

Why Students Stay: Unpacking the Psychological Drivers of E-Learning Continuance Intention

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ABSTRACT

Understanding what drives students to continue using e-learning platforms is critical for sustainable digital education. This study examines the mediating roles of cognitive presence and learning satisfaction in the relationship between e-learning quality dimensions and continuance intention. A survey of 447 undergraduate students from Universitas Terbuka Indonesia was analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The findings indicate that cognitive presence and learning satisfaction significantly mediate the effects of information quality, instructor quality, system quality, and support service quality on continuance intention. While information and instructor quality positively influence engagement, their direct effects on continued use are limited. Conversely, system and support service quality impact learning indirectly through cognitive and affective mechanisms. These results suggest that students remain engaged not solely because of technical infrastructure but also because of meaningful, satisfying learning experiences. This study extends the Expectation Confirmation Model and e-learning quality frameworks by integrating cognitive presence as a central explanatory mechanism, offering a more student-centered theoretical understanding of continuance intention in digital higher education.

ARTICLE INFORMATION

Keywords:

cognitive presence; continuance intention; e-learning; higher education; learning satisfaction

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INTRODUCTION

The global landscape of higher education has significantly changed due to the rapid adoption of e-learning practices. This transition has highlighted both the potential of e-learning and the challenges associated with navigating new digital environments (An et al., 2021; McCormack et al., 2021). This rapid shift revealed both the potential and the challenges of e-learning as educators and students navigated new digital environments (Turnbull et al., 2021). The need for flexible, hybrid learning approaches became evident as institutions began integrating asynchronous and synchronous learning methods to cater to diverse student needs (Konkin et al., 2021). The significance of e-learning in higher education has been emphasized by its capacity to improve accessibility and inclusivity. E-learning platforms enable institutions to reach a wider audience by breaking down geographical barriers and offering opportunities to students who may have faced educational challenges in the past. (Sawaneh et al., 2024). Moreover, integrating information and communication technology (ICT) in education has fostered innovative teaching and learning methods, leading to more engaging and effective educational experiences (Gachanja et al., 2021).

However, the transition to e-learning has not been without challenges. Issues such as technological readiness, student engagement, and the need for effective pedagogical strategies have emerged as significant concerns. We must address these challenges with innovative and effective strategies (Kibret et al., 2023). The success of e-learning systems is closely tied to students'

satisfaction and the support they receive from their peers and institutions (Sugandini et al., 2023). Furthermore, the effectiveness of e-learning depends on educational institutions' readiness to adopt and implement these technologies. Institutions play a crucial role in this, as they must invest in training and resources to ensure educators and students can thrive in an online learning environment (Hoang et al., 2024). Institutions must invest in training and resources to ensure educators and students can thrive in an online learning environment (Fattah et al., 2022).

E-learning has fundamentally transformed the delivery of educational content, facilitating a range of pedagogical approaches that accommodate diverse learning styles. The incorporation of multimedia resources, interactive modules, and virtual simulations has markedly enhanced student engagement and comprehension, fostering a more effective learning environment. (Alkhowailed et al., 2020). This shift has enabled educators to create more dynamic learning environments tailored to individual student needs, thus promoting personalized learning experiences (Rajeh et al., 2021). The flexibility inherent in e-learning allows students to access course materials at their convenience, accommodating diverse schedules and learning paces, which is particularly beneficial for working students or those with other commitments (Deepika et al., 2020). Moreover, the accessibility of e-learning has expanded educational opportunities for students who may have faced barriers to traditional classroom settings. By breaking geographical constraints, e-learning enables students from remote or underserved areas to participate in higher education (Vegas & Carter-Rau, 2022). This democratization of education is crucial for fostering equity, as it enables a broader demographic to engage in learning without the limitations imposed by physical attendance (Mukuka et al., 2021). Accessing high-quality educational resources online has also been shown to enhance student satisfaction and retention, as students perceive e-learning as a valuable and effective mode of instruction (Elsalem et al., 2021). However, the transition to e-learning has not been without its challenges. Many institutions faced difficulties ensuring that faculty and students were adequately prepared for this sudden shift. The need for training in digital tools and platforms became apparent, as effective e-learning implementation requires a certain level of technological proficiency (Maphosa et al., 2020). Additionally, concerns regarding academic integrity and the effectiveness of remote assessments have emerged, prompting institutions to rethink their evaluation strategies (Encarnacion et al., 2021). Continuation intention in e-learning refers to users' likelihood of continuing their engagement with platforms after their initial experience. This concept is critical for evaluating the long-term effectiveness of e-learning systems, as it influences user retention and the platform's overall sustainability. By focusing on factors such as user satisfaction and perceived value, stakeholders can enhance ongoing commitment and participation in e-learning initiatives. (Abdullah et al., 2022). Research indicates that various factors contribute to continuation intention, including perceived usefulness, satisfaction, self-efficacy, and the quality of the e-learning experience (Haris, 2022; Zhang et al., 2022). Satisfaction is a critical predictor of continuance intention; users who report higher satisfaction with their e-learning experiences are more inclined to maintain their engagement (Gao & Liu, 2023). For example, a study found that student satisfaction with online learning directly correlates with their intention to continue using these platforms, demonstrating a significant predictive relationship (Giday & Perumal, 2024).

