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Factors Influencing Technology Adoption for Learning among the Cambodian University Students

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Abstract

Purpose: This study identifies factors influencing technology for learning among Cambodian university students. Ten variables form a conceptual framework, including behavioral intention, use behavior, perceived ease of use, perceived usefulness, computer self-efficacy, performance expectancy, facilitating conditions, effort expectancy, social influence, and hedonic motivation. **Research design, data, and methodology:** A quantitative method was employed to gather data from 500 students (years 2-4). The content validity and reliability were evaluated using item-objective congruence and Cronbach's alpha. Confirmatory factor analysis and structural equation modeling were used to verify the goodness of fit and to test the hypotheses. **Results:** Behavioral intention had a significant impact on use behavior (β = 0.838), hedonic motivation (β = 0.278), effort expectancy (β = 0.165), social influence (β = 0.067), and hedonic motivation. The insignificant factors to behavioral intention include perceived ease of use, perceived usefulness, computer self-efficacy, performance expectancy, and facilitating conditions. These unsupported hypotheses are due to learners who have limited knowledge of digital skills, do not see the benefits of technology, have low confidence in technological competence, and lack supported facilities. **Conclusions:** The study suggests enhancing university technology adoption by addressing both support and non-support variables. It recommends incorporating all the studied variables to ensure students' experience and readiness to interact with technology, particularly in the digital age.

Keywords: Behavioral Intention, Use Behavior, Technology Adoption, E-learning, Higher Education

JEL Classification Code: E44, F31, F37, G15

1. Introduction

Technology influences people's lives every day. Nikou and Economides (2017) argue that technology holds the promise of opening new opportunities for improved learning environments through information and communication technologies (ICT), particularly the Internet. ICT enhances student performance and learning while also promoting inclusion, equity, and social responsibility, which motivates students to learn (Fokides & Kefallinou, 2020).

ICT is useful in education (i.e., computers, the internet, and various tools) for student participation. ICT is increasingly used in universities worldwide to develop curricula, acquire knowledge, and deliver lectures (Ibrahim et al., 2018). E-learning, as part of ICT development, allows learners and educators to communicate freely from any location, simplifying the learning process and helping students develop the necessary skills (Vlachopoulos, 2020). The usefulness of technology in education is gaining global recognition (Panigrahi et al., 2018).

Many universities introduced e-learning into their educational programs, but some may not be fully satisfied with this strategy. During the COVID-19 pandemic, beyond continuing their online classes, students faced limited or no access to study facilities and could not afford an Internet connection, especially for marginalized groups (Masud et al., 2023). There is a lack of investigation, particularly in developing countries like Cambodia, where there is a lack of research on students' intentions to adopt technology for learning (Tarhini et al., 2017).

Furthermore, studies demonstrated that several factors influence students to use e-learning effectively, including the perceived usefulness, ease of use of technology, performance expectancy, effort expectancy, social influences, work-life balance, internet experience, hedonic

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AU-GSB E-JOURNAL

motivation, and facilitating conditions (Y. H. S. Al-Mamary et al., 2023). In addition, Tewari et al. (2023) found that the decision to use online learning is significantly impacted by an atmosphere of encouragement and a sense of security, where Hussain et al. (2022) confirmed that using information technology for learning is strongly related to habit and behavioral intention. Some studies, such as those by L. Sharma and Srivastava (2019), have found that individuals' self-efficacy does not correlate with their behavioral intention. Meanwhile, other studies indicate that there is no relationship between behavioral intention and facilitating conditions (Prasetyo et al., 2021; Raman & Thannimalai, 2021).

There is no consistency in the studies on what components influence behavioral intention to motivate students to use technology for their learning (Khalifeh et al., 2020). Moreover, several factors have been identified that affect the acceptability of various technologies from different studies (Lai et al., 2024). Therefore, this study aims to investigate the factors influencing technology for learning among Cambodian university students: A case study at the College of Sciences, Norton University, Cambodia. Whether perceived ease of use, perceived usefulness, computer self-efficacy, performance expectancy, facilitating conditions, effort expectancy, social influence, hedonic motivation, and use behavior significantly influence behavioral intention to adopt technology for learning?

2. Literature Review

2.1 Perceived Ease of Use

Perceived ease of use is the belief that technology does not require significant effort (Davis, 1989). Studies indicate a positive correlation between perceived ease of use and behavioral intention in online education, either directly or indirectly (Venkatesh & Davis, 2000). It is crucial for innovation consideration that technology-related devices are convenient to use (Hossain et al., 2022). Mailizar et al. (2021) state that the perceived ease of use has a significant impact on the use of technology. Venkatesh and Davis (2000) noted that perceived ease of use facilitated the adaptability of technology use without any challenges. People who trust technology that is easy to use are more likely to complete tasks and solve any difficulties (Davis, 1989). In this regard, when someone completes tasks using technology, they have already adopted it for virtual learning and teaching (Abdullah & Ward, 2016).

