Environment and Social Psychology (2025) Volume 10 Issue 3 ISSN: 2424-8975 (O)
doi: 10.59429/esp.v10i3.3551 2424-7979 (P)

RESEARCH ARTICLE

Exploring factors influencing AI-powered E-learning system adoption intention: An empirical study on mediation and moderation effects

Jiyun Chen*, TsangKai Chang

International College, Krirk University, Bangkok, 10220, Thailand

*** Corresponding author:** Jiyun Chen, 459544079@qq.com

ABSTRACT

The prevalence of artificial intelligence (AI) technology in modern society has profoundly changed traditional communication and learning methods. As the application of AI technology in e-learning systems becomes increasingly pervasive, there is an urgent need for research on issues related to the behavioral intention of AI-powered e-learning systems. This study employs an integrated framework combining Innovation Diffusion Theory (IDT), the Technology Acceptance Model (TAM), and self-efficacy theory to analyze factors that empirically examine factors influencing college students' behavioral intentions in e-learning. It identifies the mediating mechanism underlying the relationship between adoption intentions and its antecedents and examines the moderating effect of self-efficacy. A purposive questionnaire was distributed online among college students. A total of 298 responses were drawn. A quantitative survey methodology included Chi-square analysis, Confirmatory Factor Analysis, and Structural Equation Modeling. The results show that college students' adoption intention determinants are AI-powered e-learning system traits (relative advantage, complexity, observability) and satisfaction. Furthermore, the impacts of AI-powered e-learning system traits on adoption intention are mediated by satisfaction. Self-efficacy positively moderates the impact of innovation traits on adoption intention. The discussion and implications present theoretical advancements in elucidating the mechanism of adoption intention and putting forward instructive recommendations for improving the adoption intention of technology-driven innovations in the digitalized education era.

Keywords: AI; e-learning system; adoption intention; IDT; TAM

1. Introduction

The emergence and prevalence of artificial intelligence (AI) technologies have profoundly changed industries in different fields, such as the finance [1–3], the healthcare industry [4], government management [5], and manufacturing industry [6], and there is no exception in the higher education domain. Internet-powered learning and teaching tools, such as Massive Open Online Courses and distance learning platforms (e.g., Blackboard, Moodle, Coursera, and edX), have revolutionized education and teaching methodologies and also obtained global success, mainly due to global events that need remote education solutions [7,8]. Various mobile learning terminals with massive digital learning resources have brought a new experience to learners, especially college [9,10]. Artificial intelligence has recently emerged as a booster in education, changing

ARTICLE INFO
Received: 20 February 2025 | Accepted: 15 March 2025 | Available online: 25 March 2025

CITATION
Chen JY, Chang TK. Exploring factors influencing AI-powered E-learning system adoption intention: An empirical study on mediation and moderation effects. *Environment and Social Psychology* 2025; 10(3): 3551. doi:10.59429/esp.v10i3.3551

traditional paradigms. As information technology advances quickly [11]. AI-powered educational solutions enhance access for students worldwide, customized support, and perfect learning experiences. Improvements in generative AI tools, such as ChatGPT for interactive content creation, emphasize tailoring educational experiences to meet each student's personalized needs and abilities [12]. Similarly, in two workshops, Cloud-based Smart Technologies for Open Education Workshop (CSTOE 2022) and Workshop on Computer Simulation in Education (CoSinE 2022), Papadakis et al. [13] illustrated that computer simulations and cloud-based technologies advance STEM (Science, Technology, Engineering, and Mathematics) education and personalized learning. Furthermore, AI-powered e-learning systems can encourage flexibility in learning paths [14], allowing students to progress at their own pace and engage with material that resonates with their learning styles. These improvements drive e-learning into a new era of hyper-personalization, real-time feedback, and high efficiency [15].

1.1. Research gap

Existing studies on AI-powered e-learning adoption often focus on isolated theoretical constructs [16,17], neglecting the interaction between innovation attributes, affective evaluations, and individual differences. For instance, while IDT emphasizes the role of relative advantage, complexity, and observability [18,19], limited research explores how these factors affect satisfaction, which is also a critical affective mediator, or how self-efficacy moderates user responses to technical innovations. This fragmentation limits our understanding of the holistic mechanisms driving AI technology acceptance, particularly among university students who represent a key demographic in digital [20,21]. Moreover, existing studies have examined the adoption mechanism of innovation technology in classic theories or models. However, higher education institutions face increased demands, which play an important role in reducing poverty and ensuring equitable education, as projected by Sustainable Development Goal 4 (SDG4) for Quality Education [22]. Higher education institutions should constantly update their understanding of how students consider and respond and finally benefit from this fast-changing and digitalized environment. The necessity of an updated evaluation of how cognitive, affective, and contextual factors collectively shape adoption behaviors in AI-powered learning contexts cannot be overstated.

1.2. Objectives

This research aims to develop AI-powered adoption intention models to enhance personalized learning, strengthen student engagement through adaptive content delivery, and optimize student performance prediction. Firstly, this study addresses these gaps by proposing an integrated theoretical framework synthesizing IDT, TAM, and self-efficacy theory in the thriving AI-powered education industry [23,24]. Secondly, it seeks to comprehensively assess the relationships and predictive associations between innovation attributes (relative advantage, complexity, observability) and adoption intention influence mechanism and multiple indices of different pathways in Chinese college students [25]. Moreover, it aims to validate the buffering effect, the mediation effect of satisfaction between AI-powered e-learning system innovation traits, and the outcome variable adoption intention. Lastly, it also explores the moderating role of one psychological, perceptual factor, the students' self-efficacy, in shaping the relationship between AI-powered e-learning system traits and satisfaction. Thus, it can identify the relative importance of AI-driven factors compared to traditional e-learning adoption drivers.

1.3. Contribution

This study contributes to the literature on innovation technology adoption in the following ways. It introduces a novel framework that combines Innovation Diffusion Theory (IDT) [26], the Technology Acceptance Model (TAM) [27], and self-efficacy theory [28], to address academic gaps in understanding AI-powered e-learning system adoption intention. Theoretically, it adds observability to include transparency in AI-driven analytics and complexity to represent skill-dependent interactions, thereby contextualizing classical constructs inside AI-specific difficulties. Unlike earlier research, it especially puts self-efficacy as a moderator of the direct pathway between AI-powered e-learning system traits (independent variables) and adoption intention (dependent variables), independent of mediation paths, indicating its function in buffering the immediate impact of technical barriers. Methodologically, the framework creates and proves relationships among innovation traits (relative advantage, complexity, observability), affective mediators (satisfaction), and behavioral intention consequences, bridging disparate ideas. Practically, the results provide actionable strategies, such as simplifying interfaces for low self-efficacy users and improving observability through real-time feedback to support fair AI adoption. This work promotes theory and practice in sustainable artificial intelligence integration for world education by aggregating technological, cognitive, and affective aspects.

1.4. Research flow

The rest of this study is structured as follows. First, the literature review focuses on fundamental theories and models. Next, the model is presented with five hypotheses and an explanation of the instrument design, sampling process, and the demographic information analysis. The following sections focus on the data quality, reliability, and validity of the model, the goodness-of-fit indices of measurement and structural models, and highlight the results of hypotheses testing. The following section illustrates the mediating effect of satisfaction and the moderating effect of self-efficacy. The last four sections discuss the results and present this study's theoretical and practical contributions, conclusion, limitations, and recommendations.

2. Literature review

2.1. Innovation Diffusion Theory (IDT)

Rogers [29] introduced the diffusion of innovations theory, which explains that innovation diffusion is influenced by five characteristics: relative advantage, compatibility, complexity, trialability, and observability. After that, scholars conducted further research based on this foundation. For example, Moore and Benbasat [26] further redefined the dimension of observability into "visibility" and "result demonstrability". Al-Rahmi et al. [30] investigated factors affecting students' intentions to use a massive open online course system. However, among all constructs, their utilization frequency varies. Scholars prioritize relative advantage and complexity as the most empirically and widely applied dimensions in related research [31-33]. Additionally, although the impact of observability has received less empirical attention than the previous two constructs, existing literature has theoretically justified its high potential relevance [29, 34, 35]. Therefore, this study empirically investigates this factor to enrich the extant literature through validation.

2.2. TAM

The Technology Acceptance Model (TAM) proposed by Davis [36] was based on the Theory of Reasoned Action [37]. Researchers have focused on TAM to explore mechanisms toward new technology usage or intention to use at individual levels [2,38,39]. TAM considered perceived usefulness and ease of use as two major decisive factors affecting users' attitudes and behaviors [27]. Moreover, users' attitudes and behavioral intentions are two constructs that are influenced by antecedent variables and mediate these predictors' effects on subsequent behavioral outcomes, such as actual system usage.

Satisfaction, as a measurement of positive affection [40], serves as the operational manifestation of the original attitudinal construct in TAM, thereby equating it with the notion of attitude in the context of technology adoption. Satisfaction is widely considered an essential variable in imposing high effects on users' future attitudes and behaviors around specific services, products, or experiences [41]. Raneem Rashad Saqr et al. [7], investigated an extended TAM for AI-driven e-learning platforms. They found that learner satisfaction is a key factor in system success, as satisfied learners are likelier to use the system.

