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THE FACTORS INFLUENCING LEARNERS' EXPERIENCE WITH E-LEARNING SYSTEMS: AN EMPIRICAL STUDY

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This study was conducted with the utmost effort and dedication from our team. However, we acknowledge that shortcomings are inevitable, and we sincerely welcome any constructive comments and feedback from esteemed lecturers and readers. We wish all respected lecturers good health as they continue their noble mission of inspiring future generations.

Tóm tắt

Nghiên cứu này nhằm đánh giá các yếu tố tác động đến sự chấp nhận và sử dụng hệ thống E-learning của sinh viên đại học tại Thành phố Hồ Chí Minh, qua đó xác định những nhân tố chủ yếu góp phần nâng cao chất lượng và hiệu quả của việc học tập trực tuyến. Để đạt mục tiêu trên, nghiên cứu đã áp dụng mô hình lý thuyết tích hợp giữa Mô hình Chấp nhận Công nghệ (TAM) và mô hình Mức độ phù hợp Nhiệm vụ - Công nghệ (TTF). Dữ liệu được thu thập từ khảo sát 374 sinh viên và phân tích thông qua mô hình phương trình cấu trúc bình phương tối thiểu từng phần (PLS-SEM). Kết quả cho thấy, các yếu tố như Hiệu quả bản thân, Chức năng hệ thống và Mức độ phù hợp giữa nhiệm vụ và công nghệ đều có tác động tích cực tới cảm nhận tính dễ sử dụng và tính hữu ích của hệ thống, từ đó ảnh hưởng rõ rệt tới ý định sử dụng E-learning của người học. Nghiên cứu khuyến nghị các cơ sở giáo dục đại học cần ưu tiên cải thiện chất lượng hệ thống, đầu tư vào đào tạo kỹ năng công nghệ số và tối ưu hóa giao diện người dùng nhằm thúc đẩy sự tham gia và tương tác hiệu quả hơn của sinh viên trong môi trường học trực tuyến.

Abstract

This research aims to examine factors influencing the acceptance and use of E-learning systems among university students in Ho Chi Minh City, thereby identifying key determinants for enhancing the quality and effectiveness of online learning environments. The study employs an integrated theoretical model combining the Technology Acceptance Model (TAM) and Task-Technology Fit (TTF). Data was collected from a survey of 374 university students and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The findings indicate that Self-Efficacy, System Functionality, and Task-Technology Fit positively influence Perceived Ease of Use and Perceived Usefulness, significantly impacting students' Intention to Use the E-learning system. The study suggests that universities should prioritize improving system quality, invest in digital skills training, and optimize user interface design to enhance student engagement and effectiveness in online learning.

Commitment

We, the undersigned research team, hereby certify that the content of this thesis, titled "The Factors Affecting Learners' Experience with E-Learning Systems: An Empirical Study", constitutes our original work conducted under the supervision of Dr. Le Thi Kim Hien. We affirm that the research presented in this thesis is entirely our own, and it does not replicate or rely upon any findings from other research, except where explicitly referenced.

We also confirm that we have followed all ethical guidelines and have appropriately acknowledged all sources and contributions from other authors. The findings, methodologies, and ideas included in this work are a direct result of our own efforts, and we take full responsibility for the integrity and accuracy of this research.

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List of abbreviations

Abbreviation/ acronym	Definition
AHP	Analytical Hierarchy Process
AVE	Average Variance Extracted
CB-SEM	Covariance-Based Structural Equation Modeling
CR	Composite Reliability
D&M IS Success Model	DeLone & McLean Information System Success Model
EFA	Exploratory Factor Analysis
f^2	Effect size
HTMT	Heterotrait-Monotrait Ratio of Correlations
ICT	Information and Communication Technology
IQ	Information Quality
IU	Intention to Use
KMO	Kaiser-Meyer-Olkin
LMS	Learning Management System
MSV	Maximum Shared Variance
OLS	Ordinary Least Squares
PEOU	Perceived Ease of Use
PLS – SEM	Partial Least Squares SEM
PU	Perceived Usefulness
Q^2	Predictive relevance
q^2	Effect Size
R^2	Coefficients of determination
SE	Self-Efficacy
SEM	Structural Equation Modeling
SEQ	Service Quality
SF	System Functionality

SN	Subjective Norm
SQ	System Quality
SRMR	Standardized Root Mean Square Residual
SU	System Use
SX	System Experience
TAM	Technology Acceptance Model
TR	Teacher Readiness
TRA	Theory of Reasoned Action
TTF	Task-Technology Fit
UTAUT	Unified Theory of Acceptance and Use of Technology
VIF	Variance Inflation Factor
WBLS	Web-Based Learning Systems
WBLS	Web-Based Learning System
β	Path coefficients

Chapter 1: Topic introduction

1.1. Reason

The rapid development of Information and Communication Technology (ICT) has had a significant impact on the education sector, particularly in the application of E-learning systems in teaching and learning. Over the years, numerous studies have highlighted both the benefits and challenges of this online learning model. Therefore, understanding the factors influencing learners' experiences with E-learning systems is essential for optimizing teaching effectiveness and enhancing learner satisfaction. Since the early 21st century, Cantoni, Cellario, and Porta (2004) have studied the impact of ICT on traditional higher education, particularly in promoting distance learning and the adoption of new learning models. They emphasized that designing multidimensional interactive interfaces and utilizing perceptual metaphors could significantly enhance the online learning experience, creating a more natural and effective learning environment. Building on these studies, in 2013, Agarwal and Pandey confirmed that E-learning offers numerous advantages over traditional education methods, including flexibility, cost-effectiveness, and the ability to personalize the learning experience. Their research emphasized that integrating ICT into education not only improves learning outcomes but also increases learners' satisfaction levels. A few years later, in 2015, Olutola Adekunle Thomas and Olatoye Olufunke Omotoke conducted research in Nigerian universities and highlighted the crucial role of E-learning in teaching and learning. However, they also identified significant challenges in implementing these systems, such as infrastructure limitations, financial constraints, and inadequate institutional support. Their study recommended that governments and private organizations collaborate to equip universities with advanced technological facilities to improve the quality of E-learning. More recently, in 2018, Shahmoradi and colleagues investigated the challenges of implementing E-learning systems at Tehran University of Medical Sciences. They found that students faced significant difficulties in accessing technology, lacked sufficient preparation, and encountered cultural and skill-related barriers to online learning. Their study concluded that to enhance the effectiveness of E-learning, improvements in ICT infrastructure, the development of a supportive learning culture, and adequate training programs for both students and instructors are necessary. In summary, studies over the past two decades have demonstrated that while E-learning holds great potential for modern education, various challenges must still be addressed. Therefore, researching the factors affecting learners' experiences with E-learning systems is crucial for improving the quality of online teaching and learning, thereby promoting the sustainable development of this educational model.

1.2. Literature review

E-learning has become an essential aspect of modern education, with numerous studies examining its adoption and effectiveness. Research in Vietnam primarily focuses on factors influencing both educators and students in using e-learning platforms, highlighting aspects such as system usability, perceived usefulness, and technical barriers. Studies emphasize that while e-learning is widely recognized as beneficial, issues related to infrastructure, engagement, and personalization remain critical challenges.

Table 1.1. Research Context in Vietnam and Related Studies

Research	Year	Detail of Finding
"Phân tích các yếu tố ảnh hưởng đến ý định tham gia E-Learning từ quan điểm của giảng viên: Một nghiên cứu điển hình về Việt Nam" (Phạm Minh, Bùi N. T. Anh. Tạp chí Khoa học Đại học Mở Thành phố Hồ Chí Minh, 15(1), 60-71)	2020	The strongest factor influencing lecturers' intention to participate in E-Learning is their attitude toward E-Learning. Perceived usefulness also has a significant impact, while the influence of trust and perceived ease of use is weaker. Recognizing the benefits of E-Learning motivates lecturers to adopt new technologies.
"Tích hợp các yếu tố ảnh hưởng đến hài lòng của người học vào hệ thống E-learning: Một tình huống tại Trường Đại học Kinh tế - Luật" của Vũ Thúy Hằng và Nguyễn Mạnh Tuân	2014	The study identifies three main categories influencing learner satisfaction and the success of the E-Learning system: User Interface, Learning Community, and Content Quality. These categories were analyzed using Fuzzy AHP to prioritize their importance. Personalization emerged as a key factor within these categories.
Công trình nghiên cứu "Các nhân tố ảnh hưởng tới dự định	2016	The study investigates key factors influencing the adoption of e-learning

sử dụng hệ thống E-Learning của sinh viên: Nghiên cứu trường hợp đại học Bách Khoa Hà Nội” của Lê Hiếu Học và Đào Trung Kiên		systems among students. From data collected from 205 students, the findings reveal that perceived effectiveness, perceived usefulness, convenience, and technical barriers significantly affect students’ intentions to use e-learning systems. Specifically, the first three factors positively influence adoption, while technical barriers negatively impact students' intentions. The study emphasizes the importance of enhancing system usability, improving technical infrastructure, and reducing technical barriers to foster e-learning acceptance.

Source: Authors' source

Internationally, research often adopts models like the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) to analyze user adoption. Key factors influencing e-learning acceptance include self-efficacy, social influence, and facilitating conditions, while technical ease of use appears less critical due to increased digital familiarity. Studies also highlight the positive impact of e-learning on both student engagement and teacher performance.

Table 1.2. International Research Context and Related Studies

Research	Year	Detail of Finding

Sulistiyani, E. T., & Nugroho, W. (2022). The Learning Management System (LMS) Acceptance Level in Learning Teacher Performance (TAM Approach)	2022	The study investigates the impact of Teacher Readiness (TR) and the Technology Acceptance Model (TAM) on teacher performance in public high schools in Depok City during the Covid-19 pandemic. Using a quantitative survey of 221 teachers, the findings reveal that both TR and TAM positively and significantly influence teacher performance, with TR explaining 26.8% and TAM explaining 29.9% of the performance variance. The combined effect of both variables explains 37.5% of teacher performance. The study suggests that enhancing teacher readiness and applying TAM effectively can significantly improve teacher performance during online learning.
Ibrahim, R. et al. (2017). E-learning acceptance based on Technology Acceptance Model (TAM).	2017	The study "E-Learning Acceptance Based on Technology Acceptance Model (TAM)" by Ibrahim et al. (2017) explored the factors influencing students' acceptance of e-learning in higher education. It found that computer self-efficacy significantly impacts perceived ease of use (path coefficient: 0.75, $p<0.001$), which, in turn, strongly affects students' intention to use e-learning (path coefficient: 0.57, $p<0.001$). Interestingly, instructor characteristics and perceived usefulness did not significantly influence e-learning adoption, diverging from prior studies. These findings highlight the importance of improving students' technological confidence and ensuring

		system usability to enhance e-learning adoption (Ibrahim et al., 2017).
“Factors Influencing Students’ Use of E-Learning Technologies” by Oyetade, Harmse, and Zuva (2023).	2023	The study "Factors Influencing Students’ Use of E-Learning Technologies" by Oyetade, Harmse, and Zuva (2023) examines factors shaping e-learning adoption among 250 South African university students using the UTAUT framework. Key findings indicate that utility expectancy, social influence, and facilitating conditions positively impact e-learning usage, while effort expectancy has no significant effect, likely due to students' digital familiarity. With a 59% explanation of variance in usage (Adjusted $R^2 = 0.591$) and strong validity (KMO = 0.896, Cronbach's $\alpha > 0.8$), the study emphasizes the importance of aligning e-learning tools with students’ goals, fostering supportive social environments, and ensuring robust technical infrastructure to enhance engagement and adoption.

Source: Authors' source

1.3. Research objective and purpose

1.3.1. Research objective

This study aims to examine the level of acceptance and the key factors influencing the adoption of E-learning in higher education. By identifying the determinants of student engagement, motivation, and satisfaction, the research seeks to provide a comprehensive understanding of the effectiveness of E-learning systems. Through data collection and analysis, the study will develop a measurement framework incorporating factors such as ease of use, content quality, interaction levels, and technical support.

1.3.2. Research purpose

Beyond theoretical insights, this study has a practical purpose: to enhance the overall E-learning experience and support digital transformation in education. The findings will serve as a basis for improving E-learning systems through user interface optimization, content enhancement, and greater personalization to align with students' learning needs. Additionally, the study will propose strategies for strengthening technological infrastructure, providing better technical support, and integrating digital skills training to ensure that both students and instructors can effectively navigate and maximize the benefits of online learning. Ultimately, this research contributes to the advancement of digital education by fostering a more engaging, efficient, and sustainable E-learning environment.

1.4. The significance of the research

1.4.1. Scientific significance

Although numerous studies have explored E-learning, there remains a lack of a comprehensive theoretical framework that integrates technological factors, pedagogy, and learner interaction. Most previous research has focused on individual aspects rather than connecting them into a holistic model to assess the acceptance and effectiveness of E-learning. This study introduces a novel approach by integrating the Technology Acceptance Model (TAM) and Task-Technology Fit (TTF), considering both technological factors and learner behavior in the context of higher education in Vietnam. By combining these models, the research provides a more comprehensive evaluation of how well technology aligns with learners' needs and identifies key factors influencing the acceptance and effectiveness of E-learning. As a result, the study proposes practical solutions to enhance learner engagement, improve the online learning experience, and optimize the effectiveness of E-learning systems in higher education.