H1: Perceived ease of use has significant influence on behavioral intention in adopting technology for learning.

2.2 Perceived Usefulness

Saleem et al. (2022) explain that perceived usefulness is a person's perception of implementing a specific method to improve performance. Individual performance improves when the person accepts the need to adapt and use new technology (Davis, 1989). Malik and Annuar (2021) describe perceived usefulness as the belief that a person uses technology and innovation to increase productivity and output. The view toward adopting technology was significantly influenced by its perceived usefulness; people are more likely to adopt when they see the improved outcome (Luo et al., 2024). When students participate in an online education system, they believe that technology can improve learning outcomes, which has a positive influence on student performance (Tahar et al., 2020).

H2: Perceived usefulness has significant influence on behavioral intention to adopt technology for learning.

2.3 Computer Self-Efficacy

Self-efficacy refers to an individual's belief in their capacity to perform specific tasks effectively to meet the demands (Bowden, 2021). Student self-efficacy is the attitudes and beliefs that students have about their ability to succeed academically, as well as their confidence in completing academic assignments and effectively utilizing educational materials (Hayat et al., 2020). Similarly, studies conducted by Reddy et al. (2020) indicated that computer-savvy students are more interested in using library electronic resources and exhibit higher self-efficacy. Based on Zhang et al. (2022), self-efficacy encourages people to do more work and increases efforts, which makes the workplace better.

H3: Computer self-efficacy has significant influence on behavioral intention to adopt technology for learning.

2.4 Performance Expectancy

Performance expectancy refers to the person's belief that the current system acknowledges and respects their work performance (Zhao & Bacao, 2021). Performance expectancy is a crucial component in determining the adoption and consistent use of relevant innovations and is considered a powerful determinant of behavioral intention in utilizing technology (Chen et al., 2021). A study by Ciftci et al. (2023) showed that setting performance expectancy led to greater use of the computer system. The examination by Rahi et al. (2019) suggests that performance expectancy predicts how long people will continue to use technology in the long term. Moreover, the literature on financial technology also spells out that performance expectancy is one of the key motivators for adopting technology. Research

AU-GSB E-JOURNAL

from a healthy lifestyle perspective confirms that performance expectancy influences the intention to use technology (Wei et al., 2020).

H4: Performance expectancy has significant impact on behavioral intention to adopt technology for learning.

2.5 Facilitating Conditions

Facilitating conditions refer to the availability of conditions that encourage people to use technology (Hsu, 2023). Ali et al. (2018) provide support for the availability of sufficient resources by explaining the facilitating condition as the presence of satisfactory resources that facilitate the use of technology. Regarding distance education, facilitating conditions have influenced users (Salloum & Shaalan, 2018), fostered motivation, and promoted the use of e-learning systems (Tarhini et al., 2017). Salloum and Shaalan (2018) consider facilitating conditions as a measure of students' perceptions regarding their access to resources and support for e-learning systems. Suhail et al. (2024) validated that facilitating conditions play an essential role in influencing behavioral intention to employ e-learning.

H5: Facilitating conditions have significant influence on the behavioral intention to adopt technology for learning.

2.6 Effort Expectancy

Effort expectancy refers to the perspective of a learner who can utilize a computerized system with minimal additional effort (Mafuna & Wadesango, 2016). Faqih and Jaradat (2021) define effort expectancy as the effortless use of technology. Moreover, Thongsri et al. (2018) explain effort expectancy as a straightforward and easily adaptable approach to distance education. Choi-Meng et al. (2020) argue that e-learning is a viable option for effort expectancy and is intended to continue. The success and efficacy of online learning are highly dependent on educational materials, with indications for effort expectancy and persistent intentions (Zabidi et al., 2017). Samsudeen and Mohamed (2019) confirm that effort expectancy is crucial when online learning is in its initial stage of development, a finding supported by Tarhini et al. (2017), who explain that if people find it easy to use the technology, they are more likely to use it. Ragheb et al. (2022) and Strzelecki (2023) found that effort expectancy played a valuable role in behavioral intention to use e-learning.

H6: Effort expectancy has significant influence on behavioral intention to adopt technology for learning.

