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Artificial intelligence learning satisfaction and continuance intention among students in Ho Chi Minh City

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ABSTRACT

Artificial intelligence (AI) is increasingly used in higher education, but there is limited evidence explaining why students continue to use it after initial adoption. This study examines the factors influencing students' continuance intention (CI) to use AI for learning, with learning satisfaction (LS) mediating the relationship. Unlike previous technology acceptance model (TAM) studies that mainly focus on technology acceptance, this study integrates technological quality, educational support, individual capability, and perceived ease of use (PEOU) to explain post-adoption behavior. Data were collected from 250 university students in Ho Chi Minh City, Vietnam, and analyzed using SPSS 26 and SmartPLS 4. The results show that digital skills (DS) had the strongest effect on LS, followed by PEOU, technical infrastructure (TI), service quality (SEQ), instructor support (IS), and information quality (IQ). System quality (SQ) had no significant effect. LS strongly influenced CI and significantly transmitted the effects of six antecedents, whereas the indirect effect of SQ was not significant. The findings suggest that sustained use of AI in higher education depends not only on the quality of the technology but also on students' digital competence, supportive learning conditions, and positive learning experiences.

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1. INTRODUCTION

Artificial intelligence (AI) is becoming increasingly embedded in higher education, reshaping how students search for information, complete academic tasks, and interact with learning materials. Generative AI tools such as ChatGPT provide instant responses, writing support, translation assistance, personalized explanations, and flexible academic guidance [1], [2]. These functions can improve students' learning experiences and encourage more active participation in academic activities [3]. Recent reports show that 86% of university students use AI in their studies, while 89% have used ChatGPT to support homework or essay writing [4], [5]. In Vietnam, the use of AI in learning has also expanded rapidly. Hoa [6] reported that more than 72% of surveyed university students in Hanoi had used ChatGPT for academic purposes at least once.

However, the rapid spread of AI in higher education also creates important challenges. Students differ in their digital skills (DS), ability to evaluate AI-generated content, and capacity to use AI responsibly. At the institutional level, universities may also differ in technical infrastructure (TI), instructor guidance, and readiness to support AI-based learning. Without sufficient skills and institutional support, students may use AI in suboptimal or unethical ways, including overreliance, plagiarism, reliance on inaccurate information, passive learning, and academic misconduct [7], [8]. Therefore, the main issue is no longer merely whether

students adopt AI, but whether they can use it effectively, ethically, and continuously within a supportive learning environment. Previous research has provided valuable insights into AI adoption in education, including students' intention to adopt and use ChatGPT in Vietnamese higher education [9], graduate instructors' experiences with ChatGPT [10], and teachers' perspectives on AI adoption [11]. Although these studies have advanced understanding of AI use in education, many have focused primarily on initial adoption or educators' perspectives. Studies based on the technology acceptance model (TAM) have also tended to emphasize individual perceptions, such as perceived usefulness and perceived ease of use (PEOU). Consequently, limited evidence explains how technological quality, institutional support, individual capability, and learning satisfaction (LS) jointly influence students' post-adoption behavior, particularly in developing-country higher education contexts.

To address this research gap, the present study proposes a multidimensional framework that draws on the information systems success model, the TAM, and the expectation–confirmation perspective. The framework investigates how seven antecedents—system quality (SQ), information quality (IQ), service quality (SEQ), instructor support (IS), TI, DS, and PEOU—shape students' satisfaction with AI-supported learning. It further evaluates whether LS serves as the mechanism by which these factors influence students' intention to continue using AI for academic purposes.

