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Abstract

Universities are integrating e-learning into their programs. However, many factors influence students' adoption of technology for learning, and there is no consistent research agreement on this topic. This study identifies the factors that affect the behavioral intention and use behavior of virtual learning among students at Norton University, Cambodia. This study followed the three models: the Unified Theory of Acceptance and Use of Technology, the Extended Unified Theory of Acceptance and Use of Technology, and the Technology Acceptance Model. A questionnaire and a quantitative method were used to gather data from 500 respondents in years 2, 3, and 4. The item-objective congruence was used to evaluate content validity, and a pilot test of the questionnaire was conducted to assess Cronbach's alpha for reliability. Confirmatory factor analysis and structural equation modeling are employed to evaluate the goodness of fit and hypothesis testing. As a result, behavioral intention was found to have a strong relationship with use behavior, followed by effort expectancy, social influence, and hedonic motivation. The insignificant factors include perceived ease of use, perceived usefulness, computer self-efficacy, performance expectancy, and facilitating conditions. This study recommends improving students' engagement in virtual learning by enhancing effort expectancy, social influence, hedonic motivation, and behavioral intention. The insignificant variables, such as perceived ease of use, perceived usefulness, computer self-efficacy, performance expectancy, and facilitating conditions, are also necessary for improvement. Universities and course designers should prioritize educating students on digital literacy to ensure their effective engagement with technology for learning. This will increase their experiences and prepare them to interact with e-learning in the future, especially in the digital age.

Keywords: Behavioral Intention, Use Behavior, Technology Adoption, Virtual Learning, Digital Technology

Introduction

Technology influences people's lives every day (Haddock et al., 2022), and a future trend is that society will increasingly utilize more advanced technology to acquire knowledge (Voudoukis & Pagiatakis, 2022). The United Nations Educational, Scientific, and Cultural Organization (2023) reported that with the increasing competition among universities to succeed and attract new students, the use of technology for educational purposes has risen significantly over the past two decades. Virtual or e-learning was developed as part of digital technology, allowing all learners to have open communication without any barriers, creating a space for learning, simplifying the learning process, and helping students develop the necessary skills, talents, and mindsets (Vlachopoulos, 2020). Nikou and Economides (2017) argue that technology holds the promise of opening new opportunities for improved education through virtual learning environments, which motivates students to have a strong emphasis on technology (Fokides & Kefallinou, 2020).

Among other things, one of the most valuable aspects of virtual learning is the rapid advancement of technology, which is increasingly becoming a helpful component of education, necessitating consideration of methods to engage students in the online classroom beyond the computer and Internet (Martin & Bolliger, 2018). Technology is being increasingly utilized in higher education institutions worldwide, including curriculum development, knowledge sharing, and experience sharing, as well as lectures (Ibrahim et al., 2018). The benefits of virtual learning are gaining global recognition (Panigrahi et al., 2018). As a result, e-learning has been effectively utilized in both universities and industry, leading to improvements in the quality of teaching and learning, increased earnings, student achievement, and satisfaction (Chang, 2016).

Research Problem

Many universities introduced e-learning into their educational programs several years ago, but they may not be satisfied with this strategy. However, the satisfactory factors for learners have received little investigation in earlier studies (Nia et al., 2023), particularly in developing countries like Cambodia, where there is a lack of studies on students' intentions to adopt e-learning (Tarhini et al., 2017). Different studies showed both factors of influence and do not influence the behavioral intention, for example perceived usefulness and ease of use (Rahman et al., 2023) and performance expectancy, effort expectancy, social influences, work-life quality, internet experience, hedonic motivation, and facilitating conditions have relationship with e-learning (Al-Mamary et al., 2023; Tewari et al., 2023) where the self-efficacy does not correlate with behavioral intention (Sharma & Srivastava, 2019).

There is a lack of consistency in the studies on what elements influence behavioral intention to motivate students to use virtual learning. Moreover, several alternatives have been identified that affect students' willingness to apply virtual learning (Lai et al., 2024). This research examines the factors that influence behavioral intention and use behavior in virtual learning among undergraduate students at the College of Social Sciences at Norton University, the first private university in Phnom Penh, Cambodia, which integrates both traditional classroom and hybrid learning environments.

