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AN INTEGRATED PERSPECTIVE ON CONTINUOUS INTENTION TO USE E-LEARNING IN INDONESIAN HIGHER EDUCATION: THE ROLES OF ENJOYMENT, SELF-EFFICACY, AND SATISFACTION

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ABSTRACT

Aim/Purpose	This study examines the factors influencing the actual use of e-learning in higher education institutions (HEIs) by integrating the Technology Acceptance Model, the Theory of Planned Behavior, and the Expectation-Confirmation Model, while incorporating self-efficacy and perceived enjoyment to enrich the framework.
Background	The use of e-learning serves as a technology-based alternative to enhance learning efficiency. Despite numerous studies on e-learning, research on its actual use remains limited and requires further exploration.
Methodology	This study used a quantitative cross-sectional survey to examine a conceptual model integrating the Expectation-Confirmation Model (ECM), Technology Acceptance Model (TAM), and Theory of Planned Behavior (TPB), with self-efficacy and perceived enjoyment added to explain sustainable e-learning adoption. Data were collected through simple random sampling of university students in Indonesia who had used e-learning in the past year and had completed an entrepreneurship course. An online questionnaire distributed via Google Forms from

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	April to July 2025 produced 308 valid responses. Measurement items were adapted from previous studies and assessed key constructs using a five-point Likert scale. Data were analyzed using Partial Least Squares–Structural Equation Modeling (PLS-SEM) to evaluate the measurement and structural models and test the hypotheses.
Contribution	This paper contributes to the body of knowledge by providing empirical evidence on how perceived enjoyment, self-efficacy, and satisfaction influence students' continuous intention to use e-learning, thereby enriching the understanding of psychological factors that sustain technology adoption in higher education contexts.
Findings	Findings show that self-efficacy significantly influences perceived ease of use and perceived usefulness. Perceived ease of use affects perceived enjoyment and usefulness, while perceived usefulness and perceived behavioral control influence satisfaction, which, in turn, affects continued intention. Perceived enjoyment also positively impacts continuous intention, and continuous intention strongly predicts actual use. However, subjective norm and perceived usefulness do not significantly affect the intention to continue. These findings highlight key psychological and behavioral factors supporting sustained e-learning use and extend understanding of technology acceptance and continued engagement in digital learning environments.
Recommendations for Practitioners	Educational institutions and e-learning developers should enhance interactive, user-friendly features, provide continuous technical support and training to improve students' self-efficacy, and create engaging learning environments that increase enjoyment and satisfaction, thereby strengthening students' continuous intention to use e-learning platforms.
Recommendations for Researchers	For researchers, it is recommended to explore additional psychological, technological, and contextual factors that affect continuous intention to use e-learning and to apply diverse research methods with broader samples to improve the generalizability and depth of the findings.
Impact on Society	The results imply that universities should enhance students' self-efficacy and create engaging, user-friendly e-learning environments to encourage sustained use. Moreover, since enjoyment and satisfaction strongly influence continued intention, institutions should focus on providing meaningful, enjoyable learning experiences rather than relying solely on social or perceived usefulness.
Future Research	Future research could expand this study by incorporating additional variables, such as social influence, system quality, and learning outcomes, and by examining different educational contexts and longitudinal data to understand better the long-term determinants of students' continued intention to use e-learning platforms.

Keywords	technology acceptance model, theory of planned behavior, expectation confirmation model, perceived enjoyment, self-efficacy, e-learning

INTRODUCTION

The rapid growth of digital technology has accelerated the adoption of e-learning in higher education due to its flexibility, accessibility, and potential to improve learning efficiency. However, despite its widespread implementation, the sustainability of e-learning use among university students remains a critical issue that has not been sufficiently understood, particularly in Indonesia. Continued use of e-learning cannot be explained solely by technological availability, as differences in students' digital readiness, engagement, and learning autonomy may influence their intention to continue using e-learning over time (El-Sabagh, 2021; Gligorea et al., 2023). E-learning leverages adaptive intelligence, dynamic content, diverse learning resources, interactive activities, and flexibility to accommodate students' learning preferences and needs. Its use indirectly provides students with greater opportunities to engage in the learning process, thereby optimizing learning outcomes. The implementation of e-learning emphasizes the benefits of technology and ease of use, which, in turn, foster students' continued intention and intensive use of e-learning systems (Sprenger & Schwaninger, 2021). The use of technology in education has become an essential means of leveraging internet access and penetration. Given the large number of internet users, particularly among learners, and the opportunities technology offers to enhance the efficiency of the learning process, it is crucial to identify the factors that influence sustained e-learning use in higher education.

Despite the rapid expansion of digital technology in education, a critical issue remains insufficiently addressed: the sustainability of e-learning use among university students. While e-learning systems offer flexibility, cost efficiency, and broad access to learning resources, their continued use is not guaranteed, particularly in Indonesia, where disparities in digital readiness, student engagement, and learning autonomy persist. Existing studies have predominantly focused on initial adoption rather than sustained usage and often rely on fragmented theoretical approaches (Al-Fraihat et al., 2020). As a result, there is limited understanding of how key psychological and experiential factors drive students to engage with e-learning platforms continuously. In this regard, perceived enjoyment, self-efficacy, and satisfaction emerge as central constructs. Perceived enjoyment reflects the intrinsic motivation that makes learning engaging; self-efficacy represents students' confidence in their ability to use e-learning systems effectively; and satisfaction captures the overall evaluation of their learning experience. These factors are crucial in shaping students' continuous intention to use e-learning, which ultimately determines the long-term success of digital learning implementation (Alyoussef, 2021).

Furthermore, the integration of technology into the learning process supports students' ability to access, acquire, manipulate, construct, create, and communicate information effectively (Pliakos et al., 2019). Although numerous studies have examined the use of educational technologies to assess technology acceptance, including the adoption of e-learning in the learning process, the e-learning environment itself is supported by technologies, technological innovations, and tools with various functionalities designed and developed to facilitate student learning. Although previous studies have examined technology acceptance and e-learning adoption, comprehensive evidence regarding sustainable e-learning use in higher education remains limited. Most studies rely on separate theoretical perspectives, yielding fragmented findings and insufficient explanations of students' continued engagement. Therefore, this study investigates sustainable e-learning usage through an integrated framework combining the Technology Acceptance Model (TAM), the Theory of Planned Behavior (TPB), and the Expectation-Confirmation Model (ECM) (Al-Emran et al., 2020; Alyoussef, 2023; Martins et al., 2024; Nikou & Maslov, 2023). Most academic research does not use integrated theoretical frameworks, leading to findings limited to isolated variables. Therefore, this study investigates e-learning usage by examining factors adapted from TAM, TPB, and ECM.

Previous studies have rarely combined TAM, ECM, and TPB within a single framework, leaving a gap in providing a comprehensive understanding of the sustainable use of technology in the learning process. Mohammadi (2015) combined TAM and the Information Systems Success Model (IS Success Model) to provide a perspective on the use of e-learning in the learning process. Several studies have integrated TAM, ECM, and TPB (Abu-AlSondos et al., 2023; Al-Emran et al., 2020). However, a limitation of these studies is that they did not incorporate the satisfaction (SF) variable, which serves as the foundation of an individual's confidence in using e-learning continuously. The integration of TAM, ECM, TPB, and SF as a theoretical foundation offers a compelling framework for investigation, as these theories collectively determine the sustainable use of e-learning among university students. In addition, the ECM can be further refined as a fundamental theory for continuously analyzing intention to use e-learning (Dai et al., 2020). Perceived usefulness, a construct embedded in both TAM and ECM, is directly associated with students' intention to adopt and use e-learning in higher education (Al-Emran et al., 2020). Incorporating variables that influence the intention to use e-learning continuously extends and enriches TAM (Liu et al., 2010), ECM, and TPB (Abu-AlSondos et al., 2023; Al-Emran et al., 2020). The examination of SF as a foundation for the TAM provides insights into the dimensions that drive the enhancement of perceived enjoyment (PE). Perceived ease of use (PEU), in turn, describes the extent to which an individual believes that a system can be used effortlessly (Alyoussef, 2023). Previous studies have shown that PEU has a significant relationship with perceived usefulness (PU) (Abu-AlSondos et al., 2023; Park et al., 2012; Tawafak et al., 2023). Moreover, PEU has been found to strongly affect PU in e-learning use, highlighting the critical role of system usability in shaping students' perceptions of its usefulness (Kashive & Mohite, 2023). Furthermore, Chelawat et al. (2025) found that PEU, PU, and PE are significant predictors of students' behavioral intention to use e-learning in higher education. In addition, Ruiz et al. (2024) reported that perceived enjoyment and computer self-efficacy are significant determinants of PEU. Similarly, Al Arif et al. (2024) revealed that SE and PEU significantly influence PU, while PE significantly affects both PU and PEU.

