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Research Article

AI-Supported E-Learning Systems and Continuance Intention: Extending the ECM Model in the Context of Education, Communication, and Management

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ABSTRACT

Artificial intelligence (AI) has proven to be a disruptive educational technology in the e-learning system environment, offering significant practical value to both learners and educational institutions. AI plays a critical role in facilitating users' acceptance and adoption of e-learning systems. However, the way AI characteristics influence users' continuance intention to use AI-supported e-learning systems from the perspective of the Expectation-Confirmation Model (ECM) has not been thoroughly studied. To address this research gap, this paper develops a research model that incorporates three constructs related to AI characteristics: perceived intelligence, perceived anthropomorphism, and perceived personalization. The model explores users' continuance intention within this context using the ECM framework. A survey method was employed, and 425 valid responses were collected through random sampling. The model was tested using Partial Least Squares (PLS). The results indicate that intelligence, anthropomorphism, and personalization not only directly influence users' perceived usefulness and satisfaction, thereby promoting their intention to continue engaging with e-learning systems, but also enhance user satisfaction through confirmation and perceived usefulness, further encouraging continued use. This paper contributes to theoretical advancements, discusses future directions for e-learning system research, and offers practical guidance for application developers on designing and developing suitable e-learning systems using AI technology.

Keywords: Expectation Confirmation Model, AI Characteristics, E-Learning, Continuance Intention.

INTRODUCTION

As an emerging technology platform in the field of educational technology, e-learning systems provide users with more convenient educational services and reduce the impact of physical barriers (Al Amin et al., 2023). Users can participate in online courses anytime and anywhere, easily and efficiently, thus becoming lifelong learners (Asiry, 2017). For educational institutions, e-learning systems can lower operational costs and increase competitiveness, while for learners, e-learning is often more effective than traditional learning methods (Popovici & Mironov, 2015; Vitoria et al., 2018).

In recent years, artificial intelligence (AI) technology has become closely linked with e-learning systems (Stracqualursi and Agati, 2024). AI refers to the use of machines that operate through computer systems to simulate human intelligence activities, providing services or completing a series of tasks in various contexts to assist users or businesses (Huang & Rust, 2020; Prentice et al., 2020). The integration of AI transforms traditional e-learning systems into intelligent e-learning systems, meeting users' basic needs for personalized and intelligent services while enhancing user experience and learning efficiency (Kashive et al., 2020). For example, in the case of Duolingo, the intelligent learning assistant interacts with users using human-like language, collects user data, and adjusts the learning content and difficulty in real-time through AI technology. It provides instant feedback and uses predictive analysis to identify learning bottlenecks, offering targeted, personalized learning solutions, thus improving learning efficiency and motivation (Bicknell et al., 2023).

Users' continuance intention to use e-learning systems is crucial for the successful development of e-learning programs (Cheng, 2014; Saeed Al-Maroof et al., 2020). Most scholars have employed the Technology Acceptance Model (TAM) (e.g., Wu & Zhang, 2014; Wang et al., 2023; Ismail et al., 2012) to study users' continued adoption of e-learning systems. However, unlike these models focused on technology acceptance and adoption, the Expectation-Confirmation Model (ECM) (Bhattacherjee, 2001) emphasizes the impact of users' confirmation of expectations, perceived usefulness, and satisfaction on their continuance intention. ECM is regarded as a robust theoretical model for explaining continuance intention in the context of e-learning systems (e.g., Lee, 2010; Cheng, 2014, 2020; Suzianti & Paramadini, 2021; Rekha et al., 2023).

Research has shown that users' adoption decisions regarding AI-based applications and systems are significantly influenced by AI itself (Balakrishnan & Dwivedi, 2021; Cabrera-Sánchez et al., 2021; Moussawi et al., 2021, 2022; Pillai & Sivathanu, 2020). E-learning systems have utilized AI to enhance their functionality. The literature indicates that, unlike traditional systems, AI systems are characterized primarily by intelligence, anthropomorphism, and personalization, which shape users' perceptions when interacting with such systems (Balakrishnan & Dwivedi, 2021; Moussawi et al., 2021, 2022). In AI-supported e-learning systems, intelligence reflects the use of AI technology to autonomously, efficiently, and dynamically meet learners' needs. Anthropomorphism refers to AI systems that simulate human behavior and communication styles, fostering closer interaction with learners and enhancing the overall learning experience. Personalization refers to AI systems that can dynamically adjust learning content and recommendations based on users' learning habits, preferences, and progress, effectively addressing the unique needs of each learner (Ni & Cheung, 2023;

Stracqualursi & Agati, 2024; Gligorea, 2023; Kashive, 2020). Therefore, it is crucial to explore and investigate whether and how these AI features influence users' adoption of AI-supported e-learning systems.

Thus, traditional e-learning systems have evolved into AI-supported e-learning systems, and the Expectation-Confirmation Model (ECM) serves as a fundamental theoretical framework for studying users' continuance intention in the context of e-learning. In this scenario, the impact of AI characteristics—intelligence, anthropomorphism, and personalization—on the ECM remains unclear and requires further investigation. This leads to the following research question:

Do intelligence anthropomorphism and personalization influence users' continuance intention toward e-learning systems through the functions of the ECM, and if so, how do they affect it?

To address this question, the objective of this study is to develop a research model that explores the influence of intelligence, anthropomorphism, and personalization on users' expectation confirmation, perceived usefulness, and satisfaction, and subsequently their continuance intention toward AI-supported e-learning systems. We employed a survey research method to collect 425 valid responses and utilized Partial Least Squares (PLS) to test the model. By integrating intelligence, anthropomorphism, and personalization into the ECM, this study uncovers the mechanisms through which AI characteristics impact users' expectation confirmation, perceived usefulness, satisfaction, and continuance intention, contributing to the existing literature. In other words, this research enhances the applicability and explanatory power of the ECM, enabling it to predict and explain users' continuance adoption in AI-supported e-learning systems. The structure of this paper is as follows: literature review and hypothesis development, research methodology, results, discussion and contributions, limitations and future research, and conclusion.

