

ACTUAL USAGE OF MOBILE-LEARNING MANAGEMENT SYSTEM: EVIDENCE FROM FULL-TIME ONLINE PROGRAM

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ABSTRACT. *Designing an interactive Mobile-Learning Management System (Mobile-LMS) improves students' actual usage. Therefore, this study investigates the actual usage of the Mobile-LMS by testing Davis's Technology Acceptance Model (TAM). Data were obtained by randomly distributing questionnaires to 500 students and analyzed using the SEM-PLS. The result showed that the perceived ease of use and perceived usefulness affects behavioral intention and vice versa. This study filled the gap from previous research, which stated that perceived ease of use does not affect behavioral intention.*

Keywords: Mobile-learning management system, TAM, Actual use, Online learning, Higher education, SEM-PLS

1. Introduction. Currently, universities that operate online learning programs use the Learning Management System (LMS) to ensure proper interaction between lecturers and students. However, the LMS is only operated through a laptop; hence there is a feeling of limited flexibility among students. Therefore, to increase online learning flexibility to prospective students, a Mobile-Learning Management System (Mobile-LMS) was introduced. Researchers have reported that perceived usefulness and satisfaction in using the Mobile-LMS can predict students' continuous intention compared to accessing LMS via computers [1]. In other words, students who are satisfied and trusting the Mobile-LMS interface on mobile tend to keep using the system, even though there is an alternative to access it via a personal computer [2]. Therefore, we need to investigate more about the actual usage of Mobile-LMS.

Mobile-LMS is a software designed to operate on mobile devices such as smartphones and tablets to ensure students have access to lectures, irrespective of space and time boundaries [1]. Smartphones are mobile phones with numerous capabilities, such as resolution and computing features, including the presence of a mobile operating system. As technology information advances, studies are carried out to study the process required in combining M-learning in their different educational systems [3-6].

BINUS Online Learning is a faculty at Bina Nusantara University that uses a Web and Mobile-LMS system interconnected for students to carry out their studies easily. Creating a mobile version of the LMS is an investment for increased study flexibility. It is based on the characteristics of students that participate in a full-time online program, such as workers in industries with an average age of over 25 years and willing to experience learning while working without having to open their laptops. The authors' first survey was interviewing students, with the majority stating that they had not fully used Mobile-LMS to support their academic activities. Although this software was already installed on their smartphone, they were still close and comfortable with the LMS-based website mode.

Several authors have successfully tested the role of Mobile-LMS in the online learning context [1,2]. According to them, the Mobile-LMS does not ensure learners use scholastic goals; therefore, they need to be aware of the gains and apply them for learning purposes [1,7-9]. Presently, there are still limited observed studies on the actual use of Mobile-LMS for college students in online programs. Although Joo et al. [1] have researched the actual use of LMS, they failed in answering that perceived ease of use did not predict students' continuing intentions. However, perceived ease of use predicted students' perceptions of usefulness, and continued intention predicted students' actual usage of Mobile-LMS. Therefore, we reexamine the gap in the results of Joo et al. [1].

Therefore, this research aims to explain the actual usage of Mobile-LMS in Binus Online Learning students based on the concepts that affect technology acceptance. This research was carried out using Davis's Technology Acceptance Model [10] to analyze the relationship between perceived ease of use, perceived usefulness, behavioral intention, and actual usage of Mobile-LMS.

1.1. Mobile learning. Mobile learning is an educational innovation supported by mobile devices [11]. It is also an electronic means of learning using mobile devices and wireless transmission that enables learning anytime and anyplace [12,13]. Therefore, in conclusion, mobile learning is a new learning model that grants students access to course materials, irrespective of their location and time.

A mobile learning concept is associated with learning outside the classrooms and lecture halls. Therefore, this concept takes account of the use of universal knowledge-sharing technology [4]. Online learning using Mobile-LMS is meaningful when students actively participate in the learning process and use mobile devices in an educational atmosphere [3-5,9]. Therefore, several studies have discussed the characteristics of workers interested in online lectures using Mobile-LMS [8,14].

The center of mobile learning has changed to "actual participation and meaningful experiences of learners" [5]. The mobile device used does not warrant an actual impact on student academic activity. Therefore, lecturers need to pay attention to three dimensions of mobile learning, i.e., students and teachers, design, and institutions [3]. These three dimensions need to support each other to obtain students' attention on the use of mobile learning.

