Artificial Intelligence Quality and Vietnamese University Students' Continuance Intention of Learning-oriented AI Tools: Mediating Effects of Perceived Usefulness and Learning Satisfaction

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***Abstract*—Generative Artificial Intelligence (AI) tools, especially conversational systems such as ChatGPT, are becoming increasingly influential in higher education because they can support personalized learning, interactive communication, and flexible access to academic information. Although previous research has examined AI acceptance and adoption, less is known about how the quality of AI tools contributes to students' continued use in emerging higher education contexts such as Vietnam. Drawing on the Information Systems Success Model (ISSM), the Technology Acceptance Model (TAM), and the Expectation-Confirmation Model (ECM), this study examines how the information, system, and service quality of AI tools shape Vietnamese university students' intention to continue using these tools for learning. It also examines the mediating roles of perceived usefulness and learning satisfaction. Survey data were obtained from 517 university students in Vietnam and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The results indicate that each of the three AI quality dimensions significantly enhances perceived usefulness. AI System Quality also has a significant positive effect on learning satisfaction, whereas AI information quality and AI service quality do not directly predict learning satisfaction. In addition, perceived usefulness significantly enhances both learning satisfaction and continuance intention, and learning satisfaction further increases continuance intention. The mediation analysis shows that AI quality influences students' continued academic use of AI through perceived usefulness and learning satisfaction. These findings emphasize the need to improve both the technical quality of AI tools and students' post-adoption learning experiences in order to sustain meaningful AI use in higher education.**

***Keywords*—artificial intelligence, continuance intention, higher education, learning satisfaction, perceived usefulness, service quality, system quality**

I. Introduction

In recent years, Artificial Intelligence (AI) has advanced considerably and become increasingly prominent across various sectors, especially higher education. The rise of generative AI applications, especially ChatGPT, has created new possibilities for teaching and learning by enabling interactive communication, individualized feedback, and timely academic support [1, 2]. These technologies enable students to access information more efficiently, receive instant feedback, improve academic performance, and engage more actively in learning activities [3].

AI use in higher education has become increasingly common across different countries. Recent evidence indicates that approximately 66% of university students have used ChatGPT for academic purposes, and 89% for homework or essays [4, 5]. In the Vietnamese context, over 72% of surveyed university students in Hanoi indicated that they had used ChatGPT for academic purposes at least once, making it the most commonly used AI tool in that sample [6]. These figures suggest that AI is no longer a peripheral technology but has become increasingly embedded in students' learning practices.

Despite these benefits, the use of AI in education remains controversial. On the one hand, AI can enhance learning efficiency, support personalized learning, and reduce cognitive workload. However, its use also raises concerns about academic integrity, plagiarism, inaccurate information, excessive dependence on AI-generated outputs, and unequal access to digital technologies [7, 8]. Therefore, the value of AI in higher education is shaped not merely by access to the technology but also by students' evaluations of its quality, usefulness, and role in supporting satisfying learning experiences.

Existing studies have made important contributions to understanding AI adoption in education. For instance, Maheshwari [9] investigated the determinants of students' intention to adopt and use ChatGPT in Vietnamese higher education. Parker *et al.* [10] analyzed how graduate instructors experienced ChatGPT in higher education, whereas Al-Mughairi and Bhaskar [11] focused on teachers' views regarding AI adoption. However, much of the existing literature focuses on initial adoption intentions or educators' perspectives, while students' continuance intentions remain relatively underexplored.

Moreover, prior research in Vietnam remains fragmented and often focuses on isolated adoption factors rather than the mechanisms by which AI quality drives continued use. Previous evidence further indicates that students' perceptions of usefulness strongly shape their AI-related behavior, underscoring the role of academic value in evaluating AI tools. However, limited evidence explains whether AI Information Quality, AI System Quality, and AI Service Quality influence continuance intention through perceived usefulness and learning satisfaction.

Although students' adoption of ChatGPT and other AI tools has been investigated in Vietnam, most studies have focused on initial acceptance rather than continued use. Furthermore, earlier studies have mainly examined individual-level perceptions, including usefulness, ease of use, and behavioral intention, but have paid less attention to

the distinct roles of AI quality dimensions in explaining continued use. Accordingly, this study advances prior research by treating AI Information Quality, AI System Quality, and AI Service Quality as distinct predictors and examining their indirect relationships with continuance intention through perceived usefulness and learning satisfaction.

In this study, AI tools refer mainly to generative and conversational AI applications used for academic learning, such as ChatGPT and Google Gemini. These tools support students in information searching, writing assistance, problem-solving, explanation generation, and self-directed learning. Because such tools may differ in accuracy, accessibility, responsiveness, and learning support functions, examining AI quality is important for understanding students' continued use after initial adoption.

Continuance intention is also important from an institutional perspective because sustained and appropriate use of AI tools can support learning outcomes, academic quality assurance, and outcome-based education. Understanding the mechanisms that encourage students to continue using AI responsibly can help universities design better AI-related policies, training programs, and support systems.

To fill this research gap, the present study develops an integrated framework that explains how AI quality shapes Vietnamese university students' intention to continue using AI tools for learning. Within the proposed framework, AI quality is conceptualized through three distinct dimensions: information quality, system quality, and service quality. Drawing on the Technology Acceptance Model and a post-adoption perspective, the study proposes that perceived usefulness and learning satisfaction clarify how AI quality contributes to students' continuance intention.

This study offers three main contributions. First, it moves beyond initial AI adoption to examine continuance intention, offering a post-adoption view of AI use in higher education. Second, it combines AI quality, perceived usefulness, and learning satisfaction into a single model to more fully explain students' sustained use of AI tools. Third, by focusing on Vietnamese university students, this study provides empirical evidence from an emerging higher education context in which AI use is expanding rapidly yet still requires further academic and institutional guidance.