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

The Application of AI in e-learning systems The application of artificial intelligence (AI) in e-learning systems has gained considerable attention. Stracqualursi and Agati (2024) investigated public perceptions of AI-driven technologies such as ChatGPT, virtual reality (VR), and adaptive learning, revealing generally positive attitudes and trust in AI's potential to improve educational efficiency and offer personalized learning experiences. Adaptive learning, as noted by Zahabi and Abdul Razak (2020), Raj and Renumol (2021), and Al-Badi et al. (2022), demonstrates AI's capacity to tailor learning pathways based on individual needs. Yu and Guo (2023) emphasize generative AI's transformative role in educational reform, fostering innovations in teaching methods. Immersive learning technologies, including VR and augmented reality (AR), allow learners to engage deeply with simulated environments, as evidenced by medical students practicing surgical techniques in virtual settings (Tang et al., 2021) and engineering students visualizing complex machinery through AR (Wilkerson et al., 2022). AI's role in personalization and improved learning outcomes is further supported by Laanpere et al. (2014), Luckin et al. (2016), and Mayer-Schönberger and Cukier (2014). Smart classroom models, as proposed by Kim et al. (2018), integrate data collection and computational systems to enhance learning. Uskov et al. (2015) introduced an ontology for smart classrooms with varying intelligence levels to support self-learning, while Montebello (2019) describes how sensor-equipped devices can collect user data in ambient intelligent classrooms. AI-driven assessments, focused on personalized learning and learner progression, employ intelligent tutoring systems (Nye, 2015; VanLehn, 2011) that analyze log files and clickstream data to measure success (Crossley et al., 2016). Ultimately, AI in e-learning connects learners to personalized learning environments (PLE) through personal learning networks (PLN), facilitating a more tailored educational experience (Montebello, 2017).

THE ECM AND CONTINUANCE INTENTION TOWARDS E-LEARNING SYSTEMS

The Expectation-Confirmation Model (ECM) has been widely utilized to explain and predict learners' continuance intention in e-learning systems, with various studies extending its applicability. Cheng (2019) integrated ECM with the Task-Technology Fit (TTF) model, demonstrating that the alignment between task characteristics and technological features significantly influences perceived usefulness and satisfaction, which in turn affects continuance intention in cloud-based e-learning systems. Cheng (2020) further expanded ECM by incorporating Flow Theory and the Human-Organization-Technology Fit (HOT-fit) framework, revealing the influence of human, organizational, and technological factors on medical professionals' continuance intention to use cloud-based learning platforms. Obeid et al. (2024) extended ECM by introducing perceived enjoyment, interactivity, social influence, and computer self-efficacy, showing that satisfaction plays a central role in shaping continuance intention, with perceived enjoyment and self-efficacy also contributing significantly. Rekha et al. (2023), in their study on MOOCs, found that confirmation and perceived usefulness strongly impact satisfaction, highlighting the need for platforms to meet learner expectations to sustain engagement. Sasono and Pramana (2023) applied ECM to gamification in e-learning, identifying that user engagement, flow experience, and perceived enjoyment positively influence continuance intention. Soria-Barreto et al. (2021), in a cross-national study, emphasized self-management of learning, habit, and computer anxiety as key factors affecting students' continuance intention to use online learning platforms. Overall, these studies underscore the critical roles of satisfaction, perceived usefulness, and confirmation in explaining continuance intention, with extended models incorporating factors such as gamification, self-efficacy, and cultural context to enhance their explanatory power.

Confirmation refers to the extent to which users perceive alignment between their expectations and a system’s actual performance, indicating whether the system meets or exceeds their expectations (Bhattacherjee, 2001; Sinha and Singh, 2022). In this study, confirmation is defined as users' recognition of their expectations being met when using an AI-supported e-learning system. Perceived usefulness (PU), a key belief in the Technology Acceptance Model, reflects users' perception of a system's value in enhancing performance (Davis et al., 1989; Bhattacherjee, 2001). Here, PU is defined as users' confidence in the AI-supported e-learning system's ability to improve their learning performance. Satisfaction refers to the pleasure users derive when the system's actual benefits align with expected benefits. It is critical to system success, with higher satisfaction driving stronger continuance intention (Esterhuyse et al., 2016; DeLone and McLean, 2003; Liaw and Huang, 2013). Satisfaction, often viewed as the difference between expected and actual benefits, is influenced by factors such as system design, technology, and the environment (Teo, 2014).

Prior research shows that confirmation significantly impacts perceived usefulness and satisfaction in e-learning systems. When actual experiences meet or exceed expectations, confirmation increases, enhancing perceived usefulness and satisfaction (Wang and Lin, 2021). Studies on MOOCs and language-learning apps (Luo et al., 2021; Ünal and Güngör, 2021) affirm this, demonstrating that user confirmation positively influences perceived usefulness. Furthermore, perceived usefulness directly affects satisfaction and significantly strengthens continuance intention. Numerous studies have consistently highlighted confirmation's positive impact on perceived usefulness, satisfaction, and continuance intention (Larsen et al., 2009; Lee, 2010; Cheng, 2019; Obeid et al., 2024).While most research focuses on traditional e-learning, these relationships hold true in AI-supported e-learning systems. AI's ability to offer intelligent feedback and personalized content may amplify the impact of confirmation on perceived usefulness and satisfaction (Laanpere et al., 2014; Luckin et al., 2016; Montebello, 2017). The established influence of perceived usefulness on satisfaction and continuance intention suggests that these mechanisms are applicable in AI-supported environments. Thus, building on existing research, this study proposes the following hypotheses:

H1: Confirmation positively influences perceived usefulness.

H2: Confirmation positively influences satisfaction.

H3: Perceived usefulness positively influences satisfaction with AI-supported e-learning systems.

H4: Perceived usefulness positively influences continuance intention in AI-supported e-learning systems.

H5: Satisfaction positively influences continuance intention in AI-supported e-learning systems.

AI CHARACTERISTICS

Artificial intelligence (AI) has made significant progress in the field of education, gradually becoming a driving force for personalized learning and improved learning outcomes. AI-supported e-learning systems exhibit three key characteristics: intelligence, anthropomorphism, and personalization. These features not only transform traditional education methods but also drive technological innovation in

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Research Article

the field. Through intelligent data analysis, anthropomorphic interactions, and personalized learning plans, AI can offer learners a richer and more tailored learning experience, enhancing learning outcomes and satisfaction.

