PREDICTING STUDENTS' USE OF MOBILE-LEARNING MANAGEMENT SYSTEMS IN INDONESIA

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ABSTRACT

A mobile learning management system (mobile LMS) facilitates the interaction between lecturers and students to transfer knowledge flexibly. With the high possibility of universities adopting a mobile LMS into their learning systems, predicting student acceptance of mobile LMS is critical. Based on an extension of the unified theory of acceptance and use of technology (UTAUT), this study explores the factors that contribute to the acceptance of a mobile LMS. This was carried out by involving 500 Bina Nusantara University (BINUS) Indonesia online learning students who used the mobile LMS for more than one year to share their experiences. Partial least squares structural equation modeling (PLS-SEM) is used to predict behavioral intentions and the actual usage of the mobile LMS. The results showed that the intention to use the mobile LMS was determined by performance and effort expectancy, social influence, facilitating conditions, hedonic motivation, habit, and perceived satisfaction. Furthermore, facilitating conditions, hedonic motivation, habits, and behavioral intentions contributed to the actual use of the mobile LMS. This study successfully predicted the main factors that encourage students to adopt and use a mobile LMS. In functional terms, this study provides insights for higher education institutions in designing a mobile LMS so that it has an impact on increasing student academic success.

Keywords: *Extended UTAUT, E-Learning, Mobile LMS, Higher Education.*

INTRODUCTION

Online learning during the COVID-19 (coronavirus) pandemic was challenging for instructors and educational institutions to continue producing high-quality students. The study was conducted during a pandemic, therefore after the pandemic, two dynamics will work together: the need to continuously carry out online learning and the bargaining power of online learning for administrators and students in selecting an LMS. These two dynamics are of great interest to educational institutions and students to prevent the limitation of distance learning to certain circles. To support the success of online learning, Internet network infrastructures and learning management systems are the primary means of two-way communication between teachers and students. Furthermore, the desire and awareness of students to accept and use learning technology requires more attention. The lack of research in Indonesia regarding the acceptance of a mobile LMS is due to the limited number of educational institutions that use an LMS suitable for mobile devices. They use a web-based LMS called Moodle. Moodle is an open-source LMS that is generally licensed so that users can make modifications according to their needs.

Bina Nusantara University (BINUS) online learning runs a fully online program. It is a pioneer in Indonesia for distance education using technology, which has used two versions of an LMS simultaneously since 2015. The mobile LMS is known as BINUS Mobile for Student and can be downloaded on the Google Play Store and App Store. Through the mobile version, students can access and download all learning materials and class schedules for discussion in forums with lecturers and peers.

A preliminary study was conducted, which involved interviewing students on their acceptance and use of the BINUS Mobile for Student application. Although most have used it, some still feel more comfortable using a web-based LMS. This makes it necessary to trace student behavior using the BINUS Mobile for Student application through the unified theory of acceptance and use of technology (UTAUT) expansion model focused on a mobile LMS in online learning in universities.

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Mobile LMS in Tertiary Education

Since 2015, the development of smartphones in Indonesia has increased sharply, and it is estimated that by 2025, it will reach 89% of the population (Statista, 2020). The average age of smartphone users is 18–29 years, which also constitutes the main age range of students taking distance education programs. Many researchers are currently examining the role of cellular technology for education and training purposes. Furthermore, early research focused on mobile learning, discussing the potential for new designs in personal cellular technology that could enhance lifelong learning programs and adult education opportunities (Sharples, 2000). It follows the roadmap of the National Institute of Cyber Education (NICE) Indonesia 2025, which focuses on lifelong learners and personalizing services between universities. Currently, Indonesia is still in the seeding innovation stage by implementing a blockchain and online learning platform and preparing to enter the democratization phase, namely artificial intelligence, big data, and cloud applications.

In general, mobile learning is mediated by mobile devices such as cell phones, which allow easy access everywhere (Al-Emran et al., 2020). It expands and enhances learners' ability to communicate and access information through mobile and wireless devices (El-Sofany & El-Haggar, 2020). Mobile learning should include both in-classroom and out-of-classroom learning (Kumar et al., 2020). Therefore, this theory must consider the ubiquitous use of technology to share knowledge. As an e-learning model, mobile learning refers to how students acquire knowledge, skills, and attitudes by utilizing cellular technology (Hamidi & Chavoshi, 2018). It was concluded that mobile learning is a model that adopts cellular technology and that mobile devices are used as learning media, both in organizations and universities.