II. Literature Review

A. Key Concepts

1) Artificial Intelligence (AI)

Artificial Intelligence (AI) is a field of computer science devoted to developing systems capable of carrying out functions typically linked to human intelligence, including natural language processing, learning, reasoning, and decision-making [12]. Within higher education, AI is increasingly used to support academic activities such as personalized learning, automated assessment, and intelligent tutoring. More recently, the emergence of Large Language Models (LLMs) has further expanded AI's role in education by enabling real-time interaction, adaptive feedback, and enhanced self-directed learning.

Despite these advantages, integrating AI into educational environments also raises several concerns. The literature has frequently discussed doubts regarding the correctness and dependability of AI-generated information, academic integrity, and students' excessive dependence on technology. Consequently, understanding what drives students to adopt and continue using AI technologies has become a significant issue in current educational research.

Among current AI applications, ChatGPT has become widely used in higher education because it can produce conversational responses and assist students with tasks such as writing, information retrieval, and problem-solving [1, 13].

In this study, AI tools refer specifically to generative and conversational AI tools used for academic learning, particularly Large Language Model (LLM)-based tools such as ChatGPT and Google Gemini. Therefore, the term does not refer to all types of AI applications, such as predictive analytics systems, recommendation algorithms, automated grading systems, or other non-conversational AI technologies. Accordingly, this study interprets the three AI quality dimensions within the specific context of LLM-based tools used for learning. AI information quality describes students' evaluation of whether AI-generated responses are accurate, relevant, clear, complete, and useful for learning. AI system quality captures students' perceptions of the reliability, usability, accessibility, response speed, and technical stability of the AI tool. AI service quality reflects how students evaluate the responsiveness, personalization, interactivity, and learning support offered during AI-based interactions. This distinction is important because LLM-based tools generate probabilistic, prompt-dependent responses, meaning their quality requirements may differ from those of traditional AI applications or conventional e-learning systems.

2) Continuance Intention (CI)

Continuance intention denotes a user's willingness to keep using a technology after having prior experience with it [14]. Unlike initial adoption intention, which focuses on users' willingness to try a new system, continuance intention reflects sustained usage behavior and long-term engagement with the technology. According to the Expectation-Confirmation Model (ECM), users' decisions to continue using a technology depend largely on how they evaluate it after use, especially perceived usefulness and satisfaction. When users perceive that a technology provides meaningful benefits and fulfills their expectations, they are more likely to continue using it over time [14].

In higher education, AI continuance intention refers to students' willingness to keep using tools such as ChatGPT for academic purposes, including learning support, problem-solving, information retrieval, and knowledge acquisition. This construct is important because AI-supported learning can be effective only when students move beyond initial acceptance and incorporate AI tools into their regular academic practices. Thus, both cognitive evaluations, such as perceived usefulness, and affective evaluations, such as learning satisfaction, are expected to play important roles in shaping students' intention to continue using AI in learning.

B. Theoretical Foundations

This study integrates the Information Systems Success

Model, the Technology Acceptance Model (TAM), and the Expectation-Confirmation Model (ECM) to explain how AI quality influences students' continuance intention through perceived usefulness as a cognitive mechanism and learning satisfaction as an affective mechanism.

1) Technology Acceptance Model (TAM)

Proposed by Davis [15], the Technology Acceptance Model (TAM) explains technology acceptance primarily through users' perceptions of a system's usefulness and ease of use. Perceived usefulness describes the degree to which users believe that a technology can improve their task performance. In education, perceived usefulness has frequently been shown to be an important factor shaping students' adoption and use of digital learning technologies. In this study, perceived usefulness is employed as a central cognitive mechanism through which AI quality influences students' learning outcomes and behavioral intentions.

2) Expectation-Confirmation Model (ECM)

Developed by Bhattacherjee [14], the Expectation-Confirmation Model (ECM) explains users' decisions to continue using a technology after their initial experience. Within ECM, continuance intention is mainly shaped by users' post-use evaluations of a system, especially its perceived usefulness and satisfaction. When users perceive that a system meets their expectations and delivers meaningful benefits, they are more likely to continue using it. In AI-supported higher education, ECM is useful for explaining how perceived usefulness and learning satisfaction encourage students to continue using AI tools.

3) Information Systems (IS) success model

Developed by DeLone and McLean [16], the Information Systems Success Model identifies information quality, system quality, and service quality as key determinants of users' evaluations and overall information system success. These quality factors influence users' evaluations of a system and, in turn, affect their satisfaction and behavioral outcomes. In this study, the model is applied to conceptualize AI quality as a multidimensional construct, capturing the technical and service-related attributes of AI systems that shape students' perceived usefulness and learning satisfaction.

In this study, these three theoretical perspectives are combined to explain why students continue using AI tools for learning. The Information Systems Success Model is used to identify three quality-related dimensions of AI tools: AI Information Quality, AI System Quality, and AI Service Quality. These quality dimensions represent students' evaluations of the content, technical performance, and support functions of AI tools. TAM is used to explain perceived usefulness as the key cognitive mechanism through which AI quality influences students' learning evaluations and behavioral intention. ECM is used to explain the post-adoption process in which perceived usefulness and learning satisfaction shape continuance intention.

Although ECM originally includes confirmation, this study does not include confirmation as a separate construct because the focus is not on comparing students' pre-use expectations with post-use experiences. Instead, the study focuses on how students' perceived quality of AI tools after use influences their perceptions of usefulness, satisfaction, and continuance intention. Similarly, perceived ease of use from TAM is not included as a separate construct because the technical and usability-related aspects of AI tools are already captured by AI system quality, including reliability, accessibility, responsiveness, and ease of operation. This approach helps avoid conceptual overlap and keeps the model parsimonious.

In addition, AI quality is not modeled as a higher-order construct in this study. Rather, the term is used as an umbrella concept that encompasses three distinct first-order dimensions: AI Information Quality, AI System Quality, and AI Service Quality. These dimensions are examined independently to identify their distinct effects on perceived usefulness and learning satisfaction.

C. Influencing Factors and Hypothesis Development

1) AI Information Quality (AIQ)

Information quality describes the extent to which system-provided information is accurate, relevant, timely, and reliable [16]. In this study, AI Information Quality (AIQ) refers to the extent to which AI tools provide accurate, relevant, complete, and timely information to support students' learning activities.

