An Application of Model Unified Theory of Acceptance and Use of Technology (UTAUT): A Use Case for a System of Personalized Learning Based on Learning Styles

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***Abstract*—This research aims at investigating the factors that influence learners' behavioral intention toward personalized learning through the System of Personalized Learning Based on Learning Styles (PLBLS) using the Unified Theory of Acceptance and Use of Technology (UTAUT) model supported bythe Technology Acceptance Model (TAM) model to understand learners' intentions and behaviors when using the system. A survey of 144 learners enrolled in the Introduction to Educational Technology course at a university was conducted employing a quantitative research approach to examine the factors influencing the UTAUT model. The results indicate that Perceived Usefulness, Perceived Ease of Use, Habit, and Facilitating Conditions all influenced both the Behavioral Intention and the Behavioral Use of the PLBLS system. The findings suggest that habitual usage, effective communication about the benefits and user-friendliness of the PLBLS system, and the availability of convenient conditions enhance the intention to use the software, thereby promoting actual use among learners.**

***Keywords*—Unified Theory of Acceptance and Use of Technology (UTAUT), Technology Acceptance Model (TAM), personalized learning, learning style**

I. Introduction

Enhancing the application of information technology in management, organization, and training at universities is essential to improve the quality and effectiveness of these activities. Many studies on the acceptance and utilization of technology using the Unified Theory of Acceptance and Use of Technology (UTAUT) model are being conducted in public and higher education sectors worldwide. Examples include research on factors influencing teachers' behavioral intentions toward technology in Singapore [1], acceptance and usage of technology when using the learning management system at Northern University of Malaysia [2], and acceptance of the interaction board between lecturers and students at a university in New Zealand [3]. A recent systematic review evaluated the application of the Unified Theory of Acceptance and Use of Technology (UTAUT) model in higher education, revealing a predominant focus on student participants from Asia and North America [4].

However, there is a lack of reputable research on the use of the acceptance model of technology in higher education institutions in Vietnam. Notable studies include the adaptation of the extended Unified Theory of Acceptance and Use of Technology (UTAUT2) to research the acceptance and use of e-learning based on cloud computing in Vietnam [5], the factors influencing teachers' behavioral intention and usage behavior of Information Technology (IT) in lectures using the UTAUT model with Structural Equation Modeling (SEM) supported by AMOS 20 software [6], and a mixed-methods study employing the Technology Acceptance Model (TAM) to investigate the factors affecting continuance intention toward Coursera Massive Open Online Courses (MOOCs) Blended Learning (CMBL) with undergraduate students at a Vietnamese private higher education institution [7].

This study focuses on the relationship between perceived usefulness, perceived ease of use, the application of new technology (supporting content, learning materials in the learning style of learners), habits, and convenient conditions supporting the use of the system software, using intention that may impact the Behavioral for Use of learners.

The Personalized Learning Based on Learning Styles (PLBLS) system is an educational software designed to meet the diverse learning needs of each learner based on their individual learning style. The goal of PLBLS is to enhance learning performance and provide appropriate learning materials and learning paths for learners. We have researched and developed a PLBLS system built on the platform of a free online learning management system (Moodle). Through the application of technology and artificial intelligence, this system customizes content, teaching methods, and study time for each individual. In addition to the basic functions of the LMS system, our PLBLS system features tools to identify learners' learning styles and suggest appropriate learning materials and paths accordingly.

Personal assessment: PLBLS conducts an assessment or survey of the learners' learning styles, including how they absorb and process new information and their learning priorities.

Customization of content/learning materials: Based on the assessment results, PLBLS automatically customizes the content/learning materials, adjusting the presentation of information to suit the learner's learning style.

Progress tracking and evaluation: PLBLS tracks each learner's learning progress and evaluates their learning performance, allowing both learners and teachers to evaluate progress and adjust learning materials and paths effectively.

PLBLS plays an important role in promoting the progress and effectiveness of the learning process. It helps learners become more engaged and passionate about learning, thereby

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maximizing the potential of each individual.

By examining these factors, this study contributes to a deeper understanding of how technology acceptance models, particularly UTAUT, can be applied to personalize learning in higher education. The findings could offer valuable insights for educators and policymakers aiming to implement and optimize personalized learning systems in diverse educational settings.

II. Literature Review

A. Consumer Behavior, Behavioral Intention, and Technology Acceptance

Within the scope of this study, the concept of Behavior is specifically referred to as "Consumer Behavior", which is regarded as emotional reactions, perceptions, or observable reactions in relation to the purchase and handling of goods and services by consumers [8]. Consumer behavior involves decision-making process and physical activities, including purchasing, evaluating, using, and disposing of products and services. At the micro level, it pertains to understanding consumers in order to assist a company or organization in achieving its objectives [9].