1.2. Technology Acceptance Model (TAM). The model that describes how an individual accepts and uses technology is called the Technology Acceptance Model (TAM) [10,15]. Its usage is associated with the endpoint of individual behavior, while attitude is an overall impression factor that encourages the use of technology. In the context of education that uses technology, the perceived ease of use refers to students' attitude that using technology in learning can be affordable and more convenient. Meanwhile, the perceived usefulness relates to students' attitudes that think using technology improves their academic performance.

The authors adopted TAM to analyze student acceptance of learning technology, i.e., Mobile-LMS. Joo et al. [1] specifically studied the acceptance of Mobile-LMS in the context of online learning. The results showed that perceived ease of use positively and significantly affects perceived usefulness and none on behavioral intention. However, perceived usefulness has a positive and significant effect on behavioral intention. Finally, the use of behavioral intention has a positive and significant effect on real usage. Furthermore, to analyze the factors that affect the intention to use and actual usage of e-learning, Limayem and Cheung [16] tested the expectation-confirmation model simultaneously. They examined students' actual frequency of using e-learning and the relationship between intention to use and actual usage. According to them, the behavioral intention to use and past happenings significantly influenced actual usage. However, this study's limitations only explained from a perceptual point of view the actual perceived frequency.

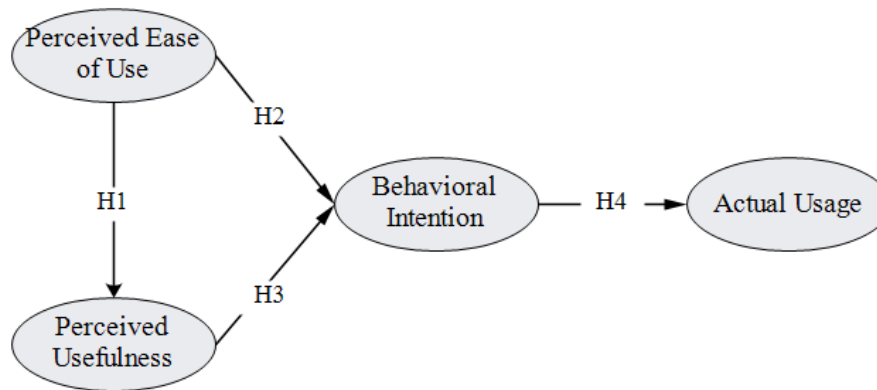


FIGURE 1. Hypothesis model

This study uses TAM in examining the determinants of acceptance of Mobile-LMS technology in students that take full-time online program. Based on the literature, the following hypotheses were obtained:

- H1: Perceived ease of use has a positive effect on the perceived usefulness of students.
- H2: Perceived ease of use has a positive effect on the behavioral intention of students.
- H3: Perceived usefulness has a positive effect on the behavioral intention of students.
- H4: Behavioral intention has a positive effect on the actual usage of students.

2. Methodology. This research was carried out on the BINUS Online Learning Faculty of the Bina Nusantara University, one of Indonesia's best universities. An introductory survey was conducted on 30 students to clarify the authors' questionnaire at the initial stage. The total number of students at the BINUS Online Learning Faculty from the Business Management, Accounting, Information Systems, Computer Science, and Industrial Engineering study programs is 4,104. However, for this study, the proportional sampling method was used to obtain data from 500 students from 5 study programs. The selection of BINUS Online Learning students as the unit of analysis is because it has implemented Mobile-LMS since its inception.

Furthermore, the authors compiled a questionnaire regarding previous studies to measure student perceived ease of use, perceived usefulness, behavioral intention, and actual usage using the measurements model designed by Venkatesh et al. [17]. All question items totaled 15, as shown in Table 1, with a Likert scale of 5 points (1 – strongly disagree to 5 – strongly agree) used for analysis.

SEM-PLS equation modeling was used to estimate and test the hypothesized models [18]. It comprises two steps, i.e., measurement and structural models [19]. The measurement model is used to ensure data quality, while the structure is divided into four parts. The first is hypothesis testing, which refers to the t-statistic, with a 95% confidence level. The second is the R-Square (R^2) evaluation with a substantial, moderate, and weak values of 0.67, 0.33, and 0.19 [20]. The third testing is the effect size (f^2) with moderate, large, and non-effect values of 0.02, 0.15, and 0.35 [21]. The last test is the Stone-Geisser (Q^2), which tests the PLS model with the predictive relevance Q^2 value. When the value is over null, it confirms that the observed values can be reconstructed well [22].