Research Question

The main research question asks, "What factors influence behavioral intention and use behavior among undergraduate students in the College of Social Sciences at Norton University, Cambodia, to adopt technology for learning?"

Research Objectives

The specific objectives are set as follows:

1. To identify the significant difference in perceived ease of use and behavioral intention to adopt technology for learning.
2. To identify the significant difference in perceived usefulness and behavioral intention in adopting technology for learning.
3. To identify the significant difference in computer self-efficacy and behavioral intention in adopting technology for learning.
4. To identify the significant difference in performance expectancy and behavioral intention in adopting technology for learning.
5. To identify the significant difference in facilitating conditions and behavioral intention in adopting technology for learning.
6. To identify the significant difference in effort expectancy and behavioral intention in adopting technology for learning.
7. To identify the significant difference in social influence and behavioral intention in adopting technology for learning.
8. To identify the significant difference in hedonic motivation and behavioral intention in adopting technology for learning.
9. To identify the significant difference in behavioral intention and use behavior in adopting technology for learning.

Significance of the Study

Based on the Cambodian Ministry of Education, Youth and Sport (2024), this study contributed to advancing the Cambodian Education Strategic Plan 2024-2028, which aims to support Cambodia's economic growth through digital learning via self-paced learning This will be achieved by utilizing e-learning to provide all educational sectors with the necessary services and to equip students with the technological knowledge and skills required for jobs in the digital era. Furthermore, the Supreme National Economic Council (2021) also confirmed that this study helped the Royal Government of Cambodia implement its Digital Economy and

Society Policy Framework 2021-2035, ensuring it is ready for the Fourth Industrial Revolution and capitalizes on digital transformation. Hence, understanding the elements that influence students' intention to employ technology for effective learning is essential. The results of this research are important for policymakers, university administration, and educators who are considering providing successful virtual learning.

Literature Review

Perceived Ease of Use

Perceived ease of use defines what people believe technology is not difficult to use (Davis, 1989). Numerous studies have shown a meaningful relationship between perceived ease of use and behavioral intention in virtual learning (Martin & Bolliger, 2018). The use of technology-related devices is crucial. This leads to the adoption of innovation, which is used without encountering any challenges (Hanafizadeh et al., 2012). People who trust technology that is easy to use are more likely to complete tasks and overcome any difficulties (Davis, 1989). They are more likely to adopt it for virtual learning and teaching (Abdullah & Ward, 2016). Perceived ease of use is the primary factor influencing undergraduate students' participation in virtual education and teaching.

Perceived Usefulness

Job performance improves when individuals accept the need to adapt and utilize new technology (Davis, 1989). Perceived usefulness refers to a person's belief in the use of technology and innovation, which is expected to increase productivity and is believed to contribute to the job's success through quick, efficient, and high-quality work (Aulia & Marsasi, 2024). The view of students toward adopting technology was significantly influenced by its perceived usefulness, especially in online education (Salloum & Shaalan, 2018). Davis (1989) confirmed that perceived usefulness has a positive influence on student performance, helping students improve their educational performance by utilizing technology, and making them most satisfied with their study program (Agudo-Peregrina et al., 2013). Perceived usefulness is a crucial factor in encouraging students to adopt new technology and enhance their academic performance.

Computer Self-Efficacy

Computer self-efficacy refers to what people believe they can accomplish in relevant roles effectively, including completing academic assignments and other educational tasks using a computer (Hayat et al., 2020). Self-efficacy in teaching-learning environments has been shown to lead to better learning opportunities when accompanied by a higher level of self-efficacy and improved student success (Alyoussef, 2021). Similarly, a study conducted by Mekheimer (2025) has indicated that students with computer-rich skills are more interested in e-learning. In this regard, computer self-efficacy is a key motivator to encourage students to increase their use of technology for learning purposes.

Performance Expectancy

Performance expectancy refers to the acknowledgment and respect for work accomplishment by others (Venkatesh et al., 2003), which leads to increased performance (Zhao & Bacao, 2021). Performance expectancy is found to be a primary factor influencing technology adoption, resulting in increased use of the computer system (Ciftci et al., 2023). Rahi et al. (2019) and Chua et al. (2018) have observed that when people rely on performance expectancy, they tend to use technology for a longer period. Performance expectancy motivates students to use technology, which in turn improves their academic performance.