The findings indicate that DS make the largest contribution to LS, whereas SQ does not exert a statistically significant influence. LS also carries the effects of IQ, SEQ, IS, TI, DS, and PEOU to continuance intention (CI). These results highlight an important contribution of the study: continued engagement with AI in Vietnamese higher education appears to depend less on basic system performance and more on learners' digital competence, supportive educational conditions, and satisfactory learning experiences.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1. Theoretical foundation

The information systems success model provides a suitable foundation for explaining how the quality of AI tools may influence students' satisfaction with learning. The success of an information system can be evaluated through three key quality dimensions: SQ, IQ, and SEQ [12]. In the context of AI-supported learning, SQ reflects the stability, accessibility, and responsiveness of AI tools; IQ refers to the accuracy, relevance, and usefulness of AI-generated content; and SEQ represents the support associated with the use of AI. These dimensions can shape students' learning experience and satisfaction when using AI for academic purposes.

The TAM is widely used to explain how users accept and respond to new technologies. PEOU is an important factor influencing users' attitudes and behavioral intentions toward technology [13]. In this study, TAM is used to explain the role of PEOU in AI-supported learning. When students perceive AI tools as easy to access, simple to operate, and requiring little effort, they are more likely to feel comfortable and satisfied during the learning process. Therefore, PEOU is expected to contribute positively to students' LS.

Expectation–confirmation theory offers a useful perspective on why individuals continue to use a technology after its initial adoption. According to this perspective, satisfaction depends on the extent to which actual usage experiences meet or exceed users' prior expectations [14]. Research on information system continuance further indicates that users' evaluations of their post-use experiences play an important role in determining whether they intend to maintain future use [15]. In AI-supported education, students who perceive their interactions with AI as beneficial and satisfactory are more likely to incorporate these tools into subsequent academic activities. LS, therefore, represents an important psychological link between students' experiences with AI-assisted learning and their willingness to continue using AI.

Viewed collectively, the three theoretical perspectives capture different but complementary aspects of students' continued engagement with AI-supported learning. The information systems success model contributes the technology-quality perspective by focusing on the system's performance, the value of the information it provides, and the support surrounding its use. The TAM adds a user-oriented perspective through PEOU, whereas expectation–confirmation theory clarifies how post-use evaluations develop into satisfaction and subsequent CI. Building on these complementary perspectives, the present study extends the framework to include IS and TI as features of the educational environment, as well as DS as a learner-level capability. This broader conceptualization recognizes that sustained use of generative AI for learning may arise from the interplay among technological characteristics, institutional conditions, students' capabilities, perceptions of usability, and satisfaction with prior learning experiences.

2.2. Influencing factors and hypothesis development

This study organizes the antecedents of LS into three interrelated dimensions. Technological quality includes SQ, IQ, and SEQ. Educational and institutional support includes IS and TI. Individual capability and technology perception include DS and PEOU. These dimensions may reinforce one another in generative AI-supported learning, as high-quality AI tools may not lead to satisfaction if students lack DS or institutional

support. Technological quality is a key condition for students' satisfaction with AI-supported learning. SQ reflects the stability, accessibility, responsiveness, and operational reliability of AI tools. When AI tools operate smoothly and reduce technical interruptions, students may experience less effort and greater satisfaction [12], [16]–[18].

- H1: SQ has a positive effect on LS.

IQ refers to the accuracy, relevance, completeness, and usefulness of AI-generated content. In learning contexts, students rely on AI to summarize documents, explain concepts, translate materials, and support problem-solving. When the information provided is clear and reliable, students are more likely to perceive AI-supported learning as effective and satisfying [12], [16], [17], [19].

- H2: IQ has a positive effect on LS.

SEQ reflects the responsiveness and helpfulness of AI-supported learning services. In generative AI use, timely responses, useful guidance, and effective assistance can help students complete learning tasks more confidently. Prior studies have shown that SEQ improves satisfaction and continuance behavior in e-learning and digital service contexts [12], [16], [20], [21].

- H3: SEQ has a positive effect on LS.

Educational and institutional support also shapes students' satisfaction with AI-supported learning. IS helps students understand how to use AI appropriately, evaluate AI-generated content critically, and avoid unethical academic practices. TI, including internet access, digital devices, learning platforms, and software availability, provides the basic conditions for effective AI use. When students receive both academic guidance and adequate technological support, they are more likely to use AI confidently and productively [3], [10], [11], [16], [22].