Behavioral intention is the set of intentions a person arranges in a specific order to perform or not perform certain behaviors in the future [10]. It is highly related to system usage and is a key constituent of user behavior decisions, influencing behavior through intention [11].

In summary, Behavioral intention can be seen as the comparative basis level that an individual is aware of, ready to plan to make a decision whether or not to perform the behavior.

B. Technology Acceptance Models (TAM)

In the Technology Acceptance Model (TAM), the Perceived Ease of Use—the degree to which an individual believes that using a particular system will require no physical or mental effort—directly affects the Perceived Usefulness—the degree to which an individual believes that using a particular system will enhance their job performance [12]. Both Perceived Usefulness and Perceived Ease of Use are found to have a direct impact on Behavioral Intention.

Technology Acceptance Model 2 was developed from the Technology Acceptance Model (TAM), as studies using TAM showed a strong relationship between intention and usage with the factors of perceived usefulness and perceived ease of use. Research results also indicate that perceived usefulness and perceived ease of use have a direct impact on behavioral intention, thus the attitude factor is removed [13].

C. Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT) was developed to identify decision factors such as Effort Expectancy, Performance Expectancy, Social Influence, Facilitating Conditions, and moderating factors such as Gender, Age, Experience, and Voluntariness of use [14]. Effort Expectancy is defined as the degree of ease associated with using the system; Performance Expectancy is defined as the degree to which an individual believes that using new systems will help them be productive at work; Social Influence is seen as the degree to which an individual feels the importance of being influenced by the idea of those around them to use new systems; Facilitating Conditions are defined as the degree to which an individual has confidence that the technical infrastructure of the organization is sufficient to support the system [14]. UTAUT is a model that combines some of the previous models on user acceptance of new systems, including TAM. From a theoretical perspective, UTAUT provides insight into how factors influence Intention and Behaviour development over time. UTAUT has been tested and shown to be more effective than other competing models [14, 15].

UTAUT2 is proposed as a useful model to understand general consumers' technology usage. In this model, individuals' characteristics are seen to influence their Behavioral Intention through Habit. Habit is a cognitive structure that reflects the outcomes of previous experiences. UTAUT2 model shows how Habits directly and indirectly influence the use behavior through Behavioral Intention. Additions and significant modifications of the factors that explain behavioral intention and technology use were proposed for UTAUT2 [16].

The Unified Theory of Acceptance and Use of Technology (UTAUT) is a model that predicts technology usage behavior and is widely used in researching information technology users' behavior. This model first appeared in 2003, proposed by Venkatesh *et al.* [14], and subsequently became one of the most popular models in this field.

The UTAUT model combines and extends previous models, such as the Technology Acceptance Model (TAM) [12], the Theory of Reasoned Action (TRA) [17], and the Theory of Planned Behavior (TPB) [18]. It includes four main factors that influence technology usage behavior:

- Perceived Usefulness: Users' belief that using technology will enhance work performance or meet specific goals.
- Perceived Ease of Use: Users' belief that using technology is easy and requires minimal effort.
- Social Influence: The impact of social pressure or support from others on technology usage.
- Facilitating Conditions: Technical and organizational support for technology usage.

The UTAUT model shows that perceived usefulness and perceived ease of use of technology impact usage intention. Venkatesh *et al*. [14] proposed the original UTAUT model and tested its effectiveness using multiple datasets from different information systems. The main aim of the study was to build the UTAUT model, which combines factors from previous models to create a unified theory explaining users' technology acceptance behavior. The UTAUT model consists of four main factors: perceived usefulness, perceived ease of use, perceived credibility, and social influence. This study provided reliable evidence for the effectiveness of the UTAUT model in predicting and explaining users' information technology acceptance behavior [14].

Belief in the usefulness and ease of use of information technology significantly influences users' intention to use it.

If users believe in the usefulness and ease of use of technology, they may intend to use it actively [19]. Davis [11] emphasizes the importance of both Perceived usefulness and Perceived ease of use in technology acceptance and use. Venkatesh *et al.* [16] meta-analysis of 26 previous studies on UTAUT reveals that all the key factors in UTAUT, including perceived usefulness, perceived ease of use, perceived reliability, and support from colleagues and management have a positive impact on the intention to use technology.

