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Research article

Factors Influencing Students' Behavioral Intention on Using Mobile Learning (M-Learning) in Tourism and Hospitality Major in Phnom Penh, Cambodia

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Abstract

Technology has rapidly improved and become a crucial tool for education. It provides both new content and opportunities that learners could employ for learning, especially mobile learning. To get an effective adoption and operation of new technology, it is imperative to understand factors influencing student's intentions to use it. The paper presents student behavioral intentions on using mobile learning among university students in Phnom Penh, Cambodia, by adopting the extended technology acceptance model (TAM). A quantitative method was employed using a survey with a 5-Point-Likert scale. Questionnaires were administered to 420 students majoring in Tourism and Hospitality in Cambodia through a stratified sampling method, with the return rate of 98.33 percent. Structural equation modeling (SEM) was employed to analyze the relationship between the proposed determinants of the research model by employing AMOS. The results illustrate that self-efficacy, personal innovativeness, perceived enjoyment, and social influence have significant effects on the perceived ease of use and perceived usefulness towards students' behavioral intention to use mobile learning in the proposed model. Based on these results, some recommendations for implications and further research have been proposed.

Keywords

behavioral intention;

mobile learning;

tourism;

hospitality

1. Introduction

Technology has changed people's lifestyles dramatically. It has become a core component that is fundamentally involved with their daily lives and a key driver for improving our society. People utilize technologies for different purposes such as traveling, communicating, doing business, and

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studying or learning [1]. There are many benefits of employing and integrating technology in the education system since it can avoid limitations of time, space, and cost [2]. The education system in developing countries is different from that in developed countries. Governments in rich countries give an assortment of instructive help to students at all levels, which include funds and technology accessibility. Providing a better education framework for a nation is necessary because it can influence the quality of life of the people within the country [3].

Producing better educated people in Cambodia is a priority for driving economic growth in the future and for competing with other countries in the region. According to the Global Competitiveness Index (GCI) 2017-2018, Cambodia was positioned 124th among 137 nations, and had the poorest tertiary instruction levels and the training sector [4]. Skills gap is the critical challenge because it can lead to a mismatch between skills supplied by the available workforce and skills demanded by markets; therefore, qualified trainers and financial support to the poor family students as well as to the outstanding students should be set in the strategic plan and implemented in order to motivate them to keep developing their competency that meet market demand in the technology era [5, 6]. In the meantime, realizing the importance of information and communication (ICT) in education, the Cambodian government has start to incorporate ICT in instruction policy [7]. The speedy adoption of ICT into the Cambodian instruction framework offers benefits and a timely opportunity to initiate an innovative distance education system that allows possible access for learners at all levels, especially through smartphones [8]. For instance, the number of web clients was 12.5 million in 2018 and over 19.16 million mobile connections, a 3.18 percent increase compared to 18.57 million in 2017 [9]. Moreover, the Royal Government of Cambodia (RGC) envisions updating the Cambodian industry from labor-intensive to knowledge and skilled labor by 2025 by setting up a technology-driven and knowledge-based modern industrial economy. Following this, the Ministry of Education, Youth, and Sports (MoEYS) has considered ICT as an accelerator (catalysts) for human resource development in the 21st-century economy. MoEYS [10] plans to mix ICT within the educational system, making ICT a means of teaching, learning, and knowledge distribution. With this statement, MoEYS has planned to adopt e-learning to leverage education delivery for students and organization capacity building, and for lifelong learning purposes.

In line with the RGC's vision and MoEYS's commitment, this study intends to explore the factors that impact student behavioral intention to use mobile learning (M-learning) after the RGC has included it in the education sector at all levels. It looks difficult to make it sustainable since it is new technology for Cambodian users, especially students and trainers/teachers. Hence, there are many problems that MoEYS needs to identify and solve in advance. To successfully adopt and implement new technology as a learning tool, research on factors affecting user intentions to adopt new technology in advance is considered necessary because it is unclear whether learners and educators will intentionally use this technology. Moreover, the shortage of previous studies on learners' mindset of technology use in studying and in the perspective of M-learning usage individually has encouraged this recent research. This study, therefore, will investigate factors that influence student perceptions concerned with accepting and taking advantage of M-learning through the extended technology acceptance model (TAM) [11].

A number of previous studies on M-learning have been conducted in many different parts of the world. For example, Ali *et al.* [12] investigated how experiences and other determinants influence student intention to adopt Second Life (SL) at the University of Bahrain. They used TAM by focusing on computer self-efficacy, computer playfulness, and computer anxiety. Calisir *et al*. [13] also employed TAM to examine factors influencing employee intention to consume a web-based learning platform in the automotive firm. Their explanatory variables included image, perceived content quality, and perceived system quality. Furthermore, Walczuch *et al*. [14] explored the correlation of personality of the workers and technology acceptance by blending the technology readiness index (TRI) with TAM, focusing on such variables as optimism, innovativeness, discomfort, and insecurity. Moreover, Jackson *et al*. [15] applied three theories, Innovation Diffusion Theory (IDT), Theory of Planned Behavior (TPB), and Unified Theory of Acceptance and use of Technology (UTAUT), to test the correlation in the mediation model between personal innovativeness and user acceptance of technology at hospitals in South Korea. Those mediators are usefulness, ease of use, subjective norm, perceived behavioral control, compatibility, image, and result demonstrability towards behavioral intention.

Although many pieces of research and literature can be found about M-learning overseas, few if any have specifically addressed challenges in the adoption of ICT for education in Cambodia. These few pieces include Richardson's qualitative study [16], which used the theory of the diffusion of innovation to address the barriers, challenges, and successes in the adoption of technology training by trainers in Cambodia, and Phin's opinion-based research which discussed issues and benefits of the adoption of E-learning [17].