- H4: IS has a positive effect on LS.
- H5: TI positively affects LS.

Individual capability further determines how effectively students benefit from AI tools. DS enable students to write prompts, evaluate AI-generated information, and apply AI outputs to academic tasks. PEOU reduces learning effort and helps students interact with AI tools more comfortably. In generative AI-supported learning, these two factors may work together because students with stronger DS are more likely to benefit from tools that are simple, accessible, and convenient to use [1], [2], [7], [9], [22]–[24].

- H6: DS have a positive effect on LS.
- H7: PEOU has a positive effect on LS.

LS refers to students' overall positive evaluation of their learning experience when using AI tools for academic purposes. CI reflects students' willingness to keep using AI tools in future learning activities. From the perspective of Expectation–Confirmation Theory, satisfaction is a central factor influencing users' post-adoption behavior, as they are more likely to continue using a technology when their experience meets or exceeds expectations [15], [25], [26]. In AI-supported learning, students who are satisfied with the usefulness, convenience, and learning support provided by AI tools may be more inclined to continue using them. Previous studies have also confirmed that satisfaction significantly influences CI in digital services, AI-powered service agents, mobile applications, and technology-based learning contexts [27]–[30]. Therefore, LS is expected to positively affect students' intention to continue using AI in learning.

- H8: LS positively affects the intention to continue using AI in learning.

The proposed model integrates technological quality, institutional support, and individual capability as antecedents of LS. LS subsequently influences CI. The research model is presented in Figure 1.

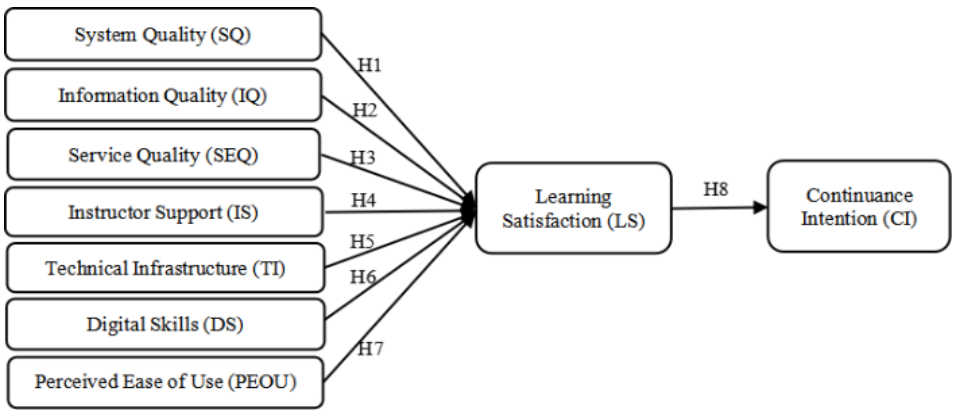


Figure 1. Research model

3. RESEARCH METHOD

3.1. Research design

A quantitative cross-sectional approach was adopted to investigate students' continued use of AI for learning purposes. The conceptual model specifies seven predictors of LS, namely SQ, IQ, SEQ, IS, TI, DS, and PEOU. LS functions as the mediating construct in the model, whereas CI represents the outcome variable.

3.2. Population and sample

The target population comprised university students in Ho Chi Minh City who had prior experience using AI tools for learning, including ChatGPT, Gemini, Microsoft Copilot, and similar applications. Ho Chi Minh City was selected because it is one of Vietnam's major centers of higher education and technology, with a large concentration of universities, students, and digital learning activities. Purposive sampling was applied to ensure that all respondents had relevant experience with AI-supported learning.

A total of 273 questionnaires were collected. After data screening, 23 responses were excluded because they were incomplete, inconsistent, showed straight-lining patterns, or failed to confirm prior experience with AI tools for learning. The final sample comprised 250 valid responses, representing a response rate of 91.58%.