A growing body of literature suggests that SF plays a significant role in shaping students' intention to use e-learning. Numerous studies have extensively investigated the relationship between SF and the intention to adopt e-learning. Satisfaction with the learning experience is a critical determinant of successful e-learning implementation, as students who feel satisfied are more likely to engage with and repeatedly use the system (Al-Fraihat et al., 2020; Sun et al., 2008). Students who are satisfied with their e-learning experience are more likely to use e-learning systems both in classroom activities and beyond the university environment. The relationship between SF and the intention to continuously use e-learning is also supported by previous findings by Natarajan et al. (2017) and Saqr et al. (2023). Moreover, PU exerts a significant influence on students' satisfaction with e-learning, underscoring the role of perceived benefits in shaping positive learning experiences (Saqr et al., 2023).

Perceived enjoyment (PE) has been identified as a key predictor of students' intention to use e-learning, which in turn influences their actual use (AU) and ultimately contributes to the adoption of e-learning as a sustainable learning solution (ELSS) (Chelawat et al., 2025). Moreover, actual use of e-learning has been found to be closely linked to students' behavioral intention, highlighting the connection between intention and subsequent system utilization (Ruiz et al., 2024). In line with this relationship, intention to use is a key factor in determining system usage behavior (E. W. L. Cheng, 2019). A substantial body of prior research has employed the TPB to explain technology adoption and usage behavior (Atmono et al., 2023; E. W. L. Cheng, 2019; A. Mustofa & Setiawan, 2022). Nevertheless, the application of the TPB in explaining continuous intention (CI) through perceived behavioral control (PBC) and SN remains limited. Some studies, however, have reported that both PBC and SN positively influence students' continuous intention to use e-learning (E. W. L. Cheng, 2019). Product usage is significantly determined by perceived behavioral control (PBC), attitude, and SN, reflecting the key constructs of the TPB (Ajzen, 1991).

Although e-learning has become widely adopted in higher education, its long-term sustainability remains uncertain because students do not always continue using e-learning systems after initial adoption. Existing studies have mainly emphasized technology acceptance at the adoption stage and provide a limited understanding of the factors that influence students' continuous intention and actual use over time. As a result, there is insufficient evidence regarding how psychological, behavioral, and experiential factors interact to support sustainable e-learning use, particularly in the context of higher education in Indonesia. This study contributes to the e-learning literature in three ways. First, it develops an integrated framework by combining the Technology Acceptance Model (TAM), Theory of Planned Behavior (TPB), and Expectation-Confirmation Model (ECM) to explain sustainable e-learning use. Second, this study extends previous models by incorporating satisfaction, perceived enjoyment, and self-efficacy as determinants of continuous intention. Third, the findings provide practical insights for higher education institutions in Indonesia to design strategies that strengthen students' long-term engagement with e-learning systems.

Based on these considerations, this study aims to develop an integrated framework that combines the Technology Acceptance Model (TAM), the Theory of Planned Behavior (TPB), and the Expectation-Confirmation Model (ECM), with a specific emphasis on perceived enjoyment, self-efficacy, and satisfaction as core determinants of continuous intention. The study seeks to answer the following research questions:

(1) How does self-efficacy influence perceived ease of use and perceived usefulness in the context of e-learning?
(2) How does perceived ease of use affect perceived enjoyment, perceived usefulness, and satisfaction?
(3) To what extent do satisfaction, perceived usefulness, and perceived enjoyment influence students' continuous intention to use e-learning?
(4) How does continuous intention affect the actual use of e-learning?
(5) How do perceived behavioral control and subjective norm influence students' continuous intention to use e-learning in higher education in Indonesia?

By addressing these questions, this research provides a more focused and contextually relevant understanding of sustainable e-learning use.

LITERATURE REVIEW

TECHNOLOGY ACCEPTANCE MODEL

The Technology Acceptance Model (TAM) is one of the most widely used theoretical frameworks for explaining and predicting technology acceptance in educational contexts. Developed by Davis and based on the Theory of Reasoned Action (TRA), TAM explains how users' perceptions influence their intention to adopt and continue using information systems and emerging technologies (Davis et al., 1989; Lee et al., 2025). The model emphasizes two core constructs – perceived ease of use (PEU) and perceived usefulness (PU) – that represent users' beliefs about the ease of interacting with a technology and the extent to which it enhances performance and effectiveness (Malatji et al., 2020). These perceptions shape users' attitudes and behavioral intentions toward technology adoption, making TAM a foundational model for understanding acceptance behavior across various digital environments, including e-learning and Internet of Things applications (Al-Emran et al., 2020; Natasia et al., 2022). The Technology Acceptance Model (TAM) is relevant for explaining sustainable e-learning use because students' continued engagement with digital learning depends on how easy and useful they perceive the system to be. Perceived ease of use reduces effort in using e-learning, while perceived usefulness strengthens beliefs about its benefits for learning outcomes. These perceptions influence students' intentions and encourage continuous use of e-learning in higher education.

THEORY OF PLANNED BEHAVIOR

Planned behavior theory originates in the theory of reasoned action and has been widely applied to understand and explore a range of individual behaviors (Erul & Woosnam, 2022; Qiu et al., 2025). Individual behavioral intentions are a central factor in the SDG model, which consists of attitudes towards behavior, subjective norms, and perceived behavioral control (Ajzen, 1991). This theory can also be the main determinant of research on the intention to perform the target's behavior in the future, and this intention can mediate the effect of the perception on subsequent behavior (Hagger, 2019; Hagger & Hamilton, 2025). TPB and its models are widely adopted for the use of learning technology (Al-Emran et al., 2020). Therefore, this study uses the concept of the SDGs as an important and feasible theoretical framework to determine the use of learning technology. Planned behavior theory is a prototype of the social cognition approach commonly used to predict social behavior (Ajzen, 2020; Hagger & Hamilton, 2025). The Theory of Planned Behavior (TPB) is relevant for explaining sustainable e-learning use because students' intention to continue using learning technology is influenced not only by personal attitudes but also by social influence and perceived control over technology use. Through subjective norms and perceived behavioral control, TPB helps explain how students develop intentions that ultimately shape their actual behavior in using e-learning continuously.

Expectation-Confirmation Model

The Expectation-Confirmation Model (ECM) is a theory in marketing that examines consumer satisfaction before and after a purchase (Oliver, 1980). These expectations refer to consumers' anticipation of the performance, quality, and value of an item before consuming it. The results of the comparison will have an impact on consumer satisfaction (Bhattacherjee, 2001; Xie, 2026). ECM is also a theory that examines user perceptions of the compatibility between expectations for information system use and actual performance. ECM is a theory used to determine the impact on system user satisfaction (Al-Emran et al., 2020). ECM is relevant for explaining sustainable e-learning use because students' continued intention to use e-learning is influenced by whether their actual learning experience meets or exceeds their initial expectations. When students perceive that the system performs effectively and provides value, their satisfaction increases and encourages continued use. Therefore, ECM helps explain how satisfaction becomes an important mechanism in sustaining e-learning engagement over time.

Conceptual Model and Hypothesis

Self-Efficacy, Perceived Enjoyment, and Perceived Ease of Use

Prior studies have largely examined the importance of e-learning acceptance in various educational contexts and countries. Nevertheless, this research addresses the growing implementation of e-learning platforms in the Gulf region using a hybrid conceptual model (Elnagar et al., 2021). Self-efficacy in digital literacy has an influence on the acceptance of technology (Yang & Lou, 2026). Based on the technology acceptance model (TAM) used in this study, self-efficacy has the opportunity to influence perceived ease of use and perceived usefulness (Yang & Lou, 2026). In addition, self-efficacy also has an impact on the use of technology among teachers in higher education (Al-Adwan et al., 2025; Thien & Hallinger, 2026). Hence, the study also proposes the following hypotheses:

H1: Self-efficacy has a positive effect on perceived ease of use.

H2: Self-efficacy has a positive effect on perceived usefulness.