1.4.2. Educational significance

From an educational perspective, this research contributes to improving the quality and effectiveness of online learning in universities. By identifying key factors influencing student engagement and learning outcomes, the study provides valuable insights for educators, administrators, and policymakers to refine teaching strategies and enhance digital learning environments. Furthermore, the study offers recommendations for designing user-friendly E-learning platforms with improved interactivity, personalized learning experiences, and robust technical support. These enhancements can help bridge the gap between traditional and digital learning, ensuring that students not only adopt E-learning but also achieve meaningful academic success. Ultimately, the findings support the broader goal of digital transformation in education, fostering a more inclusive, accessible, and effective learning experience for students in Vietnam and beyond.

1.5. Research focus, population, sample, scope and research questions

1.5.1. Research focus

This study focuses on analyzing the acceptance and effectiveness of E-learning among university students in Ho Chi Minh City. It aims to identify key factors influencing students' engagement, motivation, and satisfaction when using E-learning platforms. By examining both technological and behavioral aspects, the study assesses how well E-learning aligns with students' learning needs and contributes to their academic success. The findings will provide a comprehensive understanding of E-learning adoption and its impact on the student learning experience.

1.5.2. Research population

The research population consists of university students in Ho Chi Minh City who use E-learning platforms as part of their academic activities. These students come from various universities and represent diverse academic disciplines, learning environments, and technological backgrounds. Since students are the primary users of E-learning systems, their perspectives are crucial for evaluating the effectiveness and usability of these platforms.

1.5.3. Research sample

The study is conducted in two phases to ensure reliability and representativeness. In the preliminary study, a pilot survey was conducted with 90 students from different universities in Ho Chi Minh City. This phase aimed to assess the reliability and validity of the measurement scales and refine the questionnaire based on student feedback. Following the preliminary study, the main study was conducted with a larger sample of 350 – 400 students to ensure data representativeness. The finalized survey was distributed online through various channels, including email, social media platforms, and online student communities. The questionnaire, developed based on the validated scales from the pilot study, used a five-point Likert scale to measure students' perceptions and experiences with E-learning. This approach allowed for the collection of quantitative data to analyze key factors affecting student engagement and learning outcomes in E-learning environments.

1.5.4. Research scope

In terms of subject scope, it focuses exclusively on the use of E-learning among university students, examining factors such as system usability, learning effectiveness, and student satisfaction. Regarding population scope, the study targets university students in Ho Chi Minh City who actively engage with E-learning platforms as part of their academic coursework. The geographical scope is confined to universities in Ho Chi Minh City, a major educational hub in Vietnam with a strong focus on digital learning integration. Lastly, the time scope covers a research period of four months, with data collection taking place during the 2024–2025 academic year. By clearly defining these parameters, the study ensures a structured and focused approach to understanding E-learning adoption among university students. The findings will provide valuable insights for improving digital learning experiences and enhancing the overall effectiveness of E-learning in higher education.

1.5.5. Research question

1. Which factors significantly affect university students' intention to use E-learning systems in Ho Chi Minh City?
2. How does self-efficacy influence students' perceived ease of use and intention to use E-learning systems?
3. What role do system functionality and quality play in shaping students' perceptions of task-technology fit and perceived ease of use in E-learning environments?
4. In what ways does task-technology fit impact students' perceptions of the usefulness and ease of use of E-learning systems?
5. Between perceived usefulness and perceived ease of use, which factor plays a more critical role in determining students' intention to use E-learning systems?
6. Based on the research findings, what specific managerial recommendations can be proposed to assist universities in enhancing the effectiveness and quality of online learning environments?

1.6. The structure of a scientific research

Chapter 1: Introduction

This chapter provides an overview of the research, including its background, objectives, significance, and scope. It lays the foundation for the study by explaining its importance and defining key research questions.

Chapter 2: Theoretical background and Research model

This chapter presents the theoretical framework and relevant research models related to E-learning adoption and effectiveness. It reviews established theories and prior studies to develop the research model.

Chapter 3: Research Methodology and Design

This chapter describes the research design, including data collection methods, measurement scale development, sampling strategy, and data analysis techniques. It outlines the methodological approach used to test the research model.

Chapter 4: Research Findings

This chapter presents the results of data analysis, including descriptive statistics, hypothesis testing, and model validation. It discusses key findings and their implications for E-learning adoption and effectiveness.

Chapter 5: Conclusion and Recommendations

This chapter summarizes the research findings, highlights the study's contributions, and provides recommendations for improving E-learning systems. It also discusses study limitations and suggests directions for future research.

Chapter 2: Theoretical foundation and related research model

2.1. Theoretical foundation

2.1.1. E-Learning systems and factors affecting the acceptance of E-Learning systems

2.1.1.1. E-Learning system

The formal learning system with the help of electronic resources is known as e-learning. Whereas teaching can be inside (or outside) the classrooms, the use of computer technology and the Internet is the main component of e-learning (Aboagye et al. 2020).

E-learning is playing a vital role in the existing educational setting, as it changes the entire education system and becomes one of the greatest preferred topics for academics (Samir et al. 2014). It is defined as the use of diverse kinds of ICT and electronic devices in teaching (Gaebel et al. 2014).

Because of e-learning, participants can save time and effort for living in distant places from universities where they are registered, so, many scholars support online courses (Ms & Toro, 2013). Many users of e-learning platforms see that online learning helps ensure that e-learning can be easily managed, and the learner can easily access the teachers and teaching materials (Gautam, 2020; Mukhtar et al. 2020). It also helped reduce the effort and travel expenses and other expenses that accompany traditional learning. E-learning significantly reduced the administrative effort, preparation and lectures recording, attendance, and leaving classes.

Ülker and Yılmaz (2016) highlighted that one method of implementing e-learning is through a Learning Management System (LMS). In this context, e-learning involves facilitating, structuring, and overseeing educational activities within a digital system, encompassing key functions such as student enrollment, assessments, coursework submissions, course outlines, lesson structures, communication tools, and instructional content (Haghshenas, 2019). Transitioning from traditional classroom-based learning to an LMS-based approach allows learners to access platforms like Blackboard at any time, offering advantages such as enhanced learning efficiency, improved interaction with educators, and easier access to academic resources (Idris & Osman, 2015).

Teachers, as well as students, see that online learning methods encourage pursuing lessons from anywhere and in difficult circumstances that prevent them from reaching universities and schools. The student becomes a self-directed learner and learns simultaneously and asynchronously at any time. However, there are many drawbacks of e-learning, the most important of which is getting knowledge only on a theoretical basis and when it comes to using everything that learners have learned without applied practical skills. The face-to-face learning experience is missing, which may interest many learners and educators. Other problems are related to the online assessments, which may be limited to objective questions. Issues related to the security of online learning programs and user reliability are among the challenges of e-learning in addition to other difficulties that are always related to the misuse of technology (Gautam, 2020; Mukhtar et al. 2020).

2.1.1.2. Factors affecting the acceptance of E-Learning systems

The acceptance of e-learning systems has been extensively studied through various theoretical models, providing a structured understanding of the determinants shaping user behavior. For technology-based services, including e-learning systems, the Technology Acceptance Model (TAM) is widely used to assess technology adoption and usage (King & He, 2006). The Technology Acceptance Model (TAM), introduced by Davis (1989), represents the second approach for assessing the effectiveness of information systems. It is considered the most extensively applied framework for evaluating the success of new technologies, particularly in terms of user adoption and utilization (Surendran, 2012).

The theoretical foundation of the Technology Acceptance Model (TAM) is the Theory of Reasoned Action (TRA) by Fishbein and Ajzen. The Technology Acceptance Model (TAM) proposes that when individuals are introduced to a new technology, various factors influence their decision regarding how and when they will adopt it (Davis, 1989). According to this model, elements such as external factors, social factors (e.g., skills and language), cultural factors, and political factors (i.e., the implications of technology usage in politics) shape perceived usefulness and perceived ease of use (Surendran, 2012). These two perceptions, in turn, play a crucial role in shaping users' attitude toward the technology and their intention to use it. Ultimately, behavioral intention to use serves as the primary predictor of actual system adoption and usage.

- *Perceived usefulness* is the extent to which an individual believes that using a specific system will enhance their job performance.

- *Perceived ease of use* refers to the degree to which an individual believes that using a specific system will require minimal effort.

- Both of these beliefs influence the user's attitude toward using the information system.

Based on the study by Almaiah et al. (2020), the successful adoption of e-learning systems during the COVID-19 pandemic is influenced by five critical factors: technological factors, e-learning system quality factors, trust factors, self-efficacy factors, and cultural aspects. The research highlights that technological infrastructure, including stable internet access and system usability, plays a vital role in e-learning adoption. Additionally, the quality of the e-learning system, such as accessibility, interactive features, and well-structured course content, directly impacts students' engagement and learning effectiveness. Trust in the system, including concerns about privacy, security, and reliability, is another key determinant influencing user confidence. Furthermore, self-efficacy, which refers to students' confidence in their ability to use e-learning platforms effectively, significantly affects adoption rates. Lastly, cultural aspects, including resistance to digital learning and traditional learning preferences, can act as barriers to e-learning acceptance. The study concludes that addressing these factors through improved digital infrastructure, faculty training, strong cybersecurity measures, and awareness programs will enhance e-learning adoption and long-term effectiveness.

Additionally, based on the study by Al-Fraihat et al. (2019), the factors influencing the acceptance of e-learning systems are categorized into seven main groups: technical system quality, information quality, service quality, educational system quality, support system quality, learner quality, and instructor quality. These factors impact satisfaction, perceived usefulness, and system use, which in turn influence the benefits derived from the system. The findings indicate that technical system quality, information quality, and support system quality significantly affect perceived usefulness and satisfaction among learners. Additionally, instructor quality and learner quality play a crucial role in driving system usage. Moreover, satisfaction and perceived usefulness strongly influence actual system use, ultimately determining the overall benefits of e-learning for learners

According to Julander (2003), barriers refer to the disadvantages or obstacles that hinder users from accessing and utilizing a service. Shawai and Almaiah (2018) emphasized that insufficient utilization of e-learning systems hinders the realization of their potential benefits (Almaiah et al., 2019a; Almaiah et al., 2019b; Almaiah & Al-Khasawneh, 2020). As a result, the system may fail to achieve its intended objectives, leading to financial losses for universities (Naveed et al., 2017). Research in this area remains in its early stages, with limited exploration of students' perspectives (Tarhini et al., 2017; Almaiah & Alamri, 2018). Examining e-learning adoption can provide universities with deeper insights into students' needs, ultimately contributing to the successful implementation of e-learning systems (El-Masri & Tarhini, 2017; Alksasbeh et al., 2019).

2.2. Reference research model

2.2.1. Conceptual framework of the reference model

In the study "An Empirical Study of Instructor Adoption of Web-Based Learning Systems", Wei-Tsong Wang and Chun-Chieh Wang (2009) developed an integrated model to analyze university instructors' acceptance and use of Web-Based Learning Systems (WBLS). The model was constructed by combining the Technology Acceptance Model (TAM) and the DeLone & McLean Information System Success Model (D&M IS Success Model). The TAM model emphasizes two key factors: Perceived Usefulness (PU) - the extent to which the system enhances work efficiency and meets user needs and Perceived Ease of Use (PEOU) - the system's ease of learning, use, and navigation. These two factors influence Intention to Use (IU), which subsequently leads to System Use (SU) - actual usage behavior. Meanwhile, the D&M IS Success Model complements the analysis by incorporating system quality aspects, including System Quality (SQ) - performance, interface, and system features; Information Quality (IQ) - accuracy, usefulness, and timeliness of the information provided by the system; and Service Quality (SEQ) - the level of technical support and user training. Additionally, the model integrates psychological factors such as Subjective Norm (SN) - social pressure from the organization, colleagues, or the learning environment and Self-Efficacy (SE) - an individual's belief in their ability to use the system independently and effectively.

2.2.2. Structural composition of the reference model

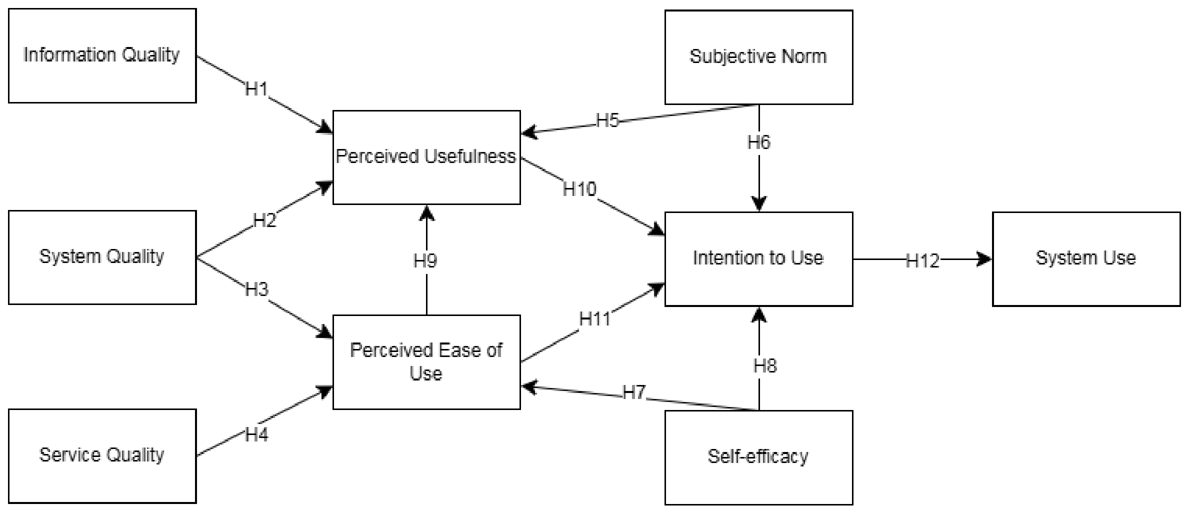

Figure 2.1. Reference proposed research model for the acceptance of web-based learning systems

(Sources: Wang, W. T., & Wang, C. C. (2009). An empirical study of instructor adoption of web-based learning systems. Computers & Education, 53(3), 761-774.)