Additionally, perceived value and self-efficacy are essential in shaping users' continuance intention; individuals who feel confident in navigating and utilizing e-learning resources are more likely to persist in their use (Rekha et al., 2023). Furthermore, self-efficacy has been shown to mediate the relationship between various influencing factors and e-learning continuance intention, highlighting its importance in fostering positive user attitudes (Rodríguez-Ardura & Meseguer-Artola, 2016). Social presence and external factors also affect users' intention to continue; a solid social presence within online learning environments enhances students' commitment to engaging with the

material (Suryanto et al., 2024). This multifaceted nature of continuance intention underscores the need for e-learning providers to consider personal motivations and contextual elements to sustain user engagement effectively (Jiang & Liang, 2023). The rapid growth of e-learning technologies has transformed educational practices by providing scalable and flexible solutions that cater to diverse student needs worldwide. As e-learning continues to evolve, it is essential to understand the factors that promote user engagement and enhance learning satisfaction. Previous research indicates that system quality, cognitive presence, and instructor effectiveness are crucial in fostering positive student outcomes, particularly in digital learning environments (Dangiso et al., 2023). Cognitive presence is vital to the Community of Inquiry framework, as it reflects how students create meaning through reflection and discussion.

This construct is pivotal for enhancing student engagement and fostering meaningful educational experiences, making it indispensable in digital learning settings (Jung, 2010). Moreover, empirical evidence suggests that cognitive presence significantly contributes to students' acceptance of e-learning systems by enabling a more profound understanding of course content, thereby supporting sustained engagement and system adoption (Yakubu & Dasuki, 2018). Similarly essential to effective e-learning is Information Quality, which refers to the accuracy, relevance, and clarity of information on e-learning platforms, and is also necessary for effective learning outcomes. Research has shown that information quality directly affects user satisfaction, which is crucial for the successful use of e-learning systems (Al-Fraihat et al., 2020). Similarly, the quality of information in e-learning environments has positively influenced students' satisfaction levels (Kunjukunju et al., 2020). Further studies indicate that information quality is a significant predictor of user satisfaction in these contexts (Seta et al., 2018).

Instructor Quality represents instructors' effectiveness in content delivery and learning facilitation and significantly impacts student satisfaction and engagement. For example, instructional quality has been identified as a key determinant of satisfaction in e-learning, highlighting the role of effective teaching practices in enhancing the learning experience (Merrydian, 2023). Additionally, instructor responsiveness and interaction quality are critical factors in fostering user satisfaction and encouraging continued e-learning engagement (Aldholay et al., 2018). Research indicates that e-learning effectiveness is significantly influenced by instructor quality, course design, and student engagement, with instructional quality playing a primary role in students' intentions to continue online learning (Alterkait & Alduaij, 2024; Kumar et al., 2021). Additionally, interactive course design and user-friendly platforms are crucial for maintaining student interest and satisfaction (Zhao et al., 2019), while motivational factors positively correlate with the quality of the online learning experience, further enhancing retention (Al-Said, 2023). The transition to online learning during the COVID-19 pandemic has emphasized the importance of adaptive strategies in higher education to improve student engagement and retention, particularly in synchronous learning environments (Badali et al., 2022; Dubey et al., 2023; Stoian et al., 2022).