2.7 Social Influence

Social influence is an individual's perception that relevant stakeholders, such as family and friends, should benefit from the technology (Garcia-Milon et al., 2021). At the university level, students may feel the need to use online learning to complete a course and may be convinced by their instructors and friends (Strzelecki, 2023; Tarhini et al., 2017). Other studies confirmed that social influence stimulates students to use e-learning as well as any innovations (Ali et al., 2018; Tarhini et al., 2017). It is revealed that social influence has a relationship with behavioral intention in higher education institutions (Salloum & Shaalan, 2018; Strzelecki, 2023; Suhail et al., 2024).

H7: Social influence has significant influence on behavioral intention to adopt technology for learning.

2.8 Hedonic Motivation

Jajic et al. (2022) define hedonic motivation as the actions taken for pleasure, imagination, and enjoyment. Hedonic motivation has the most significant influence on behavioral intention to utilize various technologies, as it measures the practical aspect of technology promotion (Tamilmani et al., 2019). Studies by Beh et al. (2019), Strzelecki (2023), and Suhail et al. (2024) mentioned that hedonic motivation and behavioral intention are positively correlated when people continue using technology with enjoyment. Several others reported a significant influence of hedonic motivation and behavioral intention towards technology adoption (Baabdullah, 2018; Faqih & Jaradat, 2021; Jajic et al., 2022; Patel et al., 2020).

H8: Hedonic motivation has significant influence on behavioral intention to adopt technology for learning.

2.9 Behavioral Intention

Behavioral intention refers to someone who agrees to use technology for learning (Al-Rahmi et al., 2022). Salloum and Shaalan (2018) shaped behavioral intention as the acceptance of an e-learning system by people, from traditional learning methods to the future. In addition, behavioral intention is characterized by the implementation and utilization of technology (Motahhir & Bossoufi, 2021). A study by Ba et al. (2023) found that behavioral intention has a positive influence on people's behavior when technology is applied. Hoque and Sorwar (2017) and Al-Rahmi et al. (2022) showed that behavioral intention has a relationship with use behavior in employing technology. Strzelecki (2023) asserts that behavioral intention has the most impact on use behavior.

H9: Behavioral intention has significant influence on use behavior to adopt technology for learning.

AU-GSB E-JOURNAL

3. Research Methods and Materials

3.1 Research Framework

The study is based on three models: the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Extended UTAUT (UTAUT2), which have been used to formulate a conceptual framework. The theoretical framework is formed from the three previous studies involving two dependent and eight independent variables. Six variables adopted from Lantu et al. (2023): performance expectancy, effort expectancy, social influence, facilitating conditions, behavioral intention, and use behavior; three variables taken from Riyath et al. (2022): perceived ease of use, perceived usefulness, computer self-efficacy, and one variable from Hussain et al. (2022): hedonic motivation. Figure 1 summarizes the conceptual framework of this study.

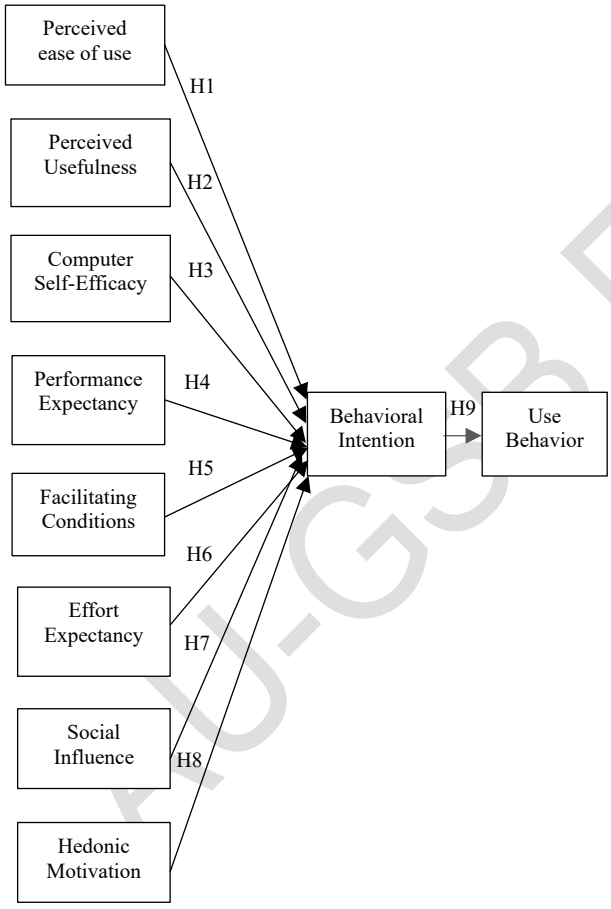

Figure 1: Conceptual Framework

H1: Perceived ease of use has significant influence on behavioral intention in adopting technology for learning.

H2: Perceived usefulness has significant influence on behavioral intention to adopt technology for learning.

H3: Computer self-efficacy has significant influence on behavioral intention to adopt technology for learning.