Other studies also validate the influence of these factors on technology acceptance and usage behavior: Adams *et al.* [20] focuses on important factors (perceived usefulness, ease of use, usage of information technology) that influence user Behavioral Intention related to the acceptance and use of information technology. Segars and Grover [21] validates previous studies' contributions to the field of user experience and technology assessment, helping to understand how the factors of perceived usefulness and perceived ease of use influence the acceptance and use of information technology in various contexts. Doll *et al*. [22] confirmed the validity and reliability of the "perceived usefulness" and "ease-of-use" measurement tools in decision support.

The UTAUT model has been proven to be effective in assessing the level of acceptance and usage intention towards healthcare technologies, with perceived usefulness and perceived ease of use being recognized as key factors determining usage intention. The UTAUT model on the relationship between Perceived usefulness and Perceived ease of use indirectly affects Behavioral Intention via Behavioral for Use.

Gefen and Straub [23] analyzed the relationship between perceived ease of use and the adoption of electronic commerce and concluded the importance of this factor in users' decisions and behavior with electronic commerce information systems. By expanding and enhancing the TAM model through longitudinal studies, Venkatesh and Davis [24] contribute to the field of technology acceptance research and help understand the factors and processes that affect users' decisions and behavior with new technology. Lederer *et al.* [25] focuses on combining the TAM model, a popular theoretical framework for explaining user behavior towards new technology, with the study of the acceptance and usage process of the World Wide Web, focusing on two main factors of perceived usefulness and perceived ease of use to explain technology acceptance and use.

The UTAUT model shows that habit affects both behavioral intention and Usage behavior. Kim *et al.* [26] argue that the automatic use of information systems is seen as a natural and optimal response from users. Automatic use occurs when users respond quickly and automate tasks by forming habits and behavioral patterns. The research results of Limayem *et al.* [27] show that when the use of information systems becomes a habit, users' intention no longer has a strong predictive power in continuing to use the system. In other words, habit has a powerful impact on the behavior of continued use. This has important implications for understanding and predicting user interactions with information systems over the long term. Gaitán *et al.* [28] focuses on the relationship between user intention and habit when they continue to use online banking services after it has been implemented. UTAUT2 model is a theoretical model developed to understand the factors influencing the acceptance and use of new technology.

The UTAUT model shows that both facilitating conditions and usage intention have an impact on usage behavior. Wardat *et al.* [29] revealed that AI could be used as an educational tool to facilitate teaching and develop students' performance by including AI systems and applications in the curricula. Pham *et al.* [6] analyze and evaluate factors that may affect the decision of university lecturers to use information technology in teaching which may be related to technology competence, training and support, attitude towards technology, or influence from others. Teo [1] points out that support and training from educational management or organizations should be provided for lecturers to use technology. In other words, if lecturers receive the facilitating conditions (reliable support and training), they may have stronger motivation to apply technology in teaching. Wang [30] focused on factors that can mutually influence and contribute to users' final decisions on accepting and using the online learning system in the national industrial sector of Taiwan. As such, the support of Taiwanese organizations or national industry can provide facilitating conditions for online learning system usage. Kim and Kankanhalli [31], Lippert and Davis [32], and Sharma [33] suggest that when introduced new technologies, acceptance of change begins from within each individual. This can be influenced by how they perceive the new applications, which will affect their work performance. The success of change acceptance depends on users' acceptance and the new technology adoption of the organizations [34]. Users' acceptance level is an important factor to consider because it determines the implementation, installation, and use of information technology [19, 32]. This research will address the following research questions: What are the key factors affecting the acceptance and use of The Personalized Learning Based on Learning Styles?

III. MATERIALS AND METHODS

A. Research Hypotheses and Models

1) The relationship between perceived usefulness, perceived ease of use, and behavioral intention

Perceived ease of use has been found to have a significant influence on Behavioral intention and Behavioral for Use [11]. Agarwal and Karahanna [19], Davis [11], Adams *et al.* [20], Segars and Grover [21], Doll *et al.* [22] have confirmed that Perceived usefulness and Perceived ease of use are key factors in the individual acceptance structure. To verify the arguments above, we propose the following hypotheses:

H1: Perceived usefulness will directly impact Behavioral Intention to use the PLBLS system.

H2: Perceived ease of use will directly impact Behavioral Intention to use the PLBLS system.

2) The relationship between perceived ease of use and Perceived usefulness

Perceived ease of use continuously influences intention and behavior either directly or indirectly through perceived usefulness [19, 35]. Some arguments in previous studies affirm that there is a positive relationship between Perceived usefulness and Perceived ease of use when accepting information technology [23, 24], and this finding has also been confirmed in the use of internet technology [25, 36]. Therefore, we propose the following hypothesis:

H3: Perceived ease of use has a positive relationship with Perceived usefulness of the PLBLS system.