Learning satisfaction has consistently been linked to system quality, which encompasses the reliability, usability, and technical performance of e-learning platforms. Well-designed systems enhance user experience and are associated with greater engagement and satisfaction (Nachvak et al., 2021), while system quality is widely recognized as a key determinant of e-learning adoption in higher education (Bustamam & Hartini, 2022; Elansari & Laachach, 2024; Millidonis et al., 2024). In addition, support service quality, including technical and instructional assistance, plays an important role in shaping positive learning experiences and facilitating effective platform utilization (Idkhan, 2023; Jung et al., 2021). However, the extent to which these quality dimensions directly explain students' continuance intention remains theoretically contested (Yu et al., 2025). Although some studies report significant direct effects, others find that these relationships diminish once student-centered

constructs such as satisfaction or engagement are introduced (Adeshola & Agoyi, 2023; Martínez-Martínez et al., 2025), suggesting that quality perceptions may operate through indirect psychological pathways rather than exerting straightforward behavioral influence. This inconsistency reveals a conceptual limitation in prevailing e-learning models, which often privilege system-centric explanations while under-theorizing how students cognitively process and internalize their online learning experiences. Consequently, the field lacks a coherent account of the mechanisms through which perceived quality translates into sustained platform use, particularly in large-scale distance education contexts where student autonomy is central (Alkhwaldi & Abdulmuhsin, 2021; Meng et al., 2025; Négyesi et al., 2026). To address this theoretical tension, the present study positions cognitive presence and learning satisfaction as key mediating mechanisms linking e-learning quality dimensions to students' continuance intention.

METHOD

This study adopted a quantitative research approach, using PLS-SEM, to explore factors influencing students' continuance intentions to use e-learning platforms. The strategy aligns with previous studies that validate the effectiveness of PLS-SEM for analyzing relationships in e-learning contexts (Tawafak et al., 2023). The selection of this approach was guided by its robustness in analyzing complex relationships among latent variables and its suitability for exploratory studies in educational contexts (Shmueli et al., 2019). The study population consisted of undergraduate students at Universitas Terbuka in Indonesia who were active users of e-learning platforms. Stratified random sampling was employed to ensure representativeness across faculties, a method supported in similar e-learning research for capturing diverse participant profiles (Dangaiso et al., 2023). 447 valid responses were collected, and the power analysis was used to ensure sufficient statistical power (Cohen, 1992). The research instrument was a structured questionnaire adapted from validated scales in previous studies, as shown in Table 1. The questionnaire included constructs such as System Quality (SQ), Information Quality (IQ), Instructor Quality (IQ), Learning Satisfaction (LS), and Continuance Intention (CI), as shown in Table 1, measured using a 5-point Likert scale ranging from "Strongly Disagree" to "Strongly Agree." Reliability and validity were assessed through Cronbach's Alpha and Composite Reliability, with all values exceeding the threshold of 0.7 (Shmueli et al., 2019).

Table 1 Measurement Constructs and Instrument Sources

Construct	Code	Number of Items	Sample Item	Source of Adaptation
E-learning Continuance Intention	EC	5	"I intend to continue using the e-learning system in the future."	(Cheng, 2021, 2022; Dangaiso et al., 2023)
Cognitive Presence	CP	5	"Online learning activities help me think critically about the content."	(Banu et al., 2024; Spante et al., 2018; Wang, 2023)
Information Quality	IF	3	"The information provided in the e-learning system is accurate and useful."	(Dangaiso et al., 2023; Sewandono et al., 2023)
Instructor Quality	IQ	3	"The instructor provides clear and helpful explanations online."	(Alterkait & Alduaij, 2024; Soleimani et al., 2024)
Learning Satisfaction	LS	6	"Overall, I am satisfied with my experience using the e-learning system."	(Sandiwarno et al., 2024; Zalazar-Jaime et al., 2023)