Perceived Ease of Use, Perceived Usefulness, and Perceived Enjoyment

The Technology Acceptance Model (TAM) has become one of the most widely adopted frameworks among researchers internationally. The sudden onset of the COVID-19 pandemic accelerated its spread across multiple research domains, especially in higher education contexts (Rosli et al., 2022). Perceived ease of use (PEU) refers to an individual's perception of trust in the use of a particular system (Al-Emran et al., 2020; Davis et al., 1989). Previous research has shown that PEU has a significant impact on perceived usefulness (J. Huang et al., 2007; Joo et al., 2016). Previous studies have shown that PEU has a significant relationship with perceived usefulness (PU) (Abu-AlSondos et al., 2023; Park et al., 2012; Tawafak et al., 2023). Then, PEU also has a positive and significant relationship with perceived enjoyment (Zhang et al., 2026). Therefore, the following hypotheses are proposed in this study:

H3: Perceived ease of use has a positive effect on perceived enjoyment.

H4: Perceived ease of use has a positive effect on perceived usefulness.

Perceived Usefulness, Satisfaction, and Continuous Intention

Perceived usefulness (PU) describes the extent to which individuals have confidence that the use of a particular system can improve their performance (Al-Emran et al., 2020; Davis et al., 1989). Perceived usefulness can increase intention in using a system (Yang & Lou, 2026). Previous research has also found that PU has a significant relationship with satisfaction (Al-Emran et al., 2020; Joo et al., 2016; Oghuma et al., 2015). Satisfaction (SA) explains that there is an affective attitude towards the use of a certain computer system by the user at the end of the direct use of a certain application (Al-Emran et al., 2020). Some studies have found that there is a significant influence of SA on continuous intention (Al-Emran et al., 2020; Joo et al., 2016; Oghuma et al., 2015). Hence, the study also proposes the following hypotheses:

H5: Perceived usefulness has a positive effect on satisfaction.

H6: Satisfaction has a positive effect on continuous intention.

H7: Perceived usefulness has a positive effect on continuous intention.

Perceived Enjoyment, Continuous Intention, and Actual Use

Confirmation significantly enhances learners' continuance intention to engage in asynchronous online English courses, while perceived usefulness and perceived enjoyment act as significant mediators in this relationship (F. Huang & Liu, 2024). Continuous intention refers to the user's intention to continue using the information system continuously (Bhattacherjee, 2001). Previous research has shown that continuous intention has a significant impact on the use of actual information systems (Al-Emran et al., 2020; M. Cheng & Yuen, 2018; Joo et al., 2016). Previous research has also shown that perceived enjoyment has a positive influence on perceived ease of use and continuous intention (Ji et al., 2026). Hence, the study also proposes the following hypotheses:

H8: Perceived enjoyment has a positive effect on continuous intention.

H9: Continuous intention has a positive effect on actual use.

Perceived Behavior Control, Subjective Norm, and Continuous Intention

Perceived behavior control (PBC) is an individual's perception of the ease or difficulty of doing something they are interested in (Ajzen, 2020). Previous research has had a significant impact on continuous intention (Al-Emran et al., 2020; Yeap et al., 2016). In addition to PBC, subjective norms are defined as the perception of social pressure on good or bad performance (Ajzen, 1991, 2020). Other studies have also found that subjective norms have a significant impact on continuous intention (Al-Emran et al., 2020; Dalvi-Esfahani et al., 2020). Thus, the following hypotheses are put forward:

H10: Perceived behavioral control has a positive effect on continuous intention.

H11: Subjective norm has a positive effect on continuous intention.

This study addresses the pressing issue of the importance of utilizing e-learning in higher education. The purpose of this research is to examine the determinants of e-learning use in higher education, aiming to shed light on variables influencing the intention to use e-learning and the continued use of e-learning through a quantitative approach, and to contribute valuable insights to educational technology.

To address the gap in previous research, specifically the discussion on the use of e-learning in universities in Indonesia, this study formulates eleven hypotheses. The research model is visualized in Figure 1.

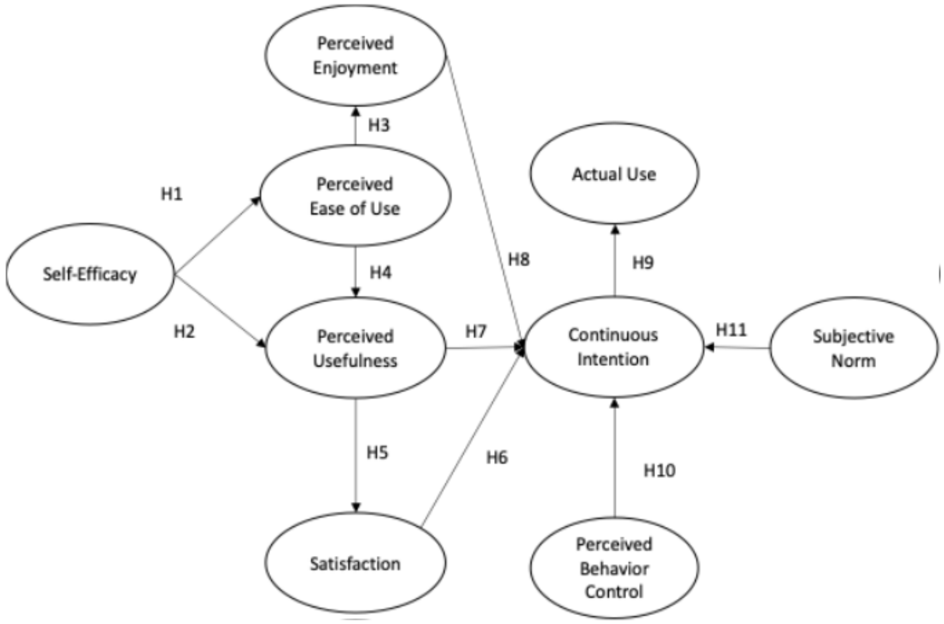

Figure 1. Research model

Source: Elaboration based on Ajzen (1991),
Al-Emran et al. (2020), and Sprenger and Schwaninger (2021)

METHODS

RESEARCH DESIGN

This study employs a cross-sectional survey with a quantitative approach to empirically validate the conceptual model. Construct validation was carried out using Partial Least Squares–Structural Equation Modeling (PLS-SEM). PLS-SEM was selected because it is well-suited for analyzing complex relationships among latent variables and for assessing prediction and mediation effects. Indonesia was chosen due to its rapid growth in e-learning adoption and its large higher education population, making it an appropriate context for examining continuance intention and actual use. Simple random sampling was applied to ensure each participant had an equal chance of selection and to improve sample representativeness while minimizing selection bias. Furthermore, this study integrates the Expectation-Confirmation Model (ECM), which has been examined in previous research (Abu-AlSondos et al., 2023; Al-Emran et al., 2020; Ashfaq et al., 2019).

The Technology Acceptance Model (TAM) that has been previously examined (Bessadok, 2022; Wu et al., 2025) as well as the Theory of Planned Behavior (TPB) as a foundation for identifying indicators of sustainable e-learning adoption, in addition to incorporating the self-efficacy variable to enrich the model further (Bandura, 1997), and perceived enjoyment (Al-Emran et al., 2020) outside of these theories as another exogenous variable. In more detail, the variables adapted from TAM include perceived ease of use (PEU), perceived usefulness (PU), continuous intention (CI), and actual use (AU), which serve to explain the acceptance and utilization of e-learning among university students (Bandura, 1997). The variables adapted from the Expectation-Confirmation Model (ECM) include satisfaction (SF), perceived usefulness (PU), and continuous intention (CI), which play a crucial role in explaining students' continuous intention to use e-learning (Al-Emran et al., 2020). The variables adapted from the TPB include perceived behavioral control (PBC), subjective norm (SN), and continuous intention (CI), which serve as the basis for understanding sustainable e-learning usage behavior (Ajzen, 1991) (see Figure 1).

Sample and Data Collection

Students, as learners who consistently engage in both in-class and out-of-class learning activities, provide a relevant research context aligned with the demands of the 21st century. The integration of technology into learning processes has become inevitable in the modern era, with e-learning recognized as one of the most efficient platforms in higher education. This study employed a sampling technique targeting active students from various higher education institutions in Indonesia who had completed entrepreneurship courses. Moreover, this sampling method has been widely applied in similar types of research (Nowiński et al., 2019; Wibowo et al., 2024). Indonesia was selected as the research setting because nearly all higher education institutions in the country have implemented technology-based academic systems, and e-learning has been widely adopted as a technology-driven learning platform.