Several researchers have discussed the dilemmas of using a mobile LMS, such as students' perceptions (Hu et al., 2020) and a mobile LMS and traditional usage behavior (Hu & Lai, 2019). This study notes some dilemmas students face when adopting a mobile LMS, including technical problems, such as when notifications do not appear for new posts from lecturers or course schedules are not updated. In addition, students still feel comfortable using a website-based LMS because there are doubts about the mobile LMS technology, which they feel is not optimal to support learning performance. This uncomfortable attitude indicates student dissatisfaction with the use of a mobile LMS. Furthermore, some of the resources needed to access a mobile LMS are not sufficient to meet the needs of students, especially hardware and Internet services, thereby reducing their motivation to adopt a mobile LMS. However, there is limited research on the preference of a mobile LMS by students. As students play a crucial role in its deployment across schools, what hinders or facilitates their adoption of new learning technologies requires continuous investigation.

MOBILE LMS IN BINUS ONLINE LEARNING

The mobile LMS used in BINUS online learning was specifically designed and created by BINUS. The mobile LMS is available to both students and lecturers. The goal is to make the online learning process more flexible and improve the student learning experience. The various available features include personal information, schedule, discussion forums, attendance, score, news ranging from finance to education, and knowledge updates. In addition, there is an additional feature (forum notification) that notifies students immediately after a lecturer starts a discussion in the forum.

Mobile LMS Adoption in Tertiary Education

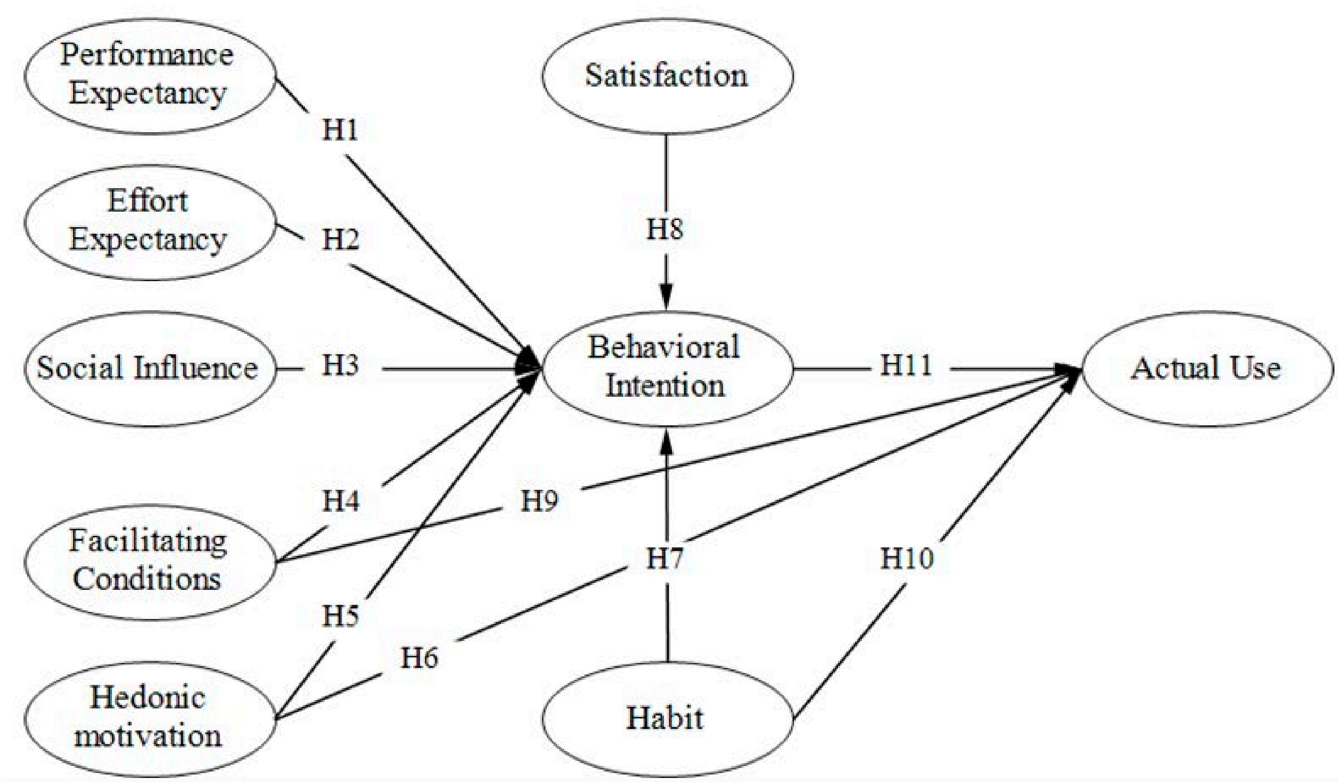
Higher education institutions should identify student behavioral intentions for the sustainable use of a mobile LMS in online learning. Several studies have successfully examined the determinants of consumers' behavioral intentions and their adoption of specific technologies. Popular models include the technology acceptance model (TAM) (Davis, 1989), the theory of planned behavior (TPB) (Ajzen, 1991), the innovation diffusion theory (IDT) (Rogers, 2002), and the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003; Venkatesh et al., 2012).