Our investigation runs in parallel with the previous literature in that we also determine the factors affecting student behavioral intention to adopt mobile learning through TAM. However, we have proposed a framework based on the Cambodian context by extending a few explanatory variables such as self-efficacy, mobile anxiety, personal innovativeness, perceived enjoyment, and social influence. They directly affect the core cognitive dimensions (perceived ease of use and perceived usefulness) toward the behavioral intention through TAM. Additionally, this paper employs a quantitative methodology to logically confirm the relationships of the constructs through the proposed model within a specific field, Tourism and Hospitality – that could give us insights about the student intention and adoption phase. Hence, it is expected that this study will yield benefits in terms of academia, both in theoretical and practical work. It can also help other researchers to verify the validity of TAM when employing those technologies.

Our research involved a study of the theory of Davis [18]; his technology acceptance model (TAM). The acceptance model aims to elucidate the determinants that anticipate the behavioral intention and describe the adoption process. The theory of reasoned action (TRA) [19] and the technology acceptance model (TAM) [20] simplify technology acknowledgment and the predecessors that make it complicated. TAM is used to investigate the causal relationship of determinants [18]. Based on the model, the attitude of users toward the proposed system indicates vital variables. It can control the core beliefs: perceived usefulness and perceived ease of use while perceived ease of use permanently determines perceived usefulness. Also, perceived usefulness and perceived ease of use are directly affected by design features or external factors and indirectly by attitude or behavior. If a system is simple to utilize for clients, their work performance will increase as they think it is beneficial. If the users' job become more fruitful using the given system via greater ease of use, they will increase productivity. Therefore, the system performance could indirectly affect usefulness by disturbing ease of use. Afterward, Venkatesh and Davis [11] developed TAM based on the experiment results. The researchers demonstrated that the two core cognitive factors, perceived ease of use, and perceived usefulness, had a relationship with behavioral intention.

The extended technology acceptance model [11] was developed to investigate determinants that affect student behavioral intention to use M-learning in Cambodia, as demonstrated in Figure 1. Both perceived ease of use (PEOU) and perceived usefulness (PU) have direct positive effects on student behavioral intention (BI). Additionally, perceived ease of use has a straightforward relationship with perceived usefulness. There are five exogenous variables: self-efficacy (SE), mobile anxiety (MA), personal innovativeness (PI), perceived enjoyment (PE), and social influence (SI). They have direct effects on PEOU as well as PU towards BI to employ M-learning as shown in Figure 1.

Behavior can be considered as control of the conscious will. If people intend to do something, they will demonstrate it as an action. Behavioral intention is also defined as how to

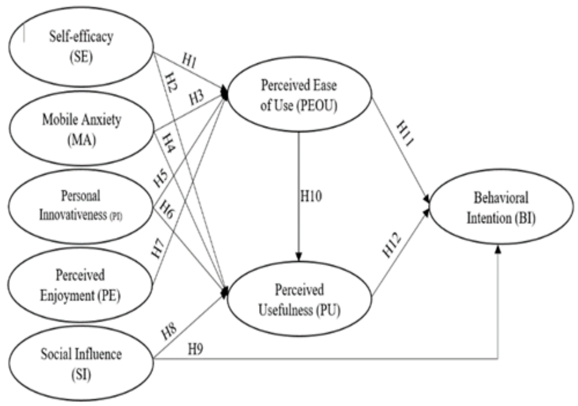

Figure 1. Conceptual Framework

inspire an individual and how appreciated he or she is in carrying out the behavior: e.g., I plan to [behavior] [21]. Consequently, people intend to do or not to do a specific task depending on their degree of salient beliefs or what they get from their society or their referents [19, 20, 22]. Design features or external factors can directly affect the two core salient beliefs towards behavior, perceived ease of use, and perceived usefulness. When a user finds a piece of technology easy to use and fruitful, they will intentionally employ it. Hence, knowing how determinants influence behavioral intention allows us to deeply understand and measure how often students intend to use mobile learning.

Self-efficacy is analyzed for its affirmative influence on perceived ease of use of utilizing mobile learning by students. Generally, it refers to an individual's self-confidence or self-judgment on his/her capacity to actualize an assigned task or work. However, in a particular context as technology, it is characterized as an individual's self-confidence or self-judgment on his/her capacity to actualize particular occupations or work using technology [23-26]. Self-efficacy provides a significant relationship with PEOU and PU [27, 28]. In learning aspects, once the students have learned how to use mobile learning effectively, they find the affirmative belief in the system that it is convenient to utilize and helpful to them. Hence, we propose the following hypotheses:

H1-Self-efficacy will emphatically influence the perceived ease of use of using mobile learning.

H2-Self-efficacy will emphatically influence the perceived usefulness of using mobile learning.

For mobile anxiety (MA), it is considered as another vital variable that impacts students' behavioral deliberation to devour mobile learning through mediators. It is defined as the negative thoughts or fears of operating mobile learning the study that users might face [25, 13, 29]. The users will intentionally use mobile learning technology if they find it positive and can easily adjust to it. Similarly, Venkatesh and Morris [30] explained that if users find there are no fears or less negative thoughts about using a specific technology, they tend to use it more often than the users who have many negative thoughts. Many studies have also confirmed that mobile anxiety features a negative impact on both PEOU and PU [27, 31]. Based on this, we posit the following hypotheses:

H3-Mobile anxiety will have a negative impact on the perceived ease of use of utilizing mobile learning.

H4-Mobile anxiety will have a negative impact on the perceived usefulness of utilizing mobile learning.

For personal innovativeness (PI), it refers an individual's opinion on an implementation object considered new or challenging by others. In technological and educational settings, it is characterized as students' acceptance to utilize the innovation or form change either in learning techniques or in the learning process. Commonly, people with highly positive personal innovativeness seem more likely to try new things or new high-tech due to its ease and benefits. On the other hand, if they are less personal innovation, they may not be likely to use it [32]. It is also assigned to be the main factor to measure the effect of behavioral deliberateness to utilize mobile learning. Few works of literature have emphatically confirmed its influence on PEOU and PU [33, 13]. Accordingly, we propose the following hypotheses:

H5-Personal innovativeness will emphatically influence the perceived ease of use of mobile learning usage.