The intelligence feature is one of AI's core strengths, reflected in its ability to process and analyze large amounts of data. In smart classrooms, devices such as smartphones, desktop computers, and laptops equipped with sensors allow AI to collect data on students' learning behaviors, including motion detection, clickstream logs, and keystroke counts (Kim et al., 2018; Uskov et al., 2015; Montebello, 2019). By analyzing this data in real-time, AI can dynamically adjust instructional content based on students' progress, offering personalized feedback and helping students enhance their self-directed learning abilities. Moreover, AI is used for personalized learning assessments, evaluating student success through log file and clickstream data analysis, which further enhances learner engagement and effectiveness (Cope & Kalantzis, 2015; Nye, 2015; VanLehn, 2011; Mislevy et al., 2014; Ventura et al, 2013). Therefore, we propose the following hypotheses:

H6a: Perceived intelligence positively influences perceived usefulness in AI-supported e-learning systems.

H6b: Perceived intelligence positively influences confirmation in AI-supported e-learning systems.

H6c: Perceived intelligence positively influences satisfaction in AI-supported e-learning systems.

In addition to intelligence, AI-supported systems also exhibit anthropomorphic characteristics that simulate the behavior of human instructors, making the learning experience feel more like face-to-face interaction. AI can recognize students' emotional states and adjust teaching strategies accordingly, providing personalized guidance to help students overcome obstacles in their learning. This anthropomorphic interaction not only enhances learner engagement but also increases motivation and learning outcomes. When students face challenges, AI provides personalized support and guidance, improving overall learning performance (Ni & Cheung, 2023; Stracqualursi & Agati, 2024). Based on this, we propose the following hypotheses:

H7a: Perceived anthropomorphism positively influences perceived usefulness in AI-supported e-learning systems.

H7b: Perceived anthropomorphism positively influences confirmation in AI-supported e-learning systems.

H7c: Perceived anthropomorphism positively influences satisfaction in AI-supported e-learning systems.

Personalization is one of the most important features of AI-supported e-learning systems, reflected in

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Research Article

the ability to tailor learning plans to students' specific needs, interests, and capabilities. AI can dynamically adjust learning content, provide personalized feedback, and offer resources that align with students' learning goals and progress. This personalized learning experience not only improves learning efficiency and satisfaction but also enhances learner engagement (Montebello, 2017; Laanpere et al., 2014; Luckin et al., 2016; Zahabi & Abdul Razak, 2020; Raj & Renumol, 2021; Al-Badi et al., 2022). Furthermore, AI creates immersive learning experiences through virtual reality (VR) and augmented reality (AR), which are particularly effective in fields like medicine and engineering (Bizami et al, 2023; Won et al., 2022; Tang et al., 2021; Wilkerson et al., 2022). Thus, we propose the following hypotheses:

H8a: Perceived personalization positively influences perceived usefulness in AI-supported e-learning systems.

H8b: Perceived personalization positively influences confirmation in AI-supported e-learning systems.

H8c: Perceived personalization positively influences satisfaction in AI-supported e-learning systems.

Based on the above assumptions, this study has developed a conceptual framework to systematically explore the relationships among relevant variables. This framework aims to elucidate the mechanisms through which AI characteristics impact users' continuance intention by integrating theoretical models and empirical data. Specifically, the framework includes the influence of AI characteristics (perceived intelligence, perceived anthropomorphism, and perceived personalization) on continuance intention through perceived usefulness, confirmation, and satisfaction. Through this framework, the study seeks to reveal how AI characteristics enhance users' continuance intention toward AI-supported e-learning systems by influencing their usage experience(See Figure 1).

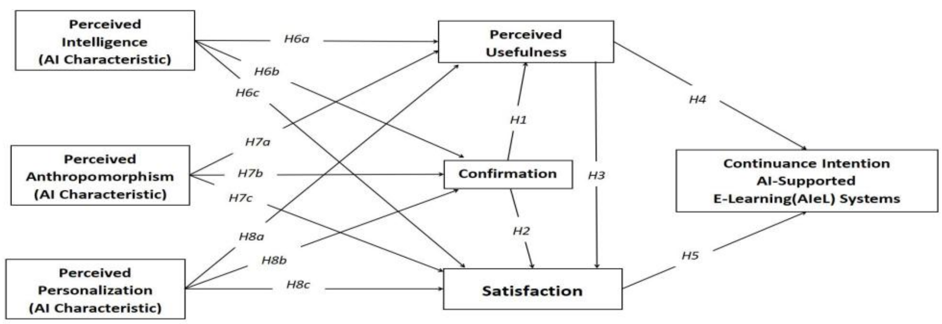

Figure 1 Research Model

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RESEARCH METHODS

Data Collection and Sample Selection

This study collected data through a questionnaire survey, aiming to empirically test the proposed model. The respondents were Chinese users with experience using AI-supported e-learning systems. These users had utilized AI technologies on actual online learning platforms and were able to experience the benefits of AI. By surveying users with AI e-learning experience, we were able to accurately capture their assessments of AI characteristics (such as perceived intelligence, anthropomorphism, and personalization), as well as how these characteristics influence their continuance intentions.

Since the original measurement tools for the variables were in English, the back-translation method was employed to translate the questionnaire into Chinese. This process ensured that the translation accurately reflected the meaning of the original instruments. To ensure the face validity and content validity of the questionnaire, the research team invited three experts in the fields of artificial intelligence and e-learning to review the preliminary Chinese version. These experts assessed the validity, clarity, and relevance of the questionnaire and provided suggestions for revisions. Based on their feedback, several adjustments were made to enhance clarity and ensure consistency with the research objectives. After revising the questionnaire, a pilot test was conducted with 30 users who had experience with AI-supported e-learning. Further adjustments were made based on their feedback, and the final version of the questionnaire was determined.

Before distributing the questionnaire, the minimum sample size required for statistical analysis (i.e., partial least squares method adopted in this study) was calculated. The G*Power software (Faul et al., 2009) was used for sample size estimation. Following previous studies (e.g., Campanelli et al., 2018; Lee et al., 2021), the parameters were set to an effect size of 0.15, a statistical power of 0.95, and a significance level of 0.05. The results indicated that a minimum sample size of 146 participants was required(See Figure 2). To quickly reach potential respondents, this study utilized the paid services of the professional online survey platform www.sojump.com. This service allowed for the rapid collection of a wide sample base, enabling random sampling from potential users rather than relying on convenience sampling (Hu et al., 2021; Shen et al., 2018;Lee and Wang, 2022;).