3. Result and Discussion. The first stage in SEM-PLS testing measured the level of validity and reliability. The calculations for all indicators give a loading factor that passes the minimum level of 0.7 [20] with an Average Variance Extracted (AVE) value above 0.5 as shown in Table 1, which indicates that the convergent validity is satisfied. Furthermore, all variables' indicators have the highest correlation for discriminant validity, as shown in Table 2. Therefore, the discriminant validity test is satisfied; hence all indicators

TABLE 1. Descriptive statistics, convergent validity and reliability test

Variable	Indicator	SLF
Perceived ease of use AVE = 0.706 CR = 0.906 CA = 0.862	For me, knowing how to use the Mobile-LMS is easy (mean = 3.79).	0.853
	My interplay with the Mobile-LMS is clear and comprehensible (mean = 4.11).	0.841
	The Mobile-LMS is easy to use (mean = 4.08).	0.845
	It is simple for me to become an expert in using the Mobile-LMS (mean = 3.87).	0.822
Perceived usefulness AVE = 0.790 CR = 0.938 CA = 0.911	Using the Mobile-LMS is beneficial in supporting all my academic activities (mean = 3.71).	0.900
	Using the Mobile-LMS can fulfil my expectations in achieving essential things during the lecture process (mean = 3.69).	0.923
	The Mobile-LMS helps me to complete all academic activities (mean = 3.93).	0.851
	Using the Mobile-LMS can improve academic performance (mean = 3.74).	0.878
Behavioral intention AVE = 0.809 CR = 0.927 CA = 0.882	I intend to continue to use the Mobile-LMS in my future studies (mean = 3.97).	0.903
	I will always try to use the Mobile-LMS in my studies (mean = 3.98).	0.915
	I plan to continue using the Mobile-LMS frequently, in my studies (mean = 4.13).	0.879
Actual usage AVE = 0.724 CR = 0.913 CA = 0.870	I regularly use the Mobile-LMS in my studies (mean = 4.03).	0.907
	Using the Mobile-LMS is an enjoyable experience (mean = 4.00).	0.899
	I am currently using the Mobile-LMS as a supporting tool in my studies (mean = 4.22).	0.847
	I spend a lot of time using the Mobile-LMS in my studies (mean = 3.65).	0.741

used meet the item validity requirements. The test results for composite reliability and Cronbach's alpha produce a value greater than 0.7, which means that it is also satisfied.

The second stage is the structural testing of the model. The aim is to determine the effect between variables by the path coefficient, as shown in Figure 2 and Table 3. Based on the results of hypothesis testing, it is concluded that all hypotheses are accepted. The research model provides three linear equations. The first model, $PU = 0.816\beta_1EU$ in a positive and significant direction; therefore, H1 is accepted, with EU contributing 66.6% to PU ($R^2 = \text{moderate}$). The second model, $BI = 0.600EU\beta_1 + 0.199PU\beta_2$, is positive and significant; therefore, H2 and H3 are accepted, with EU and PU contributing 59.4% to BI ($R^2 = \text{moderate}$). The third model is $AU = 0.752\beta_1BI$ in a positive and significant direction; therefore, H4 is accepted, with BI contributing 56.5% to the AU ($R^2 = \text{moderate}$).

The Cohen f^2 test results showed that the relationship between the EU, PU, and BI had little effect. Meanwhile, the relationship between EU, PU, BI, and AU has a strong influence. Furthermore, the Stone-Geisser evaluation (Q^2) produced a value of 0.941 and was greater than 0. It means that the observed values have been reconstructed properly with good predictive relevance.