H6-Personal innovativeness will emphatically influence the perceived usefulness of mobile learning usage.

For perceived enjoyment (PE), it alludes to the level of fun and satisfaction that students have when they operate a mobile phone in a study within their rights [29]. It is imperative to consider its influences on students' behavioral deliberative acknowledgement to utilize mobile learning through straightforwardly perceived ease of use. The clients appreciate modern innovation when they discover it is simple to use [34]. Consequently, ii is believed that perceived enjoyment can serve as the core determinant for predicting the effect of PEOU in BI to employ mobile learning [25, 35]. Thus, the following hypothesis is drawn:

H7-Perceived enjoyment will have a positive impact on perceived ease of use on utilizing mobile learning.

As for social influence (SI), it alludes to a person's degree of personal recognition that it is significant to carry out his/her behavior or not in questions because of other contemplations [19, 26]. It is not about social conditions towards decision making but also the interactions with what social-circle opinions or educational institution policy are. Therefore, those opinions might be the most critical thought and thus should be taken into account before accepting mobile learning as a new way of learning [26]. There are numerous observational thoughts about the verification that social influence has coordinated impact on behavioral purposefulness. Venkatesh *et al*. [36] confirmed that social influence directly impacts client acknowledgment and utilization behavior of innovation. Furthermore, social influence is considered by implication influences students' behavioral purposefulness to utilize mobile learning via perceived usefulness based on the TAM [18]. As a result, the hypotheses are proposed as follows:

H8-Social influence will coordinate certifiable impacts on the perceived usefulness of utilizing mobile learning students' behavioral intention.

H9-Social influence will coordinate agreed impacts on the behavioral intention of utilizing mobile learning.

Perceived ease of use (PEOU) and perceived usefulness (PU) have been defined as positive effects on students' behavioral intention to adopt mobile learning. Additionally, PEOU has a direct positive effect on PU towards the intention [20, 11]. In terms of technology use, when users feel easy to use and find that their work performance and productivities are enhanced, they will intentionally employ it. Many empirical studies confirm these relationships. Li *et al*. [37] found a correlation between e-learners' experience and perception towards behavior to re-employ the e-learning framework. The results showed that perceived ease of use and perceived usefulness affected behavioral intention to re-use e-learning. Similarly, Phatthana *et al*. [38] mentioned that perceived ease of use and perceived usefulness directly affected the deliberate re-purchase health tourism via the technology acceptance model (TAM). Subsequently, we have come up with three more hypotheses:

H10-Perceived ease of use will have positive coordinate impacts on perceived usefulness towards behavioral intention to use mobile learning.

H11-Perceived ease of use will have positive coordinate impacts on the behavioral intention to consume mobile learning.

H12-Perceived usefulness will have positive coordinate impacts on the behavioral intention to expand mobile learning.

2. Materials and Methods

The study employed a quantitative approach and a descriptive technique to determine the correlation between technology acceptance and student behavioral intention to use mobile learning in Hospitality and Tourism majors at higher education institutes in Phnom Penh, Cambodia. Questionnaires were used to collect data from students in that major according to the research objectives, scope, and limitations. The result from the surveyed questionnaires were treated as the primary data. Structural Equation Modeling (SEM) was applied to test the relationship among the variables in the core constructs of the technology acceptance model (SI, SE, MA, PI, PE, PEOU, and PU variables) and student behavioral intention to use mobile learning technology to improve their learning process in the Hospitality and Tourism major. Creswell and Creswell [39] mentioned that a quantitative approach is a better way to learn about the relationships and effects among variables. Their work focuses on experiment and survey as the research tools for collecting statistical data.

In structural equation modeling (SEM), sample size as the rule of thumb is recommended by Green [40] to be more than 10 times the number of parameters to be estimated and the minimum being a subject of parameter ratio 10:1 according to Kline [41]. Mathematically, the sample size can be calculated as 10 x 39 = 390. However, to avoid data missing, Hair *et al*. [42] recommend adding up (10 percent) in sample size, which is greater than 400 (>400), since the statistical algorithms cannot rely on small samples in SEM. It can also minimize the error of abnormal data and increase stability. Therefore, in this study, 420 sample sizes were considered acceptable based on 39 parameters.

The probability sampling method was applied in this research. Multi-steps were employed for sampling techniques (4 universities) in this study to be clear that each target population has an equal chance to be selected. In step 1, we used simple random sampling (SRS) to select four universities or institutes among nine universities or institutes located in Phnom Penh, which are under the control of the Ministry of Tourism [43]. As a result, four universities or institutes were selected, namely National Polytechnic Institute of Cambodia (NPIC), Asia Euro University, Institute of Hospitality and Tourism of Phnom Penh, and PSE Institute. Step 2, the stratified sampling method was used to select 420 respondents from the four chosen universities. We decided to select 105 respondents from each university or institute among the four to answer the questionnaire for the data collection. The returned ones were screened for missing data. Of the 420-distributed questionnaires, 413 were returned. However, 405 were fully completed. After careful checking, we eliminated five questionnaires that had improper responses. As a result, there were 400-finalized questionnaires for coding and further analysis. The actual response rate was 95.24 percent, as shown in Table 1.

The questionnaire that was employed to perform data collection. It was directly delivered to students at their site to respond, as a self-administered questionnaire. It was divided into two parts. In Part 1, the demographic profile information of respondents was separated into two sections: Respondent Profile (gender, age, degree) and Respondent Behavior (internet use and

Table 1. Survey-returned rate

	Number	Percent (%)
Target sample size	420	100
Questionnaires distributed	420	100
Questionnaires returned	413	98.33
Unusable questionnaires	13	3.15
Total usable questionnaires	400	95.24

experience using mobile digital devices). Part 2 focused on the seven independent variables (SE, MA, PI, PE, SI, PEOU, and PU) and the dependent variable (BI) (see Table 2). Thirty-nine questions were equal to 39 items. Specifically, they were: three-items of SE adjusted from Ali *et al*. [12], four-items of MA adapted from Calisir *et al*. [13], seven-items of PI selected from Walczuch *et al*. [14], six-items of PE, adopted from Tajudeen *et al*. [44], three-items of SI taken out from Jackson *et al*. [15], six-items of PEOU, and six-items of PU retrieved from Davis [20]. Finally, the dependent variable was student behavioral intention or BI, which consisted in four-items, adopted from Tajudeen *et al*. [44]. All 39 questions were used to measure respondent opinions on using mobile learning, using a 5-Points-Likert scale (1: Strongly disagree, 5: Strongly agree).