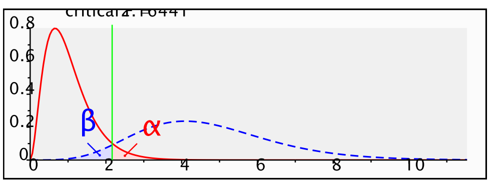

Figure 2 G*Power Test Result

To ensure that respondents had relevant experience with AI-supported e-learning systems, a brief introduction to AI-enhanced e-learning systems was provided at the beginning of the questionnaire. A binary choice question (Yes/No) then followed, asking respondents whether they had used such systems for learning activities. Only respondents who answered "Yes" (indicating they had experience using AI-supported e-learning systems) were allowed to complete the remainder of the questionnaire. A total of 500 questionnaires were distributed (both online and offline), and 473 were returned, with 425 valid responses. The valid response rate was 85%, meeting the minimum sample size requirement. To ensure the representativeness of the sample, we adopted the extrapolation method recommended by Armstrong and Overton (1977) to check for non-response bias. This method assumes that late respondents are more likely to resemble non-respondents. By comparing the first 25% of collected responses with the last 25%, the results showed no significant differences between the two groups, indicating that non-response bias was not a major issue and that the sample was representative.Table 1 shows the demographic information of the samples.

Table 1 Sample demographic information.

Demographic Variable	Category	Frequency (n)	Percentage (%)
Used AI-supported e-learning	Yes	425	100
	No	0	0
Gender	Male	191	45
	Female	187	44
	Prefer not to disclose	47	11
Age Group	18-24 years	144	34
	25-34 years	114	27
	35-44 years	88	21
	45-54 years	56	13
	55+ years	23	5
Education Level	High School	36	8
	Diploma	79	19
	Bachelor's Degree	161	38
	Master's Degree	133	31
	Doctorate	16	4
Duration of using AI-supported e-learning systems	Less than 1 year	180	42
	1-2 years	118	28
	3-5 years	74	17
	More than 5 years	53	13
Frequency of using AI-supported e-learning systems	Daily	70	16
	Weekly	205	48
	Monthly	111	26
	once a month or less	39	10

Note(s):N = 425;

Source(s): Created by authors

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Research Article

MEASUREMENT METHODS

This study utilized established scales from the existing literature and made appropriate adjustments to the measurement items to fit the context of AI-supported e-learning systems (see Appendix for details). All items were assessed using a seven-point Likert scale, with 1 indicating "strongly disagree" and 7 indicating "strongly agree." Specifically, based on the recommendations of Malhotra and Ramalingam (2023), Moussawi et al. (2021), and Balakrishnan (2022), perceived intelligence was measured using a four-item scale. Perceived anthropomorphism was assessed using a five-item scale from Malhotra and Ramalingam (2023), Moussawi et al. (2021), and Balakrishnan (2022). Perceived personalization was measured using a four-item scale from Liu and Tao (2022), Komiak and Benbasat (2006), Kang et al. (2016), and Xu (2006). Perceived usefulness was evaluated using a five-item scale from Bhattacherjee et al. (2008), Yeo et al. (2017), Al Amin et al. (2023), Ni and Cheung (2023), and Cheng (2020), while confirmation was measured using a four-item scale from Venkatesh and Davis (2000), Bhattacherjee (2001), Joo and Choi (2016), Amin et al. (2023), and Cheng (2020). Satisfaction was also measured using a four-item scale from Oliver (1980), Venkatesh and Davis (2000), Ni and Cheung (2023), and Cheng (2020). Finally, continuance intention was measured using a five-item scale from Bhattacherjee et al. (2008), Ni and Cheung (2023), Al Amin et al. (2023), and Cheng (2020)

Common method bias.

In line with the recommendations of MacKenzie and Podsakoff (2012), this study implemented several proactive strategies to minimize common method bias (CMB) and conducted three post hoc statistical tests to assess its presence. To mitigate the occurrence of CMB, the questionnaire design was carefully structured by varying scale types and anchor labels. Respondents were also informed that, although some questions might seem similar, each item had distinct characteristics, encouraging them to read and answer thoughtfully. The construct names were concealed, and the measurement items were presented in random order (Liang and Shiau, 2018).

For the post hoc statistical tests, Harman's single-factor test was first employed to check for CMB (Harman, 1967). The results indicated that the first factor accounted for only 35.7% of the total variance, with no single factor explaining more than 50%, suggesting that CMB is not a significant issue in this study (Harman, 1967). Next, we conducted a full collinearity test, appropriate for PLS analysis, as recommended by Lee et al. (2021). None of the variance inflation factors (VIFs) for the constructs exceeded the threshold of 3.3, with the VIFs for perceived intelligence (PI) ranging from 1.038 to 1.187, perceived anthropomorphism (PA) from 1.058 to 1.251, perceived personalization (PP) from 1.061 to 1.258, perceived usefulness (PU) from 1.524 to 1.606, confirmation (CONF) from 1.437 to 1.558, and satisfaction (SAT) at 1.524 (see Table 2).

Lastly, we employed the marker variable approach to assess CMB further (Simmering et al., 2015). Following the suggestions of Cao et al. (2021), the average monthly income of respondents, a demographic variable unrelated to AI characteristic (intelligence and anthropomorphism) and the ECM constructs, was used as a marker variable. The results revealed that average monthly income was not significantly correlated with any of the variables included in the model. Overall, the results indicate that CMB did not affect the findings of this study.

Table 2 The collinearity test for CMB.

	CI	CONF	PA	PI	PP	PU	SAT
CI							
CONF						1.437	1.558
PA		1.058				1.161	1.251
PI		1.038				1.128	1.187
PP		1.061				1.196	1.258
PU	1.524						1.606
SAT	1.524						

Note(s):N=425;CI:Continuance Intention; CONF: Confirmation; PA:Perceived Anthropomorphism; PI:Perceived Intelligence; PP:Perceived Personalization; PU:Perceived Usefulness; SAT: Satisfaction.

Source(s): Created by authors

RESULTS

This study employed the partial least squares (PLS) method, incorporating confirmatory composite analysis as recommended by Hair et al. (2020) and Cuesta-Valino et al. (2022), to examine the proposed model. The strengths of PLS lie in its distribution-free estimation, meaning the estimation is unaffected by model complexity, small sample size, or nonnormality of the data, and its ability to effectively mitigate multicollinearity issues (Hair et al., 2013; Lee et al., 2018). Compared to covariance-based structural equation modeling (CB-SEM), we chose the PLS approach for data analysis for several reasons. First, the model is complex, involving ten hypotheses and potentially multiple mediation paths. PLS can accommodate more complex models than CB-SEM (Hair et al., 2017; Ringle et al., 2012). Second, the study is exploratory in nature, as there is currently no clear understanding or indication of the underlying effects of AI characteristics (such as intelligence and anthropomorphism) on ECM within the context of AI-supported e-learning systems (Campanelli et al., 2018; Hair et al., 2017). Therefore, PLS is more suitable for exploratory research compared to CB-SEM (Hair et al., 2017; Ringle et al., 2012). We utilized SmartPLS 4 software (Ringle et al., 2015) for data analysis. The PLS analysis is divided into two stages: the measurement model and the structural model, which are described in detail below.