3) The relationship between habit and behavioral intention and behavioral for use

Habit has been shown to be an important factor in predicting technology usage [26, 27, 37]. The study by Pham *et al.* [6] shows that the habit of lecturers influences the use of information technology in teaching. Habit is one of the key factors that directly and indirectly explain usage behavior through behavioral intention [28]. However, Habit has an insignificant impact on the Behavioral Intention to use technology [5] and has no positive impact on behavioral intention or usage behavior [2]. To verify this relationship, we propose the following hypotheses:

H4: Habit will directly impact behavioral intention to use the PLBLS system.

H5: Habit will directly impact usage behavior of the PLBLS system.

4) The relationship between facilitating conditions for behavioral intention and behavioral for use

The research results of Alalwan *et al.* [38] show that Facilitating conditions can directly influence the actual use of computer and system. Facilitating conditions have a direct impact on Behavior [1]. Facilitating conditions for a technology have a positive correlation with the use of that technology. According to Im *et al.* [39], if there are more facilitating conditions, people are more likely to apply that technology. Nguyen *et al.* [5] conclude that Facilitating conditions have an insignificant impact on the usage behavior of e-learning based on cloud computing. Therefore, we propose the following hypothesis:

H6: Facilitating conditions will directly impact the usage behavior of the PLBLS system.

5) The relationship between behavioral intention and behavioral for use

Venkatesh *et al.* [14] acknowledge that behavioral intention is an important predictive factor of technology usage behavior. Wang [30] also concludes that behavioral intention has a direct impact on the usage behavior of the e-learning system of employees. Similarly, research findings of Nguyen *et al.* [5] indicate that behavioral intention has a positive impact on the usage behavior of cloud computing-based e-learning system. Similarly, it is pointed out in Pham *et al.* [6] that behavioral intention strongly influences the usage behavior of teachers. Based on the above reports, we propose the following hypothesis:

H7: Behavioral intention will directly impact the usage behavior of the PLBLS system.

6) Proposed model

Our proposed model, based on the UTAUT, UTAUT2, TAM, and TAM2 frameworks and experimental studies, aims to analyze the influence of factors on behavioral intention and usage behavior of the PLBLS system among students at the University of Education, Vietnam National University, Hanoi (Fig. 1).

The model comprises the following main components: Perceived Usefulness, Perceived Ease of Use, Facilitating Conditions, Habits, Behavioral Intention (5 observations), and Behavioral Use and it illustrates the impact of H1 (Perceived Usefulness, Behavioral for Use), H2 (Perceived Ease of Use on Behavioral Intention), H3 (Perceived Usefulness on Perceived Ease of Use), H4 (Habits on Behavioral Intention), H5 (Habits on Behavioral for Use), H6 (Facilitating Conditions on Behavioral for Use) and H7 (Behavioral Intention on Behavioral for Use).

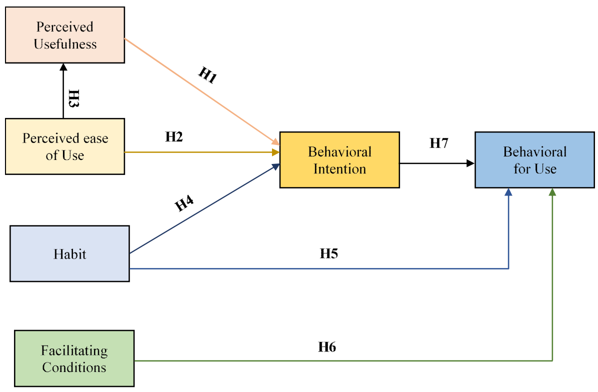

Fig. 1. Proposed research model.

B. Research Methods

This study employs a quantitative research method. The process involves reviewing concepts and related studies to develop the research model. Subsequently, tools from previous studies were referenced and adapted to propose a preliminary measurement scale. We conducted direct interview with 20 experts in information technology and education, gathered opinions, and refined the questionnaire. The survey tool utilizing a five-point Likert scale (detailed in appendix), includes Perceived Usefulness (06 variables), Perceived Ease of Use (05 variables), Facilitating Conditions (04 variables), Habits (04 variables), Behavioral Intention (05 variables), and Behavioral Use (05 variables).