Construct	Code	Number of Items	Sample Item	Source of Adaptation
System Quality	SQ	3	"The e-learning system is easy to use."	(Diansyah et al., 2023)
Support Service Quality	SSQ	3	"Technical support services are available when I need help."	(Dangaiso et al., 2023; Saputri et al., 2022)

The questionnaire was distributed online over four months via institutional email and official student communication channels. Participation was voluntary, with no incentives, and informed consent ensured anonymity and confidentiality. Participants could withdraw at any time without consequences, and no personally identifiable information was collected. Data analysis employed PLS-SEM with SmartPLS, following earlier studies on e-learning continuance intentions (Chen et al., 2021; Hair et al., 2019). The methodology involved assessing the measurement model for reliability and validity, along with the structural model for hypothesis testing. Model fit was evaluated using the Standardized Root Mean Square Residual (SRMR), with acceptable values below 0.08. (Shmueli et al., 2019). Construct validity was confirmed through Average Variance Extracted (AVE) values, which exceeded the minimum threshold of 0.5 (Dangaiso et al., 2023; Fornell & Larcker, 1981). Discriminant validity was verified using the Fornell-Larcker criterion and Heterotrait-Monotrait ratio (HTMT), ensuring distinctiveness among constructs. Cronbach's Alpha and Composite Reliability values were above 0.7, establishing internal consistency.

RESULTS AND DISCUSSION

This section evaluates the outer model to assess the reliability and validity of the construct and its associated dimensions. The analysis focuses on two essential aspects of validity: convergent validity and discriminant validity. These aspects are crucial for establishing the strength of the measurement framework. (Hair et al., 2019). The measurement model is used to assess the reliability and validity of the proposed model for all variables (EC, CP, IF, IQ, LS, SQ, and SSQ). The loading values should be at least 0.708 (Manley et al., 2021; Sarstedt et al., 2022). Table 2 shows that the calculated loading values range from 0.911 to 0.967. Cronbach's alpha, Rho_A, and composite reliability (CR) indicate the reliability of the data in the PLS-SEM procedure; all values should be greater than 0.700, and the CR should be greater than 0.700 (Manley et al., 2021). Alpha scores range from 0.917 (SQ) to 0.977 (LS); for Rho_A, 0.921 (SQ) to 0.977 (LS), and for CR, 0.948 (SQ) to 0.9981 (SQ). Average Variance Extract (AVE) checks the validity of convergence. Convergent validity refers to the number of convergent variables that measure an item's variance. The AVE value should be 0.500 or higher, indicating $\geq 50\%$ variance (Becker et al., 2023). Based on the AVE results, all variables are satisfactory. The lowest AVE was 0.858 (SQ), explaining 86% of the variance; the largest was 0.909 (SSQ), accounting for 91% of the variance, as presented in Table 2.

Table 2. VIF, loading, Alpha, Rho_A, CR, and AVE

Variable	Item	VIF	Load	Alpha	Rho_A	CR	AVE
E-learning Continuous Intention To Use (EC)	CE1	6.716	0.948	0.968	0.969	0.975	0.886
	CE2	4.825	0.922				
	CE3	9.887	0.967				
	CE4	4.689	0.921				
	CE5	6.381	0.948				
Cognitive Presence (CP)	CP1	5.083	0.928	0.965	0.966	0.973	0.879
	CP2	6.411	0.947				