Before collecting data, the validity and reliability of the questionnaire were checked. For validity checking, three experts in the Hospitality and Tourism field were asked to verify and certify items in the questionnaire form utilizing the Indexes of Objective Congruence (IOC). To prove that the questionnaire fitted the study or not, the formula used for calculation was $IOC = \sum R/N$. The consistency index value must be at least 0.5 or higher to be accepted [45].

To check reliability, a pilot study was conducted with 30 target students who were studying at a university in Phnom Penh. The aim was to find out whether the individual scores from the instruments were consistent and reliable or not, employing Cronbach's Alpha coefficient. The Cronbach's Alpha coefficient must be equal to or higher than 0.7 [46] for ensuring the reliability of the research instruments. Additionally, to ensure the understanding of the questionnaire, the English language was translated into Khmer language.

The collected data were encoded and analyzed using Statistical Package for Social Science (SPSS) version 23.0, and AMOS. The causal model (Structural Equation Modeling) was tested using AMOS version 21.0 [47]. Data analysis, preliminary estimation and model testing, were implemented. Preliminary estimation included descriptive statistics, and internal reliability testing of research variables applying Cronbach's Alpha and coefficients. Principal component factor analysis was performed to assess the construct validity of multi-item measurement. Item loadings above 0.5 are confirmed for construct validity [48]. With the confirmatory factor analyses (CFA), the average variance extracted (AVE) should be 0.5 or higher. This is considered adequate convergence. The construct reliability (CR) should be between 0.6 and 0.7 or above 0.7 [42].

Moreover, structural equation modeling (SEM) examines the path construct of the latent variables. The model was tested and modified based on the analysis of path coefficient and modification. The overall good-fit model was confirmed by Chi-Square statistic (χ^2) which is higher than .05, and the chi-square/degree of freedom ratio (χ^2 /df) must be less than or equal to 3 [49]. As a rule of thumb, threshold of goodness-of-fit models must have fit statistics above .90 for the goodness-of-fit Index (GFI), the adjusted goodness-of-fit index (AGFI), and the comparative fit index (CFI). On the other hand, the root-means-square residual (RMR) must be equal or less than .08, and the root-mean-square error of approximation (RMSEA) must be less than .05 [50].

Table 2. Research constructs and related survey items

Construct	Items	Statement	References
Self-efficacy-SE	SE1	I could complete my job using mobile learning for support my study if there was no one around to tell me what to do as I go.	[12]
	SE2	I am able to attain my job using new mobile learning for studying application if I had never used like it before.	
	SE3	I could complete my job by using mobile app if I had the software manuals to use it for reference.	
Mobile Anxiety-MA	MA1	I feel apprehensive about using mobile learning would interrupt my studying performance.	[13]
	MA2	It makes me thought that I could lose my studying performance or productivity by using mobile learning.	
	MA3	I hesitate to use mobile learning in my study for fear of making mistakes I cannot correct.	
	MA4	Using mobile learning in my studying is somewhat intimidating to me.	
Personal Innovativeness-PI	PI1	Some people come to you for advice on how to use mobile learning for any online learning.	[14]
	PI2	It seems your friends are learning more about the new mobile learning application or platform by mobile phone.	
	PI3	Generally, you are among the first in your circle of friends to acquire or know mobile app/ platform for learning when it appears through your mobile phone.	
	PI4	You can operate new mobile high-tech products and service without any help from others.	
	PI5	You keep up with latest learning mobile app or learning platforms development in your areas of interest.	
	PI6	You enjoy the challenge of figure out mobile learning high-tech gadgets.	
	PI7	You find you have fewer problems than other people in using mobile learning technology with your student performance.	
Perceived Enjoyment-PE	PE1	I can find mobile learning enjoyable to consume for my study.	[44]
	PE2	I can find mobile learning interesting to consume for my study.	
	PE3	I can find mobile learning pleasant to consume for my study.	

Table 2. Research constructs and related survey items (continued)

Construct	Items	Statement	References
	PE4	I can find mobile learning very entertaining to consume for my study.	
	PE5	I can find mobile learning uneventful to consume for my study.	
	PE6	I can find mobile learning disgusting to consume for my study.	
Social Influence-SI	SI1	At university, my friends, who are important to me think that I should use mobile learning to support my studying.	[15]
	SI2	At university, my lecturers, think that I ought to utilize mobile learning to support my study.	
	SI3	At home, my relatives or my parents think that I should use mobile learning to support my study.	
Perceived Ease of Use-PEOU	PEOU1	Utilizing mobile learning would be easy for me.	[20]
	PEOU2	I would find it easy to use mobile learning to upload and download materials from the internet.	
	PEOU3	My interaction with mobile learning would be clear and understanding.	
	PEOU4	It is easy to be skillful in using mobile learning for study.	
	PEOU5	It would be easy to access all learning materials from mobile learning.	
	PEOU6	I would find mobile learning easy to use for study.	
Perceived Usefulness-PU	PU1	Utilizing mobile learning would make my work done more easily and quickly.	[20]
	PU2	It would improve my study performance.	
	PU3	Mobile learning would increase my study productivities.	
	PU4	It would improve my study effectiveness.	
	PU5	Using mobile learning would give me total control in my learning process.	
	PU6	I would fine mobile learning useful for my study.	
Behavioral Intention-BI	BI1	I intend to use mobile learning for my study.	[44]
	BI2	I intend to use mobile learning for study purpose as much as possible.	
	BI3	I desire to use mobile learning in the future.	
	BI4	I will adopt mobile learning for study.	