UTAUT is a popular model for assessing a person's behavioral intention to adopt new information technology in various industries (Venkatesh & Bala, 2008; Venkatesh et al., 2003; Venkatesh et al., 2012). In the context of education, UTAUT explains student acceptance to take part in online learning (Abd Rahman et al., 2021; Altalhi, 2021; Buabeng-Andoh & Baah, 2020; Mahande & Malago, 2019; Tarhini, Mohammed, & Maqableh, 2016; Wan et al., 2020), whereas online learning using mobile LMS has been previously researched (Al-Sharhan et al., 2020; Aman et al., 2020; Joo et al., 2016; Lee & Jeon, 2020; Sultana, 2020; Tkachuk et al., 2021).

This research reviews and re-explains the determinants for students to adopt a mobile LMS in online learning. Therefore, the concept of UTAUT is extended, namely performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditioning (FC), hedonic motivation (HM), and habit (HB) (Venkatesh et al., 2012), by adding factors of satisfaction using a mobile LMS (Pozón-López et al., 2020). The theoretical framework that was proposed is shown in Figure 1. The following is an explanation of each of the predicted correlations between the variables to explain the actual use of mobile LMS based on the literature review.

Performance expectations signify a person's level of confidence that using certain technologies is commonplace and is considered to improve performance (Venkatesh et al., 2003). Many scholars stated that performance expectations are the

Figure 1. Theoretical Framework



main predictors in understanding many behavioral intentions toward technology types. These include the use of mobile learning (Ali & Arshad, 2016; Almaiah et al., 2019; Hamidi & Chavoshi, 2018), e-learning (Mahande & Malago, 2019; Wang et al., 2020), LMS (Sattari et al., 2017), and mobile LMS (Lee & Jeon, 2020; Persada et al., 2019; Saroia & Gao, 2019). Furthermore, this research defined performance expectancy as students' belief that using a mobile LMS improved their educational achievement. Therefore, the following hypothesis was proposed:

H1: Performance expectations positively and significantly influence the intention to use a mobile LMS.

Effort expectation defines one's ease in using technology (Venkatesh et al., 2003) and one's belief that such technology will be free from effort (Yadav et al., 2016). Effort expectations are the same as the perceived ease of use of the construct in TAM. Prior research showed that effort expectation positively affects behavioral intention (Buabeng-Andoh & Baah, 2020; Mahande & Malago, 2019). Furthermore, this construction is considered an essential determinant of behavioral intentions involving an e-learning system (Abbad, 2021; Tarhini, Teo, & Tarhini, 2016; Wang et al., 2021). In this research, it is expected that when students perceive a mobile LMS as easy to use, they are more likely to adopt it. Therefore, the following hypothesis was proposed:

H2: Effort expectation positively and significantly influences the intention to use a mobile LMS.

Social influence is defined as the degree to which an individual is convinced by others to use the technology (Venkatesh et al., 2003). Conceptually, social influence combines subjective norms (theory of reasoned action [TRA, TPB, TAM]), social factors (model of PC utilization [MPCU]), and images (IDT) in UTAUT (Venkatesh et al., 2003). Many researchers believe that social influences shape people's behavioral intention to use new technology in their activities (Alshurideh et al., 2020; Malanga et al., 2021; Tarhini et al., 2015; Zhang et al., 2020) and believe that social influences shape people's behavioral intention to use new technology in their activities. Venkatesh et al. (2003) emphasized that social influence only occurs in specific environments and has little effect on the general environment. Therefore, referring to the UTAUT guidelines as well as the mandatory use of a mobile LMS (students must use a mobile LMS during their on-campus learning), this study investigated the direct effect of social influence on students' behavioral intentions. It also confirmed that students' behavioral intentions toward using a mobile LMS were influenced by the trust of instructors provided by universities and other influential individuals. Therefore, the following hypothesis was proposed.

H3: Social influence positively and significantly influences the intention to use a mobile LMS.