The research instrument was administered through a questionnaire distributed via e-Forms (see Appendix). The survey link was shared across various academic and professional digital platforms, including WhatsApp academic groups, LinkedIn, and Instagram, to reach potential respondents. Data collection was carried out from April to July 2025.

To ensure research ethics, respondents were instructed not to provide personal identifiers such as names or identification numbers. They were informed that the data collected would be used solely for academic purposes. Confidentiality of responses was maintained, and no data were disclosed publicly. Furthermore, the research protocol was reviewed and approved by the Ethics Committee of the Department of Economics Education, Faculty of Teacher Training and Education, University of Lambung Mangkurat, Indonesia.

This study used a non-probability (convenience) sampling technique to obtain responses efficiently from students with relevant experience across different regions and institutions. While suitable for exploratory and behavioral research, this approach limits the generalizability of findings because the sample may not fully represent the broader student population. The dominance of female respondents (84.09%) may reflect participation tendencies in survey-based educational research and the high proportion of respondents from education-related disciplines, where female student representation is commonly higher. A total of 309 respondents participated in the survey (100%), with 308 (99.67%) completing the questionnaire in full and 1 (0.33%) excluded from further analysis due to incomplete responses. Detailed demographic information of the respondents is presented in Table 1.

Table 1. Demographic respondent data

Characteristics	% (n=308)
Gender	
Male	15.91 (49)
Female	84.09 (259)
Age	
< 20	20.13 (62)
20- 30	79.22(244)
>30	0.65(2)
Education Level	
Diploma	3.90(12)
Bachelor	95.13(293)
Master	0.65(2)
Doctoral	0.32(1)
University Type	
Public	89.29(275)
Private	10.71(33)

Characteristics	% (n=308)
Region/Island	
Java and Bali	27.92(86)
Kalimantan	40.58(125)
Sumatera	26.95(83)
Others	4.55(14)
Field of Study	
Economics & Business	6.82(21)
Education	91.56(282)
Others	1.62(5)

Based on Table 1, the majority of respondents were female, accounting for 259 participants (84.09%), while male respondents totaled 49 (15.91%). In terms of age distribution, most respondents were between 20 and 30 years old (244; 79.22%), followed by those under 20 years old (62; 20.13%), and a small portion above 30 years old (2; 0.65%). Regarding educational level, the majority were undergraduate students (293; 95.13%), followed by diploma students (12; 3.90%), master's students (2; 0.65%), and doctoral students (1; 0.32%). Regarding institutional background, 275 respondents (89.29%) were enrolled in public universities, while 33 (10.71%) were enrolled in private universities. Geographically, most respondents originated from Kalimantan (125; 40.58%), followed by Java and Bali (86; 27.92%), Sumatra (83; 26.95%), and other islands (14; 4.55%). In terms of academic disciplines, the majority of respondents were from the field of Education (282; 91.56%), followed by Economics and Business (21; 6.82%) and other disciplines (5; 1.62%).

Measures

This study adapted measurement items from well-established prior studies to ensure validity and comparability. The adapted items were carefully translated and adjusted to maintain semantic equivalence with the original sources. All constructs in this research were measured using a 5-point Likert scale: 1 (strongly disagree), 2 (disagree), 3 (neither agree nor disagree), 4 (agree), and 5 (strongly agree) (Preston & Colman, 2000).

In detail, Actual Use was measured using four items adapted from R. H. Mustofa et al. (2025) and Wibowo et al. (2024). Continuous Intention was measured using three items, Perceived Enjoyment with four items, Perceived Behavior Control with three items, Perceived Usefulness with three items, and Perceived Ease of Use with three items, adapted from Al-Emran et al. (2020). Furthermore, self-efficacy was measured using three items adapted from Setiawan et al. (2024) and W. Xu et al. (2025). Satisfaction was measured with three items, and subjective norm was measured using three items (R. H. Mustofa et al., 2024, 2025).

Data Analysis

PLS-SEM was employed because it is more suitable for prediction-oriented studies involving complex structural relationships and latent variables. Compared with CB-SEM and conventional regression techniques, PLS-SEM allows simultaneous evaluation of measurement validity and structural relationships while accommodating non-normal data and moderate sample sizes. This study employed Structural Equation Modeling (SEM) to test the proposed hypotheses. More specifically, it used the Partial Least Squares–Structural Equation Modeling (PLS-SEM) approach, which is well-suited for analyzing relationships between exogenous and endogenous variables with a relatively large sample size (Hair et al., 2021). In addition, PLS-SEM provides higher parameter estimation efficiency compared to covariance-based Structural Equation Modeling (CB-SEM) (Hair et al., 2017). The research procedure involved several stages, including outer model estimation and checks of the loading factor (LF), internal reliability (Cronbach's alpha and composite reliability), average variance extracted (AVE), and discriminant validity using the Fornell-Larcker criterion. They suggest an LF value of

0.700 (Hair et al., 2022), as well as inner model evaluation, structural model assessment, and hypothesis testing.

RESULTS

OUTER MODEL EVALUATION

PLS-SEM was employed to analyze the raw data obtained from 308 respondents. The first stage involved testing convergent validity by establishing a cut-off loading factor of 0.70 or higher, which served as the fundamental criterion for determining whether the variables were measured with valid items (Hair et al., 2017, 2021). Based on the analysis presented in Table 2, all items from the nine research variables had loading factor values ranging from 0.790 (AU003) to 0.945 (PBC002). All items with loading factors greater than 0.70 indicate that they are suitable for use, thereby meeting the required convergent validity criteria. Table 2 further demonstrates that the employed model satisfies the recommended criteria, confirming the adequacy of the measurement model (Hair et al., 2021). Questionnaire codes used in this study are shown in the Items column and described in the Appendix. Specifically, the model met the recommended criteria, including Cronbach's alpha (α) greater than 0.70, Composite Reliability (CR) above 0.70, and Average Variance Extracted (AVE) above 0.50 (Hair et al., 2017).

Table 2. Measurement model

Items	λ	α	CR	AVE	Mean	SD
Actual Use (AU)		0.879	0.917	0.734		
AU001	0.872				3.359	1.096
AU002	0.896				3.644	1.013
AU003	0.790				3.427	0.961
AU004	0.864				3.706	0.896
Continuous Intention (CI)		0.902	0.939	0.836		
CI001	0.914				3.864	0.852
CI002	0.904				3.696	0.823
CI003	0.925				3.770	0.922
Perceived Behavior Control (PBC)		0.912	0.945	0.850		
PBC001	0.891				3.796	0.856
PBC002	0.945				3.816	0.781
PBC003	0.930				3.832	0.838
Perceived Enjoyment (PE)		0.908	0.935	0.784		
PE001	0.907				4.071	0.825
PE002	0.898				3.994	0.816
PE003	0.887				3.955	0.823
PE004	0.848				3.945	0.801
Perceived Ease of Use (PEU)		0.879	0.925	0.806		
PEU001	0.873				4.165	0.853
PEU002	0.913				3.929	0.882
PEU003	0.906				4.055	0.805
Perceived Usefulness (PU)		0.870	0.920	0.794		
PU001	0.887				4.058	0.765
PU002	0.892				4.032	0.835
PU003	0.894				3.883	0.851
Self-Efficacy (SE)		0.764	0.864	0.680		
SE001	0.823				3.822	0.876
SE002	0.849				4.178	0.869

Items	λ	α	CR	AVE	Mean	SD
SE003	0.801				4.181	0.862
Satisfaction (SF)		0.921	0.950	0.864		
SF001	0.926				4.097	0.766
SF002	0.944				4.032	0.788
SF003	0.918				3.977	0.814
Subjective Norm (SN)		0.883	0.928	0.810		
SN001	0.889				3.874	0.840
SN002	0.899				3.951	0.867
SN003	0.912				3.977	0.822

Note: CR=composite reliability, α = Cronbach's alpha, AVE =average variance extracted, λ = loading, SD=standard deviation

The next stage, according to Hair et al. (2017, 2021), is to assess discriminant validity. Table 3 shows that discriminant validity was satisfied based on the Fornell–Larcker criterion for all variables (Franke & Sarstedt, 2019; Hair et al., 2022). This is further supported by Table 4, which indicates that the cross-loading values of each item with its respective construct are higher than those with other constructs.