H4: Performance expectancy has significant impact on behavioral intention to adopt technology for learning.

H5. Facilitating conditions have significant influence on the behavioral intention to adopt technology for learning.

H6: Effort expectancy has significant influence on behavioral intention to adopt technology for learning.

H7: Social influence has significant influence on behavioral intention to adopt technology for learning.

H8: Hedonic motivation has significant influence on behavioral intention to adopt technology for learning.

H9: Behavioral intention has significant influence on use behavior to adopt technology for learning.

3.2 Research Methodology

This study employed a quantitative approach, utilizing multiple-stage sampling techniques, including judgmental sampling, stratified random sampling, and convenience sampling. The questionnaire was distributed to undergraduate students in years 2, 3, and 4 who are studying in the College of Sciences. Respondents were interviewed using the five-point Likert scale rating questionnaire (5 indicated strongly agree and 1 indicated strongly disagree). The questionnaires are divided into three parts: screening questions, demographic data, and measurements of all variables.

Item Objective Congruence (IOC) was used to evaluate the scale item validity before data collection. Three senior educational specialists with 20 years of experience in this field were invited to review the questionnaire. Then, the pilot study was implemented with 50 respondents to test the internal consistency of the questionnaire through Cronbach's alpha (Killingsworth et al., 2016). The overall result of the pilot test showed that the Cronbach's alpha value is higher than 0.7 for all variables, confirming that all questions possess reliability and internal consistency.

The next step was to collect real data using questionnaires developed in a Google Form. These were ready to be sent to 600 respondents through existing students' Telegram groups, with assistance from the College's employees to gather their responses. Out of 600 questionnaires, 500 were completed by respondents for analysis, showing an 83 percent response rate, which is satisfactory for the study (M. Wu et al., 2022). Then, the data were analyzed using SPSS and AMOS. The Confirmatory Factor Analysis (CFA) was used to validate

AU-GSB E-JOURNAL

the measurement model, including convergent validity, discriminant validity, and reliability. Finally, the interaction of the structural model with other structures was examined using the Structural Equation Model (SEM) to test the hypothesis.

3.3 Population and Sample Size

The respondents for this study include undergraduate students from the College of Sciences at Norton University, Cambodia, majoring in Architecture, Computer Science, Civil Engineering, and Electrical and Electronic Engineering. In this regard, the target population of the study consisted of students who are studying at the undergraduate school, including male, female, or of any other gender, who have more than one year of experience by utilizing different platforms for learning, such as Google Classroom, Google Meet, Microsoft Teams, Zoom, Telegram Message Group, and YouTube. Norton University was selected due to its strong commitment to education, its pioneering role as the first private university to cooperate with foreign universities, its research in cutting-edge technologies, and its consistent high enrollment of students.

This study used the A-priori Sample Size Calculator to compute the sample size for SEM (Soper, 2023), with an expected effect size of 0.2, a desired statistical power level of 0.8, and a sample size of 500 respondents from the selected college for stronger statistical conclusions.

3.4 Sampling Strategy

This study utilized a multi-phase sampling method that included purposeful or judgmental, stratified, and convenience sampling techniques. In accordance with Etikan and Bala (2017), multiple-stage sampling techniques, developed from cluster sampling, were used with various sample technologies to achieve the most effective outcomes for the study. Firstly, the study employed judgmental sampling to choose one college from Norton University. Secondly, stratified random sampling is used to define subgroups within the study population. Thirdly, the convenience sample was selected to ensure a sufficient number of respondents willing to participate in the questionnaire. Respondents are selected using screening questions to ensure that students are undergraduates from the College chosen with at least a year of prior experience utilizing technology for learning.

In this sense, the study employed judgmental sampling to select a college, ensuring that the respondents accurately represented the target group of this study. Then, stratified sampling was used to select 500 students to represent the studied population. Lastly, a convenience sample was ultimately decided upon to reach the number of available respondents willing to reply to the questionnaire.

Table 1: Sample Units and Sample Size

Majors	Population Size	Sample Size
Architecture	1076	173
Computer	754	121
Civil Engineering	997	160
Electrical and Electronic	288	46
Total	**3115**	**500**

Source: Developed by the author

4. Results and Discussion

4.1 Demographic Information

Out of all the responses, the majority, accounting for 43 percent or 213 respondents, were between the ages of 21 and 22. Subsequently, 32 percent, or 159 participants, aged 20 to 21, were surveyed. Furthermore, 101 respondents, which accounts for 20 percent of the total, fell between 23 and 24. Only 2 percent or 11 persons, constituting a lower proportion of responders, fell between 15 and 18. Finally, 16 respondents, approximately 3 percent of the total, were over 25 years old. There were 222 junior students in the academic year, representing 23.8% of the student population. Additionally, there were 154 senior students, accounting for 31 percent, and 124 sophomore students, making up 25 percent.