The facilitating condition is an individual's belief that the existing technical infrastructure (organization) can support the use of technology (Venkatesh et al., 2003). Facilitating conditions are formed from the constructs of perceived behavioral control (TPB, TAM) and compatibility (IDT). Furthermore, these conditions are environmental factors that influence user perceptions on the ease or difficulty of doing a job or providing the external sources needed to facilitate the performance of certain behaviors (Ajzen, 1991). In this study, the conditions of facilitation were measured based on students' perceptions of whether they could access the necessary resources and support when using a mobile LMS. Meanwhile, past researchers explained the effect of facilitating conditions on adopting new technology (Teo, 2010). In the context of e-learning, it is evident that the facilitating conditions also contribute to the use of technology (Abbad, 2021; Ain et al., 2016; Buabeng-Andoh & Baah, 2020; Khan & Qudrat-Ullah, 2021; Mahande & Malago, 2019; Wang, 2016). Twum et al. (2021) failed to predict the facilitating condition as a predictor of intention to use mobile LMS; therefore, it is necessary to determine whether the facilitating conditions directly influence the intention and actual use of a mobile LMS. There are no facilitating resources that can represent barriers to its use (Wang, 2016). Therefore, the following hypotheses were proposed.

H4: Facilitating conditions positively and significantly influence the intention to use a mobile LMS.

H9: Facilitating conditions positively and significantly influence the actual use of a mobile LMS.

The level of pleasure and entertainment users feel in adopting technology is known as hedonic motivation (Venkatesh et al., 2012). This construct was included in the UTAUT extension model to express the intrinsic utility's role from the user's side (Venkatesh et al., 2012). The hedonic motivation's critical influence comes from the inherent renewal and innovation when using new technology (Venkatesh et al., 2012). Previous researchers examined the role of hedonic motivation and observed that it plays an important role when adopting technology in several industries (Alalwan et al., 2015; Arenas Gaitán et al., 2015; Yuan et al., 2015). In the online learning context (Ain et al., 2016; Al-Azawei & Alowayr, 2020; Buabeng-Andoh & Baah, 2020; Tamilmani et al., 2019; Tarhini, Mohammed, & Maqableh, 2016), this research believed that the use of a mobile LMS would be enjoyable, which would affect the desire and intention to use it. Therefore, the following hypotheses were proposed.

H5: Hedonic motivation positively and significantly influences the intention to use a mobile LMS.

H6: Hedonic motivation positively and significantly influences the actual use of a mobile LMS.

Habit refers to a person's desire to repeatedly perform a behavior (Venkatesh et al., 2012). The use of technology has become a habit due to extended usage for long periods of time (Ain et al., 2016). When an individual repeats an action regularly and is satisfied with the result, such activity becomes a habit (Venkatesh et al., 2012). Past studies that included the habit construct in understanding a person's behavior due to prior habits have favorable outcomes (Ain et al., 2016; Hsiao et al., 2016; Khan & Qudrat-Ullah, 2021; Salem & Nor, 2021; Tarhini, Mohammed, & Maqableh, 2016). Regular users of electronic devices are believed to have more potential to adopt new technologies even before using them (Venkatesh et al., 2011). However, numerous studies observed that habits harm behavioral intentions. For example, Raman and Don (2013) did not find a correlation between habits and behavioral intentions, and Khan and Qudrat-Ullah (2021) found that habits have been removed from the LMS adoption model. This research believed that if the use of a mobile LMS became a habit for students in academic activities, they would adopt and use it in a sustainable manner. Therefore, the following hypotheses were proposed.

H7: Habit positively and significantly influences the intention to use a mobile LMS.

H10: Habit positively and significantly influences the actual use of a mobile LMS.

Perceived satisfaction is often compared with a positive behavioral intention and regular use of technology. Satisfaction is an effective response from all evaluations between expectations and actual reality after using technology (Hsiao et al., 2016). This study defined the perceived satisfaction of students in using a mobile LMS as the overall perception of academic activities. Furthermore, Bhattacherjee (2001) proposed a "post-acceptance model of information system continuity" to describe user intentions and focus on the post-acceptance construct. This study attempted to add satisfaction as a predictor of the intention to use a mobile LMS. It is based on Bhattacherjee (2001), which emphasized that users with high levels of satisfaction tend to have a stronger intention to use online channels on an ongoing basis. Many studies have shown that user satisfaction is a reliable predictor of using technology in education (Pozón-López et al., 2021; Wan et al., 2020), especially LMS (Ashrafi et al., 2020; Saroia & Gao, 2019). Therefore, the following hypothesis was proposed.