3. Results and Discussion

3.1 Results

3.1.1 Descriptive statistics

The analyses of the empirical data using SPSS yielded the results as shown in Table 3. Table 3 shows respondents' profile, which consists of their personal information and their mobile device usage behavior. According to the Table, more than half of the respondents were female. This accounted for 54.5% (n=218). Most respondents were between 21 and 25 years old, or 45.8% (n= 183). This is followed by the 15-20 years-old age group which accounted for 29.3% (n=117; 29.3%). Most of the respondents had a bachelor's degree (n=337; 84.3%), while the rest were master's degree holders (11.8%, n=47).

In terms of the respondents' behavior of using a mobile device, it was found that that all respondents used mobile devices (100%, n=400) with different types and quantities, while smartphones and computers were the most popular (56%, n=224). Nearly half of the respondents had between 3 to 6 years of experience using mobile devices, accounting for 38.8% (n=155). Almost all of the respondents (96.8%, n=387) used internet-based mobiles on a daily basis. Thirty-nine percent of the respondents (n=158) spent 2 to 5 hours per day on internet use, while 9% (n=36) spent less than 2 hours whereas 72.5% (n=290) of the respondents used mobile learning daily, while 4% (n=16) used once/week. Finally, all respondents (100%) intended to acquire knowledge via mobile learning activities.

3.1.2 Measurement model

Estimation models have been used to investigate the interactions between latent variables and observed variables, while structural models are used to estimate the regression structure among latent variables [51]. Before determining the overall latent variable measurement testing, each individual model was investigated and examined separately to confirm if it gave a good fit to the empirical data or not. Previous study confirmed the correlation of the empirical data that had been collected to the theory developing the model fit [52]. The results of confirmatory factors that had been collected analysis (CFA) were evidence of the impact of latent variables on observed indicators. As a result, eight problematic items of the 39 items were omitted due to their factor loadings falling below the least conservative values (less than .5) [53]. Overall, there were 31-observed indicators left for reassessing the measurement model. Those remaining observed items had the conceptual and theoretical background that explained the latent variables.

The analysis indicated that the CFA model gave a good fit with the empirical data and significance at .05 because all criteria index values met the model fit criteria (see Table 4) as shown: Chi-square (χ^2) = 494.614, Degree of freedom (df) = 367, p-value= .000, Chi-square/df = 1.348, GFI= .927, AGFI= .902, CFI= .981, RMSEA= .030, and RMR= .033. In short, this measurement model had good construct validity and consistency with the empirical data since the CFI score (.981) was close to 1, RMSEA score was less than .05, and χ^2/df was lower than 3 [50, 51]. As shown in Table 5 below, the t-value for standardized factor loadings of the indicators of each construct ranging from 9.083 to 25.606 found significance at level.01 ($p<.01$). The standardized factor loadings stayed between .512 to .908. The factor loading of the observed indicators of the construct is significant, and it can be proof of the convergent validity of the constructs [53]. Also, Fornell and Larcker [54] and Hair *et al.* [42] recommended that the Construct Reliability (CR) ought to be higher than 0.7 and the Average Variance Extracted (AVE)

Table 3. Respondents' profile

		Frequency	Percentage
Gender	Male	182	45.5
	Female	218	54.5
Age	15-20 years old	117	29.3
	21-25 years old	183	45.8
	25-30 years old	78	19.5
	30-up years old	22	5.5
Education	Associate Degree	9	2.3
	Bachelor's Degree	337	84.3
	Master's Degree	47	11.8
	Ph.D.	0	0
	Others	7	1.8
Mobile device usage	Yes	400	100
	No	0	0
Experience	Less than 1 year	11	2.8
	1-3 years	92	23
	3-6 years	155	38.8
	6-9 years	104	26
	More than 9 years	38	9.5
Frequency of Internet use	Once a week	4	1.0
	Twice a week	3	0.8
	Three Times a week	6	1.5
	Daily	387	96.8
Degree of Internet use per day	None	0	0
	Less than 2 hours/day	43	10.8
	2-5 hours/day	158	39.5
	5-8 hours/day	94	23.5
	8-12 hours/ day	69	17.3
	More than 12 hours/day	36	9
Frequency of using a mobile device to learn per week	Once a week	16	4
	Twice a week	31	7.8
	Three Times a week	63	15.8
	Daily	290	72.5
Degree of attestation via mobile learning activities	Yes	400	100
	No	0	0

higher than 0.5. Although the AVE score is less than 0.5 (which is 0.4), if the CR is greater than 0.7, the convergent validity of the construct can be established. Thus, this construct can provide adequate evidence of convergent validity even though the AVE of SE, MA, and PI were lower than the criterion 0.5 since their CR scores were greater than 0.7 [42].

Furthermore, discriminant validity clarifies the level of uniqueness of construct from other constructs [55]. As identified by Fornell and Larcker [54], discriminant validity can confirm when the AVE is greater than the average share variance (ASV) and maximum shared variance (MSV). In other words, ASV and MSV must be lower than AVE; the discriminant validity would

Table 4. Correlation coefficient matrix of constructs

Constructs	Construct Correlation Matrix							
	SE	MA	PI	PE	SI	PEOU	PU	BI
SE	1							
MA	.078	1						
PI	.521*	.068	1					
PE	.479*	-.027	.452*	1				
SI	.216*	.065	.306*	.362*	1			
PEOU	.443*	-.070	.493*	.625*	.478*	1		
PU	.387*	-.141*	.425*	.614*	.450*	.747*	1	
BI	.415*	-.110*	.442*	.610*	.452*	.698*	.741*	1

Note: χ^2= 494.614, df= 367, χ^2/df= 1.348, p-value = .000, GFI= .927, AGFI= .902, CFI= .981, RMSEA= .030, RMA= .033