High-quality AI-generated information can help students access useful knowledge more efficiently and reduce the effort needed to verify or interpret information. Previous studies indicate that information quality strengthens perceived usefulness because users tend to value systems that deliver reliable and meaningful outputs [17, 18]. By contrast, low information quality may weaken user experience and satisfaction because users must invest additional effort in checking inaccurate or unclear outputs [19].

In higher education, AI tools that provide relevant and reliable learning support are more likely to be perceived as useful and to contribute to students' satisfaction with their learning experience. Accordingly, the study proposes the following hypotheses:

H1: Higher AI information quality is associated with greater perceived usefulness.

H2: Higher AI information quality is associated with greater learning satisfaction.

2) AI System Quality (ASQ)

System quality describes the technical performance of an information system, such as its reliability, usability, response speed, accessibility, and overall functionality [16]. In this study, AI System Quality (ASQ) reflects students' of AI tools as stable, user-friendly, responsive, and easily accessible for learning.

Previous studies indicate that system quality strongly shapes users' perceptions and experiences of digital learning technologies. When a system is easy to use, reliable, and responsive, users are more likely to perceive it as useful and experience greater satisfaction [17, 20, 21]. In the context of AI-supported learning, a high-quality AI system can reduce technical difficulties, improve learning efficiency, and enhance students' learning experience.

Therefore, AI tools that operate smoothly and are easy to use are more likely to be perceived as useful and to increase students' satisfaction with the learning process. Accordingly, the study proposes the following hypotheses:

H3: Higher AI system quality is associated with greater

perceived usefulness.

H4: Higher AI system quality is associated with greater learning satisfaction.

3) AI Service Quality (ASVQ)

Service quality describes users' evaluation of whether a system or service provider delivers reliable, responsive, supportive, and personalized assistance. In this study, AI Service Quality (ASVQ) reflects the extent to which AI tools deliver timely responses, relevant support, personalized assistance, and effective interaction during students' learning activities.

Prior evidence suggests that service quality influences both user satisfaction and continued use of digital systems. When users receive responsive support and reliable service experiences, they are more likely to perceive the system as useful and feel satisfied with it [22–25]. In AI-supported learning, high service quality can help students solve learning problems more effectively, receive individualized assistance, and improve their overall learning experience.

Therefore, AI tools that provide responsive and personalized learning support are more likely to be perceived as useful and to enhance students' satisfaction with AI-assisted learning. Accordingly, the study proposes the following hypotheses:

H5: Higher AI service quality is associated with greater perceived usefulness.

H6: Higher AI service quality is associated with greater learning satisfaction.

4) Perceived Usefulness (PU)

Perceived usefulness reflects the extent to which users believe that a technology enhances their performance [15]. In AI-supported higher education, it captures students' perceptions that AI tools improve learning effectiveness, facilitate problem-solving, and contribute to academic achievement.

Prior studies have shown that perceived usefulness plays a critical role in shaping both users' satisfaction and continuance intention. Students who consider AI tools beneficial for learning are more likely to report positive learning experiences and greater satisfaction [26, 27]. Moreover, perceived usefulness is a strong predictor of continuance intention because users generally continue using technologies that offer clear value [28, 29].

Accordingly, the study proposes the following hypotheses:

H7: Greater perceived usefulness is associated with higher learning satisfaction.

H8: Greater perceived usefulness is associated with stronger continuance intention.

5) Learning Satisfaction (LS)

Learning satisfaction reflects users' overall assessment of a technology experience formed through their interactions with the system and the outcomes obtained [14]. In the context of AI-supported learning, learning satisfaction reflects the extent to which students feel satisfied with their learning experiences when using AI tools such as ChatGPT.

From the expectation–confirmation perspective, satisfaction is an important driver of continuance intention. When users have positive experiences, and their expectations are fulfilled, they are more likely to continue using the technology [14]. Empirical studies have consistently confirmed that satisfaction significantly influences users' intention to continue using digital technologies across various contexts [19, 27].

In higher education, satisfied students are more likely to keep using AI tools to support their academic activities. Therefore, the study proposes the following hypothesis:

H9: Greater learning satisfaction is associated with stronger continuance intention.

In addition to the direct relationships, this study further proposes that perceived usefulness and learning satisfaction serve as mediating mechanisms linking AI quality dimensions to students' continuance intention. Based on TAM and ECM, continued AI use is expected to be stronger when students recognize the usefulness of AI tools and experience satisfaction from AI-assisted learning. Accordingly, the study advances the following mediation hypotheses:

H10a: AI information quality influences continuance intention indirectly through perceived usefulness.

H10b: AI system quality influences continuance intention indirectly through perceived usefulness.

H10c: AI service quality influences continuance intention indirectly through perceived usefulness.

H11a: AI information quality influences continuance intention indirectly through learning satisfaction.

H11b: AI system quality influences continuance intention indirectly through learning satisfaction.

H11c: AI service quality influences continuance intention indirectly through learning satisfaction.

H12a: AI information quality has a sequential indirect effect on continuance intention through perceived usefulness and learning satisfaction.

H12b: AI system quality has a sequential indirect effect on continuance intention through perceived usefulness and learning satisfaction.

H12c: AI service quality has a sequential indirect effect on continuance intention through perceived usefulness and learning satisfaction.

Fig. 1 presents the research model developed from the integrated theoretical framework.

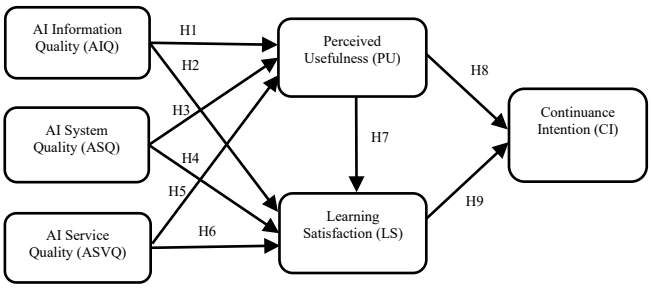


Fig. 1. Research model.