TABLE 2. Discriminant validity

	Actual usage	Ease of use	Intention	Usefulness
AU1	0.907	0.728	0.675	0.668
AU2	0.899	0.723	0.642	0.691
AU3	0.847	0.665	0.652	0.634
AU4	0.741	0.580	0.585	0.550
PEU1	0.690	0.853	0.663	0.847
PEU2	0.641	0.841	0.606	0.636
PEU3	0.644	0.845	0.601	0.599
PEU4	0.690	0.822	0.684	0.626
BI1	0.713	0.717	0.903	0.629
BI2	0.684	0.711	0.915	0.663
BI3	0.626	0.624	0.879	0.561
PU1	0.682	0.717	0.612	0.900
PU2	0.667	0.715	0.607	0.923
PU3	0.629	0.703	0.611	0.851
PU4	0.683	0.764	0.618	0.879

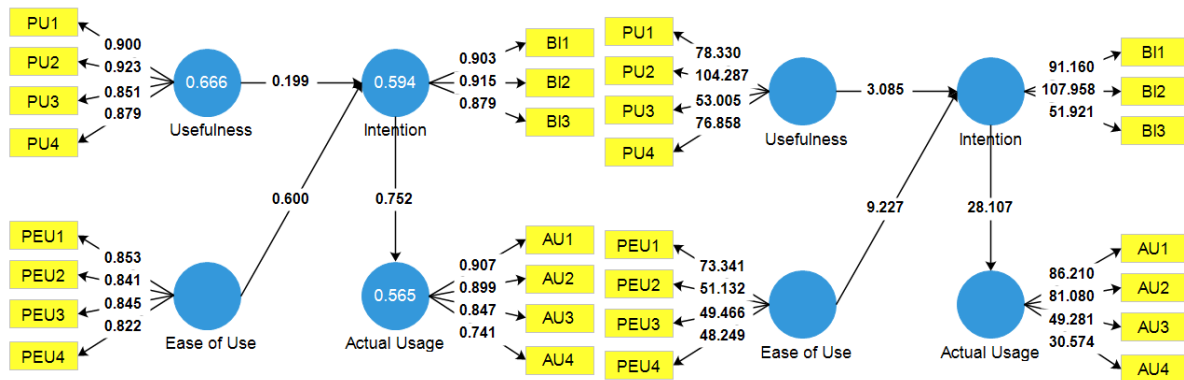


FIGURE 2. Structural model (β and T -value)

TABLE 3. Hypothesis testing

Model	Path	β	T -stats	P -value	Decision	Effect size	R-square
1	EU → PU	0.816	52.198	0.000	Accepted	1.998 (Large)	0.666 (moderate)
	EU → BI	0.600	9.227	0.000	Accepted	0.296 (Small)	0.594 (moderate)
2	PU → BI	0.199	3.085	0.002	Accepted	0.032 (Small)	0.594 (moderate)
	BI → AU	0.752	28.107	0.000	Accepted	1.298 (Large)	0.565 (moderate)

4. Conclusion. In conclusion, this study explicitly examines the Technology Acceptance Model (TAM) from Davis to implement the Mobile-LMS. This research was carried out due to the limited number of studies on the acceptance of technology for Mobile-LMS in the context of education. The authors perceived Davis’s model as an early technology acceptance model; therefore, this led to the need to analyze it before examining the UTAUT and UTAUT-2 models. The results showed that all relationships for each variable

are acceptable, even though past studies declared that the perceived ease of use does not affect behavioral intention [1], the authors succeeded in filling the gap from past studies.

In terms of actual usage of Mobile-LMS, this research did not discuss the frequency of students accessing it in a specific time frame, rather it was based on their perception. Further research needs to be carried out by paying attention to students' login time in the Mobile-LMS as quantitative data, to ensure it is more accurate to pay attention to the actual time of using the Mobile-LMS.