The model is divided into three main categories with causal relationships as follows:

User Behavior

1. Perceived Usefulness (PU): Directly affects IU.
2. Perceived Ease of Use (PEOU): Influences both PU and IU.
3. Intention to Use (IU): Determines SU.
4. System Use (SU): Represents the actual usage level of the WBLS.

Information System

1. System Quality (SQ): Impacts PEOU and PU.
2. Information Quality (IQ): Influences PU.
3. Service Quality (SEQ): Affects PEOU and indirectly influences PU.

Psychological Factors

1. Subjective Norm (SN): Directly impacts PU and IU.

2. Self-Efficacy (SE): Influences PEOU and IU.

2.2.3. Theoretical integration with the current research model

The study by Wei-Tsong Wang and Chun-Chieh Wang (2009) not only clarifies the factors influencing the adoption of WBLS but also serves as an important theoretical foundation for the development and adjustment of the current research model. This study adapts and refines the model to include six key factors that align with the research context and target audience, ensuring relevance and applicability within the scope of this study.

Chapter 3: Design and research methodology

3.1. Research process

The research process is conducted through specific steps to ensure scientific rigor, reliability, and the value of the collected data. The study includes two survey phases: a pilot study and a main study, with participants being university students in Vietnam. All data is collected over four months and analyzed using SmartPLS 4.0 software.

3.1.1. Pilot study

The pilot study is carried out using two methods: qualitative pilot research and quantitative pilot research.

- **Qualitative Pilot Research**: In-depth interviews are conducted with a small group of university students to gather insights into the factors influencing their intention to use the system. Qualitative data is analyzed to refine and optimize the survey questionnaire.

- **Quantitative Pilot Research**: A trial survey is conducted with 90 students to test the reliability and validity of the measurement scales. The validity of the questionnaire items is assessed using Cronbach's Alpha and exploratory factor analysis (EFA). Based on feedback from the pilot study, necessary adjustments are made to the survey.

3.1.2. Main study

After finalizing the pilot study, the main study is conducted with a sample size of 350–400 university students in Vietnam. Data collection takes place over 4–6 weeks. Once collected, the primary data undergoes careful screening and processing, including the removal of invalid responses and consistency checks.

Next, Cronbach's Alpha analysis is performed to ensure the reliability of the measurement scales. Exploratory factor analysis (EFA) is applied to examine and confirm the structure of the research factors. Then, structural equation modeling (SEM) is implemented using SmartPLS 4.0 to test the relationships between the study variables. The research proceeds with evaluating the structural model, specifically including the following steps: assessing multicollinearity (VIF) among constructs, path coefficients (β), and the coefficient of determination (R^2)

3.2. Scale design

3.2.1. Draft measurement scale 1

The measurement scales for the concepts in this research model are adapted from previous studies and have been adjusted to align with the research context. Specifically, they are inherited from Wang (2009), which serves as the foundation for this study.

The model is based on the Wang (2009) framework, which integrates the Technology Acceptance Model (TAM) and the D&M IS Success Model. TAM emphasizes two key factors: Perceived Usefulness (PU), which reflects how the system enhances efficiency and meets user needs, and Perceived Ease of Use (PEOU), which represents the system's ease of learning, usage, and operation. These factors influence Intention to Use (IU), which subsequently leads to System Use (SU). Meanwhile, the D&M IS Success Model supplements aspects related to system quality, including System Quality (SQ) (performance, interface, and features), Information Quality (IQ) (accuracy, usefulness, and timeliness), and Service Quality (SEQ) (technical support and training). The model also incorporates psychological factors such as Subjective Norm (SN) (social pressure from organizations, peers, or learning environments) and Self-Efficacy (SE) (users' confidence in independently and effectively using the system).

The draft scale of the research model includes **60** observed variables and utilizes a 5-point Likert scale, corresponding to five levels of choice, as follows:

- *1 - Strongly Disagree,*
- *2 - Disagree,*
- *3 - Neutral,*
- *4 - Agree,*
- *5 - Strongly Agree*

Table 3.1. Draft measurement scale 1

Sources	Observed variable
Perceived Ease of Use (PEOU)	
Davis, F. D. (1989)	It is easy for me to integrate the functions of LMS into my learning plan. It is easy for me to become proficient in using LMS. LMS is user-friendly, making it easy for me to navigate. It is easy for me to achieve my desired outcomes using LMS in relation to my learning methods. I find it easy to understand and perform tasks using LMS.
Perceived Usefulness (PU)	
Davis, F. D. (1989)	Using LMS saves me time Using LMS gives me greater control over my learning. LMS largely affects my study results and outcomes. LMS helps me get informed from lecturer for class activities. LMS effectively assists me in taking exams and other assessments. Overall, I find LMS useful in my study.
Self Efficiency (SE)	
Venkatesh, V., & Davis, F. D. (1996)	I am confident in my ability to use LMS effectively, even without prior experience in online learning. I am confident in my ability to use LMS independently, even without assistance or guidance. I am confident in my ability to use LMS, relying solely on the user manual for reference. I am confident in my ability to integrate the functions of LMS into my learning plan. I am confident that I possess the necessary skills to operate LMS proficiently.
Task-Technology Fit (TTF)	

Goodhue & Thompson, 1995; Dishaw & Strong, 1999	The LMS suits my learning style. The LMS suits all aspects of my learning. The LMS is easy to use. The LMS is user-friendly. The LMS is easy to use in my learning. The LMS provides me with up-to-date information. The LMS provides me with the information I need at the right time. The LMS provides the exact output of what I need. The LMS is suitable in supporting me in completing my learning tasks. The LMS is necessary for my learning tasks.
Intention To Use (IU)	
Taylor & Todd, 1995	I intend to use LMS to perform learning-related activities and to communicate with my friends I intend to increase my use of LMS in the future I would use LMS to perform different learning-related activities I am willing to devote the required time and energy for my learning activities via LMS I am willing to use LMS for learning on regular basis I would also recommend others to use LMS
System Use (SU)	
DeLone, W. H., & McLean, E. R. (2003)	I use LMS to communicate with the instructor. I receive assignments from the instructor via LMS. I submit my assignments through LMS. I receive course materials from the instructor via LMS. I view grades and receive feedback from the instructor through LMS. I discuss the course with the instructor and classmates through LMS.
System Functionality (SF)	

DeLone, W. H., & McLean, E. R. (2003)	LMS supplies all the features that I need for my learning. LMS meets my learning requirements. The LMS was helpful in supporting my learning tasks. LMS matches my learning demands. LMS meets my expectations. LMS works very well for me.
System Quality (SQ)	
DeLone, W. H., & McLean, E. R. (1992)	LMS allows me to have control over my learning activities. LMS offers flexibility in terms of time and place of use. LMS provides the necessary functions for me to successfully conduct my learning activities. I have appropriate and sufficient software and hardware on my personal computer to use LMS. I can easily access LMS anytime I need to use it. LMS has well-designed user interfaces.
System Experience (SX)	
Venkatesh, V., & Davis, F. D. (2000)	**SX1: Novice** You are a new user of the LMS with little or no prior experience. You rely on user guides or assistance from experienced users to navigate and participate in basic classroom activities. **SX2: Intermediate** You have gained sufficient knowledge and experience to use the LMS effectively. You can apply your basic understanding to navigate the system with ease. Unlike novice users, you rarely need to refer to guides, but you still seek answers to more complex issues to enhance your LMS experience. **SX3: Expert** You are highly experienced in using the LMS. While you may not use every feature regularly, you consider yourself a proficient user. You feel confident in utilizing LMS functions to address unclear issues. You refer to user guides for less frequently used

	features and are comfortable explaining LMS functionalities to novice, intermediate, and expert users.
Subjective Norm (SN)	
Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003)	The authorities of my institution support the use of LMS in my learning The learning environment of my institution is adequate for me to use LMS. I am capable of using LMS to facilitate my learning in my class Using LMS in university was obligatory. My friends thinks that I should use LMS for learning The trend of using LMS among people around me is increasing People around me generally believe that it is better to learn when using LMS

Source: Authors' source

3.2.2. Draft measurement scale 2

The study by Wei-Tsong Wang and Chun-Chieh Wang (2009) not only clarifies the factors influencing the adoption of Web-based Learning Systems (WBLS) but also serves as a crucial theoretical foundation for developing and refining the current research model. The model has been adjusted to include **six** key factors, ensuring its alignment with the target audience and research scope as previously outlined.

Perceived Ease of Use (PEOU)

The Perceived Ease of Use (PEOU) scale remained unchanged after the preliminary qualitative research. The original 5 observed variables were retained, as they were deemed essential in evaluating the ease of integrating, navigating, and performing tasks within the LMS. No modifications were necessary as the existing variables effectively captured the concept.

Perceived Usefulness (PU)

The Perceived Usefulness (PU) scale underwent adjustments during the qualitative research phase. Initially consisting of 6 observed variables, it was refined to 4 variables after removing ambiguous and less relevant items.

Specifically, "LMS largely affects my study results and outcomes." was removed due to an unclear level of impact, while "LMS effectively assists me in taking exams and other assessments." was excluded as it was not directly relevant to the general usefulness of LMS.

Self-Efficiency (SE)

The Self-Efficiency (SE) scale was revised from 5 observed variables to 4 variables following the qualitative review. The item "I am confident in my ability to use LMS, relying solely on the user manual for reference." was removed, as it did not align with real-world LMS usage patterns. The retained variables sufficiently measure users' confidence in effectively using the LMS.

Task-Technology Fit (TTF)

The Task-Technology Fit (TTF) scale underwent substantial modifications. Initially composed of 10 observed variables, the scale was streamlined to 5 variables after eliminating redundant and unclear items. Variables such as "The LMS is user-friendly." and "The LMS is easy to use." were removed due to overlap with PEOU. Additionally, "The LMS provides the exact output of what I need." was deemed difficult to quantify, while "The LMS provides me with up-to-date information." lacked specificity. To enhance clarity, "The LMS suits all aspects of my learning." was revised to "The LMS suits all methods of my learning.".

Intention to Use (IU)

The Intention to Use (IU) scale remained unchanged after the qualitative research. The original 6 observed variables were retained, as they adequately captured users' intent to engage with LMS for various learning-related activities, both currently and in the future.

System Use (SU)

The System Use (SU) scale, originally composed of 6 observed variables, was entirely removed. The rationale for its exclusion was that it primarily measured LMS usage behavior rather than user perceptions or intentions, which were the focus of the research model.

System Functionality (SF)

The System Functionality (SF) scale remained intact after the qualitative review. The original 6 observed variables were retained, as they effectively measured the system's ability to meet learning needs, provide necessary features, and align with user expectations. No modifications were required.

System Quality (SQ)

The System Quality (SQ) scale, which initially contained 6 observed variables, was removed entirely. The decision was based on findings that SQ overlapped with PEOU and SF, leading to redundancy in the model. Its removal improved the clarity and efficiency of the measurement framework.

System Experience (SX)

The System Experience (SX) scale, originally designed to classify users into three levels (*Novice*, *Intermediate*, *Expert*), was eliminated. The removal was justified by the observation that user experience classification did not provide sufficient explanatory power for LMS adoption behaviors within the scope of the study.

Subjective Norm (SN)

The Subjective Norm (SN) scale, initially consisting of 7 observed variables, was removed following the qualitative review. The findings indicated that subjective norms had no direct impact on the key constructs being examined. As a result, the scale was deemed unnecessary in the final model.

Table 3.2. Draft measurement scale 2

Sources	**Observed variable**
Perceived Ease of Use (PEOU)	
Davis, F. D. (1989)	PEOU1: It is easy for me to integrate the functions of LMS into my learning plan. PEOU2: It is easy for me to become proficient in using LMS. PEOU3: LMS is user-friendly, making it easy for me to navigate. PEOU4: It is easy for me to achieve my desired outcomes using PEOU5: LMS in relation to my learning methods. I find it easy to understand and perform tasks using LMS.

Perceived Usefulness (PU)	
Davis, F. D. (1989)	PU1: Using LMS saves me time PU2: Using LMS gives me greater control over my learning. PU3: LMS helps me get informed from lecturer for class activities. PU4: Overall, I find LMS useful in my study.
Self Efficiency (SE)	
Venkatesh, V., & Davis, F. D. (1996)	SE1: I am confident in my ability to use LMS effectively, even without prior experience in online learning. SE2: I am confident in my ability to use LMS independently, even without assistance or guidance. SE3: I am confident in my ability to integrate the functions of LMS into my learning plan. SE4: I am confident that I possess the necessary skills to operate LMS proficiently.
Task-Technology Fit (TTF)	
Goodhue & Thompson, 1995; Dishaw & Strong, 1999	TTF1: The LMS suits my learning style. TTF2: The LMS suits all methods of my learning. TTF3: The LMS is easy to use in my learning. TTF4: The LMS provides me with the information I need at the right time. TTF5: The LMS is necessary for my learning tasks.
Intention To Use (ITU)	
Taylor & Todd, 1995	ITU1: I intend to use LMS to perform learning-related activities and to communicate with my friends ITU2: I intend to increase my use of LMS in the future ITU3: I would use LMS to perform different learning-related activities ITU4: I am willing to devote the required time and energy for my learning activities via LMS

	ITU5: I am willing to use LMS for learning on regular basis ITU6: I would also recommend others to use LMS
System Functionality (SF)	
DeLone, W. H., & McLean, E. R. (2003)	SF1: LMS supplies all the features that I need for my learning. SF2: LMS meets my learning requirements. SF3: The LMS was helpful in supporting my learning tasks. SF4: LMS matches my learning demands. SF5: LMS meets my expectations. SF6: LMS works very well for me.