H8: Perceived satisfaction positively and significantly influences the intention to use a mobile LMS.

The degree of technology use can be predicted by the attitude of the individual's attention to technology. When these technologies have the effect of increasing their performance, users tend to utilize them regularly. This study interpreted that a mobile LMS users (students) would feel more comfortable when they believed the system was not difficult to use, increasing academic activity and productivity. Limayem and Cheung (2008) tested the confirmation–expectation model longitudinally by examining students' actual frequency of using e-learning and the relationship between the intent to use and actual use. The behavioral intention to use alongside past events significantly influences actual use. However, this study focused on the perspective of the actual frequency perceived by students in the use of mobile LMS, not the actual frequency of use. Therefore, the following hypothesis was proposed.

H11: Behavioral intention positively and significantly influences the actual use of a mobile LMS.

METHODS

A quantitative approach was used to predict the actual a mobile LMS usage in the context of online learning. Thirty-three question items were cited from the study of Venkatesh et al. (2012) and Pozón-López et al. (2020) (see Table 1). Measurement of the questionnaire items involved a Likert scale from (1) strongly disagree to (5) strongly agree. Furthermore, the original questionnaire was translated, adjusted, validated, and then distributed to the 500 students involved in this study who used a mobile LMS for more than one year. The aim was to predict the acceptance and use of the actual a mobile LMS using the UTAUT model. Online questionnaires were provided through a mobile LMS and a traditional (web-based) LMS. Afterward, data from student responses were analyzed with PLS-SEM (variant-based). The PLS-SEM predicts the goodness of the research model (Hair et al., 2017), and the best model in this study is the one that balances complexity and accuracy of predictability (Sharma & Kim, 2012).

The PLS-SEM has two measurement models: the measurement model and the structural model. Both models were evaluated based on the results of the PLS algorithm, bootstrapping, and blindfolding (Hair et al., 2017). The PLS algorithm is a sequential regression procedure to estimate all unknown elements in the PLS path model (Hair et al., 2017). This algorithm estimates the path coefficients and other parameters of a model to maximize the variance of the endogenous variables described. The bootstrapping stage is a nonparametric procedure that tests the statistical significance of various PLS-SEM results (Hair et al., 2017). Blindfolding is a sample reuse iteration procedure that systematically removes the d-data points on endogenous indicators to provide an estimate of the remaining data point parameters (Chin, 1998; Hair et al., 2017). Furthermore, the blindfolding stage aims to evaluate the Stone-Geisser's value, which determines the model's predictive relevance.

RESULTS

Student Sociodemographic

Of the 500 students who participated in the study, 283 (56.6%) were male, and 217 (43.4%) were female, with an age range between 20–30 years. During the learning process, the frequency of accessing LMS was 39 students (7.8%) two times a week, 245 students (49%) three times a week, and 216 students (43.2%) more than three times a week. This condition explained their activities in accessing the material, taking quizzes, and engaging in discussions with lecturers through the LMS forums. Ninety-five percent joined the distance education program because they had jobs.

Measurement and Evaluation Model

All the testing criteria were calculated using PLS-SEM. Table 1 shows the mean value of each indicator between 3.63 and 4.52. This signifies that each student had a positive perception of each question.

The outer loading value set up from the PLS algorithm stage tested each manifest variable, which resulted in a loading factor value greater than 0.7 (Hair et al., 2017) (see Table 1). It means the questionnaire items in each construct positively correlate with other indicators in the same construct. Therefore, the convergent validity criteria were concluded to be satisfied. The discriminant validity was tested using the heterotrait-monotrait (HTMT) (Henseler et al., 2015) ratio of correlations procedure (see Table 3). All relationships between constructs produced a value less than 0.9, which also satisfied the discriminant validity. In other words, every construct in the model is conceptually similar.

Internal consistency testing refers to the values of average variance extracted (AVE), composite reliability (CR), and Cronbach's alpha (CA). In Table 2, the AVE value of each variable ranges from 0.670 to 0.858. These values meet the minimum AVE limit recommended by Chin (1998). The CR value ranged from 0.890 to 0.948. Likewise, the CA value ranged from 0.835 to 0.917. These results suggest a high internal consistency of all study constructs used. When referring to the minimum value required to assess CA and CR of 0.7 (Hair et al., 2017), these results matched the reliability criteria.