The aim of the measurement model was to assess internal consistency reliability, convergent validity, and discriminant validity (Hair et al., 2013). Internal consistency reliability was evaluated using composite reliability and Cronbach's alpha (Hair et al., 2013, 2020). As shown in Table 3, all values for composite reliability (ranging from 0.925 to 0.952) and Cronbach's alpha (ranging from 0.892 to 0.936) exceeded the recommended threshold of 0.7, confirming the reliability of the model (Hair et al., 2013). Furthermore, in terms of convergent validity, all average variance extracted (AVE) values (ranging from 0.717 to 0.797) exceeded the threshold of 0.5, indicating good convergent validity. Additionally, all factor loadings for the constructs were above the threshold of 0.7 and statistically significant ($p < 0.001$), further supporting convergent validity (Hair et al., 2013)

Table 3 Measurement model results.

Latent variable	Items	M	S.D.	λ	CR	α	AVE
Perceived intelligence (PI)	PI1	4.96	1.494	0.848	0.934	0.906	0.779
	PI2	4.854	1.541	0.857			
	PI3	4.878	1.503	0.827			
	PI4	4.962	1.498	0.851			
Perceived anthropomorp-hism (PA)	PA1	5.014	1.545	0.85	0.94	0.92	0.757
	PA2	5.009	1.512	0.871			
	PA3	5.078	1.48	0.887			
	PA4	5.054	1.504	0.898			
	PA5	5.064	1.461	0.871			
Perceived personalization (PP)	PP1	5.056	1.373	0.885	0.925	0.892	0.756
	PP2	5.002	1.446	0.842			
	PP3	5.064	1.424	0.878			
	PP4	5.035	1.47	0.869	0.952	0.936	0.797
Perceived usefulness (PU)	PU1	4.612	1.661	0.876			
	PU2	4.605	1.622	0.880			
	PU3	4.576	1.696	0.895			
	PU4	4.593	1.684	0.887			
	PU5	4.598	1.693	0.869			
Confirmation (CONF)	CONF1	4.706	1.459	0.892	0.933	0.905	0.778
	CONF2	4.696	1.45	0.843			
	CONF3	4.753	1.466	0.873			
	CONF4	4.739	1.481	0.87			
Satisfaction (SAT)	SAT1	4.565	1.516	0.895	0.927	0.894	0.76
	SAT2	4.541	1.541	0.898			
	SAT3	4.544	1.498	0.883			
	SAT4	4.515	1.471	0.896			
Continuance intention (CI)	CI1	5.179	1.315	0.893	0.927	0.901	0.717
	CI2	5.193	1.369	0.879			
	CI3	5.139	1.354	0.850			
	CI4	5.186	1.332	0.894			

CI5	5.099	1.442	0.863

Note(s):N = 425; M: Mean; S.D.: Standard deviation; λ: Outer loadings; α: Cronbach's alpha; CR: Composite reliability; AVE: Average variance extracted.The average variance extracted (AVE) of each construct should exceed the threshold value of 0.5 (Hair et al., 2013). The acceptable level of factor loading, composite reliability,and Cronbach's α is 0.7 (Hair et al., 2013).

Source(s): Created by authors

We applied the heterotrait-monotrait (HTMT) ratio of correlations to test for discriminant validity (Hair et al., 2019). According to Table 4, all HTMT values were below the recommended threshold of 0.85, supporting the discriminant validity of the model (Hair et al., 2019). Hence, the model met the criteria for both reliability and validity.

Table 4 HTMT analysis results.

	CI	CONF	PA	PI	PP	PU	SAT
CI							
CONF	0.636						
PA	0.496	0.399					
PI	0.413	0.369	0.156				
PP	0.491	0.442	0.226	0.167			
PU	0.664	0.547	0.437	0.376	0.420		
SAT	0.699	0.618	0.482	0.437	0.454	0.641	

Note(s):N = 425; CI: Continuance Intention; CONF: Confirmation; PA: Perceived Anthropomorphism; PI: Perceived Intelligence; PP: Perceived Personalization; PU: Perceived Usefulness; SAT: Satisfaction. The heterotrait-monotrait (HTMT) ratio of correlations should be lower than the accepted value of 0.85 (Hair et al., 2019).

STRUCTURAL MODEL AND EFFECT ANALYSIS

Following the recommendations of Hair et al. (2013) and Lee et al. (2018), the structural model was assessed using path coefficients (β) and R^2 values. Path coefficients reflect the strength of the relationships between variables, while R^2 values indicate the explanatory power of the model (Hair et al., 2013). A bootstrapping resampling method (10,000 resamples) was used in this study to obtain stable coefficients and R^2 values (Hair et al., 2013).The results of the structural model analysis show that all proposed hypotheses (H1 to H8c) were supported and the path coefficients were statistically significant ($p < 0.001$). Specifically, the R^2 values for perceived usefulness (PU), confirmation (CONF), satisfaction (SAT), and continuance intention (CI) were 0.377,0.304,0.501and 0.485, respectively, indicating strong explanatory power.Additionally, the f^2 values and their effect sizes were evaluated for each hypothesis. According to Lee et al. (2021), values of 0.02, 0.15, and 0.35 indicate small, medium, and large effect sizes, respectively. The results revealed small effect sizes for most significant

Journal of Information Systems Engineering and Management
2025, 10(3)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

relationships, such as H1 (f^2 = 0.084, small), H2 (f^2 = 0.071, small), and H3 (f^2 = 0.097, small). Nevertheless, small effect sizes do not imply that these relationships are insignificant in this study. Even with small effect sizes, these findings are still meaningful for understanding user behavior in AI-supported e-learning systems, providing valuable theoretical and practical implications. Moreover, H4 (f^2 = 0.176) and H5 (f^2 = 0.214) showed medium effect sizes, indicating a stronger influence on continuance intention (CI).(See Table 5&Figure 3)

Table 5 Hypothetical relationship test results.

