2024b. "To Use or Not to Use ChatGPT in Higher Education? A Study of Students' Acceptance and Use of Technology."

14653435, 2026, 4, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/ejed.70940, Wiley Online Library on [25/11/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Interactive Learning Environments 32, no. 9: 5142–5155. https://doi.org/10.1080/10494820.2023.2209881.

Strzelecki, A., and S. ElArabawy. 2024. "Investigation of the Moderation Effect of Gender and Study Level on the Acceptance and Use of Generative AI by Higher Education Students: Comparative Evidence From Poland and Egypt." *British Journal of Educational Technology* 55, no. 3: 1209–1230. https://doi.org/10.1111/bjet.13425.

Tang, X., Z. Yuan, and S. Qu. 2025. "Factors Influencing University Students' Behavioural Intention to Use Generative Artificial Intelligence for Educational Purposes Based on a Revised UTAUT2 Model." *Journal of Computer Assisted Learning* 41, no. 1: e13105. https://doi.org/10.1111/jcal.13105.

Topal, A. D., A. T. Gökçe, C. D. Eren, and A. K. Geçer. 2025. "Artificial Intelligence Literacy Scale: A Study of Reliability and Validity in Turkish University Students." *Journal of Learning and Teaching in Digital Age* 10, no. 1: 58–67. https://doi.org/10.53850/joltida.1440845.

Ustun, A. B., F. G. Karaoglan-Yilmaz, R. Yilmaz, M. Ceylan, and O. Uzun. 2024. "Development of UTAUT-Based Augmented Reality Acceptance Scale: A Validity and Reliability Study." *Education and Information Technologies* 29, no. 9: 11533–11554. https://doi.org/10.1007/s10639-023-12321-3.

Vasuthevan, K., S. Vaithilingam, and J. W. J. Ng. 2024. "Academics' Continuance Intention to Use Learning Technologies During COVID-19 and Beyond." *PLoS One* 19, no. 1: e0295746. https://doi.org/10.1371/journal.pone.0295746.

Venkatesh, V., M. G. Morris, G. B. Davis, and F. D. Davis. 2003. "User Acceptance of Information Technology: Toward a Unified View." *MIS Quarterly* 27, no. 3: 425–478.

Venkatesh, V., J. Y. Thong, and X. Xu. 2012. "Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology." *MIS Quarterly* 36: 157–178. https://doi.org/10.2307/41410412.

Verghese, B. G., C. Iyer, T. Borse, S. Cooper, J. White, and R. Sheehy. 2025. "Modern Artificial Intelligence and Large Language Models in Graduate Medical Education: A Scoping Review of Attitudes, Applications & Practice." *BMC Medical Education* 25, no. 1: 730. https://doi.org/10.1186/s12909-025-07321-5.

Wang, B., P.-L. P. Rau, and T. Yuan. 2023. "Measuring User Competence in Using Artificial Intelligence: Validity and Reliability of Artificial Intelligence Literacy Scale." *Behaviour & Information Technology* 42, no. 9: 1324–1337. https://doi.org/10.1080/0144929X.2022.2072768.

Wang, C., H. Wang, Y. Li, J. Dai, X. Gu, and T. Yu. 2025. "Factors Influencing University Students' Behavioral Intention to Use Generative Artificial Intelligence: Integrating the Theory of Planned Behavior and AI Literacy." *International Journal of Human-Computer Interaction* 41, no. 11: 6649–6671. https://doi.org/10.1080/10447318.2024.2383033.

Wen, Z., D. Tang, and H. Gu. 2019. "A General Simulation Comparison of the Predictive Validity Between Bifactor and High-Order Factor Models." *Acta Psychologica Sinica* 51, no. 3: 383–391. https://doi.org/10.3724/SP.J.1041.2019.00383. [Article in Chinese.].

Xiao, H., X.Li, S. Cheng, and X. Chen. 2026. "Current Status and Prospects of Chinese and Foreign Research on Artificial Intelligence Literacy: Based on a Systematic Literature Review." *Library Development* 3: 155–165. https://doi.org/10.19764/j.cnki.tsgjs.20251841. [Article in Chinese.].

Xu, Z., W. Qu, and J. Xu. 2026. "Ethical Dilemmas and Resolutions in Artificial Intelligence-Empowered Medical Education." *Chinese Medical Ethics* 39, no. 3: 320–327. [Article in Chinese].

Ye, L., W. Zhou, A. Zhang, Q. Zhang, and H. Zhang. 2025. "Comparative Research on Artificial Intelligence Literacy Frameworks." *Library and Information Service* 69, no. 21: 142–153. https://doi.org/10.13266/j.issn.0252-3116.2025.21.012. [Article in Chinese.].

Yu, T., J. Dai, X. Chen, and C. Wang. 2026. "To Use or Not to Use? Generative AI Adoption in Chinese Business Schools." *International Journal of Management Education* 24, no. 1: 101323. https://doi.org/10.1016/j.ijme.2025.101323.

Zhang, S., P. Ganapathy Prasad, and N. L. Schroeder. 2025. "Learning About AI: A Systematic Review of Reviews on AI Literacy." *Journal of Educational Computing Research* 63, no. 5: 1292–1322. https://doi.org/10.1177/07356331251342081.

Zhao, J., M. Ni, and Q. Zhang. 2024. "AIGC Reconfiguring Graduate Student Academic Practice: Study on Factors Influencing Continuous Usage Intention." *Journal of Modern Information* 44, no. 7: 34–46 [Article in Chinese].

Zhao, X., J. G. Lynch Jr., and Q. Chen. 2010. "Reconsidering Baron and Kenny: Myths and Truths About Mediation Analysis." *Journal of Consumer Research* 37, no. 2: 197–206. https://doi.org/10.1086/651257.

Zhao, Y., A. M. Pinto Llorente, and M. C. Sánchez Gómez. 2021. "Digital Competence in Higher Education Research: A Systematic Literature Review." *Computers & Education* 168: 104212. https://doi.org/10.1016/j.compedu.2021.104212.

Ziv, Y., and B. S. Hadad. 2021. "Understanding the Mental Roots of Social Perceptions and Behaviors: An Integrated Information-Processing Perspective." *Heliyon* 7, no. 2: e06168. https://doi.org/10.1016/j.heliyon.2021.e06168.

14653435, 2026, 4, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/ejed.70940, Wiley Online Library on [25/11/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License