Table 1. Descriptive Analysis and Loading Factors

Variable	Item	Mean	LF
Performance Expectancy (PE)	Using a mobile LMS effectively enhances all my academic activities.	3.71	0.900
	Using a mobile LMS fulfils [sic] my expectations in achieving essential goals during the lecture process.	3.69	0.924
	A mobile LMS helps me to complete all academic activities.	3.94	0.852
	Using a mobile LMS increases my academic performance.	3.74	0.877
Effort Expectancy (EE)	For me, learning how to use a mobile LMS is easy.	3.78	0.843
	My interplay with a mobile LMS is understandable and straightforward.	4.09	0.848
	A mobile LMS is easy to use.	4.07	0.849
	It is simple for me to become an expert in handling a mobile LMS.	3.87	0.829
Social Influence (SI)	Somebody close to me suggested studying online because it involves a mobile LMS.	3.86	0.896
	My friends suggested studying online because it involves a mobile LMS.	3.63	0.937
	People whose opinions I respect suggested studying online because it involves a mobile LMS.	3.77	0.944
Facilitating Conditions (FC)	I have the resources needed to use a mobile LMS in my education.	4.15	0.855
	I have the essential knowledge for using a mobile LMS.	4.30	0.869
	My mobile LMS fits in with the separate technologies I use.	4.52	0.803
	I can get help from other people when I have difficulty using a mobile LMS.	3.95	0.742
Hedonic Motivation (HM)	Using a mobile LMS in my studies is fun.	3.78	0.875
	Using a mobile LMS in my studies is enjoyable.	3.82	0.875
	Using a mobile LMS in my studies is truly entertaining.	4.11	0.856
Habit (H)	Using a mobile LMS has become my habit.	3.97	0.814
	I must apply for a mobile LMS.	3.88	0.898
	Using a mobile LMS has become a natural thing for me.	3.95	0.893
Perceived Satisfaction (PS)	I will be satisfied with my decision to use a mobile LMS.	3.97	0.792
	If I learn with a mobile LMS, I would be overjoyed to work with it.	3.98	0.868
	I am satisfied with a mobile LMS.	4.13	0.853
	I believe a mobile LMS fits my needs.	4.03	0.838
Behavioral Intention (BI)	I will do as much learning with a mobile LMS as I can.	4.00	0.834
	I plan to continue using a mobile LMS in the future for my education.	4.22	0.904
	I will continuously try to use a mobile LMS more often in my education.	3.65	0.915
	I will continue using a mobile LMS regularly in my education.	4.31	0.879
Actual Use (AU)	I regularly use a mobile LMS in my education.	4.01	0.911
	Using a mobile LMS is a pleasurable experience.	3.97	0.903
	I am presently using a mobile LMS as a holding tool in my education.	3.93	0.847
	I significantly use a mobile LMS in my education.	3.85	0.732

LF=Loading Factors

Table 2 Internal Consistency

Variable	Cronbach Alpha	Composite Reliability	AVE
Performance Expectancy	0.911	0.938	0.790
Effort Expectancy	0.864	0.907	0.710
Social Influence	0.917	0.948	0.858
Facilitating Conditions	0.835	0.890	0.760
Hedonic Motivation	0.837	0.902	0.755
Habit	0.837	0.902	0.755
Perceived Satisfaction	0.893	0.921	0.701
Behavioral Intention	0.882	0.927	0.809
Actual Use	0.870	0.912	0.724

Table 3 Discriminant Validity with HTMT

	AU	BI	EE	FC	H	HM	PE	PS	SI
AU									
BI	0.856								
EE	0.885	0.851							
FC	0.887	0.799	0.824						
H	0.879	0.840	0.847	0.802					
HM	0.883	0.838	0.850	0.854	0.896				
PE	0.841	0.766	0.887	0.692	0.723	0.745			
PS	0.898	0.804	0.832	0.810	0.794	0.763	0.729		
SI	0.747	0.710	0.709	0.619	0.648	0.664	0.672	0.683	

The structural model was tested via a bootstrapping procedure in the second stage. The results gave the original sample value (β), t-statistics, p-value, and R^2 used to answer the research hypotheses.

Table 4 shows the results of the hypotheses testing, which signifies that all the research propositions were acceptable. Table 5 illustrates the reported variance (R^2) and predictive relevance (Q^2) of each endogenous variable. R^2 values of 0.67, 0.33, and 0.19 signify a strong, moderate, and weak model (Chin & Newsted, 1999). Therefore, the power of the model in predicting endogenous variables was strong. The model forecast was 69.6% of the variance in describing students' behavioral intentions and 72.8% explaining the mobile LMS's actual use (Figure 2). The results of the overall model are shown in Figure 2.