Variable	Item	VIF	Load	Alpha	Rho_A	CR	AVE
Information Quality (IF)	CP3	6.119	0.946	0.946	0.948	0.965	0.903
	CP4	4.652	0.919				
	CP5	6.253	0.947				
	IF1	4.228	0.941				
	IF2	5.532	0.958				
Instructor Quality (IQ)	IF3	4.775	0.952	0.922	0.923	0.950	0.865
	IQ1	4.256	0.937				
	IQ2	4.846	0.951				
	IQ3	2.663	0.901				
Learning Satisfaction (LS)	LS1	7.372	0.944	0.976	0.977	0.981	0.894
	LS2	8.944	0.957				
	LS3	8.374	0.955				
	LS4	8.305	0.947				
	LS5	8.825	0.951				
	LS6	4.861	0.919				
Sistem Quality (SQ)	SQ1	2.959	0.911	0.917	0.921	0.948	0.858
	SQ2	3.495	0.933				
	SQ3	3.445	0.934				
Support Service Quality (SSQ)	SSQ1	5.246	0.955	0.950	0.950	0.968	0.909
	SSQ2	5.002	0.954				
	SSQ3	4.798	0.951				

In the validity test of discriminant analysis using cross-loading values and the Fornell-Larcker Criterion (Henseler et al., 2015). A construct is valid if the value of the square root of the AVE (Fornell-Larcker Criterion) is compared with the correlation values among latent variables. The square root of the AVE must be greater than the correlation among the latent variables. The loading (in bold and italics in Table 3) for each variable is more significant than its cross-loading; for example, the item EC1 for EC has a higher loading value (0.948) compared to its cross-loading in other constructs (e.g., CP= 0.867, IF=0.844, IQ= 0.809, LS=0.860, SQ=0.794, SSQ=0.830). The shared variance for all model constructs should not exceed their AVE for Fornell-Larcker measurement (Fornell & Larcker, 1981). The calculations show that each construct's AVE exceeds its shared variance (Table 4). Based on the Fornell-Larcker findings and cross-loading, discriminant validity was statistically validated, resulting in 29 items in the structural model.

Table 3. Cross Loading

	CP	EC	IF	IQ	LS	SQ	SSQ
EC1	0.867	<i>0.948</i>	0.844	0.809	0.860	0.794	0.830
EC2	0.812	<i>0.922</i>	0.772	0.726	0.792	0.734	0.767
EC3	0.868	<i>0.967</i>	0.830	0.802	0.856	0.787	0.838
EC4	0.831	<i>0.921</i>	0.779	0.788	0.835	0.740	0.786
EC5	0.873	<i>0.948</i>	0.826	0.775	0.862	0.796	0.840
CP2	<i>0.928</i>	0.847	0.830	0.812	0.852	0.811	0.837
CP3	<i>0.947</i>	0.849	0.853	0.846	0.871	0.820	0.865
CP4	<i>0.946</i>	0.855	0.840	0.836	0.866	0.804	0.855
CP5	<i>0.919</i>	0.832	0.797	0.755	0.838	0.745	0.801
CP6	<i>0.947</i>	0.851	0.865	0.820	0.875	0.810	0.858
IF1	0.829	0.793	<i>0.941</i>	0.800	0.794	0.767	0.852
IF2	0.829	0.807	<i>0.958</i>	0.798	0.824	0.795	0.839

	CP	EC	IF	IQ	LS	SQ	SSQ
IF3	0.886	0.853	0.952	0.850	0.877	0.810	0.872
IQ1	0.801	0.754	0.790	0.937	0.823	0.770	0.811
IQ2	0.827	0.802	0.804	0.951	0.835	0.789	0.838
IQ3	0.795	0.757	0.804	0.901	0.760	0.749	0.824
LS1	0.869	0.833	0.852	0.833	0.944	0.790	0.857
LS2	0.899	0.874	0.836	0.847	0.957	0.785	0.836
LS3	0.865	0.844	0.824	0.799	0.955	0.771	0.819
LS4	0.848	0.823	0.802	0.811	0.947	0.758	0.800
LS5	0.844	0.818	0.815	0.812	0.951	0.755	0.809
LS6	0.880	0.877	0.843	0.816	0.919	0.794	0.859
SQ1	0.746	0.707	0.710	0.715	0.693	0.911	0.740
SQ2	0.802	0.770	0.773	0.759	0.774	0.933	0.804
SQ3	0.814	0.794	0.823	0.820	0.807	0.934	0.850
SSQ1	0.858	0.806	0.859	0.872	0.827	0.828	0.955
SSQ2	0.864	0.835	0.845	0.835	0.847	0.834	0.954
SSQ3	0.852	0.829	0.869	0.830	0.837	0.807	0.951