Table 2: Demographic Characteristics (N = 500)

Gender	Count	Percentage
Female	70	14
Male	370	74
Non-binary	12	2
Prefer not to say	48	10
Age	**Count**	**Percentage**
15 - 18 years old	11	2
19 - 20 years old	159	32
21 - 22 years old	213	43
23 - 24 years old	101	20
More than 25 years old	16	3
Year of Study	**Count**	**Percentage**
Year 4	154	31
Year 3	222	44
Year 2	124	25
Total	**500**	**100**

4.2 Confirmatory Factor Analysis

Confirmatory Factor Analysis (CFA) is an important point for the Structural Equation Model (Kline, 2023). It was relevant for measuring latent variables and supporting the measurement model (Khan & Qudrat-Ullah, 2021). Using CFA for this study allowed the assessment of the reliability and validity of the theoretical framework and

AU-GSB E-JOURNAL

measurement tools. The factor loading of each latent variable must be equal to or greater than 0.5 to be considered acceptable (Kline, 2023). Goodness-of-Fit (GOF) indices were used to evaluate the model's fit. The fit indices that were designated for this investigation include the ratio of the Chi-Square value to Degrees of Freedom (CMIN/DF), the Goodness-of-Fit Index (GFI), the Adjusted Goodness-of-Fit Index (AGFI), the Comparative Fit Index (CFI), the Normed Fit Index (NFI), the Tucker-Lewis Index (TLI), and the Root Mean Square Error of Approximation (RMSEA). These indicators comprehensively assess the overall model fit. In this study, the model fit was confirmed by the satisfactory values of the goodness-of-fit indices, as shown in Tables 3 and 4. The statistical values of the indices were compared against the acceptability standard.

Table 3: Confirmatory Factor Analysis Result, Composite Reliability (CR), and Average Variance Extracted (AVE)

Latent Variables	Source of Questionnaire (Measurement Indicator)	No. of Items	Cronbach's Alpha	Factors Loading	CR	AVE
Perceived ease of use (PEOU)	Riyath et al. (2022)	3	0.915	0.741-0.831	0.832	0.602
Perceived usefulness (PU)	Riyath et al. (2022)	4	0.913	0.712-0.899	0.894	0.681
Computer self-efficacy (CSE)	Riyath et al. (2022)	3	0.914	0.767-0.864	0.879	0.708
Performance expectancy (PE)	Lantu et al. (2023)	4	0.914	0.656-0.852	0.849	0.586
Facilitating conditions (FC)	Lantu et al. (2023)	4	0.912	0.694-0.830	0.829	0.549
Effort expectancy (EE)	Lantu et al. (2023)	4	0.910	0.839-0.884	0.918	0.737
Social influence (SI)	Lantu et al. (2023)	3	0.910	0.790-0.833	0.849	0.652
Hedonic Motivation (HM)	Hussain et al. (2022)	3	0.911	0.727-0.918	0.893	0.739
Behavioral intention (BI)	Lantu et al. (2023)	4	0.910	0.757-0.895	0.901	0.696
Use behavior (UB)	Lantu et al. (2023)	3	0.910	0.764-0.932	0.900	0.751

The overall value of Cronbach's Alpha of the 35 questions was 0.915 (Table 4), ranging from 0.910 to 0.915. Since the reliability score exceeded 0.7, the reliability statistics for the constructs under investigation are excellent, confirming the convergent validity of the assessment framework. Furthermore, according to West et al. (2023), a CR value of 0.70 or greater and an AVE value of 0.5 or higher are deemed appropriate. All the results of the CR (ranging from 0.832 to 0.918) and AVE (ranging from 0.549 to 0.751) in this investigation exceeded the threshold, validating the adequacy of convergent validity.

Table 4: Model Fit Indices for Measurement Model

Fit Index	Acceptable Criteria	Sources	Statistical Values
CMIN/DF	< 5.00	Al-Mamary & Shamsuddin, 2015; Awang, 2012	2.142
GFI	≥ 0.85	Sica & Ghisi, 2007	0.885
AGFI	≥ 0.80	Sica & Ghisi, 2007	0.860
CFI	≥ 0.80	Pedroso et al. 2016	0.949
NFI	≥ 0.80	Wu & Wang, 2006	0.908
TLI	≥ 0.80	Bentler, 1990	0.941
RMSEA	< 0.08	Sharma et al. 2005	0.048
Model Summary			**Aligned with Model Fit**

Remark: CMIN/DF = The ratio of the chi-square value to the degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, CFI = comparative fit index, TLI =Tucker-Lewis index, IFI = Incremental Fit Index, and RMSEA = root mean square error of approximation

On top of this, discriminant validity is established when the square root of the AVE surpasses the coefficient of any interrelated construct. The data presented in Table 5 shows that the square root of AVE for all constructs along the diagonal line was higher than the inter-scale correlations. Thus, the discriminant validity was ensured, as the measurement model applied in this study satisfies high standards of reliability and validity, providing a solid foundation for data analysis.