3.3. Instrument and measurement

The survey instrument was developed from established measurement scales reported in prior studies and subsequently adapted to the context of AI-supported learning. All constructs were assessed using a 5-point Likert response format. To preserve conceptual meaning across languages, the questionnaire was first translated into Vietnamese and then independently back-translated into English, allowing the researchers to check for consistency between the two versions.

Before the main data collection, the instrument was pilot-tested with 30 university students to evaluate whether the questions were clear, relevant, and easy to understand. Feedback from the pilot participants led to minor refinements in wording. The finalized questionnaire used identical introductory information, screening criteria, measurement items, item order, and response categories in the online and paper-based versions.

3.4. Data collection procedure

Data were collected from January to March 2026 through Google Forms and paper-based questionnaires. The two distribution methods were used to accommodate differences in students' online accessibility, class schedules, and availability for direct participation. Both formats included identical instructions, screening procedures, measurement items, question order, and response options to maintain consistency.

Potential respondents were first asked whether they had previously used AI tools for academic learning. Only students who confirmed relevant experience were permitted to participate in the survey. The completed questionnaires were subsequently screened before being included in the final analysis.

3.5. Data analysis

The data were analyzed using SPSS 26 and SmartPLS 4. SPSS was used for data screening, descriptive statistics, scale reliability assessment, and exploratory factor analysis, while SmartPLS was used to evaluate the measurement and structural models. The measurement model was assessed using outer loadings, Cronbach's alpha, composite reliability (CR), average variance extracted (AVE), and the heterotrait–monotrait ratio (HTMT) [31]. Common method bias was examined using full collinearity variance inflation factor (VIF) values [32]. The structural model was evaluated using path coefficients, p-values, effect sizes, VIF, R^2, adjusted R^2, Q^2, and bootstrapped specific indirect effects with 5,000 resamples. Partial least squares-structural equation modeling (PLS-SEM) was considered appropriate because the study involved a predictive model with multiple latent constructs and mediation relationships [33], [34].

3.6. Ethical considerations

Participation was entirely voluntary, and students received information about the study's academic purpose before deciding whether to take part. Consent was obtained before questionnaire completion, and respondents could discontinue their participation at any stage without any adverse consequence. The survey did not request personally identifiable information, and all responses were handled confidentially.

The information collected was used exclusively for scholarly purposes and analyzed only at the aggregate level. The research procedures were conducted in accordance with the authors' institutional standards for educational survey research. Particular attention was given to safeguarding participants' privacy, preserving their autonomy, and maintaining the confidentiality of the information they provided.

4. RESULTS

4.1. Respondent profile

The final sample consisted of 250 university students in Ho Chi Minh City, all of whom had prior experience using AI tools for learning. Female respondents represented 55.20% of the sample, while male respondents accounted for 44.80%. Most participants were aged 20–22 years (54.80%), followed by those under 20 years old (23.20%), those aged 23–25 years (16.80%), and those over 25 years old (5.20%). By academic year, second-year students were the largest group (29.20%), followed by third-year students (27.20%), first-year students (20.80%), fourth-year students (18.80%), and other students (4.00%). Regarding frequency of use, 57.20% reported using AI often or very often, 31.60% sometimes, and 11.20% rarely. ChatGPT was the most frequently used tool (62.80%), followed by Gemini (19.60%), Microsoft Copilot (10.00%), and other AI tools (7.60%).

4.2. Measurement model assessment

The assessment of the measurement model showed that the constructs met the required standards for reliability and validity, allowing the analysis to proceed to the evaluation of the structural relationships. As an initial step, internal consistency was examined using Cronbach's alpha and corrected item–total correlations. The corresponding reliability statistics for each construct are summarized in Table 1.

The reliability results indicate that Cronbach's alpha values ranged from 0.801 to 0.889, exceeding the recommended threshold of 0.70. The corrected item-total correlations were also acceptable, confirming that all measurement scales were reliable and suitable for further analysis. After confirming scale reliability, Kaiser–Meyer–Olkin (KMO), Bartlett's test, and total variance explained were examined to assess the suitability of the data for factor analysis, as presented in Table 2.