Tabel 4. Fornell lake criterion

	CP	CE	IF	IQ	LS	SQ	SSQ
CP	0.937						
CE	0.903	0.941					
IF	0.893	0.861	0.950				
IQ	0.869	0.829	0.859	0.930			
LS	0.918	0.894	0.877	0.867	0.946		
SQ	0.852	0.819	0.832	0.828	0.821	0.926	
SSQ	0.900	0.864	0.899	0.887	0.878	0.863	0.953

SmartPLS was used to assess the research model's structure. Before testing the hypotheses, the Standardized Root Mean Square Residual (SRMR) was calculated to check how well the model fits. This careful approach helps confirm the proposed relationships in the model, allowing for clear interpretations and conclusions (Kono & Sato, 2023; Magno et al., 2024). SRMR is a fit measure used to prevent model specification errors in PLS-SEM (Magno et al., 2024). The recommended SRMR value should be less than 0.05 (Manley et al., 2021), indicating a satisfactory model fit. As shown in Table 5, the SRMR for the current model is 0.03, indicating a good fit. Additionally, the squared Euclidean distance (d_ULS) and the geodesic distance (d_G) are reported, supporting the SRMR analysis (Table 5), which lacks specific measurement values; d_ULS and d_G are 0.379 and 0.709, respectively. For the structural model, we estimated the data using a bootstrap procedure (Becker et al., 2023; Cheah et al., 2023). The path coefficient values are represented by the t-values and p-values disclosed. Four hypotheses were rejected, while ten others were confirmed, as shown in Table 5. In Figure 1, the details are explained in Table 5. Hypothesis testing in the SEM-PLS model uses bootstrapping to examine t-statistics and p-values. The significance level is 0.05; the hypothesis is accepted if the t-statistic is greater than the t-table (> 1.96) and the p-value is < 0.05 (Hair et al., 2019).

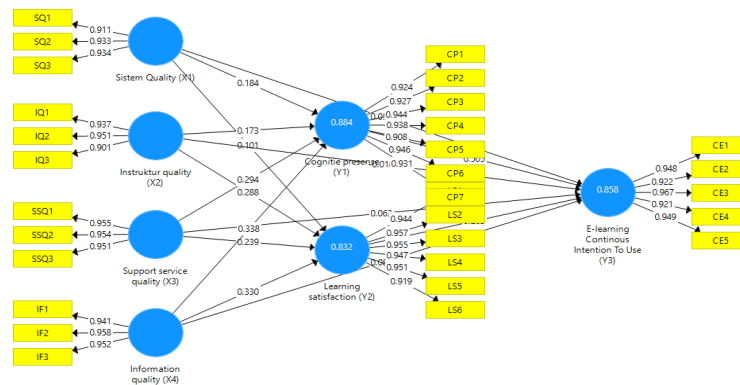


Figure 1. Diagram Model PLS

Table 5. Hypothesis Test

Model Fit	H	Relation	Mean	SD	T Value	P Values	Result
SRMR (0.030)	H1	CP -> EC	0.363	0.094	3.898	0.000	Accepted
	H2	IF -> CP	0.325	0.058	5.668	0.000	Accepted
d_ULS (0.379)	H3	IF -> EC	0.123	0.080	1.438	0.151	Accepted
	H4	IF -> LS	0.327	0.074	4.443	0.000	Accepted
D_G (0.709)	H5	IQ -> CP	0.188	0.072	2.553	0.011	Accepted
	H6	IQ -> EC	-0.018	0.076	0.229	0.819	Not Accepted
	H7	IQ -> LS	0.289	0.080	3.602	0.000	Accepted
	H8	LS -> EC	0.324	0.091	3.625	0.000	Accepted
	H9	SQ -> CP	0.174	0.060	2.963	0.003	Accepted
	H10	SQ -> EC	0.078	0.057	1.374	0.170	Not Accepted
	H11	SQ -> LS	0.099	0.058	1.757	0.080	Not Accepted
	H12	SSQ -> CP	0.291	0.081	3.595	0.000	Accepted
	H13	SSQ -> EC	0.090	0.083	1.071	0.284	Not Accepted
	H14	SSQ -> LS	0.244	0.078	3.052	0.002	Accepted