Table 3. Discriminant validity (Fornell-Larcker criterion)

	AU	CI	PBC	PEU	PE	PU	SF	SE	SN
AU	0.857								
CI	0.573	0.914							
PBC	0.591	0.675	0.922						
PEU	0.506	0.715	0.668	0.898					
PE	0.471	0.716	0.580	0.703	0.885				
PU	0.477	0.683	0.603	0.710	0.748	0.891			
SF	0.531	0.787	0.632	0.760	0.758	0.760	0.929		
SE	0.249	0.394	0.506	0.396	0.418	0.426	0.418	0.825	
SN	0.611	0.609	0.650	0.678	0.623	0.681	0.643	0.352	0.900

Note: AU= actual use, CI= continuous intention, PBC= perceived behavior control, PE= Perceived Enjoyment, PEU= perceived ease of use, PU= perceived usefulness, SE= self-efficacy, SF= satisfaction, SN= subjective norm

Table 4. Cross loading

	AU	CI	PBC	PE	PEU	PU	SE	SF	SN
AU001	**0.872**	0.466	0.443	0.358	0.390	0.355	0.206	0.436	0.494
AU002	**0.896**	0.477	0.464	0.354	0.440	0.402	0.225	0.461	0.528
AU003	**0.790**	0.466	0.480	0.360	0.365	0.332	0.147	0.375	0.437
AU004	**0.864**	0.542	0.614	0.518	0.520	0.523	0.265	0.532	0.614
CI001	0.544	**0.914**	0.618	0.679	0.689	0.661	0.314	0.773	0.592
CI002	0.523	**0.904**	0.626	0.611	0.617	0.577	0.364	0.668	0.524
CI003	0.502	**0.925**	0.606	0.672	0.651	0.631	0.406	0.712	0.551
PBC001	0.545	0.544	**0.891**	0.477	0.598	0.536	0.419	0.525	0.568
PBC002	0.551	0.645	**0.945**	0.548	0.628	0.578	0.477	0.597	0.618
PBC003	0.541	0.667	**0.930**	0.570	0.620	0.553	0.496	0.620	0.610
PE001	0.416	0.647	0.489	**0.907**	0.634	0.655	0.347	0.683	0.544
PE002	0.407	0.628	0.530	**0.898**	0.656	0.662	0.393	0.660	0.539
PE003	0.445	0.641	0.506	**0.887**	0.615	0.655	0.341	0.689	0.540
PE004	0.400	0.621	0.529	**0.848**	0.583	0.678	0.403	0.652	0.588

	AU	CI	PBC	PE	PEU	PU	SE	SF	SN
PEU001	0.439	0.559	0.569	0.588	**0.873**	0.613	0.310	0.653	0.609
PEU002	0.479	0.681	0.618	0.651	**0.913**	0.649	0.369	0.681	0.622
PEU003	0.443	0.679	0.609	0.650	**0.906**	0.648	0.383	0.710	0.596
PU001	0.419	0.599	0.536	0.642	0.655	**0.887**	0.348	0.696	0.604
PU002	0.395	0.545	0.501	0.616	0.587	**0.892**	0.377	0.625	0.593
PU003	0.457	0.672	0.569	0.732	0.650	**0.894**	0.411	0.705	0.620
SE001	0.195	0.379	0.407	0.345	0.323	0.354	**0.823**	0.343	0.286
SE002	0.239	0.327	0.419	0.372	0.317	0.366	**0.849**	0.366	0.330
SE003	0.182	0.268	0.425	0.318	0.339	0.333	**0.801**	0.324	0.252
SF001	0.527	0.718	0.561	0.721	0.703	0.717	0.357	**0.926**	0.589
SF002	0.527	0.723	0.605	0.693	0.695	0.688	0.369	**0.944**	0.599
SF003	0.428	0.751	0.597	0.699	0.719	0.715	0.437	**0.918**	0.605
SN001	0.537	0.545	0.550	0.559	0.587	0.639	0.307	0.571	**0.889**
SN002	0.584	0.536	0.606	0.543	0.618	0.606	0.314	0.566	**0.899**
SN003	0.530	0.563	0.600	0.580	0.626	0.594	0.328	0.599	**0.912**

Note: AU= actual use, CI= continuous intention, PBC= perceived behaviour control, PE= Perceived Enjoyment, PEU= perceived ease of use, PU= perceived usefulness, SE= self-efficacy, SF= satisfaction, SN= subjective norm

Assessing the Structural Model

The next stage involved assessing the inner model after the outer model measurement had been confirmed to meet the recommended guidelines (Hair et al., 2017, 2022). At the inner model stage, estimations were conducted for the coefficient of determination (R^2), F-square (f^2) test, and path coefficients using a bootstrapping procedure with 500 re-samples (Hair et al., 2022). The first step was to assess multicollinearity among the variables by measuring the Variance Inflation Factor (VIF), with a threshold of VIF < 5.00 (Hair et al., 2017, 2021). Table 5 shows that no multicollinearity was detected, as all VIF values ranged from 1.000 to 2.812, all below the threshold of 5.00. These results confirm that the variables AU, CI, PBC, PEU, PE, PU, SF, SE, and SN do not exhibit multicollinearity, indicating that all research constructs can be reliably used for inner model estimation.

Table 5. Variance inflation factor (VIF)

	AU	CI	PBC	PEU	PE	PU	SF	SE	SN
AU									
CI	1.000								
PBC		2.035							
PEU					1.000	1.186			
PE		2.878							
PU		3.158					1.000		
SF		3.185							
SE				1.000		1.186			
SN		2.317							

Note: AU= actual use, CI= continuous intention, PBC= perceived behaviour control, PE= Perceived Enjoyment, PEU= perceived ease of use, PU= perceived usefulness, SE= self-efficacy, SF= satisfaction, SN= subjective norm

In the next stage, the R-square (R^2) values were assessed to measure the predictive power of the endogenous constructs AU, CI, PEU, PE, PU, and SF within the research model. The R^2 values were interpreted based on the criteria of >0.67 (strong), 0.33 (moderate), and 0.19 (weak) (Chin, 2010). Table 6 presents the R^2 values of the endogenous constructs. The R^2 for AU is 0.327, indicating that PE and CI explain 32.7% of the variance in AU, representing moderate predictive accuracy. The R^2 for CI is 0.692, meaning that PU, SF, PBC, and SN explain 69.2% of the variance, reflecting high predictive accuracy. The R^2 for PEU is 0.157, indicating that SE explains 15.7% of the variance, representing weak predictive accuracy. The R^2 for PE is 0.494, indicating that PEU explains 49.4% of the variance and suggesting moderate predictive accuracy. The R^2 for PU is 0.529, indicating that SE and PEU explain 52.9% of the variance and have moderate predictive accuracy. Finally, the R^2 for SF is 0.578, indicating that PU explains 57.8% of the variance, corresponding to moderate predictive accuracy.

Table 6. R2 estimation

	R-Square	Category
AU	0.327	Moderate
CI	0.692	Strong/Substantial
PEU	0.157	Weak
PE	0.494	Moderate
PU	0.529	Moderate
SF	0.578	Moderate

This study also evaluated the effect size (f^2) using guidelines that classify values of 0.02, 0.15, and 0.35 as small, medium, and large effects, respectively (Chin, 2010; Hair et al., 2021). Table 7 shows that CI has a medium effect on AU (0.486). PBC, SF, and SN have small to medium effects on CI (0.098, 0.194, 0.000, respectively). PEU has a large effect on PE and PU (0.975 and 0.737, respectively). PE has a small effect on CI (0.047), and PU has a small effect on CI (0.002). PU also has a large effect on SF (1.372). SE has a medium effect on PEU (0.186) and a small effect on PU (0.053).

Table 7. f2 estimation

	f-square	Category
CI -> AU	0.486	Large
PBC -> CI	0.098	Medium
PEU -> PE	0.975	Large
PEU -> PU	0.737	Large
PE -> CI	0.047	Small
PU -> CI	0.002	Small
PU -> SF	1.372	Large
SF -> CI	0.194	Medium
SE -> PEU	0.186	Medium
SE -> PU	0.053	Small
SN -> CI	0.000	Small

In addition, the goodness-of-fit (GoF) of the model was assessed. The model is considered fit if the Standardized Root Mean Square Residual (SRMR) is less than 0.10 and the Normed Fit Index (NFI) is greater than 0.90 or approaches 1 (Hair et al., 2021; Henseler et al., 2014). Table 8 shows that the SRMR is 0.048 (<0.10) and the NFI is 0.938 (>0.90), indicating that the research model is fit.