* p<.05

Table 5. Reliability and validity of the constructs

Construct	Items	β	t-value	AVE	CR
Self-efficacy (SE)	SE1	.637**	10.103	0.45	0.71
	SE2	.671**	9.887		
	SE3	.712**	-		
Mobile Anxiety (MA)	MA1	.676**	12.491	0.49	0.79
	MA2	.787**	-		
	MA3	.631**	11.501		
	MA4	.700**	12.662		
Personal Innovativeness (PI)	PI4	.512**	9.083	0.47	0.72
	PI5	.808**	-		
	PI6	.695**	9.761		
Perceived Enjoyment (PE)	PE1	.783**	14.360	0.66	0.89
	PE2	.763**	17.903		
	PE3	.828**	19.657		
	PE4	.877**	-		
Social Influence (SI)	SI1	.775**	13.370	0.51	0.75
	SI2	.815**	-		
	SI3	.526**	9.988		
Perceived Ease of Use (PEOU)	PEOU1	.772**	16.742	0.57	0.70
	PEOU3	.797**	-		
	PEOU4	.744**	15.834		
	PEOU5	.679**	14.274		
	PEOU6	.787**	16.925		
Perceived Usefulness (PU)	PU2	.867**	25.606	0.68	0.91
	PU3	.908**	-		
	PU4	.851**	24.647		
	PU5	.752**	19.498		
	PU6	.725**	18.411		
Behavioral Intention (BI)	BI1	.767**	17.685	0.63	0.87
	BI2	.769**	17.568		
	BI3	.842**	-		
	BI4	.801**	18.601		

be available. Thus, it can occur in this study while the AVE construct value is higher than the square of the relationship [42].

3.1.3 Structural model and hypothesis testing

After finishing the validity and reliability test in the CFA model, path analysis was utilized to test the speculations to confirm the correlation and influence among the inactive (latent) variables in the structural model (see Table 6). The structural model estimation found goodness of model fit since all criteria indices reached the standard of the model fit criteria as indicated: Chi-square (χ^2)= 413.596, Degree of freedom (df)= 359, Chi-square/df= 1.152, GFI= .939, AGFI= .916, CFI= .992, RMSEA= .020, and RMR= .031. Therefore, this structural model provided the goodness of model fit. As illustrated in Table 7, twelve hypotheses were tested to check how significant they were. As a result, there were seven hypotheses providing support for the model in the study. They were illustrated as follows: (H1)- Self-efficacy will emphatically influence PEOU of using mobile learning (β = -.752, t-value = -2.854, p = .004). (H5)- Personal innovativeness will emphatically influence PEOU of mobile learning usage (β= 1.170, t-value= 4.142, p= .000). (H7)- Perceived enjoyment will have an affirmative impact on PEOU on utilizing mobile learning (β= .444, t-value= 4.514, p= .000). (H8)- Social influence will have coordinate certifiable impacts on PU of utilizing mobile learning (β = .247, t-value = 1.971, p = .049). (H10)- Perceived ease of use will have positive coordinate impacts on PU towards BI to use mobile learning (β = .913, t-value = 5.782, p = .000). (H11)- Perceived ease of use will have positive coordinate impacts on BI to consume mobile learning (β = .388, t-value = 4.411, p = .000). Lastly, (H12)- Perceived usefulness will have positive coordinate impacts on BI to expand mobile learning (β = .459, t-value = 5.548, p = .000). Conversely, five hypotheses were not found significant and did not support the model. Those were shown as follows: (H2)- Self-efficacy will emphatically not influence PU of using mobile learning (β = .670, t-value = 1.930, p = .054). (H3)- Mobile anxiety will have a negative impact on PEOU of utilizing mobile learning (β = -.082, t-value = -1.055, p = .291). (H4)- Mobile anxiety will have a negative impact on PU of utilizing mobile learning (β = -.099, t-value = -1.474, p = .141). (H6)- Personal innovativeness will emphatically influence PU mobile learning usage (β= -.808, t-value = -1.706, p = .088) and finally, (H9)- Social influence will have coordinate agreed impacts on BI of utilizing mobile learning (β = .055, t-value = 1.097, p = .273).

As illustrated in Table 8 and Figure 2, the results showed that three main factors were found to be significant to each other in the construct; they were PEOU, PU, and BI. In addition, PEOU and PU worked as moderators between exogenous (I.V) variables and endogenous variables (D.V) in the construct. The effects are seen in the following. SE was found to have a negatively direct influence on PEOU (-.752), but it had a positive effect on PU (.670) and a negatively indirect effect on BI (-.300). PI also had a positive direct effect on PEOU (1.170) while it had a negative effect on PU (-.808), and a positive indirect effect on BI (.573). Likewise, PE had an affirmatively direct effect on PEOU (.444) as well as a positive indirect effect on both PU (.406) and BI (.359). Similarly, SI had a significant influence on PU (.247), and it had a direct (.055) as well as indirect (.113) influence on BI (.168 in total effect). Additionally, PEOU was revealed to have a direct impact on PU (.913) and BI (.388). It had a significant indirect effect on BI (.807). The final direct effect was PU on BI (.459), respectively.

Table 6. The result of the structural model fit indices

Criteria Index	Model Fit Criteria	Modification Result
Chi-square (χ^2)	p> .05	.025
χ^2 /df	<=3	1.152
GFI	>.9	.939
AGFI	>.9	.916
CFI	>.9	.992
RMSEA	<=.05	.020
RMR	<=.08	.031

Table 7. Hypothesis testing

Hypotheses	Paths	β	t-value	p-value	Decision
H1	SE → PEOU	-.752**	-2.854	0.004	Support
H2	SE → PU	.670	1.930	0.054	Not Support
H3	MA → PEOU	-.082	-1.055	0.291	Not Support
H4	MA → PU	-.099	-1.474	0.141	Not Support
H5	PI → PEOU	1.170**	4.142	<0.01	Support
H6	PI → PU	-.808	-1.706	0.088	Not Support
H7	PE → PEOU	.444**	4.514	<0.01	Support
H8	SI → PU	.247*	1.971	0.049	Support
H9	SI → BI	.055	1.097	0.273	Not support
H10	PEOU → PU	.913**	5.782	<0.01	Support
H11	PEOU → BI	.388**	4.411	<0.01	Support
H12	PU → BI	.459**	5.548	<0.01	Support