Facilitating Conditions

Facilitating conditions refer to the availability of conditions that encourage people to use technology (Yuan et al., 2015). To ensure the widespread adoption of this technology, people must have access to adequate resources, satisfactory support, and personalized assistance (Ali et al., 2016). In this regard, facilitating conditions have been shown to influence users (Salloum & Shaalan, 2018), thereby fostering motivation and promoting the use of virtual learning systems (Tarhini et al., 2017). The features of facilitating conditions include personalized support, training, access to materials for skill improvement, and accessibility of e-learning systems (Salloum & Shaalan, 2018). Facilitating conditions make students more likely to use technology, promote its use to others, and continue using it.

Effort Expectancy

Effort expectancy is about the learner's perspective on using a computerized system (Mafuna & Wadesango, 2016). According to Venkatesh et al. (2012), effort expectancy refers to how people perceive interacting with others who use technology, as well as the effortless use of digitalized systems (Thongsri et al., 2018), which enables successful e-learning (Zabidi et al., 2017). The perception that students have of virtual learning as easy to use will influence their intention to use it and their continued use of it (Samsudeen & Mohamed, 2019). Effort expectancy is a key to driving students to adopt and continue using technology for e-learning.

Social Influence

Social influence refers to how family members and peers benefit from technology (Venkatesh et al., 2003). Social influence can be divided into interpersonal and media, which both teachers and peers may persuade students to adopt virtual learning, as well as by their own ability to utilize digital technology (Tarhini et al., 2017). Students are more likely to trust technology when they are informed by friends, teachers, and family members about its benefits (Gharrah & Aljaafreh, 2021). Social influence is a factor that enables students to apply technology in accordance with their peers, family, and teachers.

Hedonic Motivation

Hedonic motivation is about an individual's enjoyment and pleasure derived from using technology (Chao, 2019). Individuals who find virtual learning engaging are more likely to be proficient in technology and prepared to utilize online learning services (Venkatesh et al., 2012), which is a relatively significant finding (Tamilmani et al., 2019). Beh et al. (2019) reported that hedonic motivation is a key driver to influence people's adoption of technology and has a strong relationship with behavioral intention. Hedonic motivation is a key to stimulating students to adopt technology in online learning environments.

Behavioral Intention

Behavioral intention refers to the acceptable use of technology for learning purposes (Morton et al., 2016), encompassing both traditional and e-learning (Salloum & Shaalan, 2018). In addition, behavioral intention is characterized by the implementation and utilization of technology (Motahhir & Bossoufi, 2021). Two major factors contribute to why people adopt new technology while others do not (Venkatesh et al., 2003), including the positive impact of technology implementation and a committed relationship that influences people's behavior when applying technology (Al-Ralmi et al., 2022). Behavioral intention is a factor that positively impacts the use of technology for learning.

Hypotheses

H1: There is a significant difference between perceived ease of use and behavioral intention to adopt technology for learning.

H2: There is a significant difference between perceived usefulness and behavioral intention to adopt technology for learning.

H3: There is a significant difference between computer self-efficacy and behavioral intention to adopt technology for learning.

H4: There is a significant difference between performance expectancy and behavioral intention to adopt technology for learning.

H5: There is a significant difference between facilitating conditions and behavioral intention to adopt technology for learning.

H6: There is a significant difference between effort expectancy and behavioral intention to adopt technology for learning.

H7: There is a significant difference between social influence and behavioral intention to adopt technology for learning.

H8: There is a significant difference between hedonic motivation and behavioral intention to adopt technology for learning.