Source: Authors' source

3.2.3. Survey

The survey questionnaire is used to measure the key concepts of the study, including perceived ease of use (PEOU), perceived usefulness (PU), self-efficacy (SE), technology-task fit (TTF), intention to use (IU), and system functionality (SF). The survey questions are developed based on original measurement scales from previous studies. After conducting the preliminary survey, the questionnaire content is adjusted to fit the research context, ensuring clarity and accuracy in participants' responses.

The survey consists of **three** main sections:

Survey Introduction: This section provides an overview of the research objectives and instructions on how participants should complete the questionnaire.

Personal Information: This part collects demographic details such as age, gender, field of study, and frequency of system usage.

Main Questions: This section contains the core research questions, evaluated using a 5-point Likert scale (*1 - Strongly Disagree, 2 - Disagree, 3 - Neutral, 4 - Agree, 5 - Strongly Agree*). This scale allows for an accurate reflection of participants' agreement levels regarding each research factor.

With this research process, the study ensures systematic and scientific rigor while providing a reliable data foundation for evaluating and developing a student support system.

3.3. Sample design

3.3.1. Sampling Method

The study employed a convenience sampling method to approach the target population, which is university students currently using E-learning systems in Ho Chi Minh City. This method was chosen for its flexibility, time-saving nature, cost-efficiency, and suitability for the research's limited resources. Convenience sampling allows researchers to access easily reachable participants, thereby optimizing the data collection process under constraints of budget and time. Although this is a non-probability sampling method, it is still considered appropriate and useful for exploratory studies and when a complete sampling frame is not available.

3.3.2. Sample Size and Characteristics

A total of 374 valid survey responses were collected using Google Forms. The participants were students from over 10 universities, including both public and private institutions such as UEH, UEL, FTU, IUH, HCMUTE, USSH, RMIT, FPT, etc., ensuring diversity in educational programs and learning environments.

The online data collection approach not only broadened the sample coverage but also ensured anonymity, encouraging participants to provide honest responses. Specifically, first-year students accounted for 18%, second-year students 28.1%, third-year students 29.8%, fourth-year students 22.6%, and fifth-year or above students represented a very small percentage. Thus, the sample effectively represents various stages of the learning process, especially focusing on students from the second to fourth year who are most likely to use the E-learning system intensively.

3.3.3. Basis for Sample Size Selection and Suitability for PLS-SEM

This study applies the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach to validate the integrated model of TAM and TTF. PLS-SEM is considered a second-generation analysis tool, suitable for exploratory research, theory development, small sample sizes, non-normal data distribution, or complex models (Hair et al., 2016; Vu, 2020).

Unlike CB-SEM, which emphasizes theoretical validation, PLS-SEM focuses on predictive power and explaining variance of dependent variables through an iterative algorithm estimated using Ordinary Least Squares (OLS) regression (Vu, 2020). Therefore, it is less strict about data distribution assumptions and offers more flexibility in dealing with formative measurement models, complex models, or model identification issues (Marcoulides & Chin, 2012).

Regarding sample size, PLS-SEM allows the use of the “10 times rule” proposed by Barclay et al. (1995). According to this rule, the minimum sample size should be equal to or greater than 10 times the number of indicators (observed variables) used to measure a construct, or 10 times the number of paths leading to a construct in the structural model.

Furthermore, Hair et al. (2016) and Cohen (1992) recommend using power analysis to determine an appropriate sample size, especially when the model includes multiple independent variables.

Maximum Number of Arrows Pointing at a Construct (Number of Independent Variables)	**Significance level**											
	10%				**5%**				**1%**			
	Minimum R^2				**Minimum R^2**				**Minimum R^2**			
	0.10	**0.25**	**0.50**	**0.75**	**0.10**	**0.25**	**0.50**	**0.75**	**0.10**	**0.25**	**0.50**	**0.75**
2	72	26	11	7	90	33	14	8	130	47	19	10
3	83	30	13	8	103	37	16	9	145	53	22	12
4	92	34	15	9	113	41	18	11	158	58	24	14
5	99	37	17	10	122	45	20	12	169	62	26	15
6	106	40	18	12	130	48	21	13	179	66	28	16
7	112	42	20	13	137	51	23	14	188	69	30	18
8	118	45	21	14	144	54	24	15	196	73	32	19
9	124	47	22	15	150	56	26	16	204	76	34	20
10	129	49	24	16	156	59	27	18	212	79	35	21

Table 3.3. Sample Size Recommendation in PLS-SEM for a Statistical Power of 80%

(Source: Cohen (1992): A Power Primer. Psychological Bulletin 112: 155–159)

With 374 valid samples, this study far exceeds the minimum requirement and fully meets the sample size criteria in PLS-SEM, ensuring stability, reliability, and generalizability of the analytical results.

3.4. Data analysis methods

The chapter begins by emphasizing the importance of collecting and examining data meticulously to ensure its quality. To ensure the accuracy of measurement instruments, reliability testing is conducted. Building upon this foundation, structural equation modeling (SEM), particularly the PLS-SEM approach, is utilized to analyze complex relationships between variables. Finally, the measurement models within PLS-SEM are rigorously assessed to confirm their validity and reliability.

3.4.1. Data collection and Screening

The research data was collected using a structured questionnaire developed based on validated measurement scales from previous studies. A pilot survey was conducted beforehand to ensure the clarity, comprehensibility, and relevance of the questions for the target respondents. The data collection was carried out using a non-probability sampling method, aiming to reach the intended target group based on predefined criteria. After collection, the data was coded and entered into statistical analysis software, with each variable assigned a specific code for efficient processing. An initial data screening was conducted to identify any missing values, logical inconsistencies, invalid responses, or duplicates. Although the PLS-SEM method does not require normally distributed data, skewness and kurtosis indices were examined to better understand the data distribution. Finally, a thorough data cleaning was performed to ensure accuracy, completeness, and readiness for subsequent statistical analysis.

3.4.2. Descriptive statistics

Descriptive statistics were conducted to provide an overview of the sample characteristics and general trends within the collected data. This included summarizing respondents' background information such as academic year and university affiliation. The results showed that the number of responses across different academic years was relatively balanced, indicating a diverse and well-distributed sample. These preliminary analyses offer useful insights and help ensure the quality and suitability of the data before conducting further statistical analysis.

3.4.3. Structural equation modeling in PLS–SEM

Structural Equation Modeling (SEM) is a second-generation multivariate data analysis method that allows researchers to simultaneously test multiple complex relationships between latent variables and observed variables. In SEM, there are two common approaches: Covariance-Based SEM (CB-SEM) and Partial Least Squares SEM (PLS-SEM). While CB-SEM is primarily used to test or confirm existing theoretical models, PLS-SEM is preferred for exploratory research and theory development, where the goal is to predict and explain the variance of dependent variables (Hair et al., 2022).

PLS-SEM operates based on the Ordinary Least Squares (OLS) iterative algorithm, which allows for partial estimation of relationships within the model, thereby maximizing the R^2 value of endogenous latent variables. The advantage of PLS-SEM is its ability to handle small sample sizes, non-normal distribution data, and complex models—limitations often encountered by CB-SEM. PLS-SEM also does not require strict model identification conditions, allowing for the flexible use of both reflective and formative measurement models, as well as single-item scales (Hair et al., 2016).

In terms of the model, PLS-SEM consists of two main components: the structural model (inner model), which describes the relationships between latent variables, and the measurement model (outer model), which represents the relationships between latent variables and their corresponding observed variables. Latent variables are represented as linear composites of indicators, with weights optimized to best reflect the theoretical concept.

Compared to regression methods using sum scores, PLS-SEM allows for the estimation of individual weights for each indicator, helping to reduce bias and improve the accuracy of concept measurement. Furthermore, PLS-SEM does not assume that the weights of the indicators are equal—an assumption commonly made in sum score regression, which leads to unreliable results (Henseler et al., 2014).

However, PLS-SEM also has some limitations, such as the lack of a clear global goodness-of-fit criterion, unlike CB-SEM. Recently, indices like SRMR (Standardized Root Mean Square Residual) have been proposed to address this limitation (Henseler et al., 2014).

The reason for choosing PLS-SEM is because it is a powerful and flexible tool in social and business research, particularly useful when the research goal is theory exploration, complex models, or non-ideal data. The selection of PLS-SEM should depend on the research goal, data characteristics, and model structure, rather than viewing it as a complete replacement for CB-SEM. The two methods should be seen as complementary in modern empirical research.

3.4.4. Assessment of measurement model in PLS-SEM

By evaluating the measurement model, the research ensures that the observed variables included in the survey accurately measure the constructs they are intended to assess, thus confirming the validity and reliability of the research instrument. To achieve this, the measurement model assessment focus on three essential aspects: (1) *internal consistency reliability,* (2) *convergent validity,* and (3) *discriminant validity* utilizing the Heterotrait-Monotrait ratio of correlations (HTMT) criterion (Aburumman et al., 2022)

Internal consistency reliability is the first criterion to be evaluated, assesses the consistency of results across items within a test (Hajjar, 2018). The reliability of a construct can be assessed through two primary measures: *Cronbach's alpha (α)* and *Composite Reliability (CR)*. α provides an estimate of reliability based on the intercorrelations among observed indicators, is commonly calculated as the average value of all possible split-half coefficients (Cortina, 1993); while CR reflects the internal consistency of items measuring the latent construct by considering differing weights assigned to each indicator. The conceptual formula of Cronbach's Alpha is defined by: $\alpha = \frac{K\,\underline{r}}{[1+(K-1)\underline{r}]}$. Where K is number of factors and $\underline{r}$ is the average correlation among all factors. Generally, both reliability indicators should range from *0.70 to 0.95*. Because indicators typically do not possess equal reliability, composite reliability (which assigns varying weights to indicators) is considered more accurate compared to Cronbach's alpha (which assumes equal weights). Therefore, researchers are encouraged to prioritize reporting CR values over Cronbach's alpha (Hair Jr et al., 2020). (Hair Jr et al., 2020). A reliability value exceeding 0.95 suggests redundancy among items, meaning the indicators may lack sufficient variability to ensure validity for multi-item constructs (Hair, Risher et al., 2019).

Convergent validity is employed to assess the stability of a measurement scale. It reflects the extent to which two measures capture a common construct. In other words, for a measurement scale to achieve convergent validity, the set of observed variables measuring a research concept must exhibit a high degree of correlation (Kline, 2016). This is demonstrated through standardized regression coefficients for each variable of the latent construct, particularly if the scale is unidimensional. To establish convergent validity, the standardized coefficients (outer loadings) of the scale's components should exceed 0.5 and be statistically significant (Gerbing & Anderson, 1988). Additionally, convergent validity is evaluated through the Average Variance Extracted (AVE)

(Nguyen Thanh Nga, 2022). According to Fornell and Larcker (1981), an AVE value of 0.5 or higher confirms convergent validity. Furthermore, the outer loading of each observed variable should be at least 0.7, indicating strong reliability of the measurement scales (Pham Quang Vinh, 2022). Observed variables with outer loadings between 0.4 and 0.7 are retained or removed based on the researcher's assessment in conjunction with other indicators such as Composite Reliability (CR) and convergent validity (e.g., AVE) of the construct (Hair et al., 2016).

- If the CR or AVE values are below the recommended threshold and removing an observed variable with an outer loading lower than 0.7 helps increase CR or AVE to an acceptable level, then the variable should be removed.
- However, if both CR and AVE have already met the recommended thresholds, and the observed variable with an outer loading between 0.4 and 0.7 is deemed important for the study, it may be retained.

Composite Reliability (ρc) and Average Variance Extracted (ρvc) (Fornell & Larcker, 1981) are calculated using the following formulas:

$$\rho_c = \frac{\left(\sum_{i=1}^{p} \lambda_i\right)^2}{\left(\sum_{i=1}^{p} \lambda_i\right)^2 + \sum_{i=1}^{p} (1 - \lambda_i^{\,2})} \qquad \rho_{vc} = \frac{\sum_{i=1}^{p} \lambda_i^{\,2}}{\sum_{i=1}^{p} \lambda_i^{\,2} + \sum_{i=1}^{p} (1 - \lambda_i^{\,2})}$$

Where:

- λi is the standardized loading of the iii-th observed variable.
- 1 - λi^2 represents the measurement error variance of the iii-th observed variable.
- p is the number of observed variables in the measurement scale.

Discriminant validity indicates the extent to which a concept is statistically distinct from another concept, both in terms of correlations and the observed variables measuring each construct (Hair et al., 2019). The outer loadings of an observed variable within a construct should be higher than all of its cross-loadings with other constructs. A traditional approach to assessing discriminant validity is the **Fornell-Larcker criterion**, which requires that the square root of the AVE (Average Variance Extracted) must be greater than the correlations between constructs (inter-construct correlations) (Kline, 2016). To establish discriminant validity, the square root of the AVE for each construct should be greater than its correlations with other constructs, demonstrating both distinctiveness and reliability (Fornell & Larcker, 1981). Additionally, another evaluation criterion suggests that the correlation between two constructs should be lower than **0.85**, and the **Maximum Shared Variance (MSV)** should be smaller than the AVE (Kline, 2016).

3.4.5. Assessment of the structural model in PLS–SEM

After confirming the reliability and validity of the construct measures, the next step in the process is to assess the structural model results. This stage evaluates the model's predictive capabilities and the relationships between the constructs.