Table 1. Results of scale reliability testing

Scale code	Number of observed variables	Cronbach's alpha	Corrected item-total correlation range	Conclusion
SQ	5	0.889	0.658–0.810	Accepted
IQ	3	0.852	0.678–0.798	Accepted
SEQ	4	0.862	0.682–0.727	Accepted
IS	4	0.854	0.624–0.747	Accepted
TI	5	0.856	0.598–0.727	Accepted
DS	3	0.833	0.656–0.746	Accepted
PEOU	4	0.808	0.552–0.699	Accepted
LS	5	0.806	0.587–0.672	Accepted
CI	4	0.801	0.604–0.644	Accepted

Table 2. Results of KMO, Bartlett's test, and total variance explained

Variable group	KMO	Bartlett's test Chi-square	df	Sig.	Minimum eigenvalue	Total variance explained (%)	Conclusion
Independent variables	0.899	3759.787	378	<0.001	1.099	70.508	Accepted
Mediating variable	0.832	417.345	10	<0.001	3.286	65.723	Accepted
Dependent variable	0.798	293.213	6	<0.001	2.511	62.780	Accepted

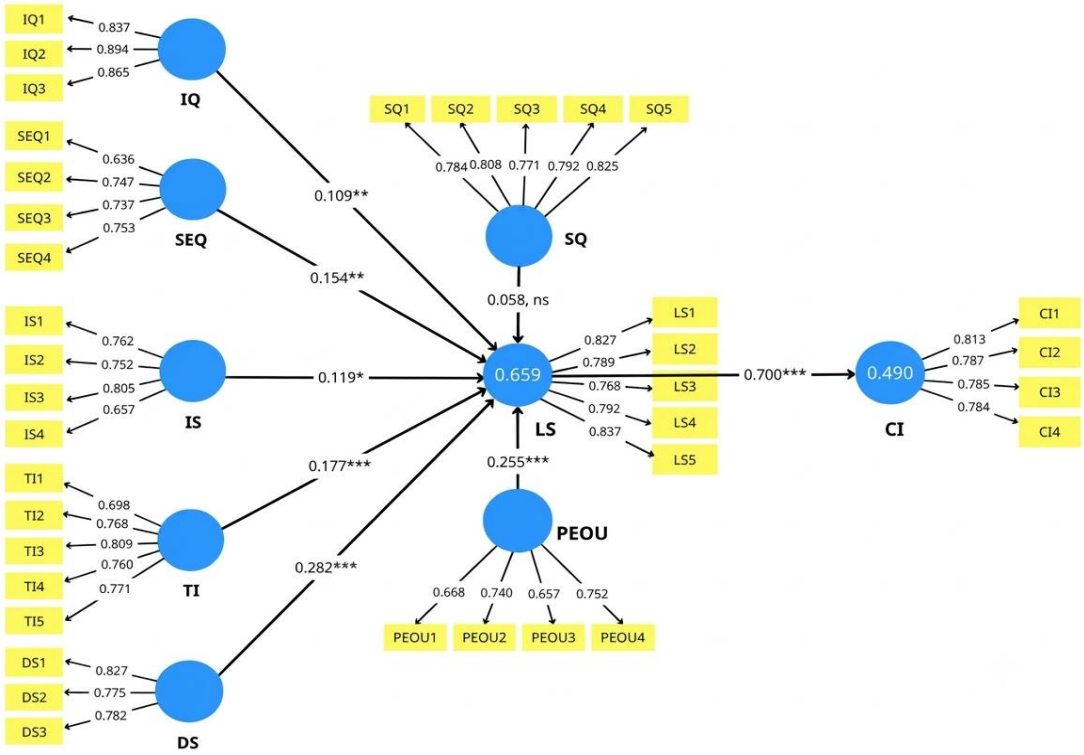
The KMO values ranged from 0.798 to 0.899, indicating adequate sampling adequacy. Bartlett's test was significant for all variable groups ($p<0.001$), and the total variance explained exceeded 50.00%. These results confirm that the data were suitable for factor analysis. Outer loadings were then examined to assess item reliability, as reported in Table 3.

Most measurement items demonstrated satisfactory indicator reliability, with outer loadings above 0.70. Five indicators (SEQ1, IS4, TI1, PEOU1, PEOU3) showed slightly lower loadings, although all remained above 0.60. These indicators were retained because the constructs continued to demonstrate acceptable overall measurement quality, and their inclusion did not materially weaken the scales' reliability or validity. The complete item-loading results are illustrated in Figure 2. The next step evaluated internal consistency and convergent validity using Cronbach's alpha, CR, and AVE, as reported in Table 4.

All constructs showed acceptable reliability and convergent validity. The AVE for PEOU was marginally below 0.50 but remained acceptable given adequate reliability. Discriminant validity was then assessed using HTMT, as presented in Table 5. All HTMT values were below 0.85, confirming adequate discriminant validity. The highest HTMT value was 0.835, which remained within the recommended threshold. Common method bias was subsequently assessed using full collinearity VIFs, as presented in Table 6. All full collinearity VIF values ranged from 1.142 to 2.105 and remained below the 3.3 threshold. These results indicate that no problematic common method bias was detected. Therefore, common method bias was unlikely to pose a serious concern in this study.

Table 3. Summary of outer loadings by construct

Scale code	Number of items	Outer loading range	Items below 0.70	Conclusion
SQ	5	0.771–0.825	None	Accepted
IQ	3	0.837–0.894	None	Accepted
SEQ	4	0.636–0.753	SEQ1	Accepted
IS	4	0.657–0.805	IS4	Accepted
TI	5	0.698–0.809	TI1	Accepted
DS	3	0.775–0.827	None	Accepted
PEOU	4	0.657–0.752	PEOU1, PEOU3	Accepted
LS	5	0.768–0.837	None	Accepted
CI	4	0.784–0.813	None	Accepted



Note: *p<0.05; **p<0.01; ***p<0.001; ns=not significant.

Figure 2. Results of the structural and measurement model

Table 4. Construct reliability and convergent validity

Construct	Cronbach's alpha	CR	AVE	Conclusion
SQ	0.889	0.896	0.634	Accepted
IQ	0.852	0.900	0.749	Accepted
SEQ	0.862	0.811	0.518	Accepted
IS	0.854	0.833	0.556	Accepted
TI	0.856	0.874	0.581	Accepted
DS	0.833	0.837	0.632	Accepted
PEOU	0.808	0.798	0.498	Marginally acceptable
LS	0.806	0.901	0.645	Accepted
CI	0.801	0.871	0.628	Accepted

Table 5. Discriminant validity assessment using the HTMT ratio

Construct	SQ	IQ	SEQ	IS	TI	DS	PEOU	LS	CI
SQ	—								
IQ	0.157	—							
SEQ	0.458	0.073	—						
IS	0.430	0.237	0.614	—					
TI	0.288	0.164	0.474	0.470	—				
DS	0.381	0.195	0.505	0.637	0.468	—			
PEOU	0.480	0.276	0.661	0.676	0.478	0.580	—		
LS	0.495	0.338	0.695	0.735	0.638	0.780	0.818	—	
CI	0.631	0.275	0.725	0.812	0.631	0.793	0.824	0.835	—

Table 6. Full collinearity VIF assessment for common method bias

Code	Full collinearity VIF	Threshold	Assessment
SQ	1.385	<3.3	No problematic CMB indicated
IQ	1.142	<3.3	No problematic CMB indicated
SEQ	1.892	<3.3	No problematic CMB indicated
IS	1.984	<3.3	No problematic CMB indicated
TI	1.425	<3.3	No problematic CMB indicated
DS	1.710	<3.3	No problematic CMB indicated
PEOU	1.956	<3.3	No problematic CMB indicated
LS	2.105	<3.3	No problematic CMB indicated
CI	1.840	<3.3	No problematic CMB indicated

4.3. Structural model assessment

After the measurement model was confirmed, the explanatory power and predictive relevance of the structural model were assessed. The analysis focused on LS and CI as the two endogenous constructs. Table 7 presents the R^2, adjusted R^2, and Q^2 values for these constructs.