Hypothesis	β	S.D.	T	f^2	f^2 Effect Size	Test Result
H1:CONF -> PU	0.274	0.046	5.900***	0.084	Small	Supported
H2:CONF -> SAT	0.234	0.040	5.799***	0.071	Small	Supported
H3:PU -> SAT	0.278	0.045	6.206***	0.097	Small	Supported
H4:PU -> CI	0.372	0.044	8.494***	0.176	Medium	Supported
H5:SAT -> CI	0.410	0.042	9.678***	0.214	Medium	Supported
H6a:PI -> PU	0.193	0.042	4.566***	0.053	Small	Supported
H6b:PI -> CONF	0.251	0.039	6.381***	0.087	Small	Supported
H6c:PI -> SAT	0.172	0.037	4.674***	0.05	Small	Supported
H7a:PA -> PU	0.238	0.038	6.206***	0.078	Small	Supported
H7b:PA -> CONF	0.267	0.041	6.586***	0.097	Small	Supported
H7c:PA -> SAT	0.186	0.040	4.716***	0.056	Small	Supported
H8a:PP -> PU	0.196	0.043	4.572***	0.052	Small	Supported
H8b:PP -> CONF	0.307	0.039	7.837***	0.127	Small	Supported
H8c:PP -> SAT	0.142	0.042	3.381**	0.032	Small	Supported

Note(s):N = 425; *p < 0.05. **p < 0.01. p < 0.001; β:Path coefficient; S.D.: Standard deviation; CI: Continuance Intention; CONF: Confirmation; PA: Perceived Anthropomorphism; PI: Perceived Intelligence; PP: Perceived Personalization; PU: Perceived Usefulness; SAT: Satisfaction. f^2Values of 0.02, 0.15, and 0.35 indicate a small, medium, and large f2 effect size, respectively (Lee et al., 2021).

Source(s): Created by authors.

Journal of Information Systems Engineering and Management
2025, 10(3)
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Research Article

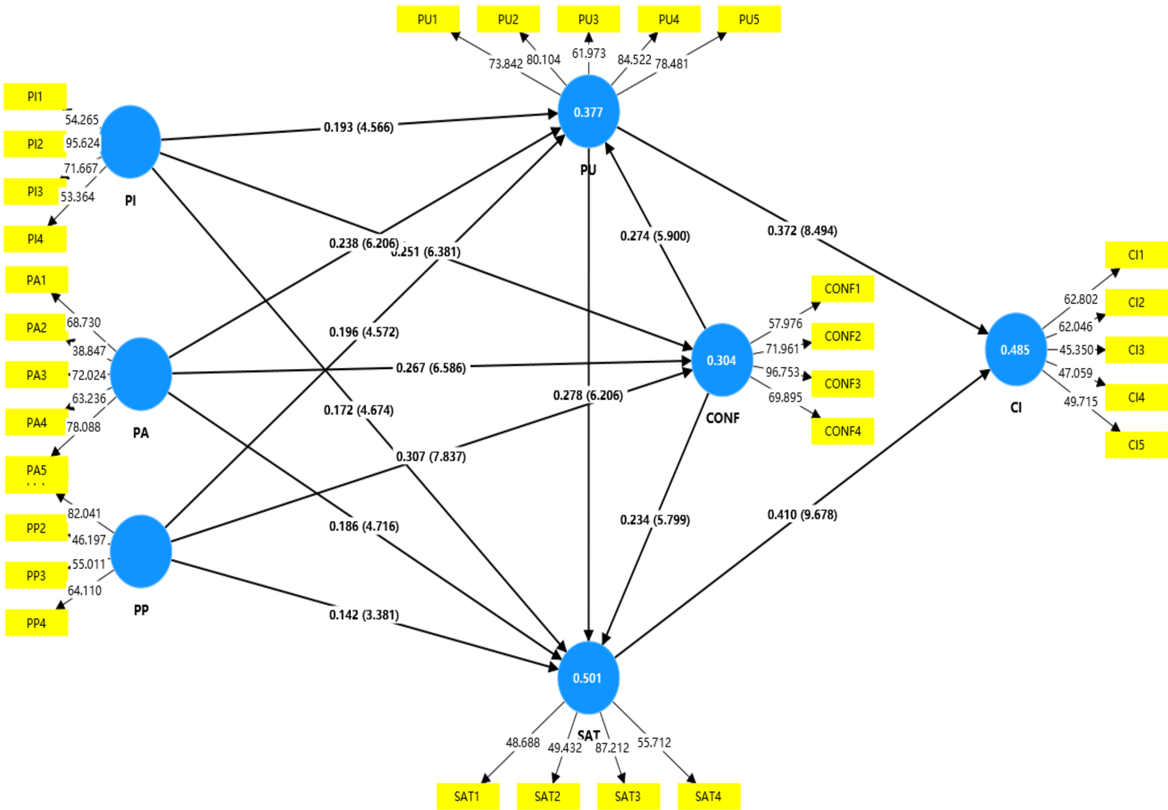

Figure 3 Results of the model analysis.

Regarding the model's predictive performance, we employed the PLSpredict procedure, as suggested by Shmueli et al. (2019) and Barta et al. (2023). PLSpredict, with 10-fold cross-validation and one repetition, demonstrated that the Q^2 values for the indicators of continuance intention were all greater than 0, confirming the model's predictive relevance. Specifically, the RMSE for CI1 was 1.117, while the linear regression model (LM) had an RMSE of 1.115, indicating that for the CI1 indicator, the PLS model's predictive accuracy was slightly lower than that of the LM. However, for CI2 to CI5, the RMSE values of the PLS model were all lower than those of the LM, suggesting that overall, the PLS model improved predictive performance (Gong and Wang, 2023; Shmueli et al., 2019)(See Table 6)

Mediation occurs when the independent variable affects the dependent variable through an additional theoretically relevant variable. Based on the structural model analysis results, our model may exhibit mediation effects. To verify this, we applied Zhao et al.'s (2010) method for mediation testing. Specifically, mediation is absent when both the direct and indirect effects are insignificant (Zhao et al., 2010). When both the direct and indirect effects are significant and have the same sign (either positive or negative), complementary mediation (or competitive mediation) occurs (Zhao et al., 2010).