3.4.5.1. Collinearity assessment

Collinearity refers to the potential issue when predictor variables in the model are highly correlated, which can lead to biased estimates of path coefficients. In PLS-SEM, this is assessed by calculating the Variance Inflation Factor (VIF) and tolerance values for each set of predictor constructs. VIF values greater than 5 or tolerance values lower than 0.20 indicate a high degree of collinearity, which can distort the model's estimates. In such cases, researchers should consider eliminating or combining collinear constructs, or creating higher-order constructs to address the issue.

3.4.5.2. Assessing path coefficients

Once the PLS-SEM algorithm is run, the path coefficients (representing the hypothesized relationships between constructs) are obtained. These coefficients range from -1 to +1, with values closer to +1 indicating strong positive relationships, and those closer to -1 indicating strong negative relationships. The statistical significance of these path coefficients is assessed through bootstrapping, which generates t-values and p-values. If the t-value exceeds a critical value (typically 1.96 for a 5% significance level), the path coefficient is considered statistically significant. Bootstrapping also provides confidence intervals for each path coefficient, offering additional stability information about the estimates.

3.4.5.3. Coefficient of determination (R^2 Value)

The R^2 value measures the model's predictive power and represents the proportion of variance in an endogenous construct that is explained by the exogenous constructs. Higher R^2 values suggest a stronger predictive power of the model. In general, R^2 values of 0.75, 0.50, and 0.25 are considered substantial, moderate, and weak, respectively.

Researchers should also be cautious when comparing R^2 values across different models. The adjusted R^2 (R^2adj) accounts for model complexity, penalizing models that add unnecessary constructs. This measure is more appropriate when comparing models with varying numbers of exogenous constructs.

3.4.5.4. Effect size f^2

The f^2 effect size assesses the impact of an exogenous construct on the endogenous constructs by comparing the R^2 values when a specific exogenous variable is included versus when it is excluded. The effect size can be categorized as small (0.02), medium (0.15), or large (0.35). For example, if removing a construct from the model leads to a significant decrease in the R^2 value, this indicates a larger effect size. This step helps identify which constructs have a substantial impact on the endogenous variables.

3.4.5.5. Predictive relevance (Q^2)

The predictive relevance of the model is evaluated using the Q^2 value, which indicates how well the model predicts out-of-sample data. Q^2 values greater than 0 suggest that the model has predictive relevance. This is determined through the blindfolding procedure, where data points are omitted in a systematic manner, and the model is re-estimated to predict the omitted values. The difference between the actual and predicted values provides the basis for calculating the Q^2 value. A higher Q^2 indicates a better out-of-sample prediction.

3.4.5.6. Effect Size q^2

Similar to the f^2 effect size, the q^2 effect size assesses the relative contribution of an exogenous construct to the predictive relevance of an endogenous construct. A q^2 value of 0.02, 0.15, or 0.35 indicates small, medium, or large predictive relevance, respectively. Researchers can use this measure to determine which constructs have a significant impact on the model's predictive accuracy.

The assessment of the structural model in PLS-SEM involves examining several aspects, including the collinearity between predictor variables, the significance and relevance of path coefficients, the R^2 values, effect sizes (f^2 and q^2), and predictive relevance (Q^2). Each of these steps provides insights into the quality and robustness of the model. The focus of PLS-SEM is on prediction rather than goodness-of-fit, making these criteria crucial for evaluating the model's ability to generalize and predict new data.

Chapter 4: Research results

4.1. Preliminary quantitative study

The preliminary quantitative study was conducted using a convenience sampling method. The data collection process lasted approximately four weeks, yielding a total of 400 samples. After data processing, the final dataset consisted of 374 samples. The data collected from this preliminary study was used to assess the suitability of the quantitative measurement scale.

With the support of SmartPLS software, the study evaluated the reliability and validity of the measurement scale. Specifically, using 374 collected samples, the preliminary quantitative study assessed the measurement scales of the constructs through tests of internal consistency reliability (Composite Reliability - CR), convergent validity (Average Variance Extracted - AVE, outer loadings), and discriminant validity (Fornell-Larcker criterion, cross-loadings). Based on the evaluation results, necessary adjustments were made promptly if the measurement scale did not meet the required standards.

Testing the Reliability of the Measurement Scale and Measurement Model with 374 Samples

The PLS-SEM (Partial Least Squares Structural Equation Modeling) method is applied to assess the internal consistency reliability, convergent validity, and discriminant validity of the measurement scale (Hair et al., 2016).

The analysis involves evaluating six constructs and their corresponding 29 observed variables, namely: *System Functionality (SF), Task-Technology Fit (TTF), Perceived Ease of Use (PEU), Self-Efficacy (SE), Perceived Usefulness (PU), and Intention to Use (IU).*

The Cronbach's alpha analysis was conducted, and the results indicate that the internal consistency reliability, assessed through Composite Reliability (CR) for the six constructs, ranges from 0.717 to 0.798, all meeting the required threshold (> 0.7).

To assess convergent validity, it is necessary to evaluate the Average Variance Extracted (AVE) and the outer loadings of the variables. If the AVE is below 0.5 but the CR is above 0.7, convergent validity can still be considered acceptable. The outer loadings of the observed variables range from 0.404 to 0.770. These variables may be retained if their inclusion improves Composite Reliability (CR) and Average Variance Extracted (AVE).

Table 4.1. Construct reliability and validity

	Cronbach's alpha	**Composite reliability (rho_a)**	**Composite reliability (rho_c)**	**Average variance extracted (AVE)**
IU	0,641	0,676	0,772	0,375
PEU	0,523	0,527	0,724	0,346
PU	0,492	0,533	0,717	0,400
SE	0,570	0,580	0,757	0,441
SF	0,682	0,683	0,798	0,442

Source: Compiled and calculated using SmartPLS 4.0 software

Table 4.2. Outer loadings

	IU	**PEU**	**PU**	**SE**	**SF**	**TTF**
IU1	0,263					
IU2	0,659					
IU3	0,684					
IU4	0,652					
IU5	0,692					
IU6	0,612					
PEU1		0,557				
PEU2		0,527				
PEU3		0,687				

PEU4		0,572				
PEU5		0,586				
PU1			0,404			
PU2			0,584			
PU3			0,756			
PU4			0,724			
SE1				0,559		
SE2				0,770		
SE3				0,675		
SE4				0,635		
SF1					0,601	
SF2					0,663	
SF3					0,744	
SF4					0,692	
SF5					0,615	
TTF1						0,617
TTF2						0,640
TTF3						0,452
TTF4						0,588
TTF5						0,619

Source: Compiled and calculated using SmartPLS 4.0 software

Discriminant validity assessed using the Fornell-Larcker criterion meets the required conditions (the AVE of each construct is greater than the squared correlations between that construct and all other constructs). Additionally, the cross-loadings of the constructs satisfy the condition that the outer loadings of an item belonging to a specific construct are higher than all of its cross-loadings with other constructs.

Table 4.3. Discriminant Validity Testing Results (Heterotrait-monotrait ratio (HTMT))

	IU	**PEU**	**PU**	**SE**	**SF**
IU					
PEU	0,732				
PU	0,807	0,827			
SE	0,858	0,806	0,462		
SF	0,758	0,865	0,847	0,608	

Source: Compiled and calculated using SmartPLS 4.0 software

From the above results, it can be concluded that this preliminary scale meets the requirements to be used as the official scale in the formal quantitative study.

4.2. Formal quantitative study

The dataset was collected using a convenience sampling method over a period of more than two months *(December 2024 – February 2024)*. A total of 400 survey samples were collected. However, these 400 samples were cleaned before being processed and analyzed to minimize errors during the interview and data entry processes. Surveys with missing information (unanswered questions) and those with identical responses for all questions (indicating insincere answers) were excluded.

As a result, 374 valid survey samples were obtained for analysis after cleaning the data by eliminating surveys that did not meet the requirements, such as:

1. Surveys that were not fully completed.
2. Respondents provide answers with the same pattern or tendency.
3. Respondents deemed unsuitable and excluded during the screening process.

Therefore, the formal quantitative study was conducted with 374 valid survey samples.

4.3. Descriptive statistic of qualitative variables

With 374 survey samples meeting the research requirements, the descriptive statistics will provide simple summaries about the sample as follows:

Table 4.4. Descriptive Statistics Table of Qualitative Variables

	Frequency (People)	**Percentage (%)**
University Name		
University of Economics and Law	20	5,38%
FPT University	10	2,67%
University of Information Technology	12	3,21%
Ho Chi Minh City University of Technology and Education	5	1,34%
University of Social Sciences and Humanities, Vietnam National University Ho Chi Minh City	17	4,55%
Van Hien University	3	0,80%
Ho Chi Minh City University of Technology	8	2,14%
Industrial University of Ho Chi Minh City	15	4,01%
RMIT University	19	5,08%
Ho Chi Minh City University of Agriculture and Forestry	2	0,53%
Foreign Trade University	2	0,53%
Hoa Sen University	6	1,60%
University Of Science	11	2,94%

National Economics University	12	3,21%
Hong Bang University International	4	1,07%
University of Economics Ho Chi Minh City	4	1,07%
Sai Gon University	3	0,80%
Hanoi National University of Education	7	1,87%
International University	11	2,94%
Ho Chi Minh City University of Law	18	4,81%
University of Medicine and Pharmacy at Ho Chi Minh City	1	0,27%
University of Transport Ho Chi Minh City	3	0,80%
Ho Chi Minh University of Banking	2	0,53%
Vietnam Aviation Academy	7	1,87%
Ton Duc Thang University	13	3,48%
Academy of Journalism and Communication	19	5,08%
University of Economics and Business	10	2,67%
Van Lang University	14	3,74%
University of Industry and Trade	2	0,53%
Thuongmai University	5	1,34%
The University of Finance and Marketing	3	0,80%

University of Architecture Ho Chi Minh City	6	1,60%
Hanoi University of Business and Technology	15	4,01%
Diplomatic Academy of Vietnam	8	2,14%
Hanoi University of Science and Technology	10	2,67%
Can Tho University of Medicine - Pharmacy	5	1,34%
Duy Tan University	14	3,74%
University of Economics and Finance	7	1,87%
Dalat University	12	3,21%
Posts and Telecommunications Institute of Technology	4	1,07%
Ho Chi Minh City Open University	5	1,34%
Hue University of Education	10	2,67%
Academy of Finance	3	0,80%
Thang Long University	1	0,27%
Can Tho Medical College	1	0,27%
Thu Dau Mot University	5	1,34%
Current Academic Year		
Year 1	70	18,72%
Year 2	111	29,68%
Year 3	107	28,61%

Year 4	80	21,4%
Year 5 or above	6	1,6%
Educational level		
College/University	368	98,4%
Postgraduate	6	1,6%

Source: Authors' source

The survey was conducted with 374 students from various universities across the country. Among them, several universities had a high number of participants, including the University of Economics and Law (20 students, accounting for 5.38%), RMIT University (19 students, accounting for 5.08%), Academy of Journalism and Communication (19 students, accounting for 5.08%), Industrial University of Ho Chi Minh City (15 students, accounting for 4.01%), and Hanoi University of Business and Technology (15 students, accounting for 4.01%). Other universities had fewer participants, reflecting the diversity of the survey sample.

The table illustrates the distribution of respondents according to their current academic year and educational level. The majority of respondents are undergraduate students, with 98.4% at the college or university level and only 1.6% pursuing postgraduate studies. Regarding their academic year, most participants are in their second and third years, accounting for 29.68% and 28.61% of the total sample, respectively. This suggests that students in the middle stages of their studies are more actively involved in the survey. Meanwhile, first-year students make up 18.72%, fourth-year students comprise 21.4%, and only a small proportion of respondents (1.6%) are in their fifth year or higher. The findings reflect that the sample is predominantly composed of undergraduate students in their early to middle years of study.

4.4. Descriptive statistics of quantitative variables

Descriptive statistics of quantitative variables are presented in detail in Table 4.5. The criteria for assessing normal data distribution are that Skewness and Kurtosis values fall within the range of (-1,1). According to the descriptive statistics table, most of the variables meet this condition.

Table 4.5. Descriptive Statistics of Quantitative Variables

	Mean	Median	Observed min	Observed max	Standard deviation	Excess kurtosis	Skewness
IU1	3,874	4,000	1,000	5,000	0,980	-0,247	-0,602
IU2	3,987	4,000	1,000	5,000	0,851	-0,295	-0,497
IU3	4,051	4,000	1,000	5,000	0,847	-0,152	-0,601
IU4	4,061	4,000	1,000	5,000	0,823	0,351	-0,692
IU5	4,179	4,000	1,000	5,000	0,876	0,336	-0,908
IU6	4,160	4,000	1,000	5,000	0,857	-0,132	-0,699
PEU1	3,914	4,000	1,000	5,000	0,921	-0,226	-0,551
PEU2	4,051	4,000	2,000	5,000	0,878	-0,674	-0,504
PEU3	4,104	4,000	2,000	5,000	0,835	-0,333	-0,613
PEU4	4,024	4,000	1,000	5,000	0,873	-0,286	-0,580
PEU5	4,166	4,000	2,000	5,000	0,770	-0,402	-0,541
PU1	4,019	4,000	2,000	5,000	0,912	-0,437	-0,632
PU2	3,981	4,000	2,000	5,000	0,851	-0,371	-0,513
PU3	4,094	4,000	1,000	5,000	0,889	-0,193	-0,711
PU4	4,070	4,000	1,000	5,000	0,791	0,376	-0,677
SE1	4,080	4,000	2,000	5,000	0,804	-0,718	-0,395
SE2	3,992	4,000	1,000	5,000	0,864	-0,226	-0,560
SE3	3,955	4,000	2,000	5,000	0,869	-0,637	-0,403
SE4	4,080	4,000	2,000	5,000	0,849	-0,222	-0,654
SF1	4,035	4,000	2,000	5,000	0,789	-0,582	-0,357
SF2	4,016	4,000	2,000	5,000	0,834	-0,245	-0,558
SF3	3,976	4,000	1,000	5,000	0,879	-0,142	-0,570
SF4	3,979	4,000	1,000	5,000	0,837	0,474	-0,675
SF5	4,070	4,000	1,000	5,000	0,824	-0,579	-0,417
TTF1	4,024	4,000	2,000	5,000	0,854	-0,352	-0,563
TTF2	3,866	4,000	2,000	5,000	0,839	-0,577	-0,289
TTF3	4,201	4,000	2,000	5,000	0,763	-0,406	-0,574
TTF4	4,166	4,000	1,000	5,000	0,777	0,314	-0,710
TTF5	4,182	4,000	2,000	5,000	0,833	-0,280	-0,714

Source: Compiled and calculated using SmartPLS 4.0 software

4.5. Research model testing

4.5.1. Measurement model

By evaluating the measurement model, the research will confirm the validity and reliability of the research instrument by using evaluation criteria on three essential aspects: *internal consistency reliability*, *convergent validity*, and *discriminant validity* (Aburumman et al., 2022) with the support of SmartPLS 4.0 software.