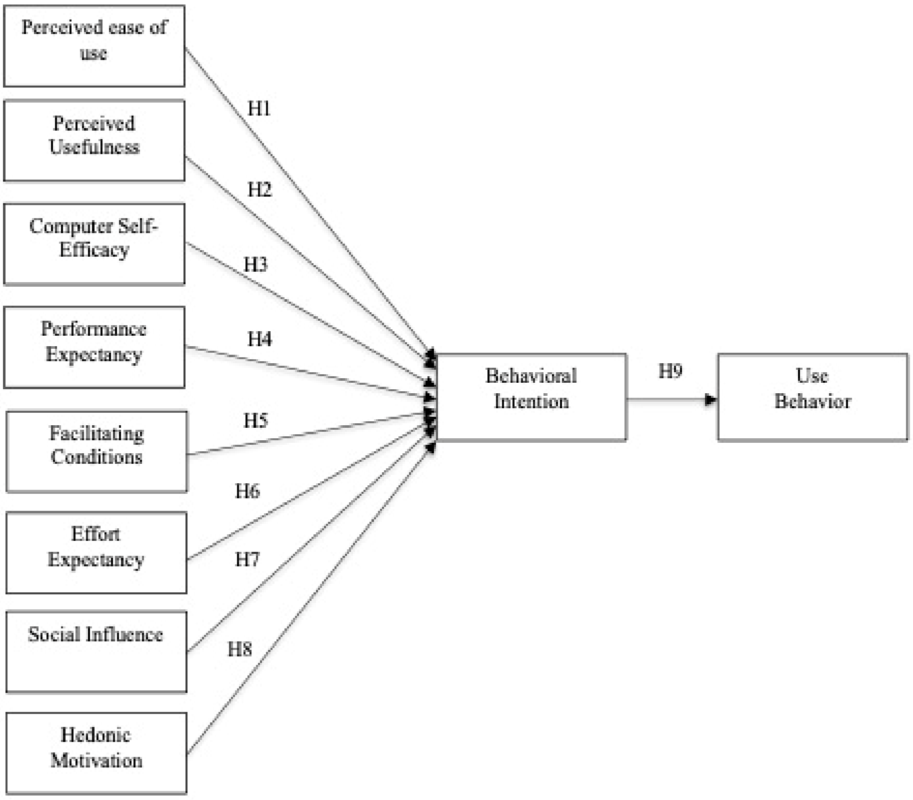
H9: There is a significant difference between behavioral intention and use behavior to adopt technology for learning

Research Framework

The study employs three models: the Technology Acceptance Model, the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Extended UTAUT (UTAUT2). These models are used to formulate a conceptual framework that aims to identify the factors influencing behavioral intention and use behavior among undergraduate students in virtual learning at the College of Social Sciences, Norton University, the first private university in Cambodia, as illustrated in Figure 1.

Figure 1

Conceptual Framework



Source: Developed by the author (2023)

Research Methodology

Research Design

This study employed a quantitative approach, utilizing a survey questionnaire. Item Objective Congruence was used to evaluate the scale item validity before data collection. Three senior educational specialists with 20 years of experience were invited to examine the questionnaire. The pilot study was conducted with 50 respondents to assess the internal consistency of the questionnaire using Cronbach's alpha (Killingsworth et al., 2016). The questionnaire was distributed to undergraduate students in years 2, 3, and 4 who are studying in the College of Social Sciences through the existing Telegram groups with the assistance of the College's employees. Respondents completed the questionnaire by self-administering it using the five-point Likert scale (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. Apart from the demographic information from the first section, the survey consists of 35 items: three items for perceived ease of use, four items for perceived usefulness, three items for computer self-efficacy, four items for performance expectancy, four items for facilitating conditions, four items for effort expectancy, three for social influence, three for hedonic motivation, four items for behavioral intention, and three items for use behavior. These items were developed based on the findings of previous studies (Hussain et al., 2022; Lantu et al., 2023; Lee, 2006).

The data were analyzed using Statistical Package for the Social Sciences (SPSS) and AMOS. Confirmatory Factor Analysis (i.e., validity, discriminant validity, and reliability) was used to validate the measurement model. Finally, the Structural Equation Model (SEM) is used to test for the relationship among the studied variables.

Population and Sampling Size

This study targeted undergraduate students in years 2, 3, and 4 from the College of Social Sciences at Norton University, who had some experience in virtual learning. The sample size for this study was calculated by using the A-priori Sample Size Calculator (Soper, 2023) for a structural equation model, with the expected effect size of 0.2, the desired statistical power level of 0.8, the number of latent variables of 10, the number of observed variables of 35, and the probability scale of 0.05. The small sample size for SEM was 138, the least detectable result was 475, and the recommended minimal sample size was 475. Therefore, this study gathered 500 respondents as the sample size for stronger statistical conclusions. Undergraduate students in their second to fourth years were selected for this study. Year-one students, who had less experience, were not included.