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REFERENCES

- [1] Y. J. Joo, N. Kim and N. H. Kim, Factors predicting online university students' use of a mobile learning management system (m-LMS), *Educational Technology Research and Development*, vol.64, pp.611-630, DOI: 10.1007/s11423-016-9436-7, 2016.
- [2] A. Antee, Student perceptions and mobile technology adoption: Implications for lower-income students shifting to digital, *Educational Technology Research and Development*, vol.69, pp.191-194, DOI: 10.1007/s11423-020-09855-5, 2020.
- [3] D. Vogel, D. Kennedy and R. C.-W. Kwok, Does using mobile device applications lead to learning?, *Journal of Interactive Learning Research*, vol.20, no.4, pp.469-485, 2009.
- [4] S.-S. Liaw, M. Hatala and H.-M. Huang, Investigating acceptance toward mobile learning to assist individual knowledge management: Based on activity theory approach, *Computers & Education*, vol.54, pp.446-454, DOI: 10.1016/j.compedu.2009.08.029, 2010.
- [5] L. Sha, C.-K. Looi, W. Chen and B. H. Zhang, Understanding mobile learning from the perspective of self-regulated learning, *Journal of Computer Assisted Learning*, vol.28, no.4, pp.366-378, 2012.
- [6] C.-K. Looi et al., Implementing mobile learning curricula in a grade level: Empirical study of learning effectiveness at scale, *Computers & Education*, vol.77, pp.101-115, DOI: 10.1016/j.compedu.2014.04.011, 2014.
- [7] J. R. Corbeil and M. E. Valdes-Corbeil, Are you ready for mobile learning?, *Educause Quarterly*, vol.30, no.2, pp.51-58, 2007.
- [8] K. Shelley, B. Jeffrey and M. Trishita, Challenging mobile learning discourse through research: Student perceptions of Blackboard Mobile Learn and iPads, *Australasian Journal of Educational Technology*, vol.28, no.4, DOI: 10.14742/ajet.832, 2012.
- [9] L. Nguyen, S. M. Barton and L. T. Nguyen, iPads in higher education – Hype and hope, *British Journal of Educational Technology*, vol.46, no.1, pp.190-203, DOI: 10.1111/bjet.12137, 2015.
- [10] F. D. Davis, Perceived usefulness, perceived ease of use, and user acceptance of information technology, *MIS Quarterly*, vol.13, no.3, pp.319-340, DOI: 10.2307/249008, 1989.
- [11] S. K. Sharma and F. L. Kitchens, Web services architecture for m-learning, *Electronic Journal of e-Learning*, vol.2, no.1, pp.203-216, 2004.
- [12] N. Pinkwart, H. U. Hoppe, M. Milrad and J. Perez, Educational scenarios for cooperative use of personal digital assistants, *Journal of Computer Assisted Learning*, vol.19, no.3, pp.383-391, 2003.
- [13] H. Hoppe, R. Joiner, M. Milrad and M. Sharples, Guest editorial: Wireless and mobile technologies in education, *Journal of Computer Assisted Learning*, vol.19, no.3, pp.255-259, 2003.
- [14] D. Corlett, M. Sharples, S. Bull and T. Chan, Evaluation of a mobile learning organiser for university students, *Journal of Computer Assisted Learning*, vol.21, no.3, pp.162-170, 2005.
- [15] F. D. Davis, R. P. Bagozzi and P. R. Warshaw, User acceptance of computer technology: A comparison of two theoretical models, *Management Science*, vol.35, no.8, pp.982-1003, DOI: 10.1287/mnsc.35.8.982, 1989.
- [16] M. Limayem and C. Cheung, Understanding information systems continuance: The case of Internet-based learning technologies, *Information & Management*, vol.45, no.4, pp.227-232, DOI: 10.1016/j.im.2008.02.005, 2008.
- [17] V. Venkatesh, J. Y. L. Thong and X. Xu, Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology, *MIS Quarterly*, vol.36, no.1, pp.157-178, DOI: 10.2307/41410412, 2012.

- [18] H.-D. Lin and H.-L. Chen, Detection of surface flaws on textured LED lenses using wavelet packet transform based partial least squares techniques, *International Journal of Innovative Computing, Information and Control*, vol.15, no.3, pp.905-921, 2019.
- [19] J. Hair, M. Sarstedt, L. Hopkins and G. K. Volker, Partial least squares structural equation modeling (PLS-SEM): An emerging tool in business research, *European Business Review*, vol.26, no.2, pp.106-121, DOI: 10.1108/EBR-10-2013-0128, 2014.
- [20] W. W. Chin and P. R. Newsted, Structural equation modeling analysis with small samples using partial least squares, in *Statistical Strategies for Small Sample Research*, R. H. Hoyle (ed.), Thousand Oaks, CA, Sage Publications, 1999.
- [21] J. Cohen, P. Cohen, S. G. West and L. S. Aiken, *Applied Multiple Regression/Correlation Analysis for the Behavioral Sciences*, 3rd Edition, Lawrence Erlbaum Associates, Mahwah, New Jersey, 2003.
- [22] J. Henseler, G. Hubona and P. A. Ray, Using PLS path modeling in new technology research: Updated guidelines, *Industrial Management & Data Systems*, 2016.