III. Methodology

A. Measurement and Data Collection

The questionnaire incorporated measurement items adapted from prior research on information systems, technology acceptance, and AI-supported learning. The study includes six constructs: AI Information Quality (AIQ), AI System Quality (ASQ), AI Service Quality (ASVQ), Perceived Usefulness (PU), Learning Satisfaction (LS), and Continuance Intention (CI). The measurement items were

drawn from validated scales and modified to fit the context of AI use among Vietnamese university students. Table A1 in Appendix A provides the complete set of items adapted and contextualized for AI-supported learning.

Responses were recorded on a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree. The questionnaire was pilot-tested with 30 university students to evaluate the clarity, relevance, and wording of its items. Based on the pilot feedback, minor wording adjustments were made to improve readability and contextual suitability. The questionnaire was first developed in English, translated into Vietnamese, and then independently translated back into English by bilingual academic researchers. The original and back-translated versions were compared to ensure semantic equivalence, and any discrepancies were discussed and resolved before the final survey was administered.

Table 1 summarizes the measurement constructs, number of items, and their corresponding sources adapted from prior studies.

Table 1. Measurement scales

Construct	Code	Items	Source
AI Information Quality	AIQ	5	Ashfaq *et al*. [19]
AI System Quality	ASQ	4	Abbasi *et al*. [30]
AI Service Quality	ASVQ	6	Ashfaq *et al.* [19]
Perceived Usefulness	PU	4	Bhattacherjee [14]; Davis [15]
Learning Satisfaction	LS	4	Wang *et al.* [27]
Continuance Intention	CI	5	Abbasi *et al.* [30]

A quantitative design was employed, with data collected through a structured questionnaire. The target respondents were Vietnamese university students who had previously used AI tools, such as ChatGPT or Google Gemini, for academic purposes. This criterion ensured that the respondents were suitable for examining post-adoption constructs, including perceived usefulness, learning satisfaction, and continuance intention.

The questionnaire began with a screening question to confirm respondents' eligibility for the post-adoption analysis. Respondents were asked whether they had used AI tools, such as ChatGPT or Google Gemini, for academic learning before participating in the survey. Only those who answered "Yes" were allowed to continue the survey, while respondents without prior AI learning experience were excluded. In this study, prior experience was defined as having used at least one AI tool for learning-related activities, such as academic information searching, writing support, problem-solving, explanation generation, or assignment-related learning.

Data collection was conducted via an online survey distributed via academic networks, student groups, and online platforms. Convenience sampling was used to reach students from different universities, majors, and years of study. Although this approach was appropriate for accessing respondents with prior AI learning experience, it may limit the generalizability of the findings. In particular, students with higher levels of digital engagement or stronger interest in AI tools may have been more willing to participate in the survey. In total, 534 responses were collected. After data screening, 17 responses were removed for incompleteness or failure to meet eligibility criteria, leaving 517 valid responses for analysis. Therefore, the reported valid response rate is 96.8% after data screening, rather than the overall survey response rate. Table 2 summarizes the demographic profile of the valid respondents.

Table 2. Demographic characteristics of respondents (N = 517)

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	248	48.0
	Female	269	52.0
University	Economics/Business universities	172	33.3
	Technical universities	141	27.3
	Multidisciplinary universities	204	39.4
Major	Business & Management	148	28.6
	Information Technology	112	21.7
	Economics	96	18.6
	E-commerce	87	16.8
	Other	74	14.3
Year of Study	First Year	84	16.2
	Second Year	141	27.3
	Third Year	153	29.6
	Fourth Year	139	26.9
AI Usage Frequency	Rarely (≤1 time/week)	96	18.6
	Occasionally (2–3 times/week)	181	35.0
	Frequently (≥4 times/week)	240	46.4

Ethical considerations were addressed before data collection. Ethical approval was granted by the Ethical Committee of the Industrial University of Ho Chi Minh City, Vietnam, on 24 February 2023 (Ref. No. 296/QD-DHCN). Before completing the questionnaire, participants received information about the study purpose, the voluntary nature of participation, and their right to discontinue at any time. Verbal informed consent was obtained from each participant. Responses were collected anonymously and used exclusively for academic research to safeguard participants' confidentiality.

As a result of the screening process, all respondents had used AI tools for learning-related activities, including assignments, academic information searching, and problem-solving. The final sample size was adequate for PLS-SEM analysis and hypothesis testing.

Table 2 indicates a relatively balanced gender composition, with women accounting for 52.0% of the sample and men for 48.0%. Most respondents came from multidisciplinary universities and business-related majors, reflecting a reasonable diversity in academic backgrounds. Notably, 46.4% of students reported frequent use of AI, indicating that AI has become a widely used learning tool among the surveyed group.

B. Data Analysis

Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed to evaluate the proposed research model. The data analysis was conducted using SmartPLS. PLS-SEM was considered appropriate because the study focuses on prediction and seeks to explain Vietnamese university students' continuance intention to use AI tools for learning through several antecedents and mediating pathways. Compared with covariance-based SEM, PLS-SEM is well-suited to models that emphasize explained variance, prediction, and theory extension, especially when survey data may not fully satisfy the strict assumptions of multivariate normality.

All constructs were specified as reflective because their measurement items were viewed as indicators of the

underlying latent variables and were expected to correlate strongly with one another. In addition, AI quality was not modeled as a higher-order construct. Instead, it was analyzed through three separate first-order dimensions: AI Information Quality, AI System Quality, and AI Service Quality.

Several procedural measures were applied to reduce the risk of common method bias. Participants were informed that participation was voluntary and anonymous and that no answer was considered right or wrong. The questionnaire items were adapted from established scales, reviewed by lecturers, and refined through pilot testing before the main data collection. In addition, potential common method bias was further examined using Harman's single-factor test. The first unrotated factor accounted for 37.42% of the total variance, remaining below the recommended 50% threshold. Therefore, common method bias was unlikely to be a serious concern in this study.

Statistical significance for the outer loadings, structural paths, and indirect effects was evaluated through a 5,000-subsample bootstrapping procedure following PLS-SEM recommendations [31].