Internal consistency reliability can be assessed through two primary measures: *Cronbach's alpha* (α) and *Composite Reliability* (CR). The results indicated that the CR of the measurement scales ranged from 0.717 to 0.798, all above the recommended threshold of 0.7 (see Table 4.6). The assessment results also revealed that all scales had Cronbach's Alpha values below 0.7, while their CR values exceeded 0.7. Although the Cronbach's Alpha values fell below the recommended threshold of 0.7, suggesting potential concerns regarding internal consistency, all constructs achieved acceptable Composite Reliability levels (CR > 0.7). Considering that CR provides a more precise measure of internal consistency reliability due to its weighted approach, these findings suggest that the measurement scales remain reliable for further analysis (Hair et al., 2020).

Table 4.6. Convergent Validity and Internal Consistency Reliability of Measurement Scale

Latent variable	Indicators	Outer loadings	Rho_C	AVE	α
IU	IU1	0.263	0.772	0.375	0.641
	IU2	0.659			
	IU3	0.684			
	IU4	0.652			
	IU5	0.692			
	IU6	0.612			

PEU	PEU1	0.557	0.724	0.346	0.523
	PEU2	0.527			
	PEU3	0.687			
	PEU4	0.572			
	PEU5	0.586			
PU	PU1	0.404	0.717	0.400	0.492
	PU2	0.584			
	PU3	0.756			
	PU4	0.724			
SE	SE1	0.559	0.757	0.441	0.570
	SE2	0.770			
	SE3	0.675			
	SE4	0.635			
SF	SF1	0.601	0.798	0.442	0.682
	SF2	0.663			
	SF3	0.744			
	SF4	0.692			
	SF5	0.615			
TTF	TTF1	0.617	N/A (formative)	N/A (formative)	N/A (formative)
	TTF2	0.640			

	TTF3	0.452			
	TTF4	0.588			
	TTF5	0.619			

Source: Compiled and calculated using SmartPLS 4.0 software

The construct abbreviations are as follows: IU - Intention to Use, PEU - Perceived Ease of Use, PU - Perceived Usefulness, SE - Self-Efficacy, SF - System Functionality, TTF - Task-Technology Fit. Outer loadings range from 0.263 to 0.770, indicating potential reliability issues with certain observed variables. Specifically, IU1 (0.263), PEU2 (0.527), PU1 (0.404), and TTF3 (0.452) exhibit relatively low outer loadings (< 0.6), with IU1 being particularly low (< 0.4). These indicators may not adequately represent their respective latent constructs. The remaining indicators fall within an acceptable range (0.5–0.7) or are considered strong (> 0.7). Given its extremely low loading (0.263), IU1 should be considered for removal as it may negatively impact the scale's measurement quality. The Average Variance Extracted (AVE) values range from 0.346 to 0.442, all below the recommended minimum threshold of 0.5 (Hair et al., 2016). This indicates that convergent validity has not been achieved, suggesting that the observed variables do not sufficiently converge to measure their corresponding latent constructs (see Table 4.7). To improve AVE, low-loading indicators such as ***IU1 and PU1 will be removed***.

Table 4.7. Average Variance Extracted from the measurement scale before modification

	IU	**PEU**	**PU**	**SE**	**SF**
AVE	0.375	0.346	0.400	0.441	0.442

Source: Compiled and calculated using SmartPLS 4.0 software

After removing IU1 and PU1, AVE improved for some constructs, particularly PU, which increased from 0.400 to 0.506 (exceeding the 0.5 threshold, meeting the requirement for convergent validity). The CR of PU also increased slightly from 0.717 to 0.750, indicating that removing low outer loading indicators helped enhance composite reliability (see Table 4.8).

Table 4.8. Average Variance Extracted from the measurement scale after modification

	IU	PEU	PU	SE	SF
AVE	0.448	0.347	0.506	0.441	0.442

Source: Compiled and calculated using SmartPLS 4.0 software

To assess ***discriminant validity***, Fornell and Larcker (1981) proposed that the square root of the Average Variance Extracted (AVE) for each latent variable can be used to establish discriminant validity, provided that this value is greater than the inter-construct correlations (Hair et al., 2016). The square root of the AVE values for the constructs are IU (0.732), PEU (0.827), PU (0.807), SE (0.462), and SF (0.608) (see Table 4.9). When compared to inter-construct correlations, some constructs do not meet the criterion. Specifically, the AVE square root values for IU, PEU, and SE are lower than their respective correlations with other constructs. However, PU (0.807) successfully meets the criterion, as its AVE square root exceeds its correlations with other constructs. Despite these findings, the Heterotrait-Monotrait (HTMT) ratio values for all constructs remain below 0.9, indicating that discriminant validity is still acceptable according to this more robust criterion.

Table 4.9. Discriminant Validity of Measurement Scales

Latent variable	IU	PEU	PU	SE	SF
IU					
PEU	0.732				
PU	0.807	0.827			
SE	0.858	0.806	0.462		
SF	0.758	0.865	0.847	0.608	

Source: Compiled and calculated using SmartPLS 4.0 software

4.5.2. Structural model

The evaluation of the structural model aims to test the research hypotheses, ensuring the validity and reliability of the model. The structural model assessment is conducted following the methodology proposed by Hair et al. (2016), with the support of SmartPLS 4.0.

Collinearity Statistic Assessment

As a rule of thumb, the first aspect to consider when evaluating the structural model is collinearity. The Variance Inflation Factor (VIF) should be 5 or lower (equivalent to a tolerance level of 0.2 or higher) to avoid multicollinearity issues (Hair et al., 2011).

Multiple regression analysis in SPSS can be used to generate VIF and Tolerance values to assess multicollinearity (Wong, 2013). The results indicate that all VIF values range from 1.000 to 1.646, remaining below the threshold of 5, meaning that all indicators fall within the acceptable range and the model does not exhibit serious multicollinearity issues (Hair et al., 2016). The latent variables in the model demonstrate a relatively high degree of independence, with no signs of excessive dependency among variables.

Table 4.10. Collinearity Assessment (Inner Model)

	IU	PEU	PU	SE	SF	TTF
IU						
PEU			1.348			
PU	1.045					
SE	1.045	1.209				
SF		1.646				1.000
TTF		1.626	1.348			

Source: Compiled and calculated using SmartPLS 4.0 software

Evaluate the relationships between endogenous and exogenous variables based on p-values, path coefficients (β), and R^2 values.

Path coefficients (β)

Path coefficients (β) are standardized regression coefficients evaluated through their signs and magnitudes. These coefficients are particularly useful for dividing correlations into direct and indirect effects, enabling the assessment of the relative contribution of each component attribute to productivity (Singh & Narayanam, 2007). To test research hypotheses and effect sizes, a bootstrap estimation method (n = 5,000) is applied to calculate the path coefficients (β) and p-values, determining the magnitude and statistical significance of the hypothesized relationships within the research model.

All path coefficients (β) related to the effects in the model are statistically significant at the 1% level. Moreover, the bootstrap test results also confirm that all β coefficients are significantly different from zero. Therefore, it can be concluded that hypotheses from H1 to H10 are supported by the empirical data.

All hypotheses were accepted as they were statistically significant at the 1% level. The results of the path coefficient (β) evaluation are presented in Table 4.11.

Table 4.11. Structural Model Testing Results

Hypothesis		**Path Coefficient (β)**	**Significance Level**		**Conclusion**
			T statistics	**P values**	
H1	SE → IU	0.213	3.770	0.000	Accepted
H2	SE → PEU	0.378	8.703	0.000	Accepted
H3	SF → PEU	0.445	11.766	0.000	Accepted
H4	SF → TTF	0.249	5.425	0.000	Accepted
H5	TTF → PU	0.280	4.268	0.000	Accepted
H6	TTF → PEU	0.603	13.981	0.000	Accepted
H7	PU → IU	0.248	4.216	0.000	Accepted
H8	PEU → PU	0.376	6.864	0.000	Accepted

Source: Compiled and calculated using SmartPLS 4.0 software

Coefficient of Determination (R^2)

To describe the relationships among variables, multiple regression analysis uses the coefficient of determination (R^2) to indicate how effectively the independent variables explain the variance in the dependent variable (Heppner, Kivlighan & Wampold, 1992). According to Cohen (1988), the R^2 values for endogenous latent variables can be categorized as follows: 0.26 (substantial), 0.13 (moderate), and 0.02 (weak). Adjusted R^2 is a modified version of R^2, accounting for the number of independent variables included in the model.

Based on Cohen's (1988) criteria, IU ($R^2 = 0.410$) exceeds the threshold of 0.26, indicating that independent variables explain approximately 41% of the variance in IU, demonstrating a substantial explanatory power. Similarly, for PEU ($R^2 = 0.384$), independent variables account for roughly 38.4% of its variance, which is also substantial and nearly comparable to IU. Overall, the endogenous latent variables within the model are substantially explained by their respective independent variables, with IU receiving the strongest explanatory power (41%). The Adjusted R^2 values are slightly lower but close to their corresponding R^2, suggesting a stable model that is not significantly affected by redundant independent variables. Detailed results of the coefficients of determination are presented in Table 4.12.

Table 4.12. Results of the Coefficient of Determination

Latent variable	R^2	R^2 adjusted
IU	0.410	0.407
PEU	0.384	0.379
PU	0.268	0.264
TTF	0.363	0.362

Source: Compiled and calculated using SmartPLS 4.0 software

Effect Size (f^2)

In addition to evaluating the R^2 coefficient, Hair et al. (2016) suggest examining the effect size (f^2) for all relationships in the structural model to assess whether changes in R^2 occur when an exogenous variable is removed, potentially impacting the endogenous variable. Specifically, the minimum acceptable f^2 should be greater than 0.02.

Using Cohen's impact measurement, known as the effect size (f^2), the level of impact (f^2) allows for evaluating the contribution of an exogenous variable to the R^2 value of an endogenous latent variable. Cohen (1988) provides the following criteria for assessing f^2 values: $0.02 \leq f^2 < 0.15$ indicates a weak effect, $0.15 \leq f^2 < 0.35$ indicates a moderate effect, and $f^2 \geq 0.35$ indicates a strong effect. The results in Table 4.13 assess the level of impact among variables according to each structure in the model.

Table 4.13. Results of Effect Size (f^2) and Level of Impact

Hypothesis		**Cohen's f^2**	**Level of Contribution**
H1	SE → IU	0.046	Weak
H2	SE → PEU	0.231	Moderate
H3	SF → PEU	0.321	Moderate
H4	SF → TTF	0.083	Weak
H5	TTF → PU	0.077	Weak
H6	TTF → PEU	0.570	Substantial
H7	PU → IU	0.061	Weak
H8	PEU → PU	0.144	Weak

Source: Compiled and calculated using SmartPLS 4.0 software

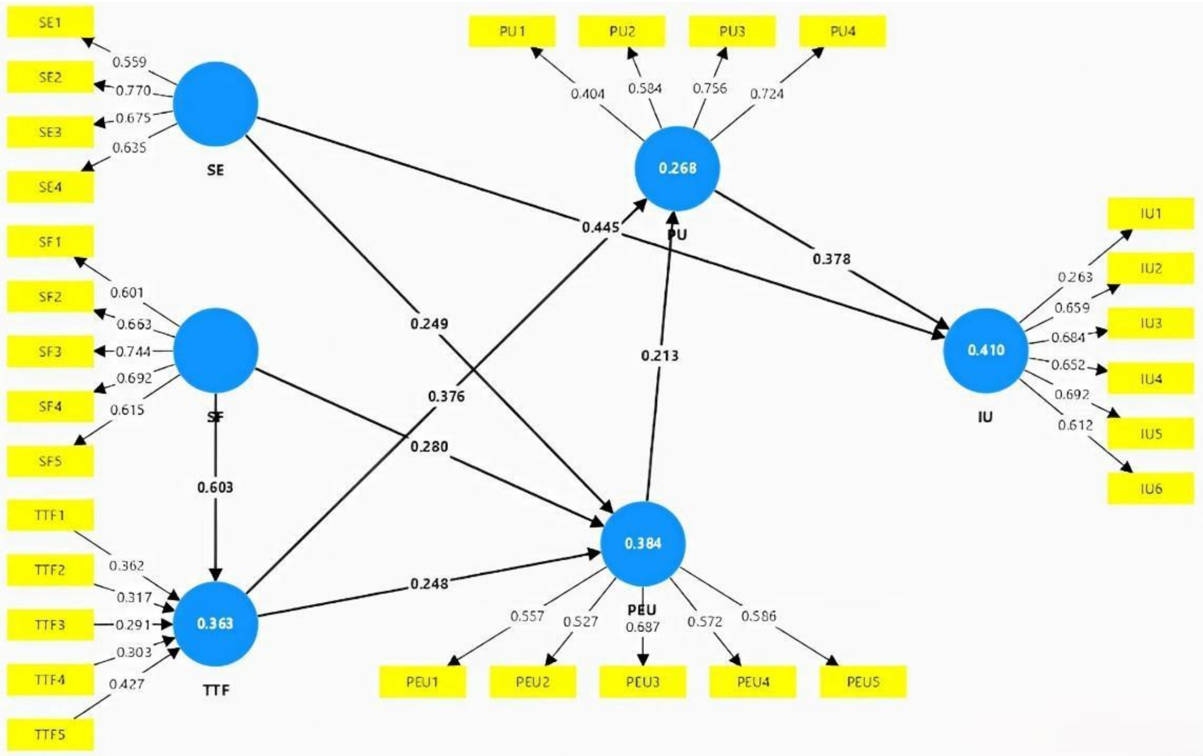

Figure 4.1. Research Model Testing Results

(Source: Compiled and calculated using SmartPLS 4.0 software)