Table 8. Direct and indirect effect matrix of model

D.V	PEOU			PU			BI		
I.V	T.E	D.E	I.E	T.E	D.E	I.E	T.E	D.E	I.E
SE	-.752 (.272)	-.752 (.272)	-	-.017 (.380)	.670 (.380)	-.687	-.300	-	-.300
PI	1.170 (.396)	1.170 (.396)	-	.260 (.705)	-.808 (.705)	1.068	.573	-	.573
PE	.444 (.081)	.444 (.081)	-	.406	-	.406	.359	-	.359
SI	-	-	-	.247 (.125)	.247 (.125)	-	.168 (.049)	.055 (.049)	.113
PEOU	-	-	-	.913 (.168)	.913 (.168)	-	.807 (.092)	.388 (.092)	.419
PU	-	-	-	-	-	-	.459 (.081)	.459 (.081)	-
R-square	.783			.770			.717		

Chi-square (χ^2)=413.596, df=359, p=.025, χ^2/df=1.152, GFI=939, AGFI=916, CFI=992, RMSEA=.020, RMR=.031

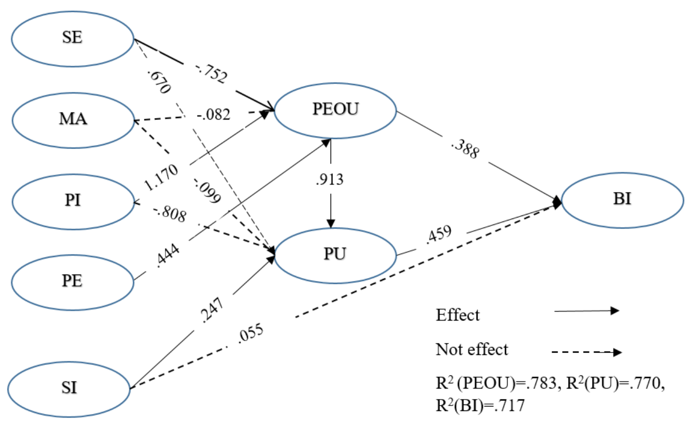

Figure 2. Factors affecting BI

3.2 Discussion

Understanding student intention to adopt various technologies is very crucial to implementation and sustainability. This research aimed to determine Hospitality and Tourism students' behavioral intention to use mobile learning by employing TAM as the solid theory. The results showed that the factors affecting student intention to adopt mobile learning were self-efficacy (SE), mobile anxiety (MA), personal innovativeness (PI), perceived enjoyment (PE), social influence (SI), perceived ease of use (PEOU), and perceived usefulness (PU). Therefore, students' behavioral intention to use mobile learning relied on their fulfillment of personal knowledge, level of fear or negative thoughts about operating new technology, the extent of individual implementation of the new technology, the degree of fun and satisfaction of mobile learning through its use, the impact of the social circle, the mobile learning ease of use and usefulness. Figure 2 summarizes the structural analysis results, and Table 5 illustrates the hypothesis testing. These results and discussions are dealt with in detail below.

3.2.1 Self-efficacy between perceived ease of use and perceived usefulness

H1 and H2 hypothesized that students' self-efficacy influences their perceived ease of use and perceived usefulness of using mobile learning significantly. The findings addressed strong support for the H1 hypothesis; whereas, H2 did not support the model. These findings implied that the self-efficacy of the learners had a significant effect on perceived ease of use while it did not have an effect on perceived usefulness. This result was in line with the previous literature, which explored the correlation between self-efficacy, perceived ease of use, and perceived usefulness. For instance, Al-Ammary *et al*. [24], Al-Ammari and Hamad [23], Al-Gahtani [25], and Chang *et al*. [56] pointed out that computer self-efficacy influences perceived ease of use in the acceptance of new technology as study tools. However, a few studies that proved self-efficacy did not show any significant support for perceived usefulness [56].

The significant effect of self-efficacy towards perceived ease of use implies that learners consider that consuming mobile learning is easy to use and improves their study performances. If they can adopt high-tech or electronic devices for themselves and find them both easier to use and helpful, they will intend to use them. Identically, even if they found it hard to adopt, they may not quit easily if they found it useful. Hence, they will intentionally keep learning about it step by step. In addition, the students with high self-efficacy feel it is easier to use mobile learning more in comparison to those with low self-efficacy. For this reason, once students have high self-efficacy, they are likely to accept e-learning although low self-efficacy students may reject it [57]. Bad experiences of platform consumption are significant; therefore, the platform should be made easy and user-friendly in order to engage students and keep them in the classroom system.

3.2.2 Mobile anxiety between perceived ease of use and perceived usefulness

As identified in the literature section, mobile anxiety harmed both perceived ease of use and perceived usefulness. In contrast, the results of hypotheses (H3 and H4) showed that there was no significant effect between the two constructs. Thus, mobile anxiety cannot be considered a variable to determine the student behavioral intentions to use mobile learning in Cambodia. In other words, the students considered that mobile anxiety did not give them trouble. Consistent with these findings, Ifinedo [58] illustrated that computer anxiety did not have a negatively significant effect on either PEOU or PU in terms of adoption of web-based learning tools. Furthermore, Shih and Huang [59] found that computer anxiety never significant affected perceived ease of use or perceived usefulness on the actual usage of ERP systems. The illustration of the study's findings did not look strange as 100 percent of the respondents intended to acquire knowledge via mobile learning. Typically, Przybylski *et al*. [60] employed video games to leverage and stimulate student performance and motivation. Kraut *et al*. [61] argued that technology usage would lead to barriers for users; it was simply not for everybody. Users could have negative feeling and fear or hesitate to utilize mobile learning. The platform of a classroom system should provide learning tools that are easy to access and use. In conclusion, students will intend to use mobile learning if they find it easy and helpful.