The results of the hypothesis testing in this study indicate that most of the proposed hypotheses were accepted, suggesting a significant relationship between the variables tested in the e-learning context. Cognitive Presence (CP) positively affects E-learning Continuance Intention (EC) with a T value of 3.898 and a P value of 0.000. Information Quality (IQ) also significantly affects CP and Learning Satisfaction (LS) with T values of 5.668 and 4.443, respectively, and a P value of 0.000. Instructor Quality (IQ) significantly affects CP and LS but does not impact EC. Learning Satisfaction (LS) significantly influences EC with a T value of 3.625 and a P value of 0.000. Support Service Quality (SSQ) also positively affects CP and LS, not EC. Conversely, System Quality (SQ) does not significantly affect EC and LS. These results indicate that information quality, instructor quality, and learning satisfaction are essential in predicting continued intention to use e-learning.

This study provides critical insights into the determinants of e-learning's continuous intention to use, particularly emphasizing the roles of cognitive presence, information quality, instructor quality, system quality, and support service quality. This study establishes that cognitive presence significantly influences users' continuous intention to use e-learning (p-value = 0.000). This finding aligns with prior research suggesting that a strong mental presence enhances students' engagement and motivation in digital learning environments (Dunmoye et al., 2024; Kuhlmann et al., 2024). The implication is that students with a high cognitive presence tend to remain engaged with e-learning platforms. However, it is essential to acknowledge that cognitive presence alone may not fully explain continued e-learning adoption. Other psychological and environmental factors, such as motivation

and social support, may interact with cognitive presence to influence behavioral outcomes (Abedini et al., 2024). Information quality significantly influences cognitive presence (p-value = 0.000) and learning satisfaction (p-value = 0.000), underscoring the importance of well-structured, relevant, and accurate information in e-learning contexts. These findings align with the Technology Acceptance Model (TAM), which posits that perceived usefulness and content quality directly affect user engagement and satisfaction (Kumar et al., 2024; Wang et al., 2023). However, the direct relationship between information quality and e-learning continuous intention to use was insignificant (p-value = 0.151). This suggests that while high-quality information is necessary for engagement, it may not be the sole determinant of long-term usage. Some scholars believe that user motivation and external incentives, such as career benefits, are crucial for sustaining e-learning participation (Aljumah, 2023; Urhahne & Wijnia, 2023).

Instructor quality significantly impacts cognitive presence (p-value = 0.011) and learning satisfaction (p-value = 0.000), reinforcing the importance of effective teaching strategies and engagement in virtual learning settings. This is consistent with previous studies that have highlighted that instructor immediacy and pedagogical effectiveness enhance students' online learning experiences (Kianinezhad, 2023; Ramlatchan & Watson, 2020; Riapina, 2021). However, its direct influence on the intention to continue using e-learning was insignificant (p-value = 0.819). This finding may suggest that while instructor quality improves learning satisfaction, its impact on long-term engagement is mediated by other factors, such as self-regulated learning and peer interaction (Luo & Zhou, 2024). Learning satisfaction emerged as a critical determinant of e-learning's continued intention to use (p-value = 0.000), corroborating the existing literature, which posits satisfaction as a key driver of technology adoption (Bossman & Agyei, 2022; Jo & Bang, 2023). Learners who perceive their e-learning experiences as valuable and fulfilling will likely continue using the platform. However, some scholars argue that satisfaction is a dynamic construct influenced by contextual and individual factors, including cultural expectations and digital literacy levels (Zheng & Xiao, 2023).