AU-GSB E-JOURNAL

Table 5: Discriminant Validity (Square root of AVE on diagonal)

	PEOU	PU	CSE	PE	FC	EE	SI	HM	BI	UB
PEOU	**0.789**									
PU	0.136	**0.825**								
CSE	0.282	0.164	**0.841**							
PE	0.116	0.236	0.342	**0.765**						
FC	0.153	0.274	0.077	0.146	**0.740**					
EE	0.076	0.240	0.200	0.236	0.456	**0.858**				
SI	0.067	0.214	0.145	0.246	0.449	0.506	**0.807**			
HM	0.029	0.196	0.049	0.141	0.298	0.360	0.523	**0.866**		
BI	0.069	0.191	0.106	0.242	0.268	0.369	0.520	0.451	**0.834**	
UB	0.098	0.204	0.086	0.159	0.334	0.413	0.438	0.376	0.643	**0.866**

Source: Generated by the author

4.3 Structural Equation Modeling (SEM)

The structural equation model (SEM) was conducted to validate its suitability, establish relationships among variables, and identify factors influencing behavioral intention and use behavior. The structural model's fit was evaluated using GOF indicators. The selected fit indices for the CFA comprised the CMIN/DF, GFI, AGFI, NFI, CFI, TLI, and RMSEA. This study used SPSS AMOS to import data and perform model verification and adjustments. The indices evaluated ten latent variables: PEOU, PU, CSE, PE, FC, EE, SI, HM, BI, and UB. The model fit was assessed by comparing the statistical values of the indices with the acceptable values of GOF. The statistical values obtained were as follows: CMIN/DF = 2.522, GFI = 0.850, AGFI = 0.818, NFI = 0.884, CFI = 0.926, TLI = 0.915, and RMSEA = 0.055. As a result, the structural model's fitness has met good fit thresholds after modification (Table 6).

Table 6: Goodness of Fit for Structural Equation Modeling

Fit Index	Acceptable Criteria	Statistical Values Before Modification	Statistical Values After Modification
CMIN/DF	< 5.00 (Awang, 2012; Al-Mamary & Shamsuddin, 2015)	3.021	2.522
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.817	0.850
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.791	0.818
CFI	≥ 0.80 (Bentler, 1990)	0.896	0.926
NFI	≥ 0.80 (Wu & Wang, 2006)	0.853	0.884
TLI	≥ 0.80 (Sharma et al., 2005)	0.888	0.915
RMSEA	< 0.08 (Pedroso et al., 2016)	0.064	0.055
Summary		**Not aligned with evidence**	**Aligned with evidence**

Remark: CMIN/DF = The ratio of the chi-square value to the degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, CFI = comparative fit index, TLI =Tucker-Lewis index, IFI = Incremental Fit Index, and RMSEA = root mean square error of approximation

4.4 Hypothesis Testing Results

Based on the findings illustrated in Table 7, four hypotheses (UB, HM, EE, and SI) were supported to have a significant relationship with BI, and five (PEOU, PU, CSE, PE, and FC) were not supported. The supported hypotheses are presented below:

Firstly, BI has the most significant influence on the UB (H9), with a β value of 0.838 and a t-value of 9.075. The intention to use e-learning to enhance learning outcomes, recognition of the benefits of e-learning, and the willingness to support e-learning, among others, all influence UB (Lantu et al., 2023). This is reflected in a fundamental finding of the technology adoption models (TAM, UTAUT, and UTAUT2).

Secondly, HM becomes the second determinant of BI (H8), exhibiting a β value of 0.278 and a t-value of 6.125, which includes the satisfaction and pleasure derived from online meeting platforms. This finding indicates that users who find online learning engaging are technologically capable and ready to utilize e-learning (Beh et al., 2019; Neeraj et al., 2019). Hence, system designers should integrate aspects that improve enjoyment in the system, and developers must also consider the elements of competing technologies that engage users' interest.

The third significant factor influencing BI is EE (H6), characterized by a β value of 0.165 and a t-value of 3.901. Studies showed that learners will apply technology when they find it easy, leading to an increase in its use (Liu & Tao, 2021; Namahoot & Jantasri, 2023; Paulo et al., 2018).