Q^2 and f^2 were required to analyze the relevance of predictions and effect sizes (Hair et al., 2019). A Q^2 value greater than null signifies that the research model possesses predictive relevance (Hair et al., 2019). As Table 5 demonstrates, all endogenous variables have good predictive relevance. This means that the data points of indicator for a construct of UTAUT and student satisfaction have the power to predict behavioral intention and the actual mobile LMS usage. Considering the effect size (f^2), the values 0.02, 0.15, and 0.35 imply small, medium, and strong effects (Cohen, 2013). Therefore, performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, habit, and perceived satisfaction had little impact on behavioral intention. Facilitating conditions, habit, hedonic motivation, and behavioral intention also had little effect on the actual mobile LMS usage.

Finally, the model's suitability was tested using standardized root-mean-square residual (SRMR). The calculated SRMR (0.055) was less than the recommended threshold value (≤0.08) (Hu & Bentler, 1999), which indicated a good fit.

Figure 2 Predicting the Students' Use of Mobile LMS

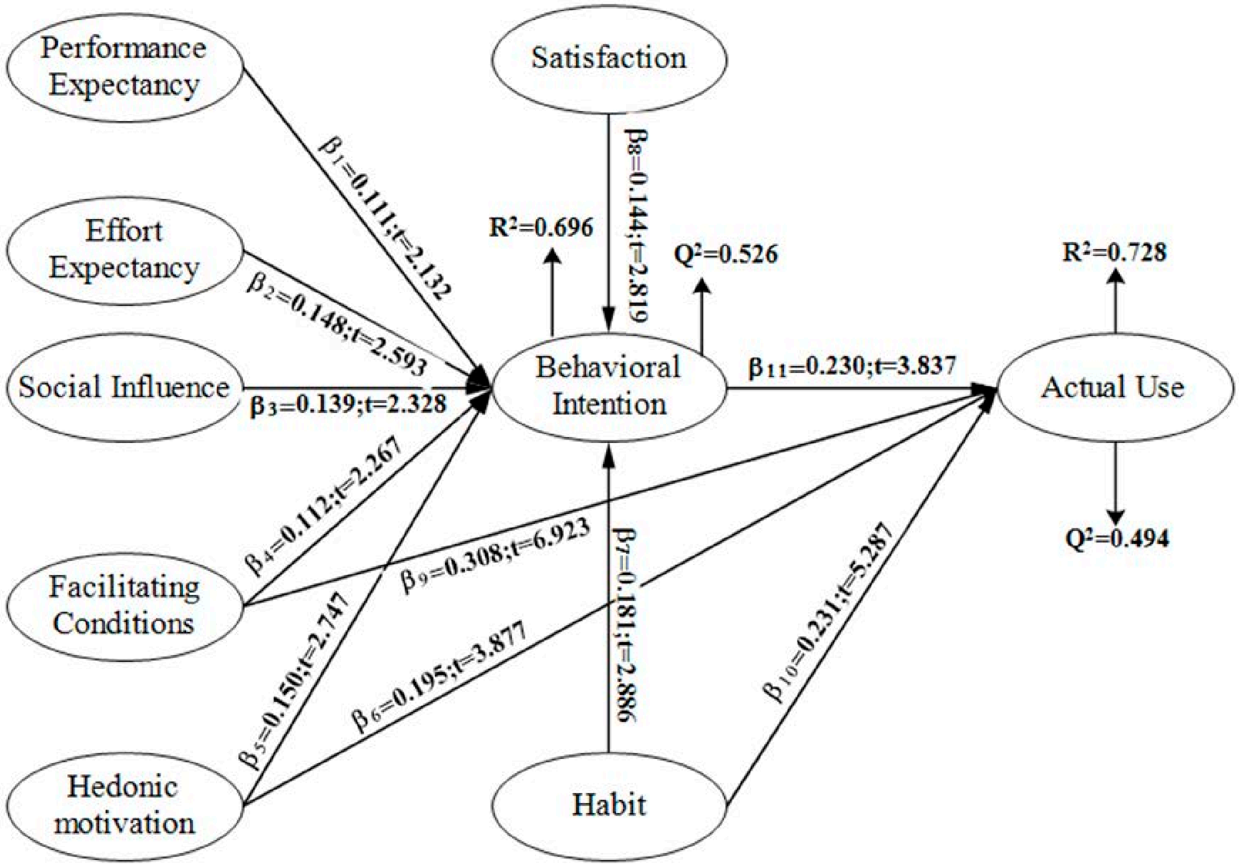


Table 4 Hypothesis Testing and Effect Size

Hypothesis	Path	Beta (β)	T Stats	P-Values	Decision	f²
H1	PE ⇒BI	0.111	2.132	0.034	Accept	0.014*
H2	EE ⇒BI	0.148	2.593	0.010	Accept	0.018*
H3	SI ⇒BI	0.139	2.328	0.020	Accept	0.033*
H4	FC ⇒BI	0.112	2.267	0.024	Accept	0.015*
H5	HM ⇒BI	0.150	2.747	0.006	Accept	0.024*
H6	HM ⇒AU	0.195	3.877	0.000	Accept	0.046*
H7	H ⇒BI	0.181	2.886	0.004	Accept	0.037*
H8	PS ⇒BI	0.144	2.819	0.005	Accept	0.024*
H9	FC ⇒ AU	0.308	6.923	0.000	Accept	0.142*
H10	H ⇒ AU	0.231	5.287	0.000	Accept	0.070*
H11	BI ⇒ AU	0.230	3.837	0.000	Accept	0.072*

Note: *= Small Effect.

Table 5 Redundancy Q2 Value and Explained Variance

	SSO	SSE	Q^2 (=1-SSE/SSO)	R2
Actual Usage	2,000.000	1,012.457	0.494	0.728
Behavioral Intention	1,500.000	710.676	0.526	0.696

DISCUSSION

This study aimed to predict the determinants influencing the ability to use a mobile LMS in BINUS online learning students. A conceptual framework of UTAUT was developed by adding a satisfaction perception factor and was supported both theoretically and empirically. The ability of UTAUT was determined to be a theoretical framework in predicting the actual (based on student perceptions) use of a mobile LMS in the context of online learning. Specifically, the results showed that students' behavioral intentions in using a mobile LMS are positively and significantly influenced by performance and effort expectancy, social influence, facilitating conditions, hedonic motivation, habit, and perceived satisfaction. Furthermore, the aforementioned factors have a positive and significant effect on the actual use of a mobile LMS.