Table 1

Sample Units and Sample Size of Undergraduate Students

Majors	Population Size	Sample Size
Business	533	266
Economics	95	47
Law and Government	312	156
Hospitality and Tourism Management	61	30
Total	**1001**	**500**

Sampling Technique

The study employed a multi-phase sampling method that included purposeful or judgmental, stratified, and convenience sampling techniques to produce the most effective outcomes for the study (Etikan & Bala, 2017). Firstly, the study employed judgmental sampling to choose one college (College of Social Sciences). 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 chosen using screening questions to ensure that students are undergraduates from the target college with at least one year of prior experience using technology for learning purposes. The questionnaire, created in Google Forms, was sent to 700 respondents through existing students' Telegram groups between November 2023 and January 2024, with assistance from the College’s employees to gather their responses. Out of 700 questionnaires, 500 were administered by respondents for analysis, showing a 71.43 percent response rate, which is satisfactory for the study. According to Wu et al. (2022), achieving a survey response rate of 50 percent or higher would be a strong result.

Pilot Test

The pilot study was conducted with 50 respondents to assess the internal consistency of the questionnaire using Cronbach’s alpha (Killingsworth et al., 2016). Tabachnick and Fidell (2007) confirm that an increase in alpha value leads to an improvement in a scale's consistency and dependability, and a value larger than 0.7 is recommended as appropriate (Straub, 1989). In this study, the overall results 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 (Table 2).

Table 2

Result of Pilot Test

Variables	No. of items	Sources	Cronbach's Alpha	Interpretation
Perceived ease of use	3	Lee (2006)	0.752	Good
Perceived usefulness	4	Lee (2006)	0.912	Excellent
Computer self-efficacy	3	Lee (2006)	0.701	Good
Performance expectancy	4	Lantu et al. (2023)	0.858	Very good
Facilitating conditions	4	Lantu et al. (2023)	0.761	Good
Effort’s expectancy	4	Lantu et al. (2023)	0.880	Very good
Social influence	3	Lantu et al. (2023)	0.825	Very good
Hedonic motivation	3	Hussain et al. (2022)	0.898	Very good
Behavioral intention	4	Lantu et al. (2023)	0.904	Excellent
Use behavior	3	Lantu et al. (2023)	0.782	Good

Results and Discussion

Demographic Information

Out of 500 respondents, 53 percent were female students, 37 percent were male students, 7 percent preferred not to disclose their gender, and 3 percent reported non-binary. The majority, 47 percent, were between the ages of 21 and 22, 29 percent were between 23 and 24, and 20 percent were in the 19 to 20-year age range. There were 3 percent who were over 25, and only 1 percent, a smaller portion of respondents, were in the 15-18 age group. For the academic year, 66 percent of the population were senior students, followed by junior students at 22 percent, and sophomore students at 12 percent.

Confirmatory Factor Analysis

Confirmatory Factor Analysis (CFA) is employed to assess the reliability and validity of the theoretical framework, as well as the measurement tools. Table 3 explains the confirmatory factor analysis (CFA), composite reliability (CR), and average variance extracted (AVE). As per Hair et al. (2017), a Composite Reliability (CR) value of 0.70 or greater and an Average Variance Extracted (AVE) value of 0.5 or above are appropriate. All the results of the CR (between 0.829 and 0.919) and AVE (between 0.549 and 0.764) in this study exceeded the threshold, validating the adequacy of convergent validity.