4.5.3. Model testing

Table 4.14. Summary of Research Model Testing Results

Hypothesis		Research Model			
		Path Coefficient (β)	Significance Level		Conclusion
			T statistics	P values	
H1	SE -> IU	0.445	11.766	0.000	Accepted
H2	SE -> PEU	0.249	5.425	0.000	Accepted
H3	SF -> PEU	0.280	4.268	0.000	Accepted
H4	SF -> TTF	0.603	13.981	0.000	Accepted
H5	TTF -> PU	0.376	6.864	0.000	Accepted
H6	TTF -> PEU	0.248	4.216	0.000	Accepted
H7	PU -> IU	0.378	8.703	0.000	Accepted
H8	PEU -> PU	0.213	3.770	0.000	Accepted

Source: Compiled and calculated using SmartPLS 4.0 software

Thus, the results of the structural model testing are as follows:

H1: SE → IU. Hypothesis H1 was stated as: “Self-Efficiency has a positive impact on Intention to Use.”

The results show that the relationship between Self-Efficiency (SE) and Intention to Use (IU) has a path coefficient $\beta = 0.445$. This estimate is statistically significant with a p-value = 0.000 (< 0.05). Therefore, this hypothesis is supported. Accordingly, Self-Efficiency has a positive influence on Intention to Use.

H2: SE → PEU. Hypothesis H2 was stated as: “Self-Efficiency has a positive impact on Perceived Ease of Use.”

The results show that the relationship between Self-Efficiency (SE) and Perceived Ease of Use (PEU) has a path coefficient $\beta = 0.249$, which is statistically significant with a p-value = 0.000 (< 0.05). Therefore, H2 is accepted. Thus, Self-Efficiency positively influences Perceived Ease of Use.

H3: SF → PEU. Hypothesis H3 was stated as: “System Functionality has a positive impact on Perceived Ease of Use.”

The analysis indicates that the relationship between System Functionality (SF) and Perceived Ease of Use (PEU) has a path coefficient $\beta = 0.280$, with a p-value = 0.000 (< 0.05). Therefore, this hypothesis is supported. Hence, System Functionality positively affects Perceived Ease of Use.

H4: SF → TTF. Hypothesis H4 was proposed as: “System Functionality has a positive influence on Task-Technology Fit.”

The results show that the relationship between System Functionality (SF) and Task-Technology Fit (TTF) is significant, with a path coefficient $\beta = 0.603$ and p-value = 0.000 (< 0.05). Therefore, H4 is supported. This indicates that System Functionality positively affects Task-Technology Fit.

H5: TTF → PU. Hypothesis H5 was stated as: “Task-Technology Fit has a positive influence on Perceived Usefulness.”

The findings indicate that the relationship between Task-Technology Fit (TTF) and Perceived Usefulness (PU) has a path coefficient $\beta = 0.376$, which is statistically significant with a p-value = 0.000 (< 0.05). Hence, H5 is accepted. Task-Technology Fit has a positive impact on Perceived Usefulness.

H6: TTF → PEU. Hypothesis H6 was stated as: “Task-Technology Fit has a positive influence on Perceived Ease of Use.”

The results indicate a significant relationship between Task-Technology Fit (TTF) and Perceived Ease of Use (PEU), with a path coefficient $\beta = 0.248$ and p-value = 0.000 (< 0.05). Thus, H6 is supported. This implies that Task-Technology Fit positively affects Perceived Ease of Use.

H7: PU → IU. Hypothesis H7 was stated as: “Perceived Usefulness has a positive effect on Intention to Use.”

The results reveal a statistically significant relationship between Perceived Usefulness (PU) and Intention to Use (IU), with a path coefficient $\beta = 0.378$ and p-value = 0.000 (< 0.05). Therefore, H7 is accepted. Perceived Usefulness positively influences Intention to Use.

H8: PEU → PU. Hypothesis H8 was stated as: “Perceived Ease of Use has a positive influence on Perceived Usefulness.”

The analysis demonstrates that the relationship between Perceived Ease of Use (PEU) and Perceived Usefulness (PU) is statistically significant with a path coefficient $\beta = 0.213$ and p-value = 0.000 (< 0.05). Thus, H8 is supported. Perceived Ease of Use has a positive effect on Perceived Usefulness.

4.6. Discussion of results

4.6.1 Measurement scale results

Internal consistency reliability

4.6.1.1. Cronbach’s alpha

Table 4.15. Cronbach’s alpha result

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
IU	0.641	0.637	0.045	14.342	0.000
PEU	0.523	0.520	0.042	12.489	0.000
PU	0.492	0.488	0.045	11.035	0.000
SE	0.570	0.567	0.039	14.562	0.000
SF	0.682	0.678	0.034	19.939	0.000

Source: Compiled and calculated using SmartPLS 4.0 software

The results of Cronbach's Alpha coefficients provide insights into the internal consistency reliability of the measurement scales. As shown in the table, most constructs exhibit acceptable reliability levels, with values ranging from 0.492 to 0.682. Specifically, the construct System Functionality (SF) demonstrated the highest internal consistency (α = 0.682), while Perceived Usefulness (PU) recorded the lowest (α = 0.492).

Although some values fall slightly below the conventional threshold of 0.7, they still remain within an acceptable range in exploratory research contexts, especially when supported by strong composite reliability and convergent validity measures. All constructs achieved statistically significant t-values ($p < 0.001$), indicating that the items reliably measure their intended constructs.

4.6.1.2. Composite reliability (CR)

The reliability of the measurement model was evaluated using Composite Reliability (CR), specifically rho_A and rho_C coefficients. The results indicate that all constructs exhibit acceptable levels of internal consistency reliability.

Table 4.16. Composite reliability rho_a result

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
IU	0.676	0.677	0.039	17.538	0.000
PEU	0.527	0.528	0.040	13.024	0.000
PU	0.533	0.534	0.042	12.720	0.000
SE	0.580	0.581	0.038	15.185	0.000
SF	0.683	0.683	0.034	19.979	0.000
TTF	1.000	1.000	0.000	n/a	n/a

Source: Compiled and calculated using SmartPLS 4.0 software

For rho_a, the reliability coefficients for IU (0.676), PEU (0.527), PU (0.533), SE (0.580), and SF (0.683) are all above the threshold of 0.5, indicating moderate to good reliability. The construct TTF shows a perfect value of 1.000, which may indicate redundancy or perfect internal consistency among its indicators. Furthermore, all constructs demonstrate statistical significance with p-values of 0.000 and t-values well above 1.96, supporting the robustness of the results.

Table 4.17. Composite reliability rho_c result

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
IU	0.772	0.770	0.022	34.488	0.000
PEU	0.724	0.723	0.018	41.085	0.000
PU	0.717	0.714	0.021	34.594	0.000
SE	0.757	0.755	0.017	44.756	0.000
SF	0.798	0.796	0.017	45.922	0.000

Source: Compiled and calculated using SmartPLS 4.0 software

In terms of rho_c, the composite reliability values are even more robust: IU (0.772), PEU (0.724), PU (0.717), SE (0.757), and SF (0.798). All these values exceed the commonly recommended threshold of 0.7, indicating high internal consistency across items within each construct. The statistical significance is further supported by high t-values (ranging from 34.488 to 45.922) and p-values of 0.000.

4.6.1.3. Convergent validity

Table 4.18. Convergent validity result

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
IU	0.375	0.375	0.026	14.306	0.000
PEU	0.346	0.347	0.019	18.088	0.000
PU	0.400	0.399	0.020	20.390	0.000
SE	0.441	0.440	0.022	20.291	0.000
SF	0.442	0.442	0.026	17.008	0.000

Source: Compiled and calculated using SmartPLS 4.0 software

Convergent validity is evaluated using the Average Variance Extracted (AVE) for each construct. According to the results, the AVE values for IU (0.375), PEU (0.346), PU (0.400), SE (0.441), and SF (0.442) are reported. Although the commonly accepted threshold for AVE is 0.50, several scholars argue that values slightly below this level may still be acceptable, especially when composite reliability is satisfactory. In this study, despite AVE values being slightly below the ideal level, they are statistically significant with high t-values (ranging from 14.306 to 20.390) and p-values = 0.000 for all constructs, indicating good indicator reliability and moderate convergent validity.

The results from the assessment phase confirm that the measurement scales meet the required standards of reliability and validity. These findings indicate that the measurement model is robust and suitable for further analysis in the structural model stage.

4.6.2 Findings of the research model and the relationships among constructs

Perceived Ease of Use (PEU) is influenced by multiple factors. The results show that System Functionality (SF) ($\beta = 0.280$), Self-Efficacy (SE) ($\beta = 0.249$), and Task-Technology Fit (TTF) ($\beta = 0.248$) all have significant positive effects on PEU, with System Functionality exerting the strongest influence. This suggests that when a system is well-designed, reliable, and user-friendly, it helps reduce complexity and facilitates smoother interactions, thereby enhancing the user experience and increasing perceived ease of use. This observation is consistent with the findings of Putra and Sylvandinata (2019), who emphasized that system quality plays a critical role in shaping user perceptions and the acceptance of e-learning platforms.

Several studies have verified that self-efficacy plays a critical role in the adoption and acceptance of e-learning systems in higher education (Lee & Mendlinger, 2011; Arpaci, 2017). Both lecturer and student self-efficacy have been found to positively influence users' perceptions of ease of use and their attitudes toward e-learning platforms (Masimba & Maguraushe, 2022). Specifically, Arpaci (2017) emphasized that students with higher levels of self-efficacy are more likely to believe in their ability to successfully navigate and utilize distance education systems. This confidence leads to a stronger perception of ease, as these users are more likely to anticipate success and engage with the system in a positive and proactive manner.

Research by (Alyoussef 2021, Alyoussef 2023) indicates that when a technology's features are well-aligned with the tasks users need to perform, it significantly enhances the system's usability. This alignment makes user interaction more intuitive and seamless, reducing the perceived complexity and minimizing potential barriers. As a result, when users feel that the technology effectively supports their task requirements, they are more likely to view it as easy to use.

Self-Efficacy (SE) is identified as the most influential factor affecting Intention to Use (IU), with a strong path coefficient ($\beta = 0.445$, $t = 11.766$, $p < 0.001$). This suggests that individuals with higher self-efficacy are more inclined to engage in technology-related tasks, overcome difficulties, and use digital learning tools with greater confidence. This finding is consistent with previous research by Budu et al. (2018), which highlights the crucial role of self-efficacy in shaping users' intention to adopt and effectively use e-learning systems.

Additionally, Perceived Ease of Use (PEU) and Perceived Usefulness (PU) also have a substantial impact on IU, aligning with the foundational Technology Acceptance Model (TAM) proposed by Davis (1989). The findings further suggest that PU serves as a mediating factor between PEU and IU, supporting the perspective of Venkatesh and Davis (2000), who emphasized that both PEU and PU have direct and indirect effects on users' behavioral intentions to adopt technology.

Chapter 5: Conclusion and recommendations

5.1. Summary of the research findings

This research focuses on examining the acceptance and key factors influencing the adoption of E-learning systems among university students in Ho Chi Minh City. With the rapid development of Information and Communication Technology (ICT), E-learning has become an essential aspect of modern education, providing flexibility, cost-effectiveness, and the ability to personalize the learning experience. Despite its potential, various challenges such as infrastructure limitations, technical barriers, and user experience issues persist. Addressing these challenges requires a comprehensive understanding of the factors that affect learners' interactions with E-learning systems.

The study integrates established theoretical models, including the Technology Acceptance Model (TAM) and Task-Technology Fit (TTF) framework, to develop a comprehensive evaluation of E-learning acceptance and effectiveness. The TAM framework focuses on Perceived Usefulness (PU) and Perceived Ease of Use (PEU) as critical determinants of technology adoption. The TTF model, meanwhile, emphasizes the importance of aligning technological features with users' learning tasks to enhance system usability and effectiveness.

Additionally, the research draws upon prior studies conducted both domestically and internationally. In Vietnam, research has highlighted aspects such as system usability, perceived usefulness, technical barriers, and personalization. Internationally, models like TAM and Unified Theory of Acceptance and Use of Technology (UTAUT) have been commonly applied to assess E-learning adoption, highlighting factors such as self-efficacy, social influence, and facilitating conditions.