System quality significantly influences cognitive presence (p-value = 0.003), suggesting that user-friendly, reliable systems enhance students' engagement. However, its direct impact on learning satisfaction (p-value = 0.080) and e-learning continuous intention to use (p-value = 0.170) was insignificant. This result contrasts with prior studies emphasizing the importance of system usability in shaping user experience (Banu et al., 2024). A possible explanation is that students prioritize content and pedagogical support over technical aspects when assessing e-learning effectiveness. Nonetheless, system reliability and accessibility remain crucial, particularly for users with limited technological expertise. Service quality significantly influenced cognitive presence (p-value = 0.000) and learning satisfaction (p-value = 0.002), underscoring the importance of adequate student support in digital learning environments. This aligns with the argument that timely technical and academic support enhances students' engagement and satisfaction (Lasekan et al., 2024; Rajabalee & Santally, 2021). However, its direct impact on e-learning's continuous intention to use was insignificant (p-value = 0.284), suggesting that while support services are beneficial, they may not directly motivate long-term adoption. Instead, their effects may be mediated through improved user experiences and reduced technical barriers. This study expands e-learning adoption models by highlighting the mediating roles of cognitive presence and learning satisfaction. While information quality, instructor quality, and support services enhance engagement and satisfaction, their direct impact on continued usage is limited. This underscores the need to incorporate factors such as student motivation and institutional support into existing frameworks (Chugh et al., 2023; Maheshwari, 2021; Urhahne & Wijnia, 2023). Several hypothesized direct effects were not supported, offering important insight into the mechanisms underlying students' continuance intention in e-learning environments. Instructor Quality did not directly influence E-learning Continuance Intention ($\beta = -0.018$, $p = 0.819$), suggesting

that the instructor's role operates indirectly through enhancing cognitive engagement and learning satisfaction rather than directly shaping technology-use decisions. Likewise, System Quality showed no significant direct effect on continuance intention ($\beta = 0.078$, $p = 0.170$) or learning satisfaction ($\beta = 0.099$, $p = 0.080$), indicating that technical performance may function as a baseline expectation; once usability standards are met, improvements alone may not increase students' motivation to continue using the platform. Similarly, Support Service Quality did not directly predict continuance intention ($\beta = 0.090$, $p = 0.284$), suggesting that institutional support facilitates the overall learning experience but does not independently determine sustained usage behavior. Collectively, these non-significant findings suggest that students' continuance decisions are driven more by meaningful cognitive involvement and affective learning experiences than by technological or support-related features alone, underscoring the central role of pedagogical and psychological factors in post-adoption e-learning behavior.

CONCLUSION

Evidence from the current research underscores that sustained engagement with e-learning platforms is not primarily driven by system features or service accessibility, but by students' cognitive presence and perceived satisfaction. These results affirm the theoretical proposition that meaningful engagement and the internalization of digital learning experiences are central to long-term adoption, especially in the context of open and distance education. The findings bridge pedagogical and technological dimensions, shifting the discourse from system-centric models toward more student-centered frameworks. A key implication is rethinking institutional strategies: rather than focusing solely on system reliability or instructor performance in isolation, higher education institutions must invest in integrative designs that stimulate cognitive engagement, emotional connection, and authentic interaction. This is vital in digitally mediated environments where students often operate independently and asynchronously. Conceptually, the study enriches the e-learning literature by validating the mediating roles of cognitive and affective engagement in the relationship between structural e-learning components and user behavior. These insights challenge linear adoption models and call for more dynamic, layered understandings of user continuance intention. The limitation of this study is its cross-sectional design based on self-reported data from a single open and distance education institution, which may limit causal inference and the generalisability of the findings across different educational and cultural contexts. Future research should adopt longitudinal and cross-institutional designs to capture temporal and contextual variations in student engagement. Further exploration into psychological constructs such as motivation regulation, digital resilience, or institutional trust may yield a more holistic understanding of how students adapt to and persist in online learning ecosystems. Such directions are crucial for informing inclusive and resilient educational strategies, particularly in the post-pandemic digital education landscape.

DECLARATION OF GENERATIVE AI

The authors declare that no generative AI or AI-assisted technologies were used in the writing process of this manuscript.

CONFLICTING INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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