Adoption intention or behavioral intention in the initial TAM refers to a user's willingness or likelihood to adopt and use a particular technology, which serves as a key predictor of actual system usage [42]. It represents the strength of an individual's intention to act on a specific behavior (in this case, adopt an AI-powered e-learning system), which is expected to improve their learning performance. As many previous studies have proven, adoption intention is a key factor that can measure or determine the likelihood of success of a system [38,43,44]. For instance, in their study on the adoption of intelligence applications for academic purposes, Konstantinos Lavidas et al. [45] defined behavioral intention as the degree of tendency to use AI applications in the European Union context.

2.3. Self-efficacy

Self-efficacy refers to as an individual's belief in their capacity to carry out specific behaviors to achieve desired learning outcomes [29]. In this context, self-efficacy can be interpreted as the students' judgment of their capability to use AI tools, such as large language models and AIGC tools, to achieve defined learning goals, confidence they have in technical operation, ability to cope with task challenges and belief in achieving human-AI cooperation. Self-efficacy affects effort, task selection, task confidence, and final success. It also affects academic desires, learning, and success [46]. According to Bandura [47], students' self-efficacy directly and indirectly affects insistence to learning task completion in the learning process consequently, students with high self-efficacy in e-learning are typically more active and achieve better academically.

3. Research hypotheses and framework

3.1. Research hypotheses

3.1.1. AI-powered e-learning system traits and satisfaction

Numerous studies have applied key constructs of the IDT theory to examine the intention to accept and the actual use of high-tech products/services in similar research contexts. Alamri [48] conducted a study regarding underlying mechanisms through which key dimensions of IDT affect the adoption of massive open online courses. Taghizadeh et al. [49] confirmed that three key predictors from IDT (relative advantage, compatibility, and complexity) can positively affect students' satisfaction with online learning. Similarly, Peng et al. [50] emphasized that technology should be user-friendly and not very complex to increase the chance of usage successfully. Mohammadi [9] empirically proved that ease of use significantly influences users' satisfaction in a study regarding m-learning. Thus, the following hypothesis is proposed:

H1: The combined effect of AI-powered e-learning system traits (AES) — including relative advantage (RA), complexity (COM), and observability (OBS) — positively enhances satisfaction.

3.1.2. Satisfaction and adoption intention

Satisfaction is an affective and cognitive evaluation reflecting an individual's perceived fulfillment of expectations or goals about a specific experience. In this context, satisfaction can be defined as students' affective and cognitive evaluation reflecting the perceived usage of e-learning [49] Many studies have found that satisfaction positively affects the intention to adopt technology-powered services. For instance, Mkhize et al. [32] uncovered that positive attitude, such as users' satisfaction, can improve the willingness to use learning management systems (LMS). Similarly, Al-Rahmi, Yahaya, Alamri, et al. [44] empirically proved that a positive attitude can significantly enhance students' behavioral intention toward utilizing Massive Open Online Course (MOOC) systems. Thus, the following hypothesis is proposed:

H2: Satisfaction positively affects adoption intention.

3.1.3. AI-powered e-learning system traits and adoption intention

Al-Rahmi, Yahaya, Alamri, et al. [44] demonstrated that IDT constructs, including RA, COM, and OBS, directly influenced students' behavioral intentions. These effects persisted when combined with other factors affecting behavioral intentions to adopt e-learning systems. Kim et al. [51] examined the factors affecting university students' resistance and intention to use of mobile learning with innovation diffusion theory (IDT). The results indicated that relative advantage being the most significant. Similarly, in a system review paper, Kumar and Chand [52] identified major predictor variables, including perceived usefulness, ease of use, and learnability, which can be considered as relative advantage, complexity, and observability constructs in this study. Thus, the following hypothesis is proposed:

H3: AI-powered e-learning system traits, specifically relative advantage, complexity, and observability, together positively affect adoption intention of the system.

3.1.4. Mediation effect of satisfaction continuance intention

Many classical theories posit satisfaction or analogous attitudinal factors as mediating variables that transmit the effects of users' technology/system experiences to continued usage intention. In TAM, a positive attitude can convey the effects of antecedent variables: perceived ease of use and usefulness [36]. In the Expectation-Confirmation Model (ECM), Bhattacherjee [53], satisfaction mediates the relationship between confirmation and continuance intention. In the D&M Model, which is also known as the Information Systems Success Model, Delone and McLean [54] indicated that system/information quality exerts its effects on behavioral outcomes through the mediating effect of satisfaction. Thus, the following hypothesis is proposed:

H4: Satisfaction mediates the relationship between AI-powered e-learning system traits and adoption intention.

3.1.5. Moderation effect of self-efficacy

The premise for testing a moderating effect is that the moderator variable interacts with the independent variable, thereby influencing the strength or direction of its relationship with the dependent variable. Bassi et al. [55] found that learners with high self-efficacy display stronger technological adaptability, showing higher successful possibility compared to low-level one. Jan [41] also demonstrated that students with higher academic self-efficacy in their ability to finish online tasks are more engaged with learning and more willing to complete an online course. In addition, Lee and Lee [56] discussed that system factors and self-efficacy contribute to greater e-learning effectiveness and that learners' computer self-efficacy moderates the relationship between system functionality and training effectiveness. Thus, the following hypothesis is proposed:

H5: Self-efficacy moderates the relationship between AI-powered e-learning system traits and adoption intention.

3.2. Framework

Drawing from the literature review and hypotheses, **Figure 1** presents the research model.

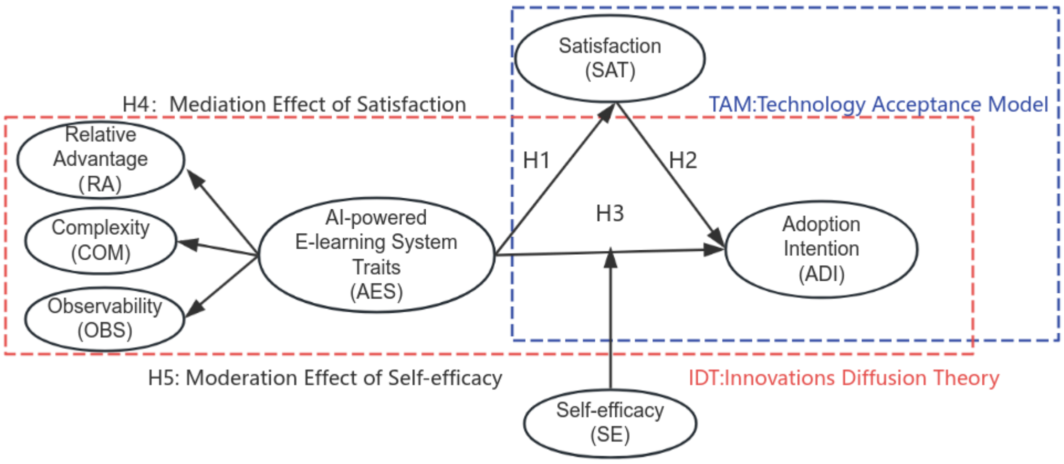

Figure 1. Research model and hypotheses.

4. Research methodology

4.1. Instrument development

This study conducted a quantitative survey using an anonymous, structured questionnaire concentrating on college students utilizing AI-powered technology in their e-learning activities. The measurement items in this research were drawn up from previous literature and were deemed to be considered to comprehensively represent various aspects of the constructs under investigation [2]. As a supplementary step, we followed expert review methodology outlined in prior studies [2,57], conducted an expert review process. Researchers consulted experts in higher education domain in their institution; to evaluate the validity of the selected measurement items to ensure they accurately reflect each construct. The questionnaire was designed in Chinese, and then translated into English. In the pilot testing stage, a scale containing seven variables with 26 items was adopted, anchored on a five-point Likert scale (1 = totally disagree to 5 = totally agree) [58]. The data obtained from the pilot were examined for scale reliability and validity. Most of the indicators had acceptable Cronbach's alpha coefficients that exceeded the 0.700 standard [59]. Three questionnaire items were removed during scale purification because they either had insufficient factor loadings or fell below the minimum criteria.

The final questionnaire was divided into two sections, where the first section focused on the measurement items of one second-order and six first-order latent constructs, together with 23 questionnaire items **(Appendix A)**. The second focuses on the socio-demographic information of the respondents, such as gender, education, academic major, and the usage duration of AI-powered e-learning. The indicators for RA, COM, and OBS were adapted from [26,35,54,60,].The indicators for adoption intention and satisfaction were adapted from [26,35,61,62]. The indicators for self-efficacy were drawn from [63,64].

4.2. Data collection and respondents

The research employed a purposive sampling method in the formal testing stage. The study consisted of distributing an online questionnaire that collected mainly quantitative data through a cloud-powered questionnaire website, similar to Google Form [65,66] among college students. Participants were initially screened powered on a qualification criterion evaluating prior experience with AI-powered e-learning systems, allowing only affirmative respondents to advance to the main study. To maintain anonymity, the introduction delineated the sole academic aim of this study, and all data was gathered anonymously, with no personal, identifiable, or sensitive information documented.