The R^2 value for LS was 0.659, indicating strong explanatory power in the context of AI-supported learning. Technological quality, institutional support, DS, and PEOU jointly explained 65.90% of students' LS, while LS explained 49.00% of CI. The positive Q^2 values further confirmed the model's predictive relevance. After assessing explanatory power and predictive relevance, the direct relationships among the constructs were tested, as presented in Table 8.

Table 7. Results of R^2, adjusted R^2, and Q^2

Dependent variable	R^2	Adjusted R^2	Q^2
LS	0.659	0.649	0.512
CI	0.490	0.488	0.334

Table 8. Results of direct effect hypothesis testing

Hypothesis	Relationship	Path coefficient (β)	Standard error	f^2	VIF	p-value	Conclusion
H1	SQ→LS	0.058	0.043	0.008	1.301	0.176	Not supported
H2	IQ→LS	0.109	0.039	0.032	1.086	0.006	Supported
H3	SEQ→LS	0.154	0.050	0.040	1.745	0.002	Supported
H4	IS→LS	0.119	0.051	0.022	1.868	0.021	Supported
H5	TI→LS	0.177	0.043	0.068	1.343	<0.001	Supported
H6	DS→LS	0.282	0.047	0.148	1.579	<0.001	Supported
H7	PEOU→LS	0.255	0.051	0.103	1.860	<0.001	Supported
H8	LS→CI	0.700	0.045	0.961	1.000	<0.001	Supported

DS had the strongest effect on LS, whereas SQ did not have a significant effect. LS strongly predicted CI, confirming its central role in the structural model. Its mediating role was further examined through the specific indirect effects reported in Table 9. LS significantly transmitted the effects of IQ, SEQ, IS, TI, DS, and PEOU to CI. However, the indirect effect of SQ was not significant. Figure 2 summarizes the final PLS-SEM results.

Table 9. Bootstrapping results for specific indirect effects

Specific indirect path	Original sample (β)	Sample mean (M)	Standard deviation	t-statistic	p-value	95% confidence interval	Conclusion
SQ→LS→CI	0.041	0.042	0.031	1.323	0.186	[−0.020, 0.103]	Indirect effect not supported
IQ→LS→CI	0.076	0.077	0.028	2.714	0.007	[0.023, 0.133]	Significant indirect effect
SEQ→LS→CI	0.108	0.109	0.036	3.000	0.003	[0.039, 0.180]	Significant indirect effect
IS→LS→CI	0.083	0.084	0.037	2.243	0.025	[0.012, 0.158]	Significant indirect effect
TI→LS→CI	0.124	0.125	0.031	4.000	<0.001	[0.065, 0.187]	Significant indirect effect
DS→LS→CI	0.197	0.198	0.035	5.629	<0.001	[0.130, 0.268]	Significant indirect effect
PEOU→LS→CI	0.178	0.179	0.037	4.811	<0.001	[0.108, 0.252]	Significant indirect effect

5. DISCUSSION

The findings indicate that students' CI to use AI in learning is shaped by the combined effects of individual capability, technological conditions, institutional support, and LS. Six antecedents significantly influenced LS, while SQ was not significant. LS, in turn, strongly predicted CI, confirming its central role in students' post-adoption behavior.