A sample size of at least N = 100 was chosen to ensure statistical significance [40, 41]. Data were sourced from the PLBLS system selecting learners with a history of logging into the system. One hundred forty-four electronic questionnaires were distributed directly to selected subjects via email or social platforms such as Zalo by the teaching staff between April and May 2023. The study received 144 responses, of which 139 were valid. Post data collection and cleaning, the data were entered into the analysis. The Structural Equation Model (SEM) is one of the most advanced statistical analysis techniques of recent decades [42]. It is a multivariate technique that combines aspects of factor analysis and regression, allowing researchers to simultaneously test the relationship between latent structures such as Perceptions, Attitudes, or Consumer intentions and their effects on organizational performance measures. The most common approaches to estimating relationships in structural equation models are CB-SEM, used when data is normally distributed, with large sample size and PLS-SEM used with small sample sizes and no normal distribution assumptions [42, 43]. Each analysis technique is suitable for a different research objective. Recently, PLS-SEM has been widely applied in various social science fields, including organizational management [44], human resource management [45], management information systems [46, 47], operations management [48]. The PLS-SEM method is used for processing small sample sizes. To evaluate the results, PLS-SEM includes testing the measurement models. If the measurement models meet the requirements, researchers need to evaluate the structural model [46].

IV. Result and Discussion

A. Description of Sample Characteristics

The official study has sent out 144 questionaires received 144 responses (response rate of 100%). After the data were processed and filtered, the final valid sample size was N = 139. Regarding gender distribution, males constituted 71.9% of the respondents, while females accounted for 28.1%, indicating a significant gender discrepancy.

The age range of the respondents was between 19 and 24 years. The majority were 21 years old, representing 43.2% of the sample, followed closely by 20-year-olds at 43%. The remaining age groups were 22 (16.5%), 19 (5.0%), 24 (2.2%), and 23 (0.7%), showing a relatively diverse age distribution.

B. Reliability Test of the Measurement Scale

For the measurement scale to be considered reliable, the loading factors must exceed the threshold value of 0.7 [42]. According to Table 1, the results indicate that the factor Perceived Usefulness (PU) has 05 observed variables with loading factors ranging from 0.896 to 0.918; the factor Perceived Ease of Use (PE) has 05 observed variables with loading factors ranging from 0.833 to 0.861; the factor Habit (HA) has 04 observed variables with loading factors ranging from 0.802 to 0.855; the factor Facilitating Conditions (FC) has 04 observed variables with loading factors ranging from 0.799 to 0.851; the factor Behavioral Intention (BI) has 05 observed variables with loading factors ranging from 0.886 to 0.910; and the factor Behavioral for Use (BU) has 05 observed variables with loading factors ranging from 0.915 to 0.921.

Table 1. Results of the reliability test of the measurement scale

Factor	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average Variance Extracted (AVE)
BE	0.933	0.934	0.949	0.788
BI	0.918	0.921	0.938	0.753
FC	0.866	0.873	0.908	0.713
HA	0.861	0.873	0.906	0.707
PE	0.876	0.891	0.908	0.665
PU	0.921	0.926	0.939	0.719

Moreover, according to Hair *et al.* [43], adequate Composite Reliability (CR) should be in the range from 0.7 to 0.9. The analysis results show that all factors have adequate CR with coefficients ranging from 0.873–0.949. The Average Variance Extracted (AVE) coefficients of the factors are all within the range of 0.665–0.788, all exceeding 0.5, thereby explaining more than 50% of the variance in the observed data and ensuring convergent validity. The Cronbach's Alpha reliability coefficient should be 0.7 or above. The Cronbach's Alpha reliability coefficients for all constructs are above the threshold of 0.7, specifically ranging from 0.861 to 0.933. To confirm the absence of correlations between the factors used to measure the dimensions, discriminant validity was assessed using the Factor Discriminant (FD) value. According to Hair *et al.* [43], discriminant validity is ensured when the squared AVE values are highest compared to those of other factors.

C. Collinearity Statistics Test

To assess the issues of collinearity in the structural model, the Variance Inflation Factor (VIF) value is the key indicator. The VIF value for each indicator must be higher than 0.2 and lower than 5. If a VIF value falls outside this range, it may be necessary to remove the indicator, consolidate it into a single index, or create higher-level constructs to address collinearity issues [43]. According to Table 2, the VIF coefficients indicate that there is no violation of the assumption of collinearity regarding the correlation between the predicted factors, as all coefficients are within an acceptable range (VIF = 1.653–4.229 < 5). This ensures that collinearity is not a concern, allowing for continued analysis.