The formal survey was administered to the students online between February and March 2025. According to Hair et al. [59], the minimum sample size for models containing with 7 constructs or less is 150. Bentler and Chou [66] also indicate that when analyzing multi-construct distributions, researchers should adhere to a minimum observation-to-parameter ratio of 10:1. After eliminating the outliers, a total of 298 valid questionnaires were received. Thus, the sample size was not an issue.

4.2.1. Demographic information

The sample demographics are as follows: 61.1% were male, 38.9% were female. In terms of education, 18.5% were in their first year of study, while 25.2% were undergraduate students in their second year of study; and 31.9% and 24.5% were in the third and final years of study, respectively. For academic majors, 39.9% were in Liberal Arts or Humanities, as well as 60.1% in Natural Science or Science. For system usage or years of experience with AI-powered e-learning systems, 39.9% reported usage duration between 3–4 years, and 32.6% had 5–6 years of experience. However, early-stage users with 1–2 years of experience comprised 16.1% of respondents. Long-term adopters were only 7.0%, reported 7–8 years of usage, and the rest 4.4% of respondents selected the “Others” category. **(Table 1).**

Table 1. Demographic statistics of the respondents.

Response variable	Options	Frequency (n)	Percentage (%)
Gender	Male	182	61.1%
	Female	116	38.9%
Education	1st-year undergraduate	55	18.5%
	2nd-year undergraduate	75	25.2%
	3rd-year undergraduate	95	31.9%
	Final year undergraduate	73	24.5%
Academic majors	Liberal Arts/Humanities	119	39.9%
	Natural Science/Science	179	60.1%
Years of usage	1-2 years	48	16.1%
	3-4 years	119	39.9%
	5-6 years	97	32.6%
	7-8 years	21	7.0%
	Others	13	4.4%

4.2.2. Chi-square analysis

Table 2. Chi-square analysis.

	Years of Usage						
	1-2 years (%)	**3-4 years (%)**	**5-6 years (%)**	**7-8 years (%)**	**Others (%)**	**χ^{2*}**	**p**
Gender							
Male	28(15.38)	64(35.16)	67(36.81)	15(8.24)	8(4.40)	6.372	0.173
Female	20(17.24)	55(47.41)	30(25.86)	6(5.17)	5(4.31)		
Education							
1st-year undergraduate	10(18.18)	22(40.00)	18(32.73)	3(5.45)	2(3.64)	5.636	0.933

	Years of Usage						
	1-2 years (%)	**3-4 years (%)**	**5-6 years (%)**	**7-8 years (%)**	**Others (%)**	**χ^2***	**p**
2nd-year undergraduate	13(17.33)	33(44.00)	22(29.33)	4(5.33)	3(4.00)		
3rd-year undergraduate	11(11.58)	35(36.84)	34(35.79)	10(10.53)	5(5.26)		
Final year undergraduate	14(19.18)	29(39.73)	23(31.51)	4(5.48)	3(4.11)		
Academic majors							
Liberal Arts/Humanities	24(20.17)	38(31.93)	38(31.93)	13(10.92)	6(5.04)	9.663	0.047*
Natural Science/Science	24(13.41)	81(45.25)	59(32.96)	8(4.47)	7(3.91)		

Table 2. (*Continued*)

* $p < 0.05$

A chi-square test [67] examined possible relationships between years of e-learning system use and demographic variables, including gender, education level, and academic discipline. The findings **(Table 2)** systematically show the statistical results assessing the difference between duration of usage and categorical characteristics within various demographic groups, such as gender, academic background, and majors.

The results of the Chi-square analysis revealed there were no statistically significant associations between AI-powered e-learning use duration and gender (χ^2=6.372, p=0.173) or academic year (χ^2=5.636, p=0.933), indicating consistent distribution patterns across these demographic groups. However, significant disciplinary differences emerged (χ^2=9.663, p=0.047<0.05), with humanities students demonstrating higher 1–2-year adoption rates (20.17% vs 13.41% in science fields), while science disciplines showed greater prevalence of 3–4-year usage (45.25% vs 31.93% in humanities).

4.3. Preliminary data analysis and procedure

4.3.1. Preliminary data analysis

Normality and multicollinearity analyses were conducted to reduce systematic errors [58]. Univariate skewness and kurtosis of each item ranged between -2 and +2, confirming the normal distribution of the data. Moreover, the variance inflation factor (VIF) was used to evaluate multicollinearity among variables, with values that should be less than 3. This investigation revealed no multicollinearity issues with VIF values ranging from 1.733 to 2.786.

4.3.2. Procedure and statistical methods

The study analyzed demographic data and measurement models utilizing frequency and Chi-square analyses, followed by Exploratory Factor Analysis and Confirmatory Factor Analysis to test the measurement model. Structural Equation Modeling was also applied to testing structural models and hypotheses. Following Preacher and Hayes [68] the bias-corrected bootstrap was performed to analyze mediating and moderating effects with PROCESS software.

5. Results

5.1. Measurement model

5.1.1. Reliability and convergent validity

Through EFA and CFA, the internal reliability, and convergent and discriminant validity of the measurement model can be obtained. The results are shown in **Appendix B.**

Firstly, the internal reliability was evaluated through Cronbach's α, factor loading, and Composite Reliability (CR) values. The Cronbach's α values ranged between 0.817 and 0.871, exceeding the cut-off value 0.70 [69]. Almost all factor loading values were ≥ 0.7, suggesting acceptable indicator reliability [60]. All values met the minimum requirements with CR ≥ 0.7 [70]. Secondly, Kaiser-Meyer-Olkin (KMO) was 0.893, exceeding the threshold value of 0.80, and Bartlett's Test of Sphericity was statistically significant, which validates the appropriateness of factor analysis[71]. Thirdly, Principal Component Analysis was applied to choose the attributes, with Parameter Eigenvalues ≥ 1 in the analytical model. Six factors were extracted that provided the best summary of information, accounting for 70.48% of the cumulative variance. Fourthly, Average Variance Extracted (AVE) was applied to examine the convergent validity, and the value of every construct was calculated above 0.50, which ranged from 0.529 to 0.693, indicating acceptable validity [72].

5.1.2. Discriminant validity

Discriminant validity was evaluated by checking the following criteria: 1) Cross-loading [70] where each indicator loads highest on the construct it is associated with, and 2) Fornell-Larcker criterion [72]. The retrieved cross-loadings values of each indicator show that each indicator loaded highest on the construct associated with **Appendix C**. As Fornell and Larcker[72]recommended, the correlations between any two shared items within a construct should be lower than the square root of the AVE. As **Table 3** shows, all diagonal values exceeded the inter-construct correlations. Thus, the instrument had satisfactory construct validity.

Table 3. Discriminant validity.

Construct	Relative Advantage	Complexity	Observability	Adoption Intention	Satisfaction	Self-efficacy
Relative Advantage	**0.753**					
Complexity	0.575	**0.769**				
Observability	0.662	0.608	**0.727**			
Adoption Intention	0.327	0.293	0.295	**0.785**		
Satisfaction	0.370	0.464	0.392	0.397	**0.832**	
Self-efficacy	0.369	0.364	0.367	0.372	0.630	**0.758**

Table 4. Goodness-of-fit indices of the single- and multi-factor model.

Model	χ^2/d.f.*	GFI*	RMSEA*	CFI*	AGFI*	TLI*	$\Delta\chi^2$	Δ d.f.	*P*
Fit criteria	<3	>0.9	<0.08	>0.9	>0.8	>0.9			
Single-factor model	7.743	0.577	0.151	0.527	0.493	0.479	1500.63	9	0.000
Multi-factor model	1.268	0.925	0.03	0.982	0.906	0.979			

** χ2/d.f.= Chi-square divided by degree of freedom. GFI = goodness-of-fit index. RMSEA = root mean square error of approximation. CFI = comparative fit index. AGFI = adjusted goodness-of-fit index.TLI=Tucker-Lewis Index*

5.1.3. Common method bias analysis

As with all self-reported data, there is a possibility for common method biases resulting from multiple sources [73]. Both procedural and statistical techniques can be used to manage common method variance [74], therefore avoiding this issue. Two rigorous techniques were conducted to apply CMB analysis.

Firstly, Harman's single-factor test was conducted with an unrotated factor solution, as suggested by [73]. All items of the constructs were entered into a factor analysis. The first principal component factor revealed an explained variance of 32.9%, below the threshold of 50%—an acceptable maximum threshold of total variance [72]. Secondly, it is an effective method to compare the goodness-of-fit indices of the CFA models between the single-factor model and the multi-factor model [74,75]. As shown in **Table 4**, the results indicated that the single-factor model exhibited well worse goodness-of-fit indices than did the multi-factor model ($\Delta \chi^2 = 1500.63$, Δ d.f. = 9, $p < 0.001$). The CMB problem in this study was not an issue.

5.2. Structural model

5.2.1. Goodness-of-fit analysis

Table 5. Summary of Goodness-of-fit indices for measurement and structural model.