Journal of Information Systems Engineering and Management
2025, 10(3)
e-ISSN: 2468-4376
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Research Article

Additionally, if the direct effect is insignificant while the indirect effect is significant, it can also be considered indirect mediation (Zhao et al., 2010). In this study, we focus solely on the mediation effects of the three AI characteristics impacting the ECM: perceived intelligence, perceived anthropomorphism, and perceived personalization. The mediation analysis results are presented in Table 7, showing that all mediation paths 1-15 exhibit partial mediation. We will discuss the mediation results further in the "Discussion and Contributions" section.

Table 6 Analysis of predictive power

Construct	Q^2predict	PLS-SEM_RMSE	PLS-SEM_MAE	LM_RMSE	LM_MAE
CI1	0.282	1.117	0.922	1.115	0.902
CI2	0.254	1.185	0.975	1.204	0.979
CI3	0.26	1.167	0.954	1.182	0.956
CI4	0.238	1.165	0.949	1.194	0.957
CI5	0.289	1.219	0.999	1.227	0.988

Table 7 Analysis of the mediating effects.

No.	Path	Indirect effect	S.D.	T-Value	95% CIs	
					LL	UL
1	PA -> PU -> SAT	0.066	0.015	4.350***	0.039	0.098
2	PI -> PU -> SAT	0.054	0.015	3.512***	0.026	0.086
3	PP -> PU -> SAT	0.055	0.014	3.826***	0.029	0.084
4	PA -> PU -> CI	0.088	0.018	4.864***	0.055	0.126
5	PI -> PU -> CI	0.072	0.018	4.048***	0.038	0.108
6	PP -> PU -> CI	0.073	0.018	3.966***	0.04	0.111
7	PA -> CONF -> PU	0.073	0.017	4.381***	0.042	0.109
8	PA -> CONF -> SAT	0.063	0.015	4.244***	0.036	0.094
9	PI -> CONF -> PU	0.069	0.017	3.973***	0.03	0.105

Journal of Information Systems Engineering and Management
2025, 10(3)
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https://www.jisem-journal.com/

Research Article

					8	
10	PI -> CONF -> SAT	0.059	0.014	4.242***	0.034	0.087
11	PP -> CONF -> PU	0.084	0.018	4.766***	0.051	0.121
12	PP -> CONF -> SAT	0.072	0.014	4.980***	0.045	0.101
13	PA -> SAT -> CI	0.076	0.019	3.939***	0.042	0.118
14	PI -> SAT -> CI	0.070	0.018	3.943***	0.038	0.108
15	PP -> SAT -> CI	0.058	0.019	3.007**	0.024	0.099

Note(s):N = 425; *p < 0.05. **p < 0.01. p < 0.001; S.D.: Standard deviation;CIs: Confidence intervals; LL: Low limit; UL: Upper limit.CI: Continuance Intention; CONF: Confirmation; PA: Perceived Anthropomorphism; PI: Perceived Intelligence; PP: Perceived Personalization; PU: Perceived Usefulness; SAT: Satisfaction.

Source(s): Created by authors.

DISCUSSION AND CONTRIBUTIONS

Discussion of results.

As AI has been incorporated into e-learning systems, it is important to consider the impact of AI on the adoption behavior of e-learning system users. The main purpose of this study was to explore the continuance intention towards AI-supported e-learning systems, in combination with AI characteristics and ECM. Based on the empirical results, all proposed hypotheses were supported. Hypotheses belonging to ECM were also established, which were extended to the AI-supported e-learning system environment (H1-H5). These findings are consistent with the results of previous studies. In addition, the results also showed Perceived intelligence, anthropomorphism, and personalization each play a significant role in enhancing AI-supported e-learning systems. Firstly, perceived intelligence has a dual effect, not only improving users' perceived usefulness by providing real-time feedback and optimizing learning paths (H6a), but also deepening their reliance and satisfy with AI systems as their learning needs are met(H6b&H6c). Beyond improving learning outcomes, AI's adaptive capabilities redefine the interaction between users and technology, reducing cognitive load and allowing learners to focus on key content rather than complex operational processes (Moussawi et al., 2021). This minimization of "technological friction" enhances learning efficiency and

Journal of Information Systems Engineering and Management
2025, 10(3)
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offers new perspectives for the future of educational technology. In addition to intelligence, anthropomorphism exerts a complex influence on emotional cognition, with this study showing that perceived anthropomorphism significantly increases users' confirmation perceived usefulness and satisfaction (H7a, H7b,H7c), enhancing emotional engagement by simulating human-like behaviors and communication styles. This reconstruction of the human-technology boundary strengthens learners' sense of security and trust, fostering long-term engagement. At a psychological level, anthropomorphic design positions AI as an emotional support provider, not just a knowledge transmitter (Balakrishnan et al., 2022). Finally, perceived personalization is identified as a key driver of continued usage, It has been verified that it simultaneously affects perceived usefulness, confirmation and satisfaction, which in turn significantly affects users' continuation intention(H8a,H8b, H8c), as AI dynamically adjusts content to meet personalized learning needs, enhancing individual outcomes while also disrupting the traditional model of standardized education. Data-driven personalized recommendation systems transcend time and space limitations, improving learning efficiency and fostering systemic innovation (Liu & Tao, 2022). AI-driven personalized learning, by balancing individual needs with large-scale efficiency, is poised to become a cornerstone of future educational technology.

In terms of mediation analysis, we observed that all mediators in the model were complementary mediators. For mediation paths 1 to 6, perceived usefulness partially mediated the relationship between the three AI characteristics and satisfaction and continuance intention. In AI-supported e-learning systems, AI characteristics can directly or indirectly promote users' perceived usefulness by increasing intelligent anthropomorphism and personalized functions, thereby enhancing users' satisfaction and continuance intention. For mediation paths 7 to 12, confirmation partially mediated the relationship between AI characteristics and perceived usefulness and satisfaction, respectively. In other words, intelligence, anthropomorphism, and personalization all directly increased users' confirmation, thereby increasing users' perceived usefulness and satisfaction in the AI-supported e-learning system environment. For mediation paths 13 to 15, satisfaction partially mediated the relationship between the three AI characteristics and continuance intention, respectively. This finding suggests that the three AI characteristics can enhance user satisfaction and ultimately encourage users to continue using AI-supported e-learning systems.