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)	Lee (2006)	3	0.924	0.751-0.816	0.829	0.618
Perceived usefulness (PU)	Lee (2006)	4	0.922	0.783-0.891	0.894	0.681
Computer self-efficacy (CSE)	Lee (2006)	3	0.923	0.764-0.876	0.863	0.678
Performance expectancy (PE)	Lantu et al. (2023)	4	0.923	0.656-0.852	0.839	0.567
Facilitating conditions (FC)	Lantu et al. (2023)	4	0.922	0.698-0.821	0.829	0.549
Effort expectancy (EE)	Lantu et al. (2023)	4	0.920	0.838-0.882	0.919	0.740
Social influence (SI)	Lantu et al. (2023)	3	0.919	0.794-0.835	0.850	0.654
Hedonic motivation (HM)	Hussain et al. (2022)	3	0.919	0.719-0.920	0.895	0.742
Behavioral intention (BI)	Lantu et al. (2023)	4	0.919	0.767-0.897	0.904	0.702
Use behavior (UB)	Lantu et al. (2023)	3	0.910	0.763-0.935	0.906	0.764

Note: Developed by the Author

On top of this, discriminant validity is implemented when the square root of the AVE surpasses the coefficient of any interrelated construct (Fornell & Larcker, 1981). For every construct along the diagonal line, the square root of AVE was higher than the inter-scale correlations (Table 4). Because the measuring model used has met strict reliability and validity requirements, discriminant validity was enhanced, providing a strong foundation for data analysis.

Table 4

Discriminant Validity

	PEOU	PU	CSE	PE	FC	EE	SI	HM	BI	UB
PEOU	**0.786**									
PU	0.261	**0.834**								
CSE	0.227	0.290	**0.823**							
PE	0.058	0.236	0.306	**0.752**						
FC	0.160	0.287	0.066	0.123	**0.746**					
EE	0.053	0.311	0.163	0.203	0.466	**0.860**				
SI	0.065	0.243	0.110	0.211	0.421	0.475	**0.808**			
HM	0.102	0.220	0.048	0.193	0.368	0.387	0.732	**0.861**		
BI	0.064	0.219	0.063	0.225	0.299	0.447	0.565	0.668	**0.837**	
UB	0.112	0.228	0.052	0.142	0.349	0.394	0.448	0.528	0.688	**0.874**

Structural Equation Model (SEM)

The structural equation model is a statistical tool used to validate its suitability and assess the relationships among the studied variables. The structural model's fit was evaluated using Goodness of Fit (GOF) indicators to compare the statistical values of the indices from the study with the acceptable criteria. The fit indices for the CFA comprised the ratio of the chi-square value to the degree of freedom (CMIN/DF), goodness-of-fit index (GFI), adjusted goodness-of-fit index (AGFI), comparative fit index (CFI), Normed Fit Index (NFI), Tucker-Lewis index (TLI), and root mean square error of approximation (RMSEA), which were calculated using SPSS AMOS to import data and perform model verification and adjustments. As a result (Table 5), the structural model's fitness has met the reasonable fit thresholds, confirming the conclusion of this study.

Table 5

Goodness of Fit for Structural Equation Modeling

Fit Index	Acceptable Criteria	Sources	Statistical Values After Modification
CMIN/DF	< 5.00	Awang (2012); Al-Mamary and Shamsuddin (2015)	2.290
GFI	≥ 0.85	Sica and Ghisi (2007)	0.868

Fit Index	Acceptable Criteria	Sources	Statistical Values After Modification
AGFI	≥ 0.80	Sica and Ghisi (2007)	0.838
CFI	≥ 0.80	Bentler (1990)	0.942
NFI	≥ 0.80	Wu and Wang (2006)	0.902
TLI	≥ 0.80	Sharma et al. (2005)	0.933
RMSEA	< 0.08	Pedroso et al. (2016)	0.051

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, NFI= Normed Fit Index, TLI =Tucker-Lewis index, and RMSEA = root mean square error of approximation

Hypotheses Testing Results

The hypotheses testing results showed that H6, H7, H8, and H9 were supported, but not for H1, H2, H3, H4, and H5 (Table 6). Behavioral intention and use behavior showed a strong correlation (β = 0.748) in this study, which is consistent with previous research (Lantu et al., 2023). Also, they reflected in key findings from technology adoption models (TAM, UTAUT, and UTAUT2). Hedonic motivation emerged as the second determinant of behavioral intention, with a β value of 0.278, aligning with the findings of Beh et al. (2019) and Dhiman et al. (2019). The third significant factor influencing effort expectancy has a β value of 0.165, consistent with other studies (Liu & Tao, 2022; Namahoot & Jantasri, 2023; Paulo et al., 2018). The fourth variable demonstrates the effects of social influence on behavioral intention, as indicated by a β value of 0.067, which is supported by Tarhini et al. (2017).