Table 2. Collinearity test results

Factor	Variance magnification factor (VIF)	Evaluate
PE	1.956–2.616	< 5: No violation
PU	2.380–4.229	< 5: No violation
BU	3.389–3.728	< 5: No violation
FC	1.898–2.597	< 5: No violation
HA	1.653–2.419	< 5: No violation
BI	2.340–3.577	< 5: No violation

D. Model—Fit Test

There are several key criteria for evaluating the structural model in PLS-SEM, including path coefficients, R^2 values, f^2 effect size, and predictive fit Q^2 [43]. The most commonly used measure to evaluate the structural model is the determination coefficient (R^2 value). The higher the R^2 value, the more accurate the prediction. The analysis results showed that the R^2 value for the PU model is 0.525; for the BU model is 0.794, and for the BI model is 0.786. In addition, the Q^2 value [49, 50] is an indicator of the model's predictive fit. In the structural model, Q^2 values greater than 0 for a latent variable reflect the degree of the path relationship prediction for this specific structure [43]. Table 3 shows that the Q^2 value of this study's results for all structures are greater than 0, indicating that all dependent variables in the proposed model have a suitable level of predictability.

Table 3. Results of R^2 and Q^2

Factor	R^2 value	Q^2 value
PU	0.525	0.522
BU	0.794	0.791
BI	0.791	0.786

Apart from evaluating the R^2 values in the latent structure, changes in R^2 due to modifications in an exogenous structure can be used to assess the impact of the omitted structure on the latent structure. This measure is called the f^2 effect size. The f^2 values of 0.02, 0.15, and 0.35, respectively reflect "small", "medium", and "large" effects [51]. The results in Table 4 show that the influence levels of FC, HA, and BI on BU are progressively increasing, with HA having a medium level of influence on BU. The largest influence level is BI, with an f^2 value of 1.198.

Table 4. Results of f^2 values and influence level

The relationship between variables	f^2 Value	Influence level
FC → BU	0.024	Small
HA → BI	0.230	Medium
PE → BI	0.258	Medium
HA → BU	0.301	Medium
PE → PU	1.106	Big
BI → BU	1.198	Big

E. Linear Structural Model Test

There is no single criterion that universally applies to evaluating estimates in PLS-SEM. Instead, evaluating measurement and structural model results in PLS-SEM is built on a set of evaluation criteria for nonparametric tests, employing techniques such as bootstrapping [43]. In this research survey, each bootstrapping sample comprises 100 observations, corresponding to the total observations of the original sample. To meet the testing requirement of the linear structural model, the bootstrapping procedure was performed 1,000 times [42]. The results of testing the relationship between variables are presented in Table 5.

Table 5. Direct impact results of the relationships

The relationship between variables	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	*T* statistics (|O/STDEV|)	*P* values
BI → BU	0.800	0.787	0.070	11.367	0.000
FC → BU	0.113	0.123	0.077	1.456	0.046
HA → BI	0.284	0.286	0.056	5.061	0.000
HA → BU	0.227	0.226	0.051	4.462	0.000
PE → BI	0.347	0.356	0.068	5.117	0.000
PE → PU	0.725	0.725	0.061	11.966	0.000
PU → BI	0.387	0.381	0.068	5.718	0.000

The results show that the Behavioral Intention model of using the PLBLS system has 03 same-directional relationships that are statistically significant at a 99% confidence level: (1) HA → BI with impact coefficient (β = 0.284); (2) PE → BI with impact coefficient (β = 0.347); (3) PU → BI with impact coefficient (β = 0.387). Comparing the impact level of the 03 variables HA, PE, PU on the dependent variable BI in increasing order, we see that the variable PU (Habit) has the strongest impact (β = 0.387), followed by the variable PU (Perceived usefulness) (β = 0.347) and finally the variable PE (Perceived ease of use) (β = 0.284). Therefore, hypotheses H1, H2, H4 are accepted with 99% confidence. This shows that Habit, perceived ease of use, perceived usefulness all contribute to the Behavioral Intention of using the PLBLS system.

The PLBLS System Behavioral for Use model has same-directional relationships that are statistically significant at a 99% confidence level: (1) HA → BU with impact coefficient (β = 0.227); (2) FC → BU with impact coefficient (β = 0.113) with 95% confidence level. Comparing the impact level of the 02 variables HA, FC on the dependent variable BU in decreasing order, we see that the variable HA (Habit) has the strongest impact (β = 0.227), followed by the variable Facilitating Conditions (FC) (β = 0.113). Therefore, hypotheses H5, H6 are accepted with 99% confidence. Accordingly, Habit and Facilitating conditions influence the Behavioral for Use of the PLBLS system.

Regarding the relationship model between the variables PE and PU, there is one same-directional relationship that is statistically significant at a 99% confidence level: PE → PU with impact coefficient (β = 0.725). Therefore, hypothesis H3 is accepted with 99% confidence. This means that Perceived ease of use has a significant impact on Perceived usefulness.