THEORETICAL CONTRIBUTIONS

Artificial intelligence (AI) technology has increasingly been applied to the development and enhancement of e-learning systems. Most studies in the literature treat AI as a contextual factor, focusing on user reactions and usage patterns in AI-supported e-learning environments. However, few studies have examined how specific AI characteristics, such as intelligence, anthropomorphism, and personalization, affect users' expectation confirmation and subsequent adoption behaviors when using

Journal of Information Systems Engineering and Management
2025, 10(3)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

AI-supported e-learning systems. Existing research mainly addresses the continued usage of e-learning systems by adding extra factors to the ECM, with limited attention to the role of AI or the combined effects of AI characteristics and ECM on users' continuance intention in AI-supported e-learning environments. To address these gaps, this study uses the ECM as a baseline theory to explore how AI characteristics influence users' continuance intention toward AI-supported e-learning systems through the functions of the ECM. The empirical findings reveal that intelligence, anthropomorphism, and personalization enhance users' expectation confirmation, perceived usefulness, and satisfaction, ultimately increasing their continuance intention toward AI-supported e-learning systems.

This study provides several theoretical contributions. First, it identifies the mechanisms through which intelligence, anthropomorphism, and personalization allow users to confirm their expectations, enhance perceived usefulness, and improve their emotional evaluations of the system in a continuance adoption context. Second, this research highlights key determinants within the ECM, such as intelligence, anthropomorphism, and personalization, extending the applicability and explanatory power of the ECM in AI-supported e-learning environments. By integrating these AI characteristics into the ECM, this study reflects the evolving trends in AI development in e-learning systems, contributing to both academic understanding and practical insights into users' continuance intention toward AI-supported e-learning systems.

PRACTICAL IMPLICATIONS

E-learning systems have revolutionized the development of education, and the integration of artificial intelligence (AI) has further accelerated this progress. Despite these advancements, user retention and the continuance intention in using e-learning platforms still remain areas for improvement. This study provides valuable practical insights into how AI can be effectively applied within e-learning systems to address these challenges. First, when designing and developing AI-supported e-learning systems, developers should integrate advanced AI algorithms that can accurately identify and cater to users' educational needs. By leveraging AI's ability to provide personalized learning experiences, the system can offer tailored courses and learning paths that match users' preferences, learning behaviors, and backgrounds. This not only enables users to make more informed educational decisions, such as selecting the most suitable learning paths, but also enhances usability and user satisfaction, ultimately increasing their intention to continue using the system. Additionally, given the low tolerance for errors in e-learning environments, developers should focus on improving AI's cognitive and decision-making abilities to minimize the risk of operational and calculation errors. This will boost the syste' s reliability and reduce user frustration, resulting in a more seamless learning experience.

Furthermore, as user expectations for AI's capabilities continue to rise, developers should invest in enhancing AI' s deep learning and predictive abilities, enabling the system to anticipate and adapt to users' evolving needs. In terms of perceived personalization, which plays a critical role in user engagement, developers should refine AI' s ability to customize learning content and interaction styles based on individual preferences, creating a more tailored learning environment. Additionally, anthropomorphism remains crucial in enhancing the user experience. Human-like features, such as avatars, personalized voice interfaces, and conversational language, can foster a deeper emotional connection between the user and the system. Developers should regularly update these anthropomorphic elements to maintain relevance, further improving user satisfaction. Educational institutions should also guide users in seeking AI assistance when facing routine challenges in e-learning systems. AI' s ability to offer emotional support by reducing anxiety and providing timely assistance can create a more comfortable, engaging learning environment, ultimately maximizing AI's positive impact in e-learning systems.

LIMITATIONS AND DIRECTIONS FOR FUTURE RESEARCH

This study offers significant theoretical and practical contributions to understanding users' continuance intention in AI-supported e-learning systems by integrating AI characteristics into the Expectation Confirmation Model (ECM). However, as with most studies, several limitations should be acknowledged, providing opportunities for future research. First, the data collected were exclusively from users in China, which limits the generalizability of the findings across different cultural and geographic contexts. While China's rapid development in educational technology provides a solid foundation, the diversity in educational cultures, technology acceptance, and AI usage habits across regions suggests that future research should explore the applicability of these findings in other countries to enhance the external validity of the model. Additionally, although the sample size of 425 valid responses met the minimum requirement for Partial Least Squares (PLS) analysis, a larger, more diverse sample would allow for more robust conclusions and minimize potential biases. Future research should therefore aim to replicate the study with larger and more varied populations to ensure the generalizability of the results. Moreover, the cross-sectional design employed in this study limits the ability to infer causal relationships between the variables. Longitudinal studies are recommended to track users' perceptions and continuance intentions over time, especially considering the evolving nature of AI-supported systems and their adaptive functionalities.

Second, while this study extends the ECM by incorporating AI characteristics such as perceived intelligence, anthropomorphism, and personalization, it does not account for potential moderating variables that could enhance the explanatory power of the model. Factors such as user trust, personal innovativeness, and prior experience with AI technologies have been shown to influence user behavior and should be incorporated in future models. Additionally, the current study focuses on three AI-driven characteristics, but other relevant factors, such as AI service quality (AISAQUAL) and user interaction experiences, were not examined. These factors could play a significant role in influencing users' satisfaction and continuance intention. As AI technologies rapidly evolve, future research should investigate how emerging AI applications, such as generative AI, virtual reality (VR), and augmented reality (AR), influence user behavior in educational settings. The inclusion of these new dimensions would provide a more comprehensive understanding of the complex interactions between AI characteristics and user behavior in e-learning systems.

CONCLUSION

Artificial intelligence (AI) is at the forefront of enhancing educational technology, particularly in e-learning systems. To explore how AI influences users' continuance intention, this study used the Expectation-Confirmation Model (ECM) as a theoretical foundation to build a research model and develop corresponding hypotheses. By extending the ECM with three key AI characteristics—perceived intelligence, perceived anthropomorphism, and perceived personalization—we effectively explained the factors influencing users' willingness to continue using AI-supported e-learning systems. Based on an empirical survey of 425 Chinese users experienced with AI-supported e-learning systems, the study concluded that perceived intelligence, anthropomorphism, and personalization enhance user satisfaction, both directly and indirectly, through perceived usefulness and confirmation, ultimately promoting continued use of these systems. This research is the first to integrate ECM with AI characteristics in the context of e-learning, positioning these AI features as critical factors in users' continuance decisions. It also provides practical guidance for educators, developers, and educational professionals on enhancing AI capabilities to improve user experience and drive sustained adoption of e-learning platforms. Furthermore, leveraging AI' s ability to personalize interactions and simulate human-like responses meets users' educational needs and expectations, fostering long-term engagement with e-learning applications.

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Research Article

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