Based on the hypothesis testing results presented in Table 9, most of the proposed relationships were empirically supported. Self-efficacy (SE) significantly influenced perceived ease of use (PEU) (β=0.396; t=6.808) and perceived usefulness (PU) (β=0.172; t=3.866). Furthermore, PEU showed a strong positive effect on perceived enjoyment (PE) (β=0.703; t=18.209) and perceived usefulness (β=0.642; t=15.282). Perceived usefulness had a substantial effect on satisfaction (SF) (β=0.760; t=24.900), while satisfaction significantly increased continuance intention (CI) (β=0.436; t=5.581).

In addition, perceived enjoyment (β=0.204; t=3.157) and perceived behavioral control (PBC) (β=0.248; t=4.828) positively affected continuance intention, which subsequently had a significant influence on actual use (AU) (β=0.572; t=14.084). However, the direct effects of perceived usefulness on continuance intention (β=0.040; t=0.606) and of subjective norm (SN) on continuance intention (β=0.012; t=0.229) were not significant, indicating that these relationships were not supported in the proposed model.

Table 8. Evaluation result of fit model

	Saturated model
SRMR	0.048
d_ULS	1.002
d_G	0.676
Chi-square	1280.895
NFI	0.938

Table 9. Path coefficient

Hypothesis	Relationship	T-value	Key statistic	Decision
H1	SE -> PEU	6.808	β=0.396, p<0,05	Supported; significant
H2	SE -> PU	3.866	β=0.172, p<0,05	Supported; significant
H3	PEU -> PE	18.209	β=0.703, p<0,05	Supported; significant
H4	PEU -> PU	15.282	β=0.642, p<0,05	Supported; significant
H5	PU -> SF	24.900	β=0.760, p<0,05	Supported; significant
H6	SF -> CI	5.581	β=0.436, p<0,05	Supported; significant
H7	PU -> CI	0.606	β=0.040, p>0,05	Not supported; insignificant
H8	PE -> CI	3.157	β=0.204, p<0,05	Supported; significant
H9	CI -> AU	14.084	β=0.572, p<0,05	Supported: significant
H10	PBC -> CI	4.828	β=0.248, p<0,05	Supported; significant
H11	SN -> CI	0.229	β=0.012, p>0,05	Not supported; insignificant

Hypothesis Test

The final step in the inner model assessment was to test the hypotheses and the final structural model (Figure 2). Hypotheses were analyzed using the PLS-SEM bootstrapping technique (version 4.1.0.9). Hypothesis testing was based on a t-value greater than 1.96 for a one-tailed test and a p-value less than 0.05 (Hair et al., 2021).

Based on the specified thresholds, it was found that SE has a significant effect on PEU and PU (t-value = 6.808 > 1.96, p < 0.05; t-value = 3.866 > 1.96, p < 0.05). PEU significantly affects PE and PU (t-value = 18.209 > 1.96, p < 0.05; t-value = 15.282 > 1.96, p < 0.05). PU significantly affects SF (t-value = 24.900 > 1.96, p < 0.05), and PE significantly affects CI (t-value = 3.157 > 1.96, p = 0.002). PU and SN do not have a significant effect on CI (t-value = 0.607 < 1.96, p > 0.05; t-value =

0.229 < 1.96, p > 0.05). SF and PBC significantly affect CI (t-value = 5.581 > 1.96, p < 0.05; t-value = 4.828 > 1.96, p < 0.05), and CI significantly affects AU (t-value = 14.084 > 1.96, p < 0.05).

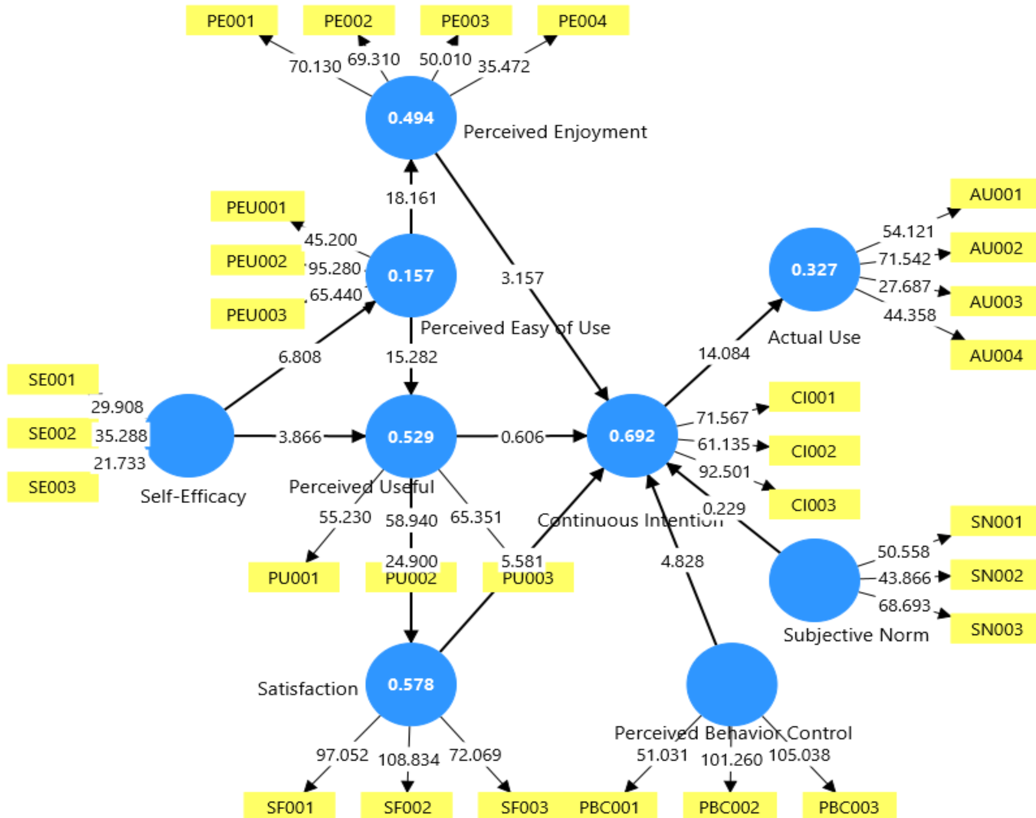

Figure 2. Structural model

Discussion

The Effect of Self-Efficacy on Perceived Ease of Use and Perceived Usefulness

The findings highlight the pivotal role of self-efficacy (SE) in shaping students' perceptions of both perceived ease of use (PEU) and perceived usefulness (PU) within e-learning environments. Students with higher self-efficacy tend to feel more confident in their ability to use digital learning systems, which directly enhances their perception that these systems are easy to use. This aligns with the theoretical assumptions of the Technology Acceptance Model, which holds that perceived ease of use is influenced by users' internal capabilities. Furthermore, self-efficacy also contributes to strengthening perceived usefulness, as students who believe in their competence are more likely to recognize the benefits and effectiveness of e-learning in supporting their academic performance. This dual influence indicates that self-efficacy not only reduces the cognitive effort required to use the system but also enhances students' evaluation of its functional value. Therefore, fostering students' self-efficacy is essential for improving both the usability and perceived benefits of e-learning, ultimately leading to more effective and sustained technology adoption in higher education (Al-Adwan et al., 2025).

This study proposes a conceptual framework to examine the factors influencing the Actual Use (AU) of e-learning in higher education by integrating the Technology Acceptance Model (TAM), Theory of Planned Behavior (TPB), and Expectation-Confirmation Model (ECM), while incorporating Self-Efficacy (SE) and Perceived Enjoyment (PE) as additional variables. The findings indicate that SE has a strong effect on PEU of e-learning. This result confirms previous studies reporting a significant relationship between SE and PEU (Alyoussef, 2023; Esiyok et al., 2025; Koutromanos et al., 2024; Qashou, 2021). The findings suggest that students' PEU can be enhanced by their level of self-efficacy in using information systems. Furthermore, it was found that e-learning self-efficacy significantly contributes to improving the ease of use of learning technologies (Pan, 2020). This result confirms previous research reporting a significant relationship between SE and PEU. Specifically, students with higher self-efficacy are more confident in using information systems, which, in turn, enhances their perception of how easily the e-learning system can be used. Furthermore, the results demonstrate that e-learning self-efficacy plays a critical role in improving the ease of use of learning technologies, highlighting the importance of fostering students' confidence and competence in engaging with digital learning platforms to optimize their learning experience. In addition to its effect on PEU, the findings also indicate that SE plays a role in enhancing the perceived usefulness (PU) of e-learning (see Table 9).