In this study, the author also considered the relationship between Behavioral Intentions and Behavioral for Use. The results show that there are 02 same-directional relationships with significant impact: BI → BU with impact coefficient (β = 0.800) at a 99% confidence level. Therefore, hypothesis H7 is accepted with 99% confidence. This means that Behavioral Intentions directly influence Behavioral for Use.

The author also looked at the indirect impact of factors on Behavioral for Use (BU) through Behavioral Intentions (BI). Smart PLS analysis showed the following indirect relationships:

Table 6. Results of the indirect impact of factors

The relationship between variables	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	*T* statistics (|O/STDEV|)	*P* values
PE → BI → BU	0.278	0.280	0.055	5.019	0.000
PU → BI → BU	0.310	0.300	0.061	5.112	0.000
HA → BI → BU	0.227	0.226	0.051	4.462	0.000
PE → PU → BI → BU	0.224	0.218	0.050	4.488	0.000
PE → PU → BI	0.280	0.277	0.057	4.961	0.000

Table 6 illustrates that that HA (Habit) and PE (Perceived Ease of Use) indirectly impact on BU (Behavioral for Use) through BI (Behavioral Intentions), where HA has an impact (β = 0.227), followed by PE (β = 0.278) with 99% confidence. Additionally, the factor PE indirectly impacts on BI through PU (β = 0.280), and indirectly impacts on BU through PU and BI (β = 0.224) with 99% confidence. Finally, PU indirectly impacts on BU through BI (β = 0.310) with 99% confidence.

F. Discussion

The research results demonstrate direct relationships between Perceived Usefulness, Perceived Ease of Use on Behavioral Intention.

The study further reveals that Perceived Ease of Use indirectly affects Behavioral Intention through Perceived Usefulness. Both Perceived Usefulness and Perceived Ease of Use also indirectly impact Behavioral for Use through Behavioral Intention. These findings support previous research [19, 22, 52, 53] as cognitive absorption, theorized as being exhibited through the five dimensions of temporal dissociation, focused immersion, heightened enjoyment, control, and curiosity, is posited to be a proximal antecedent of two important beliefs about technology use: perceived usefulness and perceived ease of use.

The study also identified a direct relationship between Perceived Ease of Use and Perceived Usefulness (H3), while also observing the indirect impact of Perceived Ease of Use and Perceived Usefulness on Use Behavior through Intention to Use, as well as the indirect impact of Perceived Ease of Use on Use Behavior through Perceived Usefulness and Intention to Use. These results are consistent with earlier studies [19, 22, 25, 35, 36, 54, 55] as both social influence processes (subjective norm, voluntariness, and image) and cognitive instrumental processes (job relevance, output quality, result demonstrability, and perceived ease of use) significantly influenced user acceptance.

The results indicate that Habit has a direct impact on both Behavioral Intention (H4) and Behavioral for Use (H5), and a significant indirect impact on Behavioral for Use through Behavioral Intention. These findings align with previous research [6, 22, 28, 37, 56] as the result shows direct positive effect of performance expectancy, effort expectancy and subject characteristics on user's behavioral intention. Moreover, behavioral intention, facilitating condition and habit later on have influenced on user's actual use behavior.

Finally, both Facilitating Conditions and Behavioral Intention have a direct impact on Behavioral for Use (H6, H7), consistent with the findings of Refs. [1, 5, 6, 14, 22, 30, 38, 39, 57] as the results indicate that while performance expectancy, effort expectancy, and social influence significantly influence the behavioral intention of e-learning, behavioral intention and facilitating conditions significantly influence use behavior for e-learning systems.

V. Limitations of the Study and Future Research Directions

Firstly, this study relied exclusively on quantitative survey data. To gain a more comprehensive understanding of participants' perspectives, opinions, and beliefs regarding factors influencing the use of the PLBLS system, future research should incorporate qualitative data. This approach could provide deeper insights into how these factors shape user behavior.

Secondly, this study is limited to learners from the Faculty of Education at Hanoi National University of Education, resulting in a relatively small sample size.

As a result, the findings may not generalize to the broader population of learners at this university or at other higher education institutions. Future research should replicate the study with larger and more diverse samples across various educational contexts and software applications to enhance the generalizability of the results.

Thirdly, this study did not analyze the moderating effects of gender and age, experience, and voluntariness. These effects may limit the generalizability of the results. This raises a potential research issue in the future where researchers can conduct exploratory studies and investigate the moderating role of these factors on learners' Behavioral Intention to use the PLBLS System.

Finally, integrating additional factors into the UTAUT model or exploring alternative models could further enrich the framework used in this study.