IV. Results

A. Measurement Model Assessment

The measurement model was assessed in terms of reliability, convergent validity, and discriminant validity using Cronbach's alpha, Composite Reliability (CR), outer loadings, and Average Variance Extracted (AVE). Following Hair *et al*. [32], Cronbach's alpha, CR, and outer loadings should exceed 0.70, while AVE should be greater than 0.50.

Item reliability was assessed by examining the outer loading values of all measurement items. Table 3 reports these results.

Table 3. Outer loadings of measurement items

Construct	Item	Outer loading
AI Information Quality (AIQ)	AIQ1	0.782
	AIQ2	0.814
	AIQ3	0.751
	AIQ4	0.735
	AIQ5	0.792
AI System Quality (ASQ)	ASQ1	0.912
	ASQ2	0.885
	ASQ3	0.921
	ASQ4	0.886
AI Service Quality (ASVQ)	ASVQ1	0.765
	ASVQ2	0.788
	ASVQ3	0.824
	ASVQ4	0.741
	ASVQ5	0.835
	ASVQ6	0.811
Perceived Usefulness (PU)	PU1	0.875
	PU2	0.892
	PU3	0.864
	PU4	0.908
Learning Satisfaction (LS)	LS1	0.915
	LS2	0.931
	LS3	0.908
	LS4	0.938
Continuance Intention (CI)	CI1	0.854
	CI2	0.882
	CI3	0.841
	CI4	0.895
	CI5	0.878

Note: All outer loading values exceeded the recommended 0.70 threshold, indicating acceptable item reliability.

Table 3 shows that all outer loading values were higher than 0.70. This result indicates adequate item reliability; therefore, all measurement items were retained for subsequent analysis.

Table 4 presents the results for reliability and convergent validity. As reported in Table 4, all Cronbach's alpha and composite reliability values exceeded 0.70, while the average variance extracted values were above 0.50. These findings indicate satisfactory internal consistency and convergent validity for all constructs.

Table 4. Construct reliability and validity test results

Latent variable	Cronbach's alpha	Composite Reliability (CR)	AVE
AIQ	0.887	0.883	0.601
ASQ	0.873	0.945	0.812
ASVQ	0.871	0.911	0.632
PU	0.902	0.935	0.783
CI	0.910	0.940	0.757
LS	0.916	0.958	0.852

Note: AIQ = AI Information Quality; ASQ = AI System Quality; ASVQ = AI Service Quality; PU = Perceived Usefulness; LS = Learning Satisfaction; CI = Continuance Intention; CR = Composite Reliability; AVE = Average Variance Extracted.

The Heterotrait-Monotrait Ratio (HTMT) was employed to assess discriminant validity. Table 5 shows that every HTMT value remained below the recommended cut-off of 0.90.

Table 5. HTMT ratio-matrix

Latent variable	AIQ	ASQ	ASVQ	PU	CI	LS
AIQ						
ASQ	0.667					
ASVQ	0.869	0.734				
PU	0.781	0.746	0.784			
CI	0.732	0.798	0.765	0.811		
LS	0.802	0.765	0.843	0.826	0.843	

Note: AIQ = AI Information Quality; ASQ = AI System Quality; ASVQ = AI Service Quality; PU = Perceived Usefulness; LS = Learning Satisfaction; CI = Continuance Intention; HTMT = Heterotrait-Monotrait Ratio.

These results provide evidence that the constructs achieved satisfactory discriminant validity. Although some HTMT values were relatively high, such as AIQ–ASVQ and CI–LS, these constructs remain conceptually distinct. AI information quality focuses on the accuracy, relevance, completeness, and timeliness of AI-generated content, whereas AI service quality reflects responsiveness, personalization, and support functions. Similarly, learning satisfaction reflects students' affective evaluation of their AI-supported learning experience, while continuance intention reflects their future intention to continue using AI tools.

B. Structural Model Assessment

Multicollinearity among the constructs was examined using the Variance Inflation Factor (VIF), with the results shown in Table 6.

The VIF values were examined to evaluate multicollinearity. As shown in Table 6, all VIF values were below 5, indicating that multicollinearity was not a serious issue in the structural model.

The explanatory and predictive performance of the structural model was assessed using the coefficient of determination (R^2) and predictive relevance (Q^2), as reported in Table 7.

The R^2 results show that the model accounts for 65.0%,

68.3%, and 70.1% of the variance in PU, LS, and CI, respectively, indicating moderate to substantial explanatory power. In addition, all Q^2 values are positive, indicating that the model has adequate predictive relevance.

Table 6. Results of the VIF test

Variable	VIF
AIQ → PU	2.523
AIQ → LS	2.892
ASQ → PU	2.254
ASQ → LS	2.211
ASVQ → PU	3.021
ASVQ → LS	3.435
PU → LS	3.215
PU → CI	3.325
LS → CI	3.254

Note: AIQ = AI Information Quality; ASQ = AI System Quality; ASVQ = AI Service Quality; PU = Perceived Usefulness; LS = Learning Satisfaction; CI = Continuance Intention; VIF = Variance Inflation Factor.

Table 7. Structural model results (R^2 and Q^2)

Endogenous construct	R^2	Q^2
PU	0.650	0.412
LS	0.683	0.438
CI	0.701	0.465

Note: PU = Perceived Usefulness; LS = Learning Satisfaction; CI = Continuance Intention; R^2 = Coefficient of Determination; Q^2 = Predictive Relevance.

C. Hypothesis Testing Results

Table 8 reports the hypothesis-testing results from bootstrapping with 5000 subsamples.

The bootstrapping results indicate that most of the hypothesized relationships are statistically significant. Specifically, AI Information Quality (AIQ), AI System Quality (ASQ), and AI Service Quality (ASVQ) significantly influence Perceived Usefulness (PU), supporting H1, H3, and H5. In addition, AI system quality has a significant positive effect on Learning Satisfaction (LS), supporting H4. In contrast, the effects of AIQ and ASVQ on LS are not statistically significant, as their confidence intervals include zero; therefore, H2 and H6 are not supported.