The findings provide important theoretical and practical insights by demonstrating that SE serves as a foundational driver of e-learning acceptance by positively influencing PU. This suggests that students' confidence in their ability to use digital learning systems not only reduces perceived complexity but also strengthens their perception of the educational value and effectiveness of e-learning. From a theoretical perspective, these results extend the TAM by confirming that internal psychological factors, particularly self-efficacy, play a critical role in shaping technology acceptance and should be considered alongside traditional cognitive determinants. The integration of TAM, TPB, and ECM further contributes to the literature by offering a more comprehensive explanation of actual e-learning use behavior in higher education. Practically, the findings imply that universities should prioritize initiatives that enhance students' digital competence, training, and confidence in using learning technologies, as improving self-efficacy may indirectly increase both system usability perceptions and long-term engagement with e-learning platforms.

The Effect of Perceived Ease of Use on Perceived Enjoyment, Perceived Usefulness, and Satisfaction.

The results of this study emphasize the central role of perceived ease of use (PEU) in shaping users' cognitive and affective evaluations of e-learning systems. In line with the assumptions of the Technology Acceptance Model, PEU not only reflects the extent to which a system is perceived as effortless to use but also serves as a critical antecedent influencing other key constructs in technology adoption. Specifically, the findings demonstrate that PEU significantly affects perceived enjoyment (PE), perceived usefulness (PU), and satisfaction (SF), indicating that when students perceive e-learning platforms as easy to operate, they are more likely to experience enjoyment, recognize the system's utility, and feel satisfied with their learning experience. This highlights that ease of use is not merely a technical attribute. However, a fundamental driver of positive user perceptions and emotional responses, ultimately contributing to sustained engagement with e-learning systems (Wangdi et al., 2023).

These results confirm previous studies that found PEU significantly enhances perceived enjoyment (PE) in e-learning (Fearnley & Amora, 2020). PEU also serves as a significant determinant of users' patronage intentions toward the human aspects of humanoid service robots (HSRs) (Said et al., 2024). Previous studies have shown that PEU has a significant relationship with PU (Abu-AlSondos et al., 2023; Tawafak et al., 2023). These findings indicate that PEU is a dominant factor in enhancing PU among users of payment apps (Al-Okaily, 2025). In addition, PU is also able to enhance PEU in mobile learning systems (Wu et al., 2025). The findings indicate that self-efficacy (SE) strongly influences both perceived ease of use (PEU) and perceived usefulness (PU) of e-learning. Higher SE enhances students' confidence, improving the ease, usefulness, and perceived enjoyment (PE) of digital learning platforms, highlighting the importance of fostering user competence for effective engagement with e-learning technologies. The findings also demonstrate that PU is a determinant factor of SF (Al-Okaily, 2025; Al-Okaily et al., 2025; Ruangkanjanases et al., 2024). In line with these findings, Lim et al. (2024) have found that PU significantly affects tourists' satisfaction in making hotel selection decisions using virtual and augmented reality. In addition, PU also positively influences digital celebrity satisfaction as a medium for customer endorsements (Kim & Park, 2024).

The findings provide deeper insight into the mechanism of e-learning adoption by demonstrating that PEU acts as a central enabling factor that shapes both cognitive and emotional responses toward technology use. The significant influence of PEU on PE, PU, and SF suggests that students are more likely to perceive e-learning as valuable, enjoyable, and satisfying when the platform requires less effort to operate. These results extend the Technology Acceptance Model by showing that ease of use not only facilitates functional acceptance but also strengthens users' affective experiences and post-adoption evaluations. The study contributes to the literature by integrating TAM with broader continuance mechanisms, indicating that sustained e-learning engagement depends not only on system performance but also on users' positive emotional experiences. From a practical perspective, higher education institutions should prioritize user-friendly platform design, intuitive interfaces, and digital support initiatives to improve students' learning experiences and encourage long-term e-learning adoption.

The Effect of Satisfaction, Perceived Usefulness, and Perceived Enjoyment on Continuous Intention

The findings of this study highlight the significant role of satisfaction (SF), perceived usefulness (PU), and perceived enjoyment (PE) in shaping students' continuous intention (CI) to use e-learning systems. Within the Expectation-Confirmation Model and the Technology Acceptance Model, these constructs represent key post-adoption factors that influence whether users continue using a technology (Davis et al., 1989). The results indicate that when students perceive e-learning as useful in supporting their academic performance, enjoyable in terms of learning experience, and satisfying in meeting their expectations, they are more likely to develop a strong intention to continue using the system. This suggests that continuous intention is driven not only by functional benefits but also by emotional and experiential factors, underscoring the importance of delivering a holistic and engaging e-learning experience.

Another finding is that SF also influences CI enhancement (Hsu & Lin, 2023; Kamboj et al., 2025; Qatawneh et al., 2025). These findings reinforce previous research (Baig & Yadegaridehkordi, 2025) showing a relationship between academic staff satisfaction and their CI in using GenAI. These results underscore the importance of fostering confidence, usefulness, and satisfaction to maintain engagement with digital learning platforms. This study finds that satisfaction with e-learning reflects the extent to which students' needs and expectations are met, thereby fostering a positive attitude that encourages continued use of e-learning (Jia et al., 2023). Furthermore, Fan and Jiang (2024) found that satisfaction supported by creative expression and innovation can enhance continued use of AI drawing tools.

Moreover, although previous studies have indicated that PU has a significant impact on CI (Khan et al., 2021; Y. Xu et al., 2021), PU is also a major factor in increasing the intention to use digital marketing continuously (Deb et al., 2024). This study found the opposite results (see Table 9). This indicates that respondents reported that PU does not have a significant impact on their CI to use e-learning. The findings suggest that students may not intend to use e-learning continuously because alternative non-digital learning media remain available, or because some instructors do not use e-learning in their teaching. Consequently, students do not perceive PU as significantly affecting their CI. These results also imply that the learning process could be optimized to maximize the potential of e-learning, enabling students to experience the benefits of PU fully. This argument aligns with the findings of Foroughi et al. (2024) and Ruangkanjanases et al. (2024), who found that PU does not have a substantial relationship with CI.

Another finding of this study is that PE has a significant influence on CI (Bhatnagr & Rajesh, 2025; Li et al., 2025; J. Luo et al., 2024). PE influences CI because the intrinsic enjoyment or pleasure derived from using a technology directly affects users' motivation to continue using it. Furthermore, PE has also been identified as a determining factor for CI among consumers of food delivery robot services (Hong et al., 2025). In addition, CI has been identified as a determining factor for increasing AU. The findings provide important insights into post-adoption behavior by demonstrating that SF and PE are stronger determinants of CI than PU in the e-learning context. This suggests that students' decisions to continue using e-learning are influenced not only by its functional value but also by whether the learning experience is enjoyable and capable of meeting their expectations. The insignificant effect of PU on CI indicates that perceived utility alone may no longer be sufficient to sustain continued use, particularly in contexts where alternative learning methods remain available or where instructor e-learning integration is inconsistent. This result extends the ECM and TAM literature by showing that affective and experiential factors may outweigh cognitive evaluations in explaining continuance behavior. Practically, these findings imply that higher education institutions should focus not only on improving the effectiveness of e-learning platforms but also on creating engaging, interactive, and satisfying learning experiences to encourage sustained use and ultimately increase AU.

The Influence of Continuous Intention on Actual Use

The results of this study underscore the crucial role of continuous intention (CI) as a direct antecedent of actual use (AU) in the context of e-learning adoption. Drawing on established theoretical perspectives, such as the Theory of Planned Behavior, Technology Acceptance Model, and Expectation-Confirmation Model, behavioral intention is widely recognized as the most immediate and powerful predictor of actual behavior. The findings indicate that when students develop a strong and sustained intention to use e-learning systems, they are more likely to translate this intention into consistent and real usage behavior (Al-Emran et al., 2020). This highlights that actual use is not merely influenced by system characteristics but fundamentally driven by users' motivational readiness and commitment to continue engaging with the technology. Therefore, strengthening students' continuous intention becomes a critical strategy for ensuring the effective and sustained utilization of e-learning platforms in higher education (E. W. L. Cheng, 2019).