These results signify that the facilitating condition is the significant primary determinant of actual a mobile LMS usage. It also indicates that students have the intention or desire to use a mobile LMS, as they believe that the technology is convenient and valuable. In addition, students' knowledge concerning the use of a mobile LMS from institutions can be an essential point for them to adopt and adapt quickly. This introduction helps students understand the use and overcome the obstacles of using a mobile LMS in the learning process. The better students dominate the operation of the mobile LMS, the more likely they are to be motivated and feel satisfied, and ultimately their expectations of the system will increase. The existence of technical support from classmates is also a factor in the sustainability of students adopting a mobile LMS technology. Even though the entire social environment supports the individual in using technology, it will not be utilized when there are no supporting facilities. Therefore, to enhance the continuous use of the system, universities, as a mobile LMS providers, can focus more on infrastructure, resources, and technical conditions that support the smooth functioning of the system.

Student satisfaction in using a mobile LMS was also shown to be a supporting factor in predicting the actual use. Increasing student satisfaction during use will increase the intention to use and encourage continuous use. Therefore, satisfied students will continue to use the technology and perceive that mobile learning is useful in their learning process.

CONCLUSION

This research successfully predicted the determinants of students using a mobile LMS in their academic activities. These factors were adopted from the UTAUT theory by adding the construct of student satisfaction perceptions. Performance and effort expectancy, social influence, facilitating conditions, hedonic motivation, habit, and perceived satisfaction positively and significantly influenced students' behavioral intention to use a mobile LMS. Furthermore, facilitating conditions, habit, hedonic motivation, and behavioral intention had a positive and significant effect on the actual use of a mobile LMS. Facilitating conditions were the dominant predictor in predicting the actual use, alongside student satisfaction perceptions.

Limitation

Difficulty getting a diverse set of students who use a mobile LMS in a university environment causes study limitations. This is because it is rare to find universities in Indonesia that use a mobile LMS in distance learning systems. This study's actual use is based on students' perceptions of having had experiences in using a mobile LMS, not on the frequency of actual use. The results of this study should be interpreted with caution in the context of a university using a mobile LMS.

Future Research

This study's results need support from the university to be considered in the delivery of distance education for students using a mobile LMS in the distance learning process. Therefore, further research is needed to investigate student behavior in using a mobile LMS. It is essential because the characteristics of distance learning are unique. Future research can focus on factors such as college image and digital competence. Based on the results of observations, it is essential to consider factors regarding IT and academic supporting teams. Also, in terms of lecturers and students, the discussion of interesting topics is enjoyable.

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