Indicator	Criteria	Measurement model	Structural model	Result	References
χ2/d.f.	<3	1.268	1.193	good	Bollen [76]; Hu and Bentler [77]; Doll et al. [78]
GFI	>0.9	0.925	0.942	good	
RMSEA	<0.08	0.030	0.026	good	Hu and Bentler [77]
CFI	>0.9	0.982	0.988	good	Fan et al. [79]
AGFI	>0.9	0.906	0.925	good	McDonald and Moon-Ho Ringo Ho [80]
TLI	>0.9	0.979	0.988	good	Bentler and Bonett [81]

As seen in **Table 5**, the goodness-of-fit indices for both measurement and structural models meet the minimum requirements.

5.2.2. Hypotheses testing

The path significance of each hypothesized association and R^2 values were calculated. **Figure 2** and **Table 6** show that AES (which consists of RA, COM, and OBS) and SAT jointly predicted the ADI. Together, these variables explained 20.3% of the variation in ADI and also explained 26.8% of the variance in SAT. Hypotheses 1 to 3 gained empirical support. The strongest relationship emerged in support of H1. AES features had significant effects on SAT ($\beta = 0.517$; T = 6.340; $p < 0.001$). It also had a positive influence on the ADI ($\beta = 0.250$; T = 2.981; $p < 0.05$), thus confirming H3. SAT significantly affected adoption intention as well ($\beta = 0.267$; T = 3.423, $p < 0.001$), thus confirming H2.

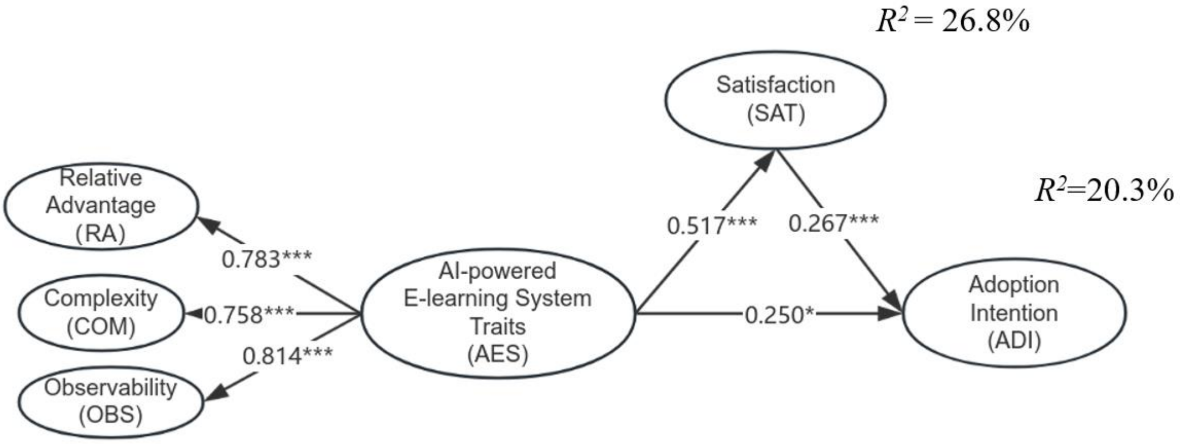

Figure 2. Structural model and path coefficient without moderator.

Table 6. Results of path analysis and hypothesis testing.

Hypotheses	**β**	**T value**	**P value**	**Results**
H1: AES→SAT	0.517***	6.340	< 0.001	Support
H2: SAT→ADI	0.267***	3.423	< 0.001	Support
H3: AES→ADI	0.250*	2.981	0.003	Support
Total, Direct, and Indirect Effects				
	Effects	**SE***	**95% CI***	
Total	0.388***	0.068	[0.329, 0.717]	
Direct	0.250*	0.087	[0.103, 0.568]	
H4: Indirect (AES→SAT→ADI)	0.138***	0.045	[0.076, 0.328]	Support

**p<0.05. ***p <0.001. *SE =Standard errors. CI=confidence intervals*

5.2.3. Mediation analysis

Mediation analysis examines the direct and indirect pathways through which an independent variable affects a dependent variable through mediator variables [82]. In this study, the AES is set as the independent variable X, with ADI serving as the dependent variable Y and SAT setting as the mediating variable M. **Table 6** also presents the direct, indirect, and total effects of AES on ADI through SAT. First, the direct effect of AES on ADI is statistically significant at 0.250. Second, the indirect effect of AES on ADI is also statistically significant at 0.138, which is quantified as the product of path coefficients 0.517 × 0.267. Third, the total effect is 0.388. The 95% confidence intervals from the bootstrap method do not encompass zero for any values, indicating the results' robustness. SAT shows a partial mediating effect between AES and ADI, confirming H4.

5.2.4. Moderation analysis

In this study, SE is positioned as the mediating variable W to moderate the direct effect of AES on ADI [83]. Thus, applying Model 5 in the PROCESS 4.0 in SPSS is more appropriate for testing the relationships among the abovementioned variables [84]. In particular, since the AES dimension is composed of three first-order constructs (RA, COM, and OBS), for better mediation and moderation analyses through applying linear regression in SPSS, all the scores from the original indicators were averaged to make a new composite AES variable. Additionally, each dimension of SE is created by centering meaning, and a composite variable was created for each interaction to avoid issues of multi-collinearity [85].

As in **Table 7** and **Table 8,** the results illustrate that, with a statistically significant change in R^2 (ΔR^2 = 0.025, $p < 0.01$), SE positively moderates the effect between AES and ADI with an interacted coefficient of 0.217 ($p < 0.01$), thereby supporting H5. Further, a simple slope test illustrates the predicted effects of AES on ADI separately for SE at a high, medium, and low level (mean and mean±1SD, respectively) in **Figure 3**. The line representing Low SE is straighten, this shows that at low level of SE, the impact of AES on ADI is weaker in comparison to High SE. At high level of SE, the line tends to be steep. This shows that the increase in AES does lead to similar change in the ADI. In addition, the gap between the lines conditioned at a specific value of AES reflects the differences in ADI resulting from different levels of SE. The progressive widening divergence between SE (low→high) systematically demonstrates the intensified effect of AES on ADI synchronously with the increase of SE. Thus, this confirms the existence of a moderation mechanism.

Table7. Results of moderation analysis.

Antecedents	Consequent		Adoption Intention	
	Satisfaction			
	Coefficients	SE	Coefficients	SE
Constant	3.628***	0.058	2.970***	0.203
AES	0.605***	0.075	0.174*	0.072
Satisfaction			0.147*	0.054
Self-efficacy			0.205**	0.064
AES×Self-efficacy			0.217*	0.071
$R^2(F)$	0.182***(65.928)		0.198***(18.130)	
$\Delta R^2(F)$			0.025**(9.250)	

Table 8. The direct and indirect effects with moderator.

Conditional indirect effects of AES on Adoption Intention through Satisfaction at two different levels of Self-efficacy				
Self-efficacy	**Effects**	**SE**	**LLCI**	**ULCI**
-1SD level - 0.940	- 0.030	0.106	- 0.239	0.179
+1SD level + 0.940	0.377***	0.089	0.202	0.552
Unconditional direct effect of AES on Adoption Intention				
Direct (Self-efficacy at mean level= 0)	0.174*	0.072	0.032	0.315
Indirect	0.089*	0.036	0.021	0.164
Index of interaction	0.217**	0.071	0.076	0.357

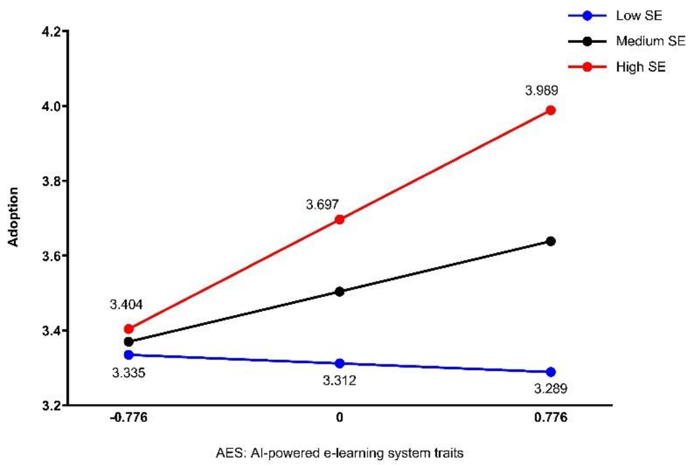

Figure 3. A visualization of moderation effect.

6. Discussion

This study systematically elucidates the viral mechanisms underlying the intention to adopt AES by integrating the IDT and the TAM from the perspective of university students. Path analysis reveals that all antecedent variables, including system relative advantage, complexity, observability of results, users' satisfaction, and self-efficacy, have a statistically significant effect on AES adoption intention with an R-square of 20.3% and an R-square of 26.8% for satisfaction. Overall, the results show that the integrated model can explain a relatively moderate proportion of variation in intention to use AES. These findings are consistent with the IDT and the TAM propositions, which posit that technical features and users' psychological reactions collectively drive adoption intentions [27,36,86]. However, the findings also indicate that not all variables equally contribute to improving students' adoption intention.