Consistent with these findings, the sustained intention to use e-learning is closely associated with the enhancement of e-learning AU (Pasupuleti et al., 2025; Ruiz et al., 2024). In line with this relationship, CI is also a key factor in determining a system's usage behavior (E. W. L. Cheng, 2019). Within the TPB, TAM, and ECM frameworks, intention is considered the primary predictor of actual behavior. This means that students who lack the intention to use e-learning are unlikely to engage in its actual use. The findings emphasize the critical role of CI as the strongest proximal predictor of AU in e-learning, confirming the assumptions of TPB, TAM, and ECM that intention is the main mechanism that translates perceptions into actual behavior. The significant relationship between CI and AU suggests that students who demonstrate greater commitment and a willingness to continue using e-learning are more likely to engage in sustained, consistent use. This study contributes to the literature by reinforcing that actual technology adoption extends beyond system availability or technical quality and depends largely on users' motivational and post-adoption evaluations. In practice, these findings imply that higher education institutions should focus on strengthening students' continuance intention by providing satisfying, enjoyable, and meaningful learning experiences, as increased intention is likely to lead to higher levels of actual e-learning utilization.

The Effect of Perceived Behavioral and Subjective Norm on Continuous Intention

The higher the PBC, the more likely individuals are to be confident in their ability to continue using e-learning, thereby fostering CI. Within the TPB framework, SN is considered a factor that influences the increase of intention (Ajzen, 1991). However, this study found the opposite: that SN does not affect CI. This indicates that respondents perceive themselves as not being significantly influenced by social pressure or others (such as peers and instructors) in forming their CI to use e-learning. Instead, the decision to use e-learning is more strongly influenced by PBC and SF (Hsu & Lin, 2023; Khan et al., 2021; Qatawneh et al., 2025; Ruiz et al., 2024). This suggests that the use of e-learning is driven by its perceived usefulness, ease of use, and relevance to students' needs, rather than solely by social expectations. Although other studies have shown that SN can enhance CI for visiting Green Hotels, this effect does not appear in the context of e-learning (Fauzi et al., 2024), It is important to focus on the quality of the system, the learning experience, and strengthening students' self-confidence in using e-learning at higher education institutions.

This study also found that PBC can enhance students' CI to use e-learning in Indonesia. Consistent with these findings, PBC has a positive impact on increasing CI (E. W. L. Cheng, 2019; A. Mustofa & Setiawan, 2022). PBC can also enhance students' CI in using generative AI at higher education institutions (HEIs) (Ivanov et al., 2024). The findings provide important insights into students' post-adoption behavior by showing that PBC plays a more influential role than SN in shaping CI toward e-learning. The significant effect of PBC suggests that students' confidence in their ability to control and effectively use e-learning systems strengthens their intention to continue using them. In contrast, the insignificant relationship between SN and CI indicates that students' decisions are not primarily driven by social influence from peers or instructors but rather by their own perceptions of capability, learning needs, and previous experiences with the system. This finding extends the TPB perspective in higher education by suggesting that continuance behavior in digital learning environments may be more autonomous and internally motivated than socially driven. In practice, these results imply that higher education institutions should prioritize improving students' digital competence, system accessibility, and the quality of the learning experience rather than relying solely on social encouragement to promote sustained e-learning adoption.

CONCLUSIONS

This study contributes to the understanding of e-learning adoption in higher education by integrating the Technology Acceptance Model (TAM), Theory of Planned Behavior (TPB), and Expectation-Confirmation Model (ECM) with Self-Efficacy (SE) and Perceived Enjoyment (PE) to explain Actual Use (AU). The findings reveal three key insights. First, self-efficacy indirectly strengthens actual use through perceived ease of use and perceived usefulness, demonstrating that students' confidence in using digital technologies shapes their evaluation and acceptance of e-learning. Second, satisfaction emerged as one of the strongest predictors of continuance intention, while perceived ease of use significantly enhanced perceived usefulness and perceived enjoyment, highlighting the importance of both cognitive and affective factors in sustaining e-learning usage. Third, continuance intention was confirmed as the strongest direct predictor of actual use, reinforcing the assumptions of TAM, TPB, and ECM that intention serves as the closest determinant of actual behavior. However, contrary to expectations, perceived usefulness and subjective norm did not significantly influence continuance intention, suggesting that students' continued use decisions are driven more by personal experience, perceived control, and satisfaction than by functional value or social influence.

These findings address the research gap by showing that explaining post-adoption e-learning behavior requires a broader theoretical integration beyond a single acceptance model and that sustained usage depends not only on system characteristics but also on students' confidence, enjoyment, and learning experience. For future research, additional variables such as habit, digital readiness, engagement, facilitating conditions, and trust may be incorporated, alongside longitudinal or comparative studies across contexts to improve generalizability. From a practical perspective, higher education institutions should prioritize strengthening students' digital competence, improving platform usability, and creating more engaging and satisfying learning experiences to encourage stronger continuance intention and ultimately increase the actual use of e-learning systems.

LIMITATIONS AND FUTURE RESEARCH

This study has several limitations that should be acknowledged. First, the use of a cross-sectional design limits the ability to capture changes in user behavior over time, particularly in understanding how continuance intention evolves into actual use. Second, the data were collected from a specific sample and context, which may restrict the generalizability of the findings to other populations or settings. Third, the study relies on self-reported measures, which may introduce response bias and affect the accuracy of the results. Additionally, the variables examined are limited to perceived ease of use, perceived usefulness, perceived enjoyment, satisfaction, continuous intention, and actual use, potentially overlooking other relevant factors that may influence user behavior.

Future research is recommended to address these limitations by employing longitudinal designs to better capture behavioral changes over time and provide stronger causal inferences. Expanding the sample across different regions, institutions, or user groups would enhance the generalizability of the findings. Further studies could also incorporate additional variables, such as trust, system quality, or social influence, to provide a more comprehensive understanding of technology usage behavior. Moreover, the use of mixed-methods approaches, combining quantitative and qualitative data, may offer deeper insights into users' experiences and motivations for adopting and continuing to use a system.

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ETHICS STATEMENT

This study has received ethical approval from the Ethics Committee of the Department of Economics Education, Faculty of Teacher Training and Education, University of Lambung Mangkurat, Indonesia. All research procedures were conducted in accordance with the ethical standards set by the committee.

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APPENDIX: QUESTIONNAIRES

Variable	Code	Item
Self-efficacy (Y. Luo & Du, 2022)	SE001	I am confident that I can work effectively on many different tasks.
	SE002	When faced with a difficult task, I am confident that I will complete it.
	SE003	I believe I can succeed in any endeavor I undertake.
Perceived enjoyment (Al-Adwan et al., 2025)	PE001	Using an e-learning education platform in learning is fun.
	PE002	Using an e-learning education platform in learning is convenient.
	PE003	Using an e-learning education platform in learning is very entertaining.
	PE004	E-learning devices will make my free time more enjoyable.
Perceived ease of use (Al-Emran et al., 2020)	PEU001	E-learning is easy to use.
	PEU002	Interaction with e-learning is clear and easy to understand.
	PEU003	E-learning is convenient and user-friendly.

Variable	Code	Item
Perceived usefulness (Al-Emran et al., 2020)	PU001	E-learning improves my efficiency.
	PU002	E-learning allows me to complete tasks faster.
	PU003	E-learning improved my performance.
Satisfaction (Al-Emran et al., 2020)	SF001	I am satisfied with using E-learning as a learning tool.
	SF002	I am satisfied with using the E-learning function.
	SF003	I am satisfied with the E-learning instruction.
Continuous intention (Al-Emran et al., 2020)	CI001	I intend to continue using e-learning rather than discontinuing its use.
	CI002	I intend to continue to use e-learning rather than other alternative means.
	CI003	If I could, I would like to continue using e-learning.
Perceived behavioral control (Al-Emran et al., 2020)	PBC001	I have enough knowledge to use e-learning.
	PBC002	I have enough control to make the decision to use e-learning.
	PBC003	I have enough confidence to make the decision to use e-learning.
Subjective norms (Al-Emran et al., 2020)	SN001	Most of the people closest to me think that it would be more efficient if they used e-learning.
	SN002	I think other students in my class would be willing to use e-learning.
	SN003	Most of the people closest to me would support the use of e-learning.
Actual use (Al-Emran et al., 2020)	AU001	I use e-learning every day.
	AU002	I use e-learning a lot.
	AU003	Doing assignments without using E-Learning feels less than optimal.
	AU004	I have been using E-Learning a lot since I learned the benefit.

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