The fourth variable illustrates the effect of SI on BI, as indicated by a β value of 0.067 and a t-value of 7.299. SI significantly affects the desire to embrace technology in

AU-GSB E-JOURNAL

developing countries, as word-of-mouth from influential friends plays a crucial role in e-learning (Tarhini et al., 2017). Students seemed to depend on the testimonials of friends, family, and instructors to engage in e-learning. The influence of peers in this technology adoption is regarded as significant.

Table 7: Hypothesis Testing Result of the Structural Equation Model

Hypothesis	Paths	Standardized Path Coefficient(β)	T-value	Testing result
H1	BI←PEOU	0.058	1.360	Not Supported
H2	BI←PU	0.053	1.282	Not Supported
H3	BI←CSE	-0.038	-0.920	Not Supported
H4	BI←PE	0.077	1.702	Not Supported
H5	BI←FC	0.056	1.313	Not Supported
H6	BI←EE	0.165	3.901*	Supported
H7	BI←SI	0.067	7.299*	Supported
H8	BI←HM	0.278	6.125*	Supported
H9	UB←BI	0.838	9.075*	Supported

Note: *=p-value<0.05
Source: Generated by the Author

Nevertheless, the research found five correlations with no substantial influence, contradicting the findings of many other researchers, which are redefined as follows:

Firstly, the study revealed no statistically significant relationship between PEOU and BI (H1), with a β value of 0.058 and a t-value of 1.360. Aydin (2017) confirmed that the younger users do not find PEOU to impact BI, but older users consider it useful. Yang et al. (2017) found that students demonstrated no significant correlation between PEOU and BI. Additionally, PEOU is not an important factor for students who have experienced using technology (Nan et al., 2020).

Secondly, PU shows no significant relationship with BI (H2), as indicated by a β value of 0.053 and a t-value of 1.282. According to Sinaga et al. (2021), this can be attributed to differences in the study, respondent profiles, and usage habits. Students who perceive technology adoption as beneficial are more likely to engage in the services. Likewise, learners who perceive little benefit in adopting technology are unlikely to support the innovation. However, the result of this study did not suggest excluding this variable in subsequent research, as it may influence the effectiveness and efficiency of technology adoption for learning (Koksal, 2016).

Thirdly, CSE indicates an insignificant relationship with BI (H3) as it has a β value of -0.038 and a t-value of -0.920. This might be because individuals' confidence in their technology-related knowledge and abilities is more associated with their judgment of the ease or difficulty of using the system (Fokides, 2016). In addition, Gil-Flores et al. (2017) confirmed that CSE is one of the critical aspects that would impact the teachers using technology among Spanish teachers. Still, it was not found to be significant in the Indian context.

Fourthly, PE is another variable that is not significant to BI (H4), with a β coefficient of 0.077 and a t-value of 1.702. The potential trigger may be the students' insufficient awareness or comprehension of the advantages of utilizing technology for educational purposes. They may not recognize any benefits in using technology compared to conventional learning techniques or may struggle to adjust to the technology. Another reason may be the inadequate infrastructure or technical support within educational institutions, as well as insufficient training and supervision from teachers, which hinders students' ability to use technology effectively, thereby supporting the denial of this hypothesis. Further research is necessary to determine the variables influencing students' behavior in adopting technology for learning (Mensah, 2019).

Finally, FC shows a negligible effect on BI (H5), as indicated by a β coefficient of 0.056 and a t-value of 1.313. It is interesting to note that in developing countries, this insignificant impact might result from the lack of supportive facilitating conditions, which undermines the intention to apply e-learning because of inadequate resources and institutional support. Students must have the necessary technology, software, tools, and training to implement the system effectively, as well as available human resources for support in utilizing these new tools for learning. The availability of resources and systems to support learning creates trust in using technology (Liu & Tao, 2021; Namahoot & Jantasri, 2023).

5. Conclusion and Recommendation

5.1 Conclusion

The study showed that BI is the most significant influence on UB regarding technology adoption for learning, followed by EE, SI, and HM. Nonetheless, PEOU, PU, PE, CSE, and FC are insignificant to BI. This investigation confirmed the significant influence of H6, H7, H8, and H9, but H1, H2, H3, H4, and H5 were deemed insignificant due to unsupported hypothesis testing results. For the non-support hypothesis, numerous studies have shown that PEOU is relevant in influencing learners' intention to use technology, unless students receive training in digital literacy skills. Meanwhile, learners are encouraged to use

AU-GSB E-JOURNAL

technology when they see its benefits and improve their work performance (PU), as well as their confidence in technological competence, which is more directly associated with assessing the system's usability (CSE). Learners might have inadequate supporting conditions, influencing the willingness to adopt e-learning due to constrained resources and institutional support (FC). However, PE needs more research since students may not fully comprehend the benefits of technology due to limited awareness, inadequate infrastructure, and a lack of supervision from educators.