Hypotheses H1, H2, and H3 all gained empirical support. The findings exhibit consistency with previous literature. Al-Fraihat et al. [2] showed that technical system quality, highly similar to AI-powered e-learning system quality, was related to ease of use, usefulness of the system, and users' satisfaction or system reliability. Also, the relationships between ease of use and usefulness of the system to users' satisfaction were significantly positive. Zhang and Gu [87] indicated that relative technical advantages could contribute to the innovation diffusion of AI in education. Higher quality of AI-powered e-learning system traits leads to higher behavioral intention. The success of e-learning strategies is attributed to the higher AES, which drives students to engage actively in tailored learning and maximizes academic efficiency using adaptive learning. AES traits affect satisfaction (β = 0.517, p <.001), showing that the antecedents of RA, COM, and OBS directly improve users' experience and psychological emotions. This finding supports the classical proposition in technology adoption research that "system quality determines user attitudes" [88-90].

H4 gained empirical support in mediation analysis. Technical utilities are shown as the main drivers of emotional involvement, in line with [7]. Then, SAT further significantly impacts ADI, showing a partial mediation effect. Satisfaction mediates the relationship between AES and ADI, which is consistent with results by [91]. Their research also found that learner satisfaction is vital as a mediating variable linking technological features to adoption intention. The result implies that affective experiences do not solely drive adoption but also depend on the technical quality of the system. This dual process captures the Cognitive-Affective-Behavioral framework, in which technical features concurrently affect decisions using rational evaluation (cognition) and emotional involvement (affect). Additionally, echoing Bhattacharjee's [92] expectation-confirmation theory, functional optimization of technology-driven systems may not be enough to transfer into usage intention. Positive adoption intention is predicted by the synergy between technology convenience and user delight [93].

H5 was supported since the interaction effect coefficient of AES and SE is statistically significant, with a beta value of 0.217. In other words, individuals with high levels of SE individuals show stronger adoption intentions using advanced AES capabilities. In contrast, users with low levels of SE may limit themselves to basic features. This differential adaptation is statistically validated in **Table 8**. It demonstrates a non-significant indirect effect coefficient at lower SE levels since its confidence intervals include 0, suggesting attenuated technological engagement capacities among less confident users. This stratification reflects differences in student technical competencies. Hence, distinct assistance measures are needed depending on disciplinary backgrounds and skill levels. Furthermore, although SE increases AES value perception, its limited explanatory power (ΔR^2=2.5%) suggests that other determinants may also interact with SE, affecting the intention of AI-powered e-learning systems, such as assistance from educators and institutions.

The findings of the Chi-square analysis revealed no statistically significant links between gender or academic year and the length of usage with the AI-powered e-learning system. Still, academic discipline was considered as a determinant of usage patterns. Students enrolled in natural science or scientific courses displayed longer system involvement times than those in liberal arts or humanities courses. These findings suggest that disciplinary differences in learning objectives, technological familiarity, or curriculum structures influence adoption behaviors [2]. As explained in Academic Habitus Theory, which was developed by [94], it clarifies how discipline-specific practices could affect digital learning behavior. Whereas humanities courses may show episodic use patterns matched with modular programs and seminar-powered pedagogy, natural sciences majors develop sustained technological engagement through spiral courses requiring continuous digital support [27]. With natural sciences developing software-driven communities against humanities' digital tool use, this dichotomy reflects structural inequalities in knowledge systems and technological dependence levels[95].

7. Implications

7.1. Academic contributions

By integrating focal predictors from IDT (specifically relative advantage, complexity, and observability) with pivotal constructs of the TAM, namely perceived satisfaction and behavioral intention, this study constructs a multi-dimensional, comprehensive model that can help evaluate the mechanism influencing college students' AI-powered e-learning system adoption intention in the context of the digitally-driven intelligent education sector.

Contrary to conventional adoption models, empirical frameworks have predominantly operationalized self-efficacy as an independent variable exerting direct or indirect effects on users' subsequent behavioral outcomes, which aligns with Bandura's [28] theory and Lee et al.s' [56] findings regarding technology adoption. In this study, self-efficacy not only significantly positively predicted the adoption intention (β = 0.205, T= 3.214, p < .001), but combined with relative advantage, complexity, and observability, it also presented a positive effect on the adoption intention with interaction effects (β = 0.217, T=3.041, p < .001). Additionally, while IDT focuses on applying relative advantage, complexity, and observability as stable predictors, this research reveals the plasticity of self-efficacy to amplify adoption drivers. All the results could be explained by the possibility that students with high self-efficacy will be more confident and skilled in using high technology-related learning systems. Students with high self-efficacy show sustained engagement through delighted learning experiences, which also reinforces their intention to persist with AI-powered learning systems. In addition, they are more confident that they can solve the challenges in use, so students are willing to participate more actively in research [96]. As a result, there would be more opportunities for students to accomplish their learning objectives with digitalized learning systems [91].

7.2. Practical implications

This research integrated the IDT and the TAM, reveals that enhancing the core attributes, including relative advantages (AI-driven personalized feedback), reducing complexity (intuitive interfaces), and amplifying observability (AI-enhanced grading system), can directly strengthen users' satisfaction, which in turn contribute to adoption intention. The findings offer valuable strategies for multiple stakeholders in AI-powered e-learning systems, such as educational institutions, educators, and system designers.

First, since the targeted respondents are university students, also known as digital natives [97], they can rapidly master new technologies to enhance technical competencies with minimal guidance with AI functionalities, optimizing the efficacy of AI-powered systems through informed utilization [98]. Creating AI-powered learning result reports helps to magnify the observability concept and encourages peer imitation in learning environments. Moreover, letting students evaluate difficulties with AI technologies under appropriate teacher direction can help to lower tasks' complexity.

Second, given that self-efficacy moderates adoption, universities and educators should use pedagogically efficient and low-complexity platforms, thus providing low-barrier AI collaborative projects and instantaneous positive feedback to encourage students' confidence and motivation to continue using the system [99]. Additionally, they should be proficient system users and be opinion leaders modeling platforms to bridge technology-classroom gaps and using self-efficacy interventions, such as teacher guidance and peer mentoring projects, to empower students, thus leveraging their moderating role in adoption [100]. In other words, educational institutions and educators should actively involve students and offer continuous direction to maximize adoption, acting as facilitators of AI-powered learning [101]. Mentioned in a study by Papadakis et al. [13], educators utilized the CNN-based (Convolutional Neural Network) speech defect recognition tool to obtain instant feedback, which enables educators to adjust interventions, thereby fostering learners' trust in AI-powered learning systems.

Third, for e-learning system designers, optimizing the IDT core attributes, thus relative advantage, compatibility, and observability are critical. The significant effect of features (RA, COM, OBS) on satisfaction underscores the need to minimize complexity through fluid and collaborative operating interfaces while amplifying benefits. Consequently, improved system functions can be a booster, improving student engagement and academic productivity, with utility-driven features like AI error diagnostics (RA) to meet fundamental user needs, interactivity enhancements like virtual collaborative spaces (COM) to encourage engagement and intuitive visualization tools (OBS) like personalized learning dashboards to progress tracking [102]. At the same time, the proposed multidimensional learning dashboard (OBS) transforms progress display by layered data representations. The combination of real-time whiteboard comments with 3D model interactivity offers a dynamic collaboration environment. The resulting ecosystem shows adaptive growth using self-optimizing designs that match the interface, promoting sustainable digital literacy progress in changing contexts [103].

8. Conclusion

Consistent with previous studies applying IDT or TAM or both regarding the adoption of new technologies, the results of this study respond to the call for in-depth exploration in digital information technology related education domain, since the application of AI technology in e-learning system has become increasingly pervasive. This study confirms the combination of IDT and TAM frameworks, thus showing that AI-powered e-learning adoption intention is driven by technological attributes (AES) and psychological mechanisms (satisfaction, self-efficacy). With AES features showing a strong direct effect on satisfaction (β = 0.517***, T = 6.340) and an indirect effect via satisfaction (β = 0.138***, [0.076, 0.328]), the model explains 20.3% of adoption variance. It is important to emphasize that, although the predicting power of the effects is relatively limited, the overall model remains statistically valid. According to previous literature, additional potential factors may influence AI adoption intention in academic background. For example, Konstantinos Lavidas et al. [45] proved that expected performance, habit, and enjoyment positively influence acceptance intention. These variables will be applied to future studies to increase the predictive power of the model. Self-efficacy, as the moderating role, with interaction effect value (β = 0.217*, [0.076,0.357]), highlights its dual function as a driver and amplifier of adoption, particularly in contexts where users possess high system compatibility and observability. These results underscore the necessity of aligning AI system design with IDT principles while addressing user-orientated cognition and behaviors.

9. Limitations and future research

First, as this study investigated participants in a college setting, the results cannot be easily generalized across other categories; thus, replicating the study in diverse cultural and institutional settings can be better. Second, this model did not fully capture the determinants of individual factors. Thus, there is still room to investigate more qualified factors. Further analysis can extend more determinants to obtain complete results.