SQ did not significantly influence LS; therefore, H1 was not supported. This finding differs from the information systems success model [12] and earlier e-learning studies that identified SQ as an important determinant of satisfaction [16], [17]. A possible explanation is that widely used AI platforms such as ChatGPT, Gemini, and Microsoft Copilot already provide relatively stable and accessible technical performance. Students may consequently regard system stability as a basic requirement rather than a factor that directly increases satisfaction. In contrast, IQ and SEQ significantly improved LS, supporting H2 and H3 and confirming that accurate, relevant, and useful content, together with responsive support, remains important in AI-supported learning [16], [20].

IS and TI also had significant effects on LS, supporting H4 and H5. TI had a stronger effect than IS, suggesting that stable internet access, available devices, digital platforms, and institutional systems are essential conditions for effective use of AI. Nevertheless, instructor guidance remains important because students require support in evaluating AI-generated content, using these tools ethically, and avoiding academic misconduct [10], [11]. These findings extend technology acceptance research by showing that institutional conditions complement individual perceptions in shaping satisfactory AI-supported learning experiences.

DS had the strongest effect on LS, followed by PEOU, TI, SEQ, IS, and IQ. This result indicates that students' ability to formulate prompts, verify information, assess output quality, and apply AI-generated content is more influential than the technical ease of operating the tools. Although the TAM emphasizes PEOU [23], the present findings show that ease of use alone is insufficient to produce meaningful LS. In the Vietnamese higher education context, where students increasingly use AI tools yet may receive uneven institutional guidance, DS become a critical resource for translating access into effective learning outcomes.

The mediation analysis further showed that LS significantly transmitted the effects of IQ, SEQ, IS, TI, DS, and PEOU to CI. Among these indirect effects, DS produced the strongest effect, followed by PEOU and TI, reinforcing the importance of individual capability and supportive learning conditions. However, the indirect effect of SQ was not significant because SQ did not significantly influence LS. These results confirm that LS is the principal psychological mechanism by which most technological, institutional, and individual factors promote continued use of AI.

Finally, LS strongly influenced CI, supporting H8 and the expectation–confirmation perspective [15]. The findings, therefore, extend the information systems success model, the TAM, and expectation–confirmation theory by demonstrating that students' continued use of AI cannot be explained by technological quality or ease of use alone. Instead, sustained use emerges from the interaction of digital capability, institutional support, technological conditions, and satisfactory learning experiences.

6. CONCLUSION

This research investigated the factors that sustain university students' use of AI for learning, with particular attention to the mediating role of LS. Evidence from 250 students in Ho Chi Minh City showed that DS exerted the strongest influence on LS, whereas SQ did not produce a statistically significant effect. LS further served as an important pathway linking IQ, SEQ, IS, TI, DS, and PEOU with students' intention to continue using AI for academic purposes.

The study contributes to the literature by shifting the focus from initial AI adoption to continued use and by integrating technological, institutional, and individual factors within a post-adoption framework. The findings suggest that universities should strengthen students' DS, guide instructors, improve TI, and promote the responsible evaluation of AI-generated content. These efforts may help transform access to AI tools into sustainable and meaningful learning experiences.

This study has several limitations. First, the cross-sectional design limits causal interpretation and does not capture changes in AI use over time. Future studies should employ longitudinal or experimental designs to examine how LS and CI evolve. Second, purposive sampling and the sample of 250 students from Ho Chi Minh City may limit representativeness and generalizability. Future research should use broader and more diverse samples, including students from different disciplines, academic levels, regions, and types of universities. Comparative studies across public and private universities may also provide additional insights. Third, the study relied on self-reported data. Although full collinearity VIF results suggested that common method bias was not a serious concern, responses may still be affected by recall or social desirability bias. Future studies could combine surveys with objective usage data, learning-platform records, or observed AI-supported learning behavior. Finally, future models could include additional variables such as trust in AI, perceived risk, academic integrity concerns, habit, and actual usage behavior. These variables may improve the model's explanatory power. They may also provide a more comprehensive understanding of students' CI to use AI in learning.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [LTKH], upon reasonable request.

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