Table 6

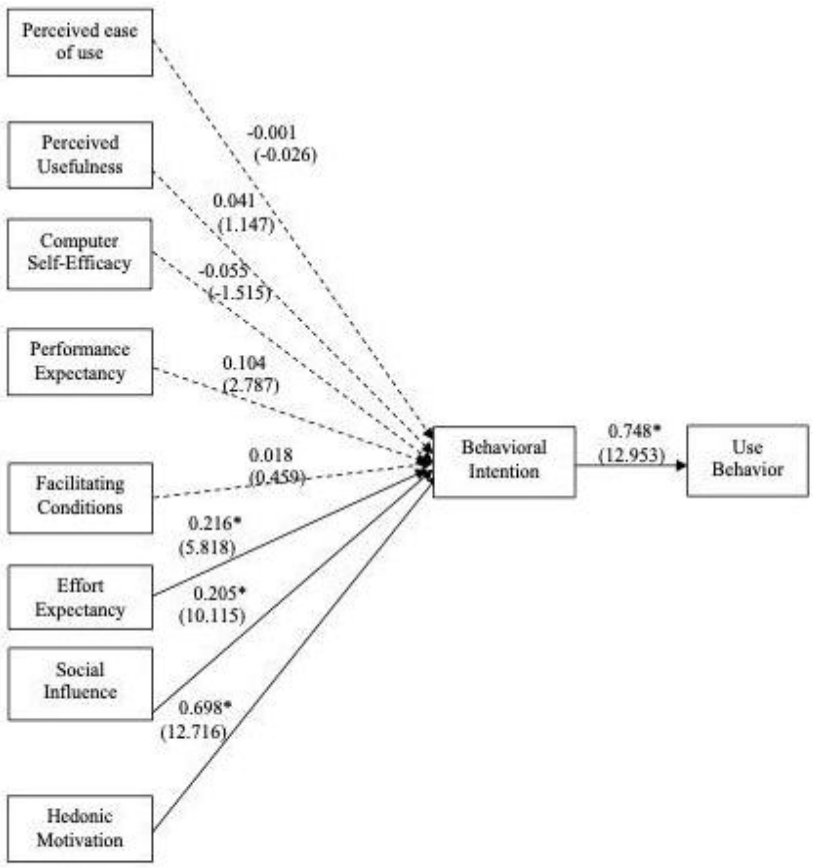
Hypothesis Result of the Structural Equation Model

Hypothesis	Paths	Standardized Path Coefficient (β)	S.E.	T-value	Testing result
H1	BI←PEOU	-0.001	0.079	-0.026	Not Supported
H2	BI←PU	0.041	0.081	1.147	Not Supported
H3	BI←CSE	-0.055	0.064	-1.515	Not Supported
H4	BI←PE	0.104	0.065	2.787	Not Supported
H5	BI←FC	0.018	0.036	0.459	Not Supported
H6	BI←EE	0.216	0.046	5.818*	Supported
H7	BI←SI	0.520	0.037	10.115*	Supported
H8	BI←HM	0.698	0.082	12.716*	Supported
H9	UB←BI	0.748	0.048	12.953*	Supported

Note: *=p-value<0.05

Figure 2

The Results of Structural Equation Modeling



Note: Solid line represents the Standardized Coefficient with * p<0.05, and t-value in Parentheses. Dash line represents Not Supported.

Five of the variables mentioned in Figure 2 do not have any statistically significant relationships in this study. First, several studies from the literature review support that perceived ease of use has a significant relationship with behavioral intention (Hanafizadeh et al., 2012; Martin & Bolliger, 2018). However, based on Aydin (2017) and Yang et al. (2017), perceived ease of use ($\beta = -0.001$) is found to be insignificant, suggesting that this variable may be unhelpful for younger users but important for older users.

Second, perceived usefulness ($\beta = 0.041$) was found to be insignificant, which is opposite to the study by Agudo-Peregrina et al. (2013), which reported a positive relationship. Another finding by Sinaga et al. (2021) reveals an insignificant difference, suggesting that variations in research methodology, respondent profiles, and usage habits contributed to the lack of support for the perceived usefulness in this study. In this sense, it recommends considering this variable in future studies (Koksal, 2016).