VI. Conclusions

The findings of this study demonstrate the impact of various factors on Behavioral Intention and Behavioral for Use when using the PLBLS System. Specifically, the Habit variable has the strongest influence on Behavioral for Use. Moreover, the study shows a close relationship between Behavioral Intention and Behavioral for Use. These results align with previous research and contribute to the understanding of factors affecting the use of the PLBLS System.

The research results also have provided additional evidence that factors influencing the Intention and Behavioral for Use of learners using the PLBLS System include: Habit, Perceived Usefulness, Perceived Ease of Use, and Facilitating conditions.

Habit factor (HA) significantly impacts both Behavioral Intention (β = 0.284) and Behavioral for Use (β = 0.227). Habit indirectly influences Behavioral for Use through Behavioral Intention. There is variation in learners' habitual use of the PLBLS system, highlighting the need to strengthen user habits by promoting system benefits.

Perceived Usefulness (β = 0.387) and Perceived Ease of Use (β = 0.347) directly affect Behavioral Intention, with Perceived Ease of Use also significantly influencing Perceived Usefulness (β = 0.725). Both factors indirectly impact Behavioral for Use through Behavioral Intention. To enhance the system, it should be intuitive and easy to navigate.

Facilitating Conditions (FC) has the lowest direct impact on Behavioral for Use (β = 0.113), but remains important. Improving technical infrastructure like network quality and security is recommended.

Behavioral Intention (BI) strongly impacts Behavioral for Use (β = 0.800). Enhancing users' intention to use the PLBLS system through raising awareness of its benefits, ease of use, and facilitating conditions can improve system integration into study practices.

This study adds additional evidence that UTAUT model is effective in explaining learners' Behavioral Intention to use the PLBLS System in education and training. The study also considers this model in the context of higher education in Vietnam. In addition, it identifies factors that are influencing awareness and behavior of using the PLBLS System to find appropriate solutions to improve the system infrastructure, technology, and create advantageous conditions and habits to promote the Behavioral for Use of technology to enhance productivity and learning efficiency.

Appendix

Table A: Survey tools

Encode	Content		Source
PU01	Using the PLBLS system in my studies allows me to complete my study tasks faster	Perceived usefulness (PU)	[11], [58], [59]
PU02	Using PLBLS support system increase my learning efficiency (avoid wasting time and effort)		
PU03	Using the PLBLS system increases the productivity of personalized learning		
PU04	Using the PLBLS system increases my learning efficiency		
PU05	The PLBLS system makes personalized learning easier for me		
PU06	Useful PLBLS system, helping me learn in my own way, supporting personalized learning		
PE01	I use the PLBLS system flexibly to study at any time	Perceived ease of use	[11], [58],

PE02	I can easily interact and connect with my classmates when using the PLBLS system	(PE)	[59]
PE03	PLBLS system is friendly, simple and easy to use		
PE04	I can quickly find the information I need in a personalized learning support system		
PE05	I have easy access to learning content and learning materials when using the PLBLS system		
FC01	I have the necessary equipment (smartphone, 3G, wifi…) to use the PLBLS system	Facilitating Conditions (FC)	[3], [5], [6], [14], [16], [30], [60]
FC02	I have the necessary knowledge to use the PLBLS System		
FC03	The PLBLS system is compatible with other technologies I use		
FC04	I can get help when I have trouble using the PLBLS system		
HA01	Using the PLBLS system becomes a habit	Habits (Habit-HA)	[5], [6], [14], [16]
HA02	I use the PLBLS system regularly		
HA03	If there is no mandatory element, I still use the PLBLS system for the learning task		
HA04	Using the PLBLS system came naturally to me		
BI01	I will use the PLBLS system when I need to do study tasks	Behavioral Intention (BI)	[3], [6], [11], [18], [24], [30], [58], [61], [62]
BI02	I think people should be encouraged to use the PLBLS system		
BI03	I believe to use PLBLS system in the future		
BI04	I believe the PLBLS system will support most learning tasks		
BI05	I will recommend the PLBLS system to everyone		
BU01	I can use the PLBLS system for subsequent courses	Behavior for Use (BU)	[24], [58], [61]
BU02	I use the PLBLS system for more than one learning task		
BU03	I will continue to use the PLBLS system for my next study		
BU04	The PLBS system makes me satisfied in overall		
BU05	I enjoy using the PLBLS system for learning		

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Hoa-Huy Nguyen conducted the research and mostly drafted papers. Viet Anh Nguyen proposed the main ideas and reviewed the manuscript. Both authors have approved the final version.

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