The research design involves two primary phases: a pilot study and a main study. The pilot study was conducted to validate the measurement scales through qualitative and quantitative methods. A total of 90 students participated in the pilot survey, with adjustments made to the questionnaire based on feedback. The main study was conducted with a larger sample of 374 university students from various institutions, ensuring data representativeness. Data collection was performed using structured surveys distributed online, with responses analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM).

The measurement scales focus on constructs such as Perceived Ease of Use (PEU), Perceived Usefulness (PU), Self-Efficacy (SE), System Functionality (SF), Task-

Technology Fit (TTF), and Intention to Use (IU). Statistical analysis through PLS-SEM helps evaluate the reliability and validity of these constructs, providing a robust framework for understanding the relationships between technological and behavioral factors.

This study aims to identify the key determinants of student engagement, motivation, and satisfaction when using E-learning platforms. Additionally, it seeks to provide practical solutions for enhancing E-learning systems by improving user interface design, content quality, personalization, and technological infrastructure. Furthermore, the research aims to propose strategies for strengthening technological infrastructure, providing better technical support, and integrating digital skills training to ensure that students and instructors can effectively navigate and maximize the benefits of online learning.

5.2. Main results of the research of contributions of the study

5.2.1. Main results of the research

The study successfully identifies and validates the key factors influencing the adoption of E-learning systems, which include Perceived Usefulness (PU), Perceived Ease of Use (PEU), Self-Efficacy (SE), System Functionality (SF), and Task-Technology Fit (TTF).

The structural model testing results confirm that Self-Efficacy (SE) significantly influences Intention to Use (IU) and Perceived Ease of Use (PEU), demonstrating that individuals with higher self-efficacy are more likely to adopt and effectively use E-learning systems.

System Functionality (SF) has a strong positive impact on Perceived Ease of Use (PEU) and Task-Technology Fit (TTF). This finding emphasizes the critical role of system quality in simplifying interactions, enhancing user satisfaction, and promoting task-technology alignment.

Task-Technology Fit (TTF) significantly impacts both Perceived Usefulness (PU) and Perceived Ease of Use (PEU). The enhancement of system intuitiveness and usability is directly linked to improved user perceptions of usefulness and ease of use.

The findings indicate that SF, SE, and TTF all positively contribute to PEU, with SF having the strongest influence, underlining the importance of ensuring high-quality system functionality to support effective user interaction.

The study also confirms that Perceived Ease of Use (PEU) and Perceived Usefulness (PU) are the primary determinants of Intention to Use (IU). This aligns well with the TAM model, where PU plays a mediating role between PEU and IU, suggesting that a system's perceived benefits are crucial in promoting its adoption. The PLS-SEM results demonstrate strong validity and reliability of the measurement scales applied in the study, reinforcing the robustness of the research model. Additionally, the research provides quantitative evidence supporting the importance of designing systems that not only meet technical standards but also address the behavioral and psychological needs of users.

5.2.2. Theoretical implications

From a theoretical perspective, this study presents several important implications for the field of technology acceptance in education.

First, the research extends existing theoretical models, specifically the Technology Acceptance Model (TAM) and the Task-Technology Fit (TTF) framework, by integrating both into a unified research model. This integration not only offers a multidimensional analytical approach to understanding E-learning adoption but also harmonizes user behavioral factors with technical aspects of technology. As a result, it enriches the theoretical foundation related to technology acceptance in modern educational contexts.

Second, the study contributes empirical evidence in the context of developing countries by identifying key factors that influence learners' satisfaction and engagement in E-learning environments. The findings reveal a strong relationship between learners' personal characteristics and the degree of task-technology compatibility in online learning, thereby expanding the practical applicability of existing E-learning acceptance theories.

Lastly, the study calls into question the universality of certain traditional theoretical constructs, most notably Subjective Norm. Empirical results indicate that this factor may not play a significant role in specific cultural or generational contexts, such as among university students in Vietnam, as examined in this study. This finding is consistent with several previous studies. For instance, Lee, Lee, and Lee (2006) found that Subjective Norm did not significantly affect technology acceptance decisions among experienced and voluntary users, while alternative constructs such as Self-Identity emerged as more influential in explaining social influence on behavior.

Similarly, Ha and Hien (2024) discovered that Subjective Norm had only a moderate influence on remote working intentions among Gen Z students in Vietnam, with peer influence being modest and family influence non-existent due to cultural differences between Western and Vietnamese contexts. Additionally, Nadri et al. (2018) also reported no significant impact of Subjective Norm on healthcare staff's intention to adopt hospital information systems, highlighting potential context-specific limitations of this construct. Contrastingly, Nguyen et al. (2020) found Subjective Norm to have a significant, albeit moderate, influence on Vietnamese students' perceived usefulness of E-learning, indicating that the importance of Subjective Norm might vary even within the same national context, possibly due to differences in the compulsory or voluntary nature of system use. Furthermore, Abbad, Morris, and De Nahlik (2009) observed inconsistent findings regarding Subjective Norm, noting that previous studies showed mixed results due to variations in cultural and technological contexts. These comparative insights underscore the necessity to reconsider or further develop theoretical models to better fit local contexts, cultures, and technological landscapes, thus paving the way for nuanced and contextually sensitive future research directions.

5.2.3. Managerial implications

First, universities and LMS providers should place significant emphasis on designing user-friendly, intuitive, and accessible interfaces to enhance the overall user experience. Research findings indicate that Perceived Ease of Use positively and significantly influences students' Intention to Use LMS. Although the impact size is moderate, it clearly underscores the importance of having an interface that is easy to navigate in promoting system adoption and boosting students' regular interaction with the LMS. Therefore, improving interface design by focusing on simplicity, ease of navigation, and accessibility will be an important solution to enhance user satisfaction and stimulate greater intention to engage with online learning systems.

Second, the study highlights the critical role of Self-Efficacy in the adoption and usage of LMS. Specifically, Self-Efficacy has a positive and statistically significant effect on students' Intention to Use, indicating a modest yet meaningful practical implication. This result suggests that when students feel confident and possess strong digital skills, they are more likely to proactively engage with the LMS and fully utilize its benefits. Consequently, educational administrators should invest in comprehensive digital skills training programs, detailed instructional materials, and timely technical support services to enhance students' confidence in using LMS. Strengthening students' self-efficacy will thus be a key factor ensuring the success of online education initiatives.

Third, the research results indicate that System Functionality has the strongest impact on students' Perceived Ease of Use. This finding demonstrates that the system's operational quality and integrated features play a more significant role in influencing user adoption decisions compared to external social pressure or promotional efforts. Thus, instead of merely focusing resources on marketing activities or social influence to encourage LMS use, universities should prioritize maintaining stable system performance, ensuring easy accessibility, and promptly addressing students' learning needs. Continuously updating and developing additional functionalities aligned with modern learning trends is also crucial for the LMS to effectively meet users' expectations, thereby increasing satisfaction and enhancing overall effectiveness in online education.

5.3. Limitations of the study and future research directions

The present study is subject to certain limitations that should be considered when interpreting its findings. Firstly, the research focuses exclusively on university students within Ho Chi Minh City, which may limit the generalizability of the results to other regions or educational levels. Additionally, the study primarily employs quantitative research methods, which may not fully capture the depth of user experiences and perceptions. The reliance on online surveys may also exclude individuals with limited access to digital platforms, potentially introducing bias. Furthermore, the influence of cultural factors on E-learning adoption is not thoroughly addressed, which could affect the applicability of the findings across different user groups.

Future research should aim to address these limitations by expanding the study's scope to include a more diverse sample from various geographical areas and educational institutions. Incorporating qualitative research methods, such as interviews and focus group discussions, would provide a deeper understanding of user experiences and enhance the robustness of the findings. Additionally, further investigation into cultural and social factors influencing E-learning adoption could offer valuable insights for developing more inclusive and effective E-learning systems. Finally, examining the long-term effectiveness of E-learning systems through user satisfaction and learning outcomes over extended periods would contribute to a more comprehensive evaluation of E-learning adoption.

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Appendix 1: Official survey form

Thân chào Anh/Chị và các bạn,

Lời đầu tiên, nhóm chúng em/mình xin gửi lời cảm ơn đến anh/chị và các bạn vì đã dành thời gian quan tâm đến bài khảo sát này.

Nhóm chúng em/mình là sinh viên khoa Hệ thống thông tin của Trường Đại học Kinh tế - Luật (ĐHQG TP.HCM). Hiện tại, nhóm đang thực hiện một dự án nghiên cứu với đề tài: "**KHẢO SÁT SỰ HÀI LÒNG CỦA SINH VIÊN VỀ HỆ THỐNG QUẢN LÝ HỌC TẬP** ".

Nhóm mình vô cùng trân trọng và biết ơn thời gian anh/chị/bạn/em đã dành ra để giúp chúng mình hoàn thành bản khảo sát này. Chúng mình xin cam kết những thông tin mọi người cung cấp sẽ được bảo mật tuyệt đối và chỉ sử dụng với mục đích cho nghiên cứu khoa học của nhóm.

Đồng thời, đối với những anh/chị/bạn đang có nhu cầu khảo sát chéo, vui lòng để lại link ở cuối phần khảo sát.

Chúc Anh/Chị và các Bạn thật nhiều sức khỏe và thành công!

Thân ái!

Phần 1: Thông tin người tham gia khảo sát

Câu 1: Bạn là sinh viên năm mấy?

- Năm 1
- Năm 2
- Năm 3
- Năm 4
- Năm 5 trở lên

Câu 2: Trường Đại học của bạn là gì? (Có thể viết tắt)

Câu 3: Trường của bạn có sử dụng hệ thống quản lý học tập trực tuyến không?

- Có
- Không

Phần 2: Nội dung khảo sát

STT		Hoàn toàn không đồng ý	Không đồng ý	Bình thường	Đồng ý	Hoàn toàn đồng ý
Về tính dễ sử dụng, bạn đánh giá rằng						
1	Dễ dàng tích hợp các chức năng của LMS vào kế hoạch học tập của tôi.	1	2	3	4	5
2	Dễ dàng trở nên thành thạo trong việc sử dụng LMS.	1	2	3	4	5
3	LMS thân thiện với người dùng, giúp tôi dễ dàng thao tác sử dụng nó.	1	2	3	4	5
4	Việc sử	1	2	3	4	5

	dụng LMS giúp tôi dễ dàng đạt được những kết quả học tập mong muốn, phù hợp với phương pháp học của tôi.					
5	Tôi thấy dễ hiểu và dễ dàng thực hiện các nhiệm vụ khi sử dụng LMS.	1	2	3	4	5
Về tính hữu ích, bạn đánh giá rằng						
1	Sử dụng LMS tiết kiệm thời gian của tôi.	1	2	3	4	5

2	Sử dụng LMS giúp tôi sự kiểm soát tốt hơn đối với việc học của mình.	1	2	3	4	5
3	LMS giúp tôi nhận thông tin từ giảng viên về các hoạt động lớp học.	1	2	3	4	5
4	Tổng quan, tôi thấy LMS hữu ích trong việc học của mình.	1	2	3	4	5
Về sự tự tin vào năng lực bản thân, bạn đánh giá rằng						
1	Tôi tự tin vào khả năng sử dụng	1	2	3	4	5

	LMS một cách hiệu quả, ngay cả khi không có kinh nghiệm trước đây trong việc học tập trực tuyến.					
2	Tôi tự tin vào khả năng sử dụng LMS 1 cách độc lập, ngay cả khi không có sự hỗ trợ hoặc hướng dẫn.	1	2	3	4	5
3	Tôi tự tin vào khả năng tích hợp các	1	2	3	4	5

	chức năng của LMS vào kế hoạch học tập của mình.					
4	Tôi tự tin rằng mình sở hữu những kỹ năng cần thiết để sử dụng LMS một cách thành thạo.	1	2	3	4	5
Về Task-Technology Fit, bạn đánh giá rằng						
1	LMS phù hợp với phương pháp học tập của tôi.	1	2	3	4	5
2	LMS phù hợp với tất cả các phương	1	2	3	4	5

	thức của học tập của tôi.					
3	Dễ dàng để học được cách sử dụng LMS.	1	2	3	4	5
4	LMS cung cấp thông tin cần thiết kịp thời.	1	2	3	4	5
5	LMS cần thiết cho các nhiệm vụ học tập của tôi.	1	2	3	4	5
Về Ý định sử dụng, bạn đánh giá rằng						
1	Tôi có ý định sử dụng LMS để thực hiện các hoạt động liên quan đến việc học	1	2	3	4	5

	và để giao tiếp với bạn bè của mình.					
2	Tôi có ý định tăng cường việc sử dụng LMS trong tương lai.	1	2	3	4	5
3	Tôi sẽ sử dụng LMS để thực hiện các hoạt động học tập khác nhau.	1	2	3	4	5
4	Tôi sẵn lòng dành thời gian và công sức cho các hoạt động học tập của mình	1	2	3	4	5

	thông qua LMS.					
5	Tôi sẵn lòng sử dụng LMS để học thường xuyên.	1	2	3	4	5
6	Tôi cũng sẽ khuyến khích người khác sử dụng LMS.	1	2	3	4	5
Về Chức năng hệ thống, bạn đánh giá rằng						
1	LMS cung cấp tất cả các tính năng mà tôi cần cho việc học của mình.	1	2	3	4	5
2	LMS đáp ứng các yêu cầu	1	2	3	4	5

	học tập của tôi.					
3	LMS phù hợp với các nhu cầu học tập của tôi.	1	2	3	4	5
4	LMS đáp ứng mong đợi của tôi.	1	2	3	4	5
5	LMS hoạt động rất tốt đối với tôi.	1	2	3	4	5