Third, computer self-efficacy was not supported ($\beta = -0.055$) in this study; however, it did support behavioral intention, as observed in research carried out by Alyoussef (2021).

According to Fokides (2016), computer self-efficacy is not a significant finding in this study, which is attributed to the confidence students have in their technological knowledge, related to the ease or difficulty of use. It is interesting to note, based on Gil-Flores et al. (2017), that computer self-efficacy is a key motivator affecting behavioral intention in various contexts. For instance, Spanish teachers see computer self-efficacy as motivating them to use e-learning, but this did not happen in the Indian environment.

Fourth, performance expectancy ($\beta = 0.104$) was found to be insignificant, suggesting that students may struggle to accept technology due to factors such as limited knowledge, inadequate infrastructure, insufficient technical support, and inadequate instructor supervision. This could make it harder for them to use technology for learning, and further research is needed (Mensah, 2019). Contrary to this finding, studies by Chua et al. (2018), Rahi et al. (2019), and Ciftci et al. (2023) suggest that performance expectancy is a key factor influencing the adoption of technology.

Finally, facilitating conditions ($\beta = 0.018$) showed a lack of support, suggesting that this may be due to a lack of institutional support and resources, which can impact students' intention to use technology efficiently. Therefore, the availability of resources and systems to support learning creates trust in using technology (Liu & Tao, 2022; Namahoot & Jantasri, 2023). In other studies, the finding shows that facilitating conditions influence students' adoption of e-learning (Salloum & Shaalan, 2018; Tarhini et al., 2017).

Although the above five hypotheses do not support this study with undergraduate students at Norton University, management may consider developing e-learning skills and competencies, as this is likely to influence future intentions to use technology for learning. This is crucial in developing countries because digital literacy is highly relevant to the adoption of technologies. Therefore, teaching students the skills of digital literacy can strengthen their effective communication with technology.

Conclusions and Recommendations

Conclusion

This study aims to determine the elements that impact behavioral intention and use behavior in employing virtual or e-learning among students at Norton University, Cambodia. The findings showed that behavioral intention is the most significant factor, followed by effort expectancy, social influence, and hedonic motivation. The insignificant elements in this study were demonstrated with perceived ease of use, perceived usefulness, performance expectancy, computer self-efficacy, and facilitating conditions. The study concludes that, to increase the number of students in e-learning, the university management must reinforce both support and non-support variables by augmenting the supported variables. Non-support variables are also necessary for strengthening. Course designers and universities should ensure the inclusion of all aspects when employing e-learning to support students. This will cultivate a favorable experience and increase their readiness to interact with e-learning, especially in the age of digitalization.

Recommendations

The study proposed several suggestions to enhance effort expectancy, social influence, hedonic motivation, and behavioral intention, thereby improving students' engagement in e-learning by allowing them to access the design and content. Policymakers, senior management, and faculty members can shape e-learning adoption. Peers and educators can significantly influence the adoption and effectiveness of virtual learning. Hedonic motivation encourages software engineers and developers to enhance the user experience and promote student-led pedagogy. Behavioral intention can help optimize costs and leverage human resources, improving financial and non-financial efficiency.

The non-support variables are also necessary for improvement. University management should prioritize promoting awareness of the importance of digital technology in daily educational activities. Moreover, the university must be equipped with an Internet infrastructure so that students can easily access it for their learning purposes. Additionally, the University should consider providing capacity-building opportunities, such as training for students on subject matters related to technology skills, to enhance their confidence in e-learning. System developers need to develop software with a user-friendly performance for students and other stakeholders.

Limitations and Further Study

The scope of this study is limited to one private university in Cambodia, which may have potential relevance to other universities. It is noteworthy that the technology standards in developing and developed countries differ. This study employs a quantitative approach only; however, a qualitative technique could be used for a comprehensive analysis and enhanced understanding in the future, or a mixed-methods approach could be employed. Numerous factors influenced the behavioral intention of both male and female learners. Future research should investigate gender disparities in technology adoption for educational purposes.

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