This study concludes that by increasing the number of students using technology for learning, the university management may wish to reinforce both support and non-support variables by augmenting the supported variables that affect BI and UB, namely EE, SI, and HM. Non-support variables, namely PEOU, PU, PE, CSE, and FC, are necessary for strengthening. Course designers and universities may wish to ensure the inclusion of all aspects when employing technology to support students. This will cultivate a favorable experience and increase their readiness to interact with technology for educational purposes, particularly in the digital age.

5.2 Recommendations

The following suggestions are proposed for university management to encourage students to utilize technology for educational purposes. Firstly, EE can be improved by allowing students to work with the technology easily, which will likely increase student engagement. Therefore, university management should provide an accessible design and content that encourages increased student engagement with technology. Secondly, SI may be predominantly shaped by the policies of university administration, senior management, and faculty members. Influential peers, who spread word of mouth, play a crucial role in e-learning. Students may depend on the suggestions of peers, family members, and other educators to engage in e-learning. The impact of peers on the individual adoption of technology is considered relevant. Thus, university administrators must implement technology as new students enroll and provide training. Educators must demonstrate the effective use of technology, as it is fundamental in influencing students' use of technology. Thirdly, HM affects the intention to utilize e-learning. It should encourage system developers to integrate features that will enhance the overall user experience. Educational administrators can make e-learning highly interactive. Policymakers and university administration should take an interest in student-led pedagogy. Fourthly, BI has the most significant impact on UB in terms of technology use for learning; a university administrator must oversee and evaluate the frequency of use or conduct surveys to assess user intention. Enhancing all supported variables in the study can assist a university in optimizing costs and leveraging human resources, improving its financial and non-financial efficiency.

The non-support variables (PEOU, PU, PE, CSE, and FC) are also necessary for improvement. Firstly, the findings from PEOU indicated that students could not entirely disregard technology since it is a fundamental component of higher education institutions, especially in the digital era. Students must interact with technology, regardless of its complexity or simplicity. University administrators and senior management must emphasize improving this area to ensure optimal utilization by selecting an appropriate and user-friendly solution. Secondly, PU can be ensured by demonstrating the advantages for students. Therefore, university administrators must provide programs to enhance students' awareness and instruction regarding the significance of utilizing technology for academic purposes. Thirdly, PE in employing technology is ensured when students are fully aware of its educational benefits, possess sufficient infrastructure, and receive guidance from instructors. University administrators may want to do further research to understand the specific demands. Fourthly, CSE is more directly linked with assessing the computer's accessibility. In this context, university administrators should equip students with both fundamental and advanced technology skills to enhance their confidence in applying technology for learning purposes. Fifthly, FC can be improved by a systematic training and evaluation process for students. Without adequate facilities and accessible human resources to enable this technology, a university may fail to optimize the efficiency of technology adoption, wasting time, effort, and financial resources invested in educational technology. University administrators may wish to collaborate closely with system developers to ensure optimal software performance through regular upgrades and provide additional resources to maximize the benefits of the technology used. Furthermore, the internet infrastructure is to be guaranteed to operate proactively and respond on time to learners' demands every day.

5.3 Limitations and Further Study

This study has some limitations. Many studies investigated several significant aspects of the BI and UB to adopt technology for educational purposes, but this research examines specific variables adapted from three models: TAM, UTAUT, and UTAUT2. The scope of study is confined to a single private university in Phnom Penh, Cambodia, which has potential relevance to other universities. It is noteworthy that the technology standards in developing and developed countries differ.

AU-GSB E-JOURNAL

In other words, this study employs a quantitative approach only. A qualitative technique (i.e., in-depth interviews or focus group discussions) can be used for comprehensive analysis and enhanced understanding. Future studies may involve interviewing those in management positions to gain a more profound knowledge of the technology for learning and organizing focus groups among teachers or students. Similarly, mixed approaches can be employed because they effectively identify inconsistencies between quantitative and qualitative results. This strategy can assist researchers in reflecting the perspectives of respondents. Mixed techniques enhance respondents' attitudes and ensure that the findings are substantiated by their experiences.

Ultimately, several factors influenced the behavior of both male and female learners. Male students' behavioral intentions are affected by system quality, but female students' behavioral intentions are influenced by information quality. Male students tend to exhibit lower responsiveness to social influence compared to female students. Men tend to show greater interest in the hardware, while women are more engaged with the content of communication. Future research should investigate gender disparities in the adoption of technology for educational purposes.

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