Expanding the current framework to include other variables may enhance explanatory power. Third, although the valid number of samples reached 100 for the minimum requirement suggested by, there was still room for a survey with more prominent participants, thus providing more convincing results.

Informed consent and ethics approval

The research involved anonymous questionnaires with no collection of personally identifiable data. Before the survey commencement, a written disclosure statement was presented to all voluntary participants, detailing the research purpose and confirming that answering the questionnaire constituted informed consent with rigorous adherence to data anonymization procedures throughout the study. This survey is part of Krirk University's PhD research program (SID6319239) and has been approved by the Evaluation Committee of Krirk University.

Conflicts of interest

The authors declare no conflict of interest.

References

1. Nasri W, Charfeddine L. Factors affecting the adoption of internet banking in Tunisia: An integration theory of acceptance model and theory of Planned Behavior. The Journal of High Technology Management Research 2012; 23(1):1–14. https://doi.org/10.1016/j.hitech.2012.03.001
2. Al-Fraihat D, Joy M, Masa'deh R, et al. Evaluating e-learning systems success: An empirical study. Computers in Human Behavior 2020; 102: 67–86. https://doi.org/10.1016/j.chb.2019.08.004
3. Liu A, Urquía-Grande E, López-Sánchez P, et al. Research into microfinance and ICTs: A bibliometric analysis. evaluation and program planning 2023; 97:102215.
4. Liu F, Zou ZJ. Determinates of the competitiveness of provincial forest health care industry in China. Ecological Economy 2023; 9(4):344–358.
5. Wang Y, Zhang N, Zhao X. Understanding the determinants in the different government AI adoption stages: Evidence of local government chatbots in China. Social Science Computer Review 2020; 40(2):089443932098013. https://doi.org/10.1177/0894439320980132
6. Habibie TJ, Yasirandi R, Oktaria D. The analysis of Pangandaran fisherman's actual usage level of GPS based on TAM model. Procedia Computer Science 2022; 197:34–41. https://doi.org/10.1016/j.procs.2021.12.115
7. Raneem Rashad Saqr, Sabah Abdullah Al-Somali, Sarhan, M. Y. Exploring the acceptance and user satisfaction of AI-driven e-learning platforms (Blackboard, Moodle, Edmodo, Coursera and edX): An integrated technology model. Sustainability 2023; 16(1): 204–204. https://doi.org/10.3390/su16010204
8. Chaka C. Is Education 4.0 a sufficient innovative, and disruptive educational trend to promote sustainable open education for higher education institutions? A review of literature trends. Frontiers in Education 2022; 7:824976. https://doi.org/10.3389/feduc.2022.824976
9. Mohammadi H. Investigating users' perspectives on e-learning: An integration of TAM and IS success model. Computers in Human Behavior 2015; 45:359–374. https://doi.org/10.1016/j.chb.2014.07.044
10. Mohammadi H. Social and individual antecedents of m-learning adoption in Iran. Computers in Human Behavior 2015; 49:191–207. https://doi.org/10.1016/j.chb.2015.03.006
11. Joo YJ, Lim KY, Kim EK. Online university students' satisfaction and persistence: Examining perceived level of presence, usefulness and ease of use as predictors in a structural model. Computers & Education 2011; 57(2):1654–1664. https://doi.org/10.1016/j.compedu.2011.02.008
12. George B, Wooden O. Managing the strategic transformation of higher education through artificial intelligence. Administrative Sciences 2023; 13(9):196. https://doi.org/10.3390/admsci13090196
13. Papadakis S, Kiv AE, Kravtsov HM, et al. Revolutionizing education: Using computer simulation and cloud-based smart technology to facilitate successful open learning. CEUR Workshop Proceedings 2023; 1–18. https://ceur-ws.org/Vol-3358/paper00.pdf
14. Aggarwal D, Sharma D, Saxena AB, et al. Smart education: An emerging teaching pedagogy for interactive and adaptive learning methods. Journal of Learning and Educational Policy 2024; 1–9. https://doi.org/10.55529/jlep.44.1.9
15. Chonraksuk J, Boonlue S. Development of an AI predictive model to categorize and predict online learning behaviors of students in Thailand. Heliyon 2024; 10(11): e32591. https://doi.org/10.1016/j.heliyon.2024.e32591

16. Al-Gahtani SS. Testing for the applicability of the TAM model in the Arabic context. Information Resources Management Journal 2008; 21(4): 1–26. https://doi.org/10.4018/irmj.2008100101
17. Chen J, Xu Z, Gu J. Construction of virtual simulation training bases in vocational colleges from the perspective of the technology acceptance model: Taking the representative intangible cultural heritage of Zishan pottery carving as an example (Chinese). Ke Chen Yu Jiao Xue 2024; 40(12):59–66.
18. Wang C, Chen C. Review of the Application of Innovation Diffusion Theory in IT Field (Chinese). Value Engineering 2012; 31(1):162–164.
19. Zhu M. Construction of accurate push service model of libraries in western hunan ethnic minority areas based on innovation diffusion theory model (Chinese). Science and Technology Information 2022; 20(2):219–222.
20. Sandberg J, Barnard Y. Interviews on AI and education: Education and technology: What do we know? and where is AI? AI Communications 1993; 6(1):47–58. https://doi.org/10.3233/aic-1993-6104
21. Sandu N, Gide E. Adoption of AI-Chatbots to enhance student learning experience in higher education in India. In: Proceedings of the 18th International Conference on Information Technology Based Higher Education and Training (ITHET); 26–28 September 2019; Magdeburg, Germany. IEEE; 2019. https://doi.org/10.1109/ithet46829.2019.8937382
22. UNESCO. Education for sustainable development goals: learning objectives. Available online: https://unesdoc.unesco.org/ark:/48223/pf0000247444
23. Furey H, Martin F. AI education matters. AI Matters 2019; 4(4):13–15. https://doi.org/10.1145/3299758.3299764
24. Hanycz SA, Antiperovitch P. A practical review of generative AI in cardiac electrophysiology medical education. Journal of Electrocardiology 2025; 90:153903. https://doi.org/10.1016/j.jelectrocard.2025.153903
25. Yang X. Accelerated move for AI education in China. ECNU Review of Education 2019; 2(3):347–352. https://doi.org/10.1177/2096531119878590
26. Moore GC, Benbasat I. Development of an instrument to measure the perceptions of adopting an information technology innovation. Information Systems Research 1991; 2(3):192–222. https://doi.org/10.1287/isre.2.3.192
27. Davis FD. Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly 1989; 13(3):319–340.
28. Bandura A. Self-efficacy: Toward a unifying theory of behavioral change. Psychological Review 1977; 84(2): 191–215. https://doi.org/10.1037/0033-295X.84.2.191
29. Rogers EM. Diffusion of innovations. 1st ed. Free Press; 1962.
30. Al-Rahmi WM, Yahaya N, Alamri MM, et al. Integrating innovation diffusion theory with technology acceptance model: Supporting students' attitude towards using a massive open online courses (MOOCs) Systems. Interactive Learning Environments 2019; 29(8): 1–13. https://doi.org/10.1080/10494820.2019.1629599
31. Yu X, Lei LH. Research on influence factors of learners adopting MOOC: Based on user surveys of Tsinghua university's "online school" (Chinese). Modern Distance Education 2014; 155(5):3–8. https://doi.org/10.13927/j.cnki.yuan.2014.05.015
32. Mkhize P, Mtsweni ES, Buthelezi P. Diffusion of innovations approach to the evaluation of learning management system usage in an open distance learning institution. The International Review of Research in Open and Distributed Learning 2016; 17(3). https://doi.org/10.19173/irrodl.v17i3.2191
33. Choe MJ, Noh GY. Combined model of technology acceptance and innovation diffusion theory for adoption of smartwatch. International Journal of Contents 2018; 14(3). https://doi.org/10.5392/IJoC.2018.14.3.032
34. Rogers EM. Diffusion of Innovations. 3rd ed. Free Press; 1983.
35. Rogers EM. Diffusion of Innovations. 5th ed. Free Press; 2003.
36. Davis FD. A Technology Acceptance Model for Empirically Testing New End-User Information Systems: Theory and Results [PhD thesis]. Massachusetts Institute of Technology; 1986. http://dspace.mit.edu/handle/1721.1/15192
37. Fishbein M, Ajzen I. Belief, attitude, intention and behavior: An introduction to theory and research. Contemporary Sociology 1975; 6(2):244. https://doi.org/10.2307/2065853
38. Abdullah F, Ward R, Ahmed E, et al. Investigating the influence of the most commonly used external variables of TAM on students' perceived ease of use (PEOU) and perceived usefulness (PU) of e-portfolios. Computers in Human Behavior 2016; 63(63): 75–90.
39. Al Masarweh M. Evaluating m-learning system adoption by faculty members in Saudi Arabia using concern-based adoption model (CBAM) stages of concern. International Journal of Emerging Technologies in Learning (IJET) 2019; 14(05): 153. https://doi.org/10.3991/ijet.v14i05.8296
40. Tarrant MA, Manfredo MJ, Driver BL. Recollections of outdoor recreation experiences: A psychophysiological perspective. Journal of Leisure Research 1994; 26(4):357–371. https://doi.org/10.1080/00222216.1994.11969967
41. Jan SK. The relationships between academic self-efficacy, computer self-efficacy, prior experience, and satisfaction with online learning. American Journal of Distance Education 2015; 29(1):30–40. https://doi.org/10.1080/08923647.2015.994366

42. Mailizar M, Burg D, Maulina S. Examining university students' behavioural intention to use e-learning during the COVID-19 pandemic: An extended TAM model. Education and Information Technologies 2021; 26. https://doi.org/10.1007/s10639-021-10557-5
43. Ratna PA, Mehra S. Exploring the acceptance for e-learning using technology acceptance model among university students in India. International Journal of Process Management and Benchmarking 2015; 5(2):194. https://doi.org/10.1504/ijpmb.2015.068667
44. Al-Rahmi WM, Yahaya N, Aldraiweesh AA, et al. Integrating technology acceptance model with innovation diffusion theory: An empirical investigation on students' intention to use e-learning systems. IEEE Access 2019; 7: 26797–26809. https://doi.org/10.1109/access.2019.2899368
45. Konstantinos L, Iro V, Papadakis, S, Stavros A, Anastasiou A, Andromachi F, Vassilis K, Nikos K. Determinants of Humanities and Social Sciences Students' Intentions to Use Artificial Intelligence Applications for Academic Purposes. Information 2024, 15(6); 314–314. https://doi.org/10.3390/info15060314
46. ÖZÜDOĞRU G. The effect of distance education on self-efficacy towards online technologies and motivation for online learning. Journal of Learning and Teaching in Digital Age 2021; 7(1). https://doi.org/10.53850/joltida.1003915
47. Bandura A. Social cognitive theory: An agentic perspective. Annual Review of Psychology 2001; 52(1): 1–26. https://doi.org/10.1146/annurev.psych.52.1.1
48. Alamri MM. Investigating students' adoption of MOOCs during COVID-19 pandemic: Students' academic Self-Efficacy, learning engagement, and learning persistence. Sustainability 2022; 14(2): 714. https://doi.org/10.3390/su14020714
49. Taghizadeh SK, Rahman SA, Nikbin D, et al. Factors influencing students' continuance usage intention with online learning during the pandemic: A cross-country analysis. Behaviour & Information Technology 2021; 1–20. https://doi.org/10.1080/0144929x.2021.1912181
50. Peng R, Xiong L, Yang Z. Exploring tourist adoption of tourism mobile payment: An empirical analysis. Journal of Theoretical and Applied Electronic Commerce Research 2012; 7(1):5–6. https://doi.org/10.4067/s0718-18762012000100003
51. Kim HJ, Lee JM, Rha JY. Understanding the role of user resistance on mobile learning usage among university students. Computers & Education 2017; 113:108–118. https://doi.org/10.1016/j.compedu.2017.05.015
52. Kumar BA, Chand SS. Mobile learning adoption: A systematic review. Education and Information Technologies 2018; 24(1):471–487. https://doi.org/10.1007/s10639-018-9783-6
53. Bhattacherjee A. Understanding and evaluating relevance in IS research. Communications of the Association for Information Systems 2001; 6. https://doi.org/10.17705/1cais.00606
54. Delone WH, McLean ER. The DeLone and McLean model of information systems success: A ten-year update. Journal of Management Information Systems 2003; 19(4):9–30.
55. Bassi M, Steca P, Fave AD, et al. Academic self-Efficacy beliefs and quality of experience in learning. Journal of Youth and Adolescence 2006; 36(3): 301–312. https://doi.org/10.1007/s10964-006-9069-y
56. Lee JK, Lee WK. The relationship of e-Learner's self-regulatory efficacy and perception of e-Learning Environmental Quality. Computers in Human Behavior 2008; 24(1): 32–47. https://doi.org/10.1016/j.chb.2006.12.001
57. Walker SL, Fraser BJ. Development and validation of an instrument for assessing distance education learning environments in higher education: The distance education learning environments survey (DELES). Learning Environments Research 2005; 8(3):289–308. https://doi.org/10.1007/s10984-005-1568-3
58. Koole S, Christiaens V, Cosyn J, et al. Facilitating dental student reflections: Using mentor groups to discuss clinical experiences and personal development. Journal of Dental Education 2016; 80(10):1212–1218. https://doi.org/10.1002/j.0022-0337.2016.80.10.tb06204.x
59. Hair J, Black WC, Babin BJ, et al. Multivariate Data Analysis. 7th ed. Prentice Hall; 2009.
60. Ly B, Ly R. Internet banking adoption under technology acceptance model—evidence from cambodian users. Computers in Human Behavior Reports 2022; 7:100224. https://doi.org/10.1016/j.chbr.2022.100224
61. Selim HM. An empirical investigation of student acceptance of course websites. Computers & Education 2003; 40(4):343–360. https://doi.org/10.1016/s0360-1315(02)00142-2
62. Shaw N. The mediating influence of trust in the adoption of the mobile wallet. Journal of Retailing and Consumer Services 2014; 21(4):449–459.
63. Schwarzer R, Mueller J, Greenglass E. Assessment of perceived general self-efficacy on the internet: Data collection in cyberspace. Anxiety, Stress & Coping 1999; 12(2):145–161. https://doi.org/10.1080/10615809908248327
64. Yang J, Tian Y. "Others are more vulnerable to fake news than I am": Third-person effect of COVID-19 fake news on social media users. Computers in Human Behavior 2021; 125:106950. https://doi.org/10.1016/j.chb.2021.106950

65. Ngah AH, Kamalrulzaman NI, Mohamad MFH, et al. The sequential mediation model of students' willingness to continue online learning during the COVID-19 pandemic. Research and Practice in Technology Enhanced Learning 2022; 17(1). https://doi.org/10.1186/s41039-022-00188-w
66. Bentler PM, Chou CP. Practical issues in structural modeling. Sociological Methods & Research 1987; 16(1): 78–117. https://doi.org/10.1177/0049124187016001004
67. Hosmane BS. Improved likelihood ratio tests and Pearson Chi-Square tests for independence in two dimensional contingency tables. Communications in Statistics - Theory and Methods 1986; 15(6):1875–1888. https://doi.org/10.1080/03610928608829224
68. Preacher KJ, Hayes AF. Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. Behavior Research Methods 2008; 40(3): 879–891. https://doi.org/10.3758/brm.40.3.879
69. Cronbach LJ. Coefficient alpha and the internal structure of tests. Psychometrika 1951; 16(3): 297–334. https://doi.org/10.1007/bf02310555
70. Urbach N, Ahlemann F. Structural equation modeling in information systems research using partial least squares. Journal of Information Technology Theory and Application 2010; 11(2): 5–14.
71. Cerny BA, Kaiser HF. A study of a measure of sampling adequacy for factor-analytic correlation matrices. Multivariate Behavioral Research 1977; 12(1): 43–47. https://doi.org/10.1207/s15327906mbr1201_3
72. Fornell C, Larcker DF. Evaluating structural equation models With Unobservable Variables And Measurement Error. Journal of Marketing Research 1981; 18(1): 39–50. https://doi.org/10.1177/002224378101800104
73. Podsakoff PM, MacKenzie SB, Lee JY, et al. Common method biases in behavioral research: A critical review of the literature and recommended remedies. Journal of Applied Psychology 2003; 88(5):879–903. https://doi.org/10.1037/0021-9010.88.5.879
74. Spector PE. Using self-Report questionnaires in OB research: A comment on the use of a controversial method. Journal of Organizational Behavior 1994; 15(5):385–392. https://doi.org/10.1002/job.4030150503
75. Wang L, Huang J. Mediating role of entrepreneurial Self-Efficacy and prosocial tendency in the relation between college students' post-traumatic growth and entrepreneurial intention in the post-COVID-19 era. Frontiers in Psychology 2022; 13. https://doi.org/10.3389/fpsyg.2022.861484
76. Bollen, KA. Structural equations with latent variables. John Wiley & Sons; 1989.
77. Hu L, Bentler PM. Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Structural Equation Modeling: A Multidisciplinary Journal 1999; 6(1), 1–55. https://doi.org/10.1080/10705519909540118
78. Doll WJ, Xia W, Torkzadeh G. A Confirmatory Factor Analysis of the End-User Computing Satisfaction Instrument. MIS Quarterly 1994; 18(4), 453. https://doi.org/10.2307/249524
79. Fan X, Thompson B, Wang L. Effects of sample size, estimation methods, and model specification on structural equation modeling fit indexes. Structural Equation Modeling: A Multidisciplinary Journal 1999; 6(1), 56–83. https://doi.org/10.1080/10705519909540119
80. McDonald RP, Moon-Ho Ringo Ho. Principles and practice in reporting structural equation analyses. Psychological Methods 2002; 7(1), 64–82. https://doi.org/10.1037//1082-989x.7.1.64
81. Bentler PM, Bonett DG. Significance tests and goodness of fit in the analysis of covariance structures. Psychological Bulletin 1980; 88(3), 588–606. https://doi.org/10.1037/0033-2909.88.3.588
82. Serrano Archimi C, Reynaud E, Yasin HM, et al. How Perceived Corporate Social Responsibility Affects Employee Cynicism: The mediating role of organizational trust. Journal of Business Ethics 2018; 151(4):907–921. https://doi.org/10.1007/s10551-018-3882-6
83. Kim S, Gopalan N, Beutell NJ. Sustainability through humility: The impact of humble leadership on work–family facilitation in the U.S. and Japan. Sustainability 2023; 15(19):14367. https://doi.org/10.3390/su151914367
84. Hayes AF. Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach. The Guilford Press; 2018. https://www.guilford.com/p/hayes3
85. Toothaker LE, Aiken LS, West SG. Multiple regression: Testing and interpreting interactions. The Journal of the Operational Research Society 1994; 45(1):119. https://doi.org/10.2307/2583960
86. Hassanzadeh A, Kanaani F, Elahi S. A model for measuring e-learning systems success in universities. Expert Systems with Applications 2012; 39(12):10959–10966. https://doi.org/10.1016/j.eswa.2012.03.028
87. Zhang L, Gu X. Research on the influencing factors of the innovation diffusion of artificial intelligence in education based on TOE theoretical framework. China Distance Education 2023; 2: 54–63. https://doi.org/10.13541/j.cnki.chinade.2023.02.008
88. Venkatesh V, Davis FD. A theoretical extension of the technology acceptance model: Four longitudinal field studies. Management Science 2000; 46(2):186–204. https://doi.org/10.1287/mnsc.46.2.186.11926
89. Venkatesh V, Bala H. Technology acceptance model 3 and a research agenda on interventions. Decision Sciences 2008; 39(2):273–315. https://doi.org/10.1111/j.1540-5915.2008.00192.x

90. Venkatesh V, Morris MG, Davis GB, et al. User acceptance of information technology: Toward a unified view. MIS Quarterly 2003; 27(3):425–478. https://doi.org/10.2307/30036540
91. Nugroho MA, Setyorini D, Novitasari BT. The role of satisfaction on perceived value and e-learning usage continuity relationship. Procedia Computer Science 2019; 161:82–89. https://doi.org/10.1016/j.procs.2019.11.102
92. Bhattacherjee A. Understanding information systems continuance: An expectation-confirmation model. MIS Quarterly 2001; 25(3): 351–370.https://doi.org/10.2307/30036540
93. Karahanna E, Straub DW, Chervany NL. Information technology adoption across time: A cross-sectional comparison of Pre-Adoption and post-adoption beliefs. MIS Quarterly 1999; 23(2):183–213. https://doi.org/10.2307/249751
94. Bourdieu, P. (1988). Homo Academicus. Stanford University Press.
95. Siemens G. Learning Analytics: The emergence of a discipline. American Behavioral Scientist 2013; 57(10): 1380–1400.https://doi.org/10.1177/0002764213498851
96. Dai X. A Study on mindful agency's influence on college students' engagement with online teaching: The mediating roles of e-learning self-efficacy and self-regulation. Acta Psychologica 2024; 243:104146. https://doi.org/10.1016/j.actpsy.2024.104146
97. Prensky M. Digital natives, digital immigrants. On the Horizon 2001; 9(5): 1–6. https://doi.org/10.1108/10748120110424816
98. Neumann MM, Finger G, Neumann DL. A conceptual framework for emergent digital literacy. Early Childhood Education Journal 2016; 45(4): 471–479.https://doi.org/10.1007/s10643-016-0792-z
99. Dogan ME, Goru Dogan T, Bozkurt A. The use of artificial intelligence (AI) in online learning and distance education processes: A systematic review of empirical studies. Applied Sciences 2023; 13(5):3056. https://doi.org/10.3390/app13053056
100. Papamitsiou ZK, Economides AA. Learning analytics and educational data mining in practice: A systematic literature review of empirical evidence. Educational Technology & Society 2014; 17(4):49–64.
101. Chonraksuk J, Boonlue S. Development of an AI predictive model to categorize and predict online learning behaviors of students in Thailand. Heliyon 2024; 10(11): e32591–e32591. https://doi.org/10.1016/j.heliyon.2024.e32591
102. Mahafdah R, Bouallegue S, Bouallegue R. Enhancing e-learning through AI: Advanced techniques for optimizing student performance. Peer J Computer Science 2024; 10: e2576. https://doi.org/10.7717/peerj-cs.2576
103. Khokhar AS. Digital literacy. International Journal of Digital Literacy and Digital Competence 2016; 7(3):1–12. https://doi.org/10.4018/ijdldc.2016070101

Appendix A: Questionnaire items.

Second-order construct	First-order construct	Measure	Related studies
AI-powered e-learning system traits (AES)	Relative Advantage (RA)	RA1: Using AI-powered E-learning improves my learning efficiency.	Moore and Benbasat [26]; Delone and McLean [54]; Rogers [35]; Ly and Ly [60]
		RA2: AI-powered E-learning systems better meet my expectations.	
		RA3: Using AI-powered E-learning helps me accomplish my tasks more quickly.	
		RA4: AI-powered E-learning systems offer more abundant learning materials.	
	Complexity (COM)	COM1: The interface of AI-powered E-learning systems is easy for me to understand.	
		COM2: I find the process of using AI-powered E-learning systems very simple.	
		COM3: AI-powered E-learning systems do not confuse or frustrate me.	
		COM4: I find the complexity of AI-powered E-learning systems acceptable.	
	Observability (OBS)	OBS1: I can easily find the functions I need in AI-powered online learning systems.	Rogers [35]; Moore and Benbasat [26]
		OBS2: The interface design of AI-powered E-learning systems is clear and intuitive.	
		OBS3: I can quickly locate and use resources in AI-powered online learning systems.	
		OBS4: The navigation features of systems are very intuitive for me.	
	Adoption Intention (ADI)	ADI1: I will continue using AI-powered E-learning systems in my future studies.	Moore and Benbasat [26]; Rogers [34]; Selim [61]; Shaw [62]
		ADI2: I would recommend AI-powered E-learning systems to my friends.	
		ADI3: AI-powered E-learning systems have played a positive role in my studies.	
		ADI4: On average, I use AI-powered E-learning systems frequently.	
	Satisfaction (SAT)	SAT1: I have a high level of satisfaction with AI-powered E-learning systems.	
		SAT2: Using AI-powered E-learning systems make me feel enjoyable and accomplished.	
		SAT3: I am pleased that the systems meet my expectations for online learning.	
	Self-efficacy (SE)	SE1: Using AI-powered E-learning systems has increased my learning abilities.	Schwarzer et al. [63]; Yang and Tian [64]
		SE2: I believe that I can effectively use AI-powered E-learning systems for my studies.	
		SE3: Through the use of AI-powered systems, I can better manage learning progress.	
		SE4: Overall, I am confident in solving problems when using AI-powered systems.	

Appendix B: Reliability and convergent validity.

Construct		Item	Reliability				Validity
			Indicator reliability	**Internal consistency Reliability***			**Convergent**
			Factor loadings ≥ 0.70	**Cronbach's α ≥ 0.70**		**CR ≥ 0.70**	**AVE* ≥ 0.50**
AI-powerede-learning system traits (AES)	Relative Advantage (RA)	RA1	0.720	0.839		0.840	0.567
		RA2	0.744				
		RA3	0.792				
		RA4	0.753				
	Complexity (COM)	COM1	0.790	0.851	0.890	0.852	0.591
		COM2	0.742				
		COM3	0.776				
		COM4	0.766				
	Observability (OBS)	OBS1	0.722	0.817		0.818	0.529
		OBS2	0.718				
		OBS3	0.711				
		OBS4	0.757				
Adoption Intention (ADI)		ADI1	0.837	0.863		0.865	0.617
		ADI2	0.796				
		ADI3	0.690				
		ADI4	0.814				
Satisfaction (SAT)		SAT1	0.823	0.871		0.872	0.693
		SAT2	0.837				
		SAT3	0.838				
Self-efficacy (SE)		SE1	0.773	0.842		0.843	0.574
		SE2	0.731				
		SE3	0.700				
		SE4	0.825				

**CR=Composite Reliability. AVE= Average Variance Extracted*

Appendix C: Cross loadings.

Construct items	Relative advantage	complexity	observability	Adoption intention	Satisfaction	Self-efficacy
RA1	0.756					
RA2	0.691					
RA3	0.765					
RA4	0.807					
COM1		0.734				
COM2		0.750				
COM3		0.799				
COM4		0.795				
OBS1			0.768			
OBS2			0.691			
OBS3			0.731			
OBS4			0.772			
ADI1				0.850		
ADI2				0.825		
ADI3				0.774		
ADI4				0.816		
SAT1					0.794	
SAT2					0.815	
SAT3					0.832	
SE1						0.762
SE2						0.801
SE3						0.777
SE4						0.760