Furthermore, Perceived Usefulness (PU) has significant positive effects on Learning Satisfaction (LS) and Continuance Intention (CI), supporting H7 and H8. Learning Satisfaction (LS) also has a significant positive impact on Continuance Intention (CI), supporting H9. Overall, the results highlight the important roles of perceived usefulness and learning satisfaction as key drivers of students' continuance intention to use AI tools for learning.

Table 8. Bootstrapping test results

Hypothesis	Variable	β (Original Sample)	Standard Deviation	t-value	95% CI LL	95% CI UL	p-value	Decision
H1	AIQ → PU	0.249	0.045	5.533	0.161	0.337	<0.001	Supported
H2	AIQ → LS	0.156	0.114	1.368	−0.067	0.379	0.171	Not supported
H3	ASQ → PU	0.202	0.069	2.928	0.067	0.337	0.003	Supported
H4	ASQ → LS	0.204	0.082	2.488	0.043	0.365	0.013	Supported
H5	ASVQ → PU	0.312	0.081	3.852	0.153	0.471	<0.001	Supported
H6	ASVQ → LS	0.157	0.132	1.189	−0.102	0.416	0.236	Not supported
H7	PU → LS	0.422	0.152	2.776	0.124	0.720	0.006	Supported
H8	PU → CI	0.245	0.112	2.188	0.025	0.465	0.028	Supported
H9	LS → CI	0.317	0.108	2.935	0.105	0.529	0.003	Supported

Note: AIQ = AI Information Quality; ASQ = AI System Quality; ASVQ = AI Service Quality; PU = Perceived Usefulness; LS = Learning Satisfaction; CI = Continuance Intention; β = Standardized Path Coefficient; CI LL = Confidence Interval Lower Limit; CI UL = Confidence Interval Upper Limit. A relationship is considered statistically significant when $p < 0.05$ or $t > 1.96$.

To examine the mediating effects of perceived usefulness and learning satisfaction in greater detail, the study analyzed the specific indirect effects among the constructs. Table 9 reports the results of the mediation analysis.

Table 9. Mediation analysis results

Indirect path	Indirect effect (β)	95% CI LL	95% CI UL	p-value	Decision
AIQ → PU → CI	0.061	0.006	0.125	0.028	Supported
ASQ → PU → CI	0.049	0.003	0.116	0.032	Supported
ASVQ → PU → CI	0.076	0.007	0.168	0.029	Supported
AIQ → LS → CI	0.049	–0.021	0.144	0.173	Not supported
ASQ → LS → CI	0.065	0.009	0.145	0.016	Supported
ASVQ → LS → CI	0.050	–0.032	0.156	0.237	Not supported
AIQ → PU → LS → CI	0.033	0.006	0.076	0.009	Supported
ASQ → PU → LS → CI	0.027	0.003	0.069	0.012	Supported
ASVQ → PU → LS → CI	0.042	0.006	0.101	0.009	Supported

Note: AIQ = AI Information Quality; ASQ = AI System Quality; ASVQ = AI Service Quality; PU = Perceived Usefulness; LS = Learning Satisfaction; CI = Continuance Intention; β = Standardized Indirect Effect; CI LL = Confidence Interval Lower Limit; CI UL = Confidence Interval Upper Limit. An indirect effect is considered statistically significant when $p < 0.05$ and the 95% confidence interval does not include zero.

To provide a more complete assessment of the mediating mechanisms, this study further examined the specific indirect relationships among the constructs. Table 9 shows that AI Information Quality, AI System Quality, and AI Service Quality each affected continuance intention indirectly through perceived usefulness. In addition, AI system quality indirectly affected continuance intention through learning satisfaction, whereas learning satisfaction did not significantly transmit the effects of AI information quality or AI service quality to continuance intention. The sequential pathways linking the three AI quality dimensions to continuance intention through perceived usefulness and learning satisfaction were statistically significant. These findings indicate that perceived usefulness and learning satisfaction help explain how students' evaluations of AI quality translate into continued use of AI tools for learning.

PLS-SEM was used to estimate the relationships among the constructs. The resulting standardized path coefficients and R^2 values are displayed in Fig. 2.

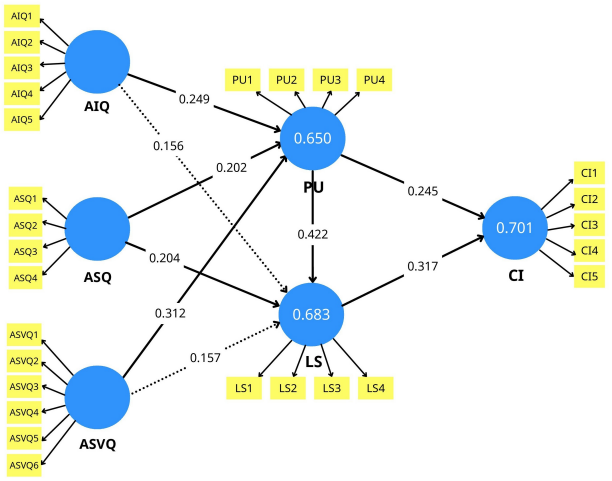


Fig. 2. Structural model with standardized path coefficients and R^2 values. Note: AIQ = AI Information Quality; ASQ = AI System Quality; ASVQ = AI Service Quality; PU = Perceived Usefulness; LS = Learning Satisfaction; CI = Continuance Intention; R^2 = Coefficient of Determination. Solid lines indicate significant paths, while dashed lines indicate non-significant paths.

V. Discussion

This study demonstrates that AI-related quality dimensions, including AI Information Quality (AIQ), AI System Quality (ASQ), and AI Service Quality (ASVQ), play important roles in explaining students' Perceived Usefulness (PU), Learning Satisfaction (LS), and Continuance Intention (CI) in academic learning contexts. The results indicate that both PU and LS act as key mechanisms through which quality perceptions translate into continued AI usage.

The empirical findings reveal that AIQ, ASQ, and ASVQ significantly influence PU, with path coefficients of $\beta = 0.249$ ($p < 0.001$), $\beta = 0.202$ ($p = 0.003$), and $\beta = 0.312$ ($p < 0.001$), respectively. These findings align with previous studies showing that information accuracy, system functionality, and service responsiveness can strengthen users' perceived usefulness of digital technologies [17, 19, 30]. In the context of AI-assisted learning, when students perceive AI outputs as reliable and systems as efficient and responsive, they are more likely to recognize the usefulness of such tools in supporting their academic tasks. Among the three AI quality dimensions, AI service quality has the strongest effect on perceived usefulness. This finding suggests that students may value AI tools not only for information accuracy or technical stability, but also for responsive, personalized, and interactive learning support. In academic contexts, students often use AI tools to ask follow-up questions, request explanations, receive writing support, or solve learning problems. Therefore, timely responses, adaptive interaction, and individualized assistance may make AI tools appear more useful for completing academic tasks. This result implies that universities should not focus only on providing access to AI technologies, but also on helping students use AI tools effectively for academic support and self-directed learning.

However, the results show that AIQ and ASVQ do not have a significant direct impact on LS ($\beta = 0.156$, $p = 0.171$; $\beta = 0.157$, $p = 0.236$, respectively), whereas ASQ has a significant effect on LS ($\beta = 0.204$, $p = 0.013$). This finding partially diverges from previous research suggesting that information, system, and service quality generally contribute to user satisfaction in e-learning and information systems contexts [20, 21]. One possible explanation is that the logic of Information System Success may operate differently in generative AI and LLM-based learning environments compared with traditional e-learning systems. In conventional e-learning platforms, information and service quality are often relatively stable and institutionally controlled, as with course materials, learning management functions, and technical support. In contrast, generative AI tools produce probabilistic, prompt-dependent, and context-sensitive responses, meaning that students' evaluations of information quality and service quality may vary across tasks, prompts, and interaction situations.

Therefore, students may not directly translate AI information quality or AI service quality into learning satisfaction. Instead, they may regard accurate answers, relevant explanations, and responsive interaction as basic expectations when using AI tools. These qualities may contribute to satisfaction only when students perceive that the AI tool is useful for completing academic tasks, solving learning problems, improving efficiency, or supporting deeper understanding. This interpretation is consistent with the mediating role of perceived usefulness in this study. It suggests that, in LLM-based learning contexts, AIQ and ASVQ may influence learning satisfaction mainly through perceived academic value rather than through a direct satisfaction pathway. By contrast, AI system quality may have a more immediate effect on learning satisfaction because system reliability, usability, speed, and accessibility directly shape students' learning experience during AI-supported academic tasks.

Importantly, PU strongly influences LS ($\beta = 0.422$, $p = 0.006$), confirming that students who perceive AI tools as beneficial for learning are more likely to experience higher satisfaction. This result supports prior research emphasizing the central role of perceived usefulness in post-adoption behavior [19, 28]. Furthermore, both PU ($\beta = 0.245$, $p = 0.028$) and LS ($\beta = 0.317$, $p = 0.003$) significantly affect CI, indicating that students' intention to continue using AI tools depends not only on perceived utility but also on their overall learning experience. This finding is consistent with studies on expectation-confirmation and continuance intention [26, 27].

In the Vietnamese higher education context, these findings have practical significance. Students increasingly use generative and conversational AI tools such as ChatGPT and Google Gemini for academic information searching, writing support, and problem-solving. However, differences in AI literacy, English proficiency, digital access, and institutional guidance may influence how students evaluate and benefit from these tools. In this context, AI system quality may be particularly important because students' satisfaction depends heavily on stable access, fast response speed, ease of use, and reliable system performance. If students face unstable internet connections, limited access to advanced AI tools, or difficulties using AI platforms in Vietnamese academic tasks, they may prioritize system reliability and usability over service-related features. In addition, limitations in Vietnamese-language processing or context-specific academic support may reduce the direct contribution of AI

service quality to learning satisfaction.

For students with limited AI literacy, high-quality AI responses may not lead to satisfaction unless they know how to verify information, formulate effective prompts, and apply AI-generated content responsibly. In addition, language-related issues and unequal access to stable digital infrastructure may affect students' learning experiences. Universities should therefore develop AI literacy training, clear academic integrity guidelines, and institutional support systems to help students use AI tools responsibly and effectively.

The model also shows moderate to substantial explanatory power, as reflected by R^2 values of 0.650 for PU, 0.683 for LS, and 0.701 for CI. These values show that the model accounts for a considerable share of the variation in perceived usefulness, learning satisfaction, and continuance intention. Overall, sustained AI use in higher education appears to depend on both cognitive evaluations, particularly perceived usefulness, and affective responses, especially learning satisfaction.

VI. Conclusion

This study investigated the effects of AI Information Quality (AIQ), AI System Quality (ASQ), and AI Service Quality (ASVQ) on students' Perceived Usefulness (PU), Learning Satisfaction (LS), and Continuance Intention (CI) in the context of AI-supported academic learning. The findings indicate that all three quality dimensions significantly enhance PU, while only ASQ directly improves LS. In contrast, AIQ and ASVQ do not directly affect LS but exert their influence indirectly through PU. Furthermore, both PU and LS significantly drive continuance intention, confirming their central roles in post-adoption behavior.

The results highlight that perceived usefulness and learning satisfaction serve as key mechanisms linking perceptions of AI quality to students' intention to continue using AI tools. In particular, LS emerges as a critical factor bridging cognitive evaluations (usefulness) and behavioral intention. The findings suggest that while improving information accuracy and service responsiveness are important, system-related factors—such as reliability, usability, and performance—play a more decisive role in shaping students' satisfaction and long-term engagement with AI. These findings extend prior research by showing how technology acceptance and information systems success perspectives can be jointly applied to AI-supported learning.

From a practical standpoint, universities and educational institutions should prioritize improving the system quality of AI-supported learning environments. This can be achieved by providing students with access to reliable AI platforms, ensuring stable digital infrastructure, and offering technical support for using AI in academic activities. Universities should also organize training programs on effective AI use, including prompt design, critical evaluation of AI-generated content, responsible citation practices, and ethical use of AI in assignments. Institutions should also establish explicit policies on academic integrity, data privacy, and acceptable AI use to support responsible student practices. At the same time, universities should balance promoting AI continuance intention with measures to reduce overreliance and protect academic integrity. Rather than discouraging AI use entirely, institutions should guide students toward responsible and purposeful use. For example, universities can require students to disclose their use of AI in assignments, verify AI-generated content against credible academic sources, and design assessments that emphasize critical thinking, reflection, problem-solving, and originality. Lecturers can also provide clear instructions on acceptable and unacceptable AI use for different types of tasks. In addition, AI literacy training should include not only prompt design but also source evaluation, ethical citation, awareness of hallucinated content, and strategies for using AI as a learning support tool rather than a substitute for independent thinking.

To reduce inequality in AI-supported learning, universities should ensure that students from different regions, income groups, and levels of digital access have fair opportunities to use AI tools for learning.

At the policy level, educational policymakers should support the development of Vietnamese-language AI tools and localized AI systems tailored to the linguistic, cultural, and pedagogical needs of Vietnamese higher education. Policies should also encourage universities to integrate AI literacy into curricula, develop institutional AI-use guidelines, establish data protection standards, and promote academic integrity frameworks for AI-assisted learning. These efforts can help ensure that AI adoption in higher education is not only technologically effective but also ethical, inclusive, and consistent with educational quality assurance.

Despite its contributions, this study has several limitations. First, reliance on convenience sampling may limit the extent to which the findings can be generalized. Students with higher digital engagement or stronger interest in AI tools may have been more willing to participate in the survey. Second, the use of self-reported data may have introduced response bias or common method bias despite the procedural safeguards applied. Third, the cross-sectional design prevents the study from capturing how students' perceptions and continuance intention evolve over time. Accordingly, the results indicate relationships among the constructs rather than establishing causality. Although the model draws on TAM, ECM, and the IS Success Model, the research design does not provide sufficient evidence to make strong causal claims about the temporal order among AI quality, perceived usefulness, learning satisfaction, and continuance intention. Longitudinal or experimental studies are therefore recommended to examine causal mechanisms better and understand how students' AI use evolves in higher education. Fourth, this study examined AI tools in general, including tools such as ChatGPT and Google Gemini, rather than comparing specific AI platforms. Because different AI tools may vary in information quality, system reliability, service interaction, language support, and learning functions, future research could compare students' experiences across specific AI platforms. Finally, this study did not examine whether the proposed relationships differ across student groups, such as gender, academic discipline, year of study, English proficiency, or AI usage frequency. These factors may influence how students evaluate the quality of AI information, AI systems, and AI services, as well as perceived usefulness and learning satisfaction. For example, students who use AI tools more frequently may be more sensitive to system reliability, response speed, and interactive support than

students with limited experience with AI. Future research should therefore conduct multi-group or moderation analyses to examine whether gender, academic discipline, AI usage frequency, AI literacy, English proficiency, or level of AI experience affects the strength of the relationships in the proposed model.

APPENDIX A: MEASUREMENT ITEMS

Table A1. Measurement items adapted for AI-supported learning

Construct	Code	Measurement item	Source
AI Information Quality	AIQ1	AI tools such as ChatGPT and Google Gemini provide clear and understandable information for my learning activities.	Adapted from Ashfaq *et al.* [19]
	AIQ2	AI tools provide accurate and reliable information relevant to my academic tasks.	
	AIQ3	AI tools provide comprehensive and sufficiently detailed explanations for my learning needs.	
	AIQ4	AI tools provide timely and up-to-date information for my learning activities.	
	AIQ5	The information generated by AI tools is relevant to my coursework and learning topics.	
AI System Quality	ASQ1	AI tools are user-friendly and easy to operate for academic learning.	Adapted from Abbasi *et al.* [30]
	ASQ2	AI tools respond quickly during my learning activities.	
	ASQ3	AI tools operate reliably and remain accessible whenever I need them for my studies.	
	ASQ4	The overall technical performance of AI tools meets my expectations for academic learning.	
AI Service Quality	ASVQ1	AI tools provide prompt and responsive assistance when I ask learning-related questions.	Adapted from Ashfaq *et al.* [19]
	ASVQ2	AI tools provide helpful support for solving academic and assignment-related problems.	
	ASVQ3	AI tools provide personalized explanations based on my prompts and learning needs.	
	ASVQ4	My interactions with AI tools are smooth and effective for learning.	
	ASVQ5	AI tools provide dependable guidance when I need academic clarification.	
	ASVQ6	AI tools are available whenever I need support for my academic learning.	
Perceived Usefulness	PU1	Using AI tools improves my academic performance.	Adapted from Bhattacherjee [14] and Davis [15]
	PU2	Using AI tools enables me to complete academic tasks more quickly.	
	PU3	Using AI tools enhances my effectiveness in academic learning activities.	
	PU4	Overall, I find AI tools useful for my university studies.	
Learning Satisfaction	LS1	I am satisfied with my overall experience of using AI tools for learning.	Adapted from Wang *et al.* [27]
	LS2	My experience of using AI tools for learning meets my expectations.	
	LS3	Using AI tools provides me with a positive learning experience.	
	LS4	Overall, I am pleased with the learning support provided by AI tools.	
Continuance Intention	CI1	I intend to continue using AI tools for academic learning in the future.	Adapted from Abbasi *et al.* [30]
	CI2	I plan to use AI tools regularly to support my studies and assignments.	
	CI3	I intend to continue using AI tools whenever I need support for academic learning.	
	CI4	I will recommend the use of AI tools for learning support to other students.	
	CI5	My intention to continue using AI tools in future university courses is strong.	

Note: AIQ = AI Information Quality; ASQ = AI System Quality; ASVQ = AI Service Quality; PU = Perceived Usefulness; LS = Learning Satisfaction; CI = Continuance Intention. All items were adapted from prior studies and contextualized for the use of generative and conversational AI tools in academic learning. Responses were measured using a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree.

CONFLICT OF INTEREST

The author declares no conflict of interest.

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