3.2.3 Personal innovativeness between perceived ease of use and perceived usefulness

In this study, the personal innovativeness was found to have a critical effect and leverage on perceived ease of use (H5); however, the data did not support its effect on perceived usefulness (H6). Similar findings suggested that personal innovativeness influence perceived ease of use [62] while it did not show a significant effect on perceived usefulness [15]. As mentioned in the literature review, personal innovativeness is the desire of students to acknowledge that unused innovations such as mobile devices can improve their learning process and add value to traditional class modes of study and learning. Once the students have high affirmative personal innovativeness, they will explore as well as adore learning new things without hesitation. They might be able to deal with a degree of suspicion and thus increase positive intentions towards acceptance. Turan *et al*. [63] concluded that people with high innovativeness might be more critical towards technology than people with low innovativeness because they are able to understand up-to-date to technology clearly so it might be easy for them to quit using even though the technology meets their needs. No matter how useful the users may think it is, they might not get involved in the system that they feel is not friendly or easy to use; they may avoid using it. Aligned with this, Walczuch *et al*. [14] also claimed that innovativeness affected usefulness negatively. For instance, Richardson [16] discussed innovation characteristics in the context of technology adopters in Cambodia by claiming that each adopter group had expected different levels of benefits of using ICT. So, Schools of Hospitality and Tourism must be certain that they have provided enough technical support, infrastructure, and appropriate facilities to encourage student behavioral intention to use mobile learning. Moreover, the institutions must make sure that learners can easily access all kinds of support resources and learning materials for the class. The department needs to provide help or consultation to the learners and trainers about the platform if possible.

3.2.4 Perceived enjoyment and perceived ease of use

The finding suggested that perceived enjoyment positively affected perceived ease of use towards user intention to use mobile learning. This was consistent with a number of previous studies that confirmed that computer enjoyment had a significant relationship with perceived ease of use [25, 64]. The students will preferably participate in-class activities if they feel ease and happiness using the platform [65]. In other words, they may not cooperate if they find it is not interesting and is difficult. Therefore, a dedicated department (Hospitality and Tourism) should also provide diversity of content, including entertainment content, which encourages students to regularly actively participate.

3.2.5 Social influence between perceived usefulness and behavioral intention

Based on the analyzed result, social influence (H8) had a positively straightforward relationship with perceived usefulness. The results were in broad agreement with previous studies that explored the factors influencing student perception and intention to use e-learning [25, 66]. However, no significant impact on student behavioral deliberation to utilize mobile learning (H9) was found. In line with this finding, Sarosa [67] identified that social influence did not impact on student acceptance of the iPad due to the users' experience of utilizing mobile devices. In general, no matter what pressures the users get to adopt new technology or social platform from their surrounding environment, they intentionally decide to utilize it when they find it useful. The results implied that the benefits of using mobile learning were considered necessary to the social circles (peers, parents, and lecturers, etc.). Administrators in the relevant department should work closely with the student social circles to show them how beneficial mobile learning is because even if the students are strictly instructed by the administrators or lecturers to utilize the new hi-tech (mobile learning), some will not get involved. Therefore, all stakeholders, especially authorities, should propose suitable means or conditions to increase student motivation to learn via the platform (mobile learning), and one way of doing this might be to offer participating students advantages.

3.2.6 Perceived ease of use and perceived usefulness towards students' behavioral intention

The results demonstrated that perceived ease of use had a significant effect on perceived usefulness and student behavioral intention to use mobile learning, and this was confirmed by other previous pieces of literature [25, 28]. The results implied that the more ease and usefulness of the platform (mobile learning) students feel, the more likely they are to have a higher probability of behavioral intention to use mobile learning. In this way, the Hospitality and Tourism departments must offer appropriate technical support and a rejuvenated system or platform that will stimulate students to use regularly. When students use such technology regularly to support their learning experience, that behavior will automatically develop. Additionally, perceived usefulness also demonstrated a direct significant effect on student behavioral intention to use mobile learning. It reflected the concept that the higher the perceived usefulness, the more opportunities of student intention to use mobile learning could be. Hence, the Hospitality and Tourism centers should make an effort to publicize the benefits of using mobile learning to students and trainers to convince them to adopt it as an extra tool for better study. Finally, the determinants, self-efficacy, personal innovativeness, perceived enjoyment, social influence, perceived ease of use, and perceived usefulness, should all be taken into account when considering ways to develop student usage intentions.

4. Conclusions

This paper explored the factors influencing student behavioral intention to use mobile learning in terms of the relationships among determinants of the technology acceptance model (TAM) framework. Five explanatory variables were chosen to be used in this paper (self-efficacy, mobile anxiety, personal innovativeness, perceived enjoyment, and social influence) to determine their relationship using SEM in the assigned model towards the intention to use mobile learning. The results showed that self-efficacy, personal innovativeness, perceived enjoyment, and social influence had significant relationships with perceived ease of use and perceived usefulness towards student behavioral intention in the model. However, mobile anxiety did not show any significant effect on perceived ease of use as well as perceived usefulness. In addition, social influence did not directly affect student behavioral intention to use mobile learning.

Based on the results, it is recommended that Department or Tourism and Hospitality Schools should build a user-friendly and useful educational platform that includes entertainment content for the students. Technical support and infrastructure should also be provided to the users because these can make them get involved with the classroom system as they feel less worried about consuming mobile learning. Students' social circles should also be considered. If these suggestions are considered, the students will embrace with enthusiasm mobile learning platform as a new learning tool.

Like other studies, this study is far from perfect because it has a number of limitations, and this suggests the need for further studies. Drawing on the Extension to Technology Acceptance Model for this study, we have considered few external factors affecting student behavioral intention to use mobile learning. However, other determinants such as age, gender, and design-learning content should be included in future research to better understand users' perceptions of the use of mobile learning.

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