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Research Article
Determinants of Mobile Learning Adoption in Higher Education Setting

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Abstract

Objective: The aim of the study is to investigate factors that could influence mobile learning adopting. Drawing upon The Unified Theory of Acceptance and Use of Technology (UTAUT) plus two other variables which are perceived playfulness and self management of learning, an empirical based framework was developed to identify predictors of mobile learning. **Methodology:** The study used a survey research method with a questionnaire as the data collection tool. A total of 282 respondents from Universiti Teknologi MARA participated in the study. **Results:** The results showed that performance expectancy, effort expectancy, social factors, facilitating conditions, perceived playfulness and self management of learning are strong determinants of intention to adopt mobile learning. **Conclusion:** The present study provides both a theoretical and practical contributions to understanding the predictors of intention to adopt mobile learning and should be of interest to both researchers and practitioners.

Key words: Mobile learning, determinants, adoption, UTAUT, structural equation modelling

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INTRODUCTION

The revolution brought about by mobile technologies have resulted in the emergence of mobile learning, which is the extension or prolongation of e-learning. Mobile learning can be described as a learning process which takes the advantages of mobile devices, ubiquitous communications technology and intelligent user interfaces[1]. In universities, mobile learning helps educational institutions to enhance the accessibility, interoperability and reusability of educational resources and also to improve flexibility and interactivity of learning behaviors at convenient times and places[2,3]. As opposed to traditional learning, mobile learning focuses on the mobility of the learner as well as the mobility of the learning process itself[3]. For learners in general, mobile learning facilitates the use of previously unproductive time, enables learning behaviors regardless of time and place and brings about the great possibilities for personalized, customized and context-aware learning support services[3]. Through mobile learning, users can download different learning apps to their smart phones or other mobile devices via Apple App Store, Google Play, Windows Phone Store and BlackBerry App World[4].

Despite the availability of studies on mobile learning, its theoretical foundations have not yet matured[5]. Despite the high degree of insertion of mobile devices in current society, the mere availability of technology itself does not guarantee that its potential will be used for learning or accepted by all evenly[6]. Others also argued that the understanding of the adoption of mobile technologies in educational environments is still incipient and in particular, questions about how to promote the acceptance of mobile learning by users are still largely unresolved[6,7]. In addition, students' needs with regard to mobile learning is still not fully understood[8]. Against this background, a study was conducted with the following objectives: (i) To identify factors that influence mobile learning adoption among students in higher learning institution in Malaysia and (ii) To ascertain whether the following factors influence intention to adopt mobile learning; Performance expectancy, effort expectancy, social factors, facilitating conditions, perceived playfulness and self management of learning.

Mobile learning is defined as "Handheld technologies, together with wireless and mobile phone networks, to facilitate, support, enhance and extend the reach of teaching and learning"[9]. It is also defined as "Acquisition of any knowledge and skill through the use of mobile technology, anywhere, anytime that results in an alteration in behavior"[10]. Mobile learning is highly situated, personal, collaborative and long term[10]. Mobile learning is also considered as truly promoting learner-centred learning because of the following features: (i) Portability-the small size and weight of mobile devices means they can be carried everywhere and help learning occur at anywhere and anytime, (ii) Connectivity-providing learners with connections to other learning such as through other people, devices or networks, (iii) Interactivity-mobile devices are potential tools for enhancing a cooperative learning environment, (iv) Context sensitivity-mobile devices enable learning to take place which can make greater use of a person's, (v) Immediate context and surroundings, (vi) Lifelong-mobile content consumption is continuous, there is no beginning, middle or end and (vii) Individuality-learning can be customised and based on previous learning experiences[11]. The advantages of mobile learning are (i) Just-enough learning-highly applied, easily digestible learning for increasingly busy executives, (ii) Just-in-time learning-convenient, flexible and relevant learning at the exact moment learning is required, (iii) Just-for-me learning-learner-driven learning in a suitable format and (iv) Cost-saving-mobile learning can be cost effective and using a learner's own mobile device eliminates technological barriers to accessing learning[10].

Since the dawn of mobile learning, researchers have studied factors that influence its adoption. Theories, models or framework such as Theory of Reasoned Action (TRA)[12], Social Cognitive Theory (SCT)[13], Technology Acceptance Model (TAM)[14], Theory of Planned Behavior (TPB)[15], Model of PC Utilization (MPCU)[16], Innovation Diffusion Theory (IDT)[17], combined TAM and TPB[18] and The Unified Theory of Acceptance and Use of Technology (UTAUT)[19] have been referred and adapted by researchers to investigate the mobile learning adoption. Among the various theories and models, UTAUT is found to be the most adopted or referred in the context of mobile learning. The UTAUT could explain up to 70% of technology acceptance behavior[20]. The UTAUT suggests that four key constructs which are, performance expectancy, effort expectancy, social factors and facilitating conditions have a direct influence on intention to adopt technology. Studies on mobile learning had empirically proof the contribution of these four constructs. Besides these four constructs, researchers have also explored the role of perceived playfulness and self management of learning. Drawing upon this premise, the present study will investigate the adoption of mobile learning based on the framework shown in Fig. 1.

Intention to adopt mobile learning is defined as "The person's subjective probability that he or she will perform the behavior in question"[19]. In the context mobile learning adoption, various factors have been identified as predictors of

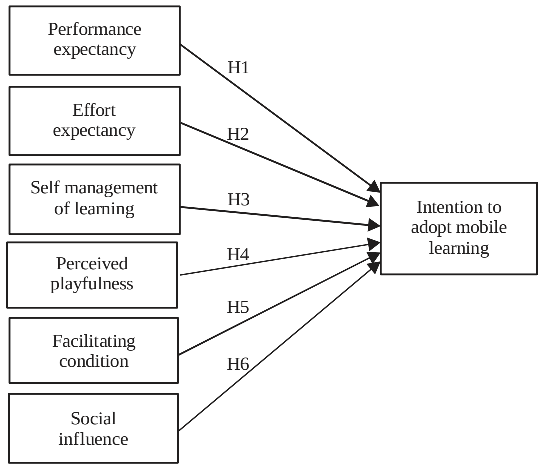

Fig. 1: Theoretical framework

intention to adopt which are perceived mobility, perceived ease of use, perceived usefulness, alignment value, intrinsic value, utility value, self-management of learning, comfort with mobile learning, perceived trust, performance expectancy, effort expectancy, social influence, perceived playfulness, relative advantage, facilitating condition, previous experience, resistance, importance of the course, integration of the technology into course assessment, lecturer modelling of the course, available tools, lecturer's feedback, mobile device and software, perceived innovativeness, perceived ICT anxiety, perceived self efficacy, compatibility, complexity, trialability, observability, image, voluntariness, cost and perceived credibility[21]. However, eight most frequently examined factors which are performance expectancy, effort expectancy, self management of learning, social influence, facilitating conditions, perceived playfulness, perceived cost and previous experience[21].

Performance expectancy refers to "The degree to which an individual believes that using the system will help him or her to attain gains in job performance"[19]. Originally, this construct is also called perceived usefulness in Technology Acceptance Model. Adapting performance expectancy to mobile learning suggests that users will find mobile learning useful because it enables learners to accomplish learning activities more quickly, effectively and flexibly[22]. A study involving 330 respondents in Taiwan discovered that performance expectancy was the strongest predictor of intention to adopt M-learning[22]. A study in the context of Malaysia also showed a consistent finding[23,24]. Besides these studies, other studies had also discovered similar findings[4,22,24-28]. A recent study in the content of language learning also indicates that performance expectancy was also influential in determining intention to adopt[4]. To this effect, this study hypothesizes:

- **H1:** Performance expectancy is a significant predictor of intention to adopt mobile learning

Effort expectancy is "The degree of ease associated with the use of the system"[19]. In the context of mobile learning, effort expectancy is about an individual's expectation of using mobile learning without much effort. The easier the mobile learning applications can be accessed by the user, the more is the intention to adopt it. Studies across different countries showed mixed results on the influence of effort expectancy on intention to adopt mobile learning. However, most studies found a positive relationship between effort expectancy on intention to adopt mobile learning[4,22,24-30]. A recent study among students in Jordanian universities found that this contract was a significant predictor of actual usage[8]. Based on the aforementioned premise, this study posits that:

- **H2:** Effort expectancy is a significant predictor of intention to adopt mobile learning

Self management of learning is defined as the extent to which an individual feels he or she is self-disciplined and can engage in autonomous learning[31]. Indeed, the need for self-direction or self-management of learning, runs clearly throughout the distance education and resource-based flexible learning studies[31-33]. Since mobile learning can be considered as a kind of e-learning via mobile devices, it is expected that a person's level of self-management of learning will have a positive influence on his or her behavioral intention to adopt mobile learning. A study in the context of mobile learning found that self management of learning positively predicts intention to adopt mobile learning[22]. To this effect, this study hypothesizes that:

- **H3:** Self-management of learning is a significant predictor of individual intention to adopt mobile learning

Perceived playfulness is considered one of the critical factors that could potentially affect learning engagement with the utilization of new teaching innovations and technology[34]. Perceived playfulness will provide intrinsic motivation when individuals become completely absorbed in a technology[35]. An intrinsic motivator refers to the individual's performance or engagement in an activity due to his or her interest in the activity[25]. Previous studies have also shown that the use of IT is influenced by perceived playfulness-related constructs[35,36]. The reason is because individuals who experience pleasure or enjoyment from using an information system are more likely to intend to use it extensively than those who do not[37,38]. Taken the above together, this study hypothesizes:

- **H4:** Perceived playfulness is a significant predictor of individual intention to adopt mobile learning

Facilitating condition is defined as "The degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system"[19]. Acceptance of any new technology is highly dependent upon the supporting conditions or environment[25]. In the context of mobile learning, these facilitating conditions can appear in the form such as resources, knowledge, internet speed and support personnel[25]. Studies showed that facilitating condition is a significant predictor of mobile learning adoption[25,28]. Given this background, this study postulates that:

- **H5:** Facilitating conditions is a significant predictor of intention to adopt mobile learning

Social influence is defined as "The degree to which an individual perceives that others believe he or she should use the new system"[19]. It is also defined as "The individual's internalization of the reference groups' subjective culture and specific interpersonal agreements that the individual has made with others, in specific social situations"[16]. Social influence can also be distinguished with three different forms in his theory, (i) Compliance; when an individual accepts influence because he hopes to achieve a favourable reaction from another person or group (social approval/disapproval from others), (ii) Identification; when an individual accepts influence because he wants to establish or maintain a satisfying self defining relationship with others and (iii) Internalization; when an individual accepts influence because it is congruent with her value system[39]. This study explained that social influence in mobile adoption appeared in two modes: one that exerts pressure on individuals to adopt and another that helps to generate benefits via social networks that are tied in with economic and business networks[40]. Consequently, grounded in UTAUT and justified by previous studies[22,27,28] the following hypothesis is put forth:

- **H6:** Social influence is a significant predictor of intention to adopt mobile learning

MATERIALS AND METHODS

The study used a survey method with questionnaire as the instrument for data collection. The questionnaire was based on the instruments used by previous studies[22,25]. Perceptual measures in the form of statements were used for measuring each variable with a corresponding Likert scale anchored as 1 for "Strongly Disagree", 2 for "Disagree", 3 for "Neither Agree Nor Disagree", 4 for "Agree" and 5 for "Strongly Agree". The questionnaire was pre-tested with several experts and prospective respondents. Subsequently, it was pilot tested with 30 students. The results of the pilot test are illustrated in Table 1 showed that the Cronbach-Alpha for all variables were well above 0.7, indicating that the questionnaire was acceptably reliable.

Table 1: Operational definition and sources of measurements of variables

Variables	No. of items	Cronbach-Aplha of pilot test
Intention to adopt mobile learning	4	0.760
Performance expectancy	4	0.723
Effort expectancy	4	0.811
Self management of learning	3	0.746
Perceived playfulness	3	0.722
Facilitating conditions	3	0.707
Social norms	3	0.812

The population of the study was students enrolled to the bachelors degree in the Faculty of Information Management, Universiti Teknologi MARA, Malaysia. Using the simple random sampling technique, a total of 350 questionnaires were sent to the targeted students. The duration of data collection was one month and after the period was over, a total of 302 questionnaires were returned. However, 20 were found to be unusable for further analysis as they were incomplete. The remaining 282 were analyzed using IBM SPSS and AMOS version 20. The statistical analyses carried out were frequency analysis, descriptive analysis focusing on median, standard deviation, variance and testing normality of distribution, an Exploratory Factor Analysis (EFA) for assessing unidimensionality, Confirmatory Factor Analysis (CFA) for assessing convergent validity and discriminant validity and Structural Equation Modelling (SEM) or structural model for testing the established hypotheses.

RESULTS

Table 2 shows the demographic profile of the respondents. Out of 282 respondents, 73.8% were female while the remaining 26.2% were male. In terms of semester of study, the majority indicated to be in semester three (22.7%) while the minority were from semester six (12.4%). With regard to program registered, the majority of the respondents was doing B.Sc. Information Management Systems (27.0%) and followed by B.Sc. Library Science (25.5%).

In order to identify whether the data is experiencing common method bias, Harman's single factor test was executed. All items from all constructs under study were entered for analysis and constrained to only a single factor. The results showed that the single factor explained only 26.29%, less than the benchmark value of 50% of the total variance, implying that the collected data is free from the problem of common method variance. Normality testing on univariate and multivariate was also accessed upon the data. To test for univariate normality the skewness and kurtosis of each observed variable was assessed. As shown in Table 2, the skewness and kurtosis requirements fulfilled the benchmark values which are 3 and 10, respectively[41]. Multivariate normality can be assumed when the Mardia's coefficient should be less than p (p+2), where p is the number of observed variables[42]. As this study has 24 observed variable, so 24 (24+2) = 624 while the Amos output for Mardia's coefficient is 68.56, which is less than 624, hence multivariate normality can be assumed.

This study used factor loadings, Composite Reliability (CR) and Average Variance Extracted (AVE) to measure the convergent validity. As shown in Table 3, all the factor loadings, CR and AVE met the requirement for SEM analysis[43]. The recommended score for factor loadings is 0.6, while the AVE and CR are 0.5 and 0.7, respectively[43]. Accordingly, the study also assessed discriminant validity and the results are presented in Table 4. The square root of the AVE values is well above the correlation values, hence suggesting discriminant validity requirement is fully complied[44].

In Structural Equation Modelling, fit criteria are assessed in terms of absolute fit measures, incremental fit measures and also parsimony fit measures. As illustrated in Table 5, the χ^2 statistic suggests that the data do not fit the model well (χ^2 = 340.232, df = 231, p<0.05). However, because χ^2 is easily affected by sample size, the χ^2 statistic is not always an appropriate measure of a model's goodness-of-fit. Therefore other fit indices as shown in Table 5 are used to examine the model's goodness-of-fit. Apparently, all fit indices surpassed the fit criteria suggesting that the SEM model fits the data very well.

Table 2: Demographic profile

Parameters	Frequency	Percentage
Gender		
Male	74	26.2
Female	208	73.8
Semester		
1	36	12.8
2	54	19.1
3	64	22.7
4	42	14.9
5	51	18.1
6	35	12.4
Program		
B.Sc. Library Science	72	25.5
B.Sc. Information Management Systems	76	27.0
B.Sc. Records Management	67	23.8
B.Sc. Resource Centre Management	67	23.8

Table 3: Results of convergent validity assessment

Model constructs	Measurement item	Loading	Composite reliability	Average variance extracted
Intention to adopt	ITU1	0.737	0.780	0.542
	ITU2	0.761		
	ITU3	0.710		
Self management learning	SML1	0.734	0.857	0.600
	SML2	0.794		
	SML3	0.775		
	SML4	0.793		
Social influence	SOI1	0.734	0.772	0.531
	SOI2	0.736		
	SOI3	0.715		
Facilitating conditions	FAC1	0.780	0.881	0.713
	FAC2	0.928		
	FAC3	0.819		
Performance expectancy	PEE1	0.704	0.837	0.563
	PEE2	0.792		
	PEE3	0.705		
	PEE4	0.794		
Perceived playfulness	PPL1	0.789	0.865	0.682
	PPL2	0.898		
	PPL3	0.785		
Effort expectancy	EFE1	0.717	0.808	0.512
	EFE2	0.707		
	EFE3	0.718		
	EFE4	0.721		

CR: Square of the summation of the factor loadings/Square of the summation of the factor loadings+Square of the summation of the error variances, AVE: Summation of the square of the factor loadings/Summation of the square of the factor loadings+Summation of the error variances

Table 4: Results of discriminant validity assessment

	1	2	3	4	5	6	7
Intention to adopt	0.736						
Self management learning	0.429	0.774					
Social influence	0.581	0.255	0.728				
Facilitating conditions	0.381	0.089	0.381	0.844			
Performance expectancy	0.486	0.202	0.486	0.202	0.750		
Perceived playfulness	0.550	0.225	0.550	0.225	0.550	0.825	
Effort expectancy	0.527	0.319	0.527	0.319	0.527	0.319	0.715

Diagonals (italicized) represent the square root of the Average Variance Extracted (AVE) while the other entries represent correlation values

Table 5: Fit indices of measurement and structural model

Fit index	Fit criteria	Measurement model
Chi square (χ^2)		340.232
Degrees of freedom		231.000
p-value (probability)	$\geq$0.5	0.000
CMIN (χ^2)/DF	3.0	1.473
Goodness of fit index	$\geq$0.9	0.913
Root mean square error of approximation	$\leq$0.05	0.041
Root mean square residual	$\leq$0.05	0.035
Normed fit index	$\geq$0.9	0.900
Comparative fit index	$\geq$0.9	0.963
Adjusted goodness of fit index	$\geq$0.8	0.887
Parsimonious normed fit index	$\geq$0.5	0.749

Table 6: Results of hypotheses testing

Hypothesis	Coefficients	t-value	p-values	Supported
H1: Performance expectancy→intention to adopt	0.197	4.297	<0.01	Yes
H2: Effort expectancy→intention to adopt	0.164	2.903	<0.01	Yes
H3: Self management of learning→intention to adopt	0.146	2.909	<0.01	Yes
H4: Perceived playfulness→satisfaction to adopt	0.184	2.448	<0.01	Yes
H5: Facilitating condition→intention to adopt	0.100	2.448	<0.01	Yes
H6: Social influence→intention to adopt	0.265	3.961	<0.01	Yes

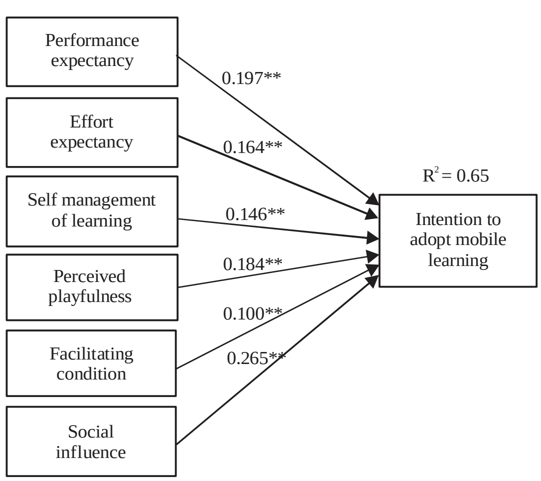

Fig. 2: Path diagram

Table 6 showcases the path coefficients between the independent variables and a dependent variable. The squared multiple correlation (R^2) value for the relationship between the six independent variables and intention to adopt was 0.650. The overall results indicate that all hypotheses were fully supported as the p-values for all paths are well below 0.05. The coefficient values (b) range between 0.100 and 0.265. Figure 2 depicts the path diagram between the independent and dependent variables.

DISCUSSION

The present study provides both a theoretical and practical contributions to understanding the predictors of intention to adopt mobile learning. The findings of this study should be of interest to both researchers and practitioners. The results generated from the path analysis indicate that the combination of the six independent variables accounts for 65% of the variance in intention to adopt mobile learning. This result suggests that 65% of the variance in intention to adopt mobile learning can be explained by performance expectancy, effort expectancy, social factors, facilitating conditions, perceived playfulness and self management of learning. For a substantial model, the study suggests that R^2 should be about

0.35 or greater[45]. In this study, the R^2 is 0.65 which indicating that the estimated model is substantial.

This study has significantly recognized the influence of performance expectancy on intention to adopt mobile learning (b = 0.197, p<0.01). The result is consistent with previous studies on mobile learning[22,23,25-27,29]. The results suggest that, the more students perceive that mobile learning is useful for learning and improves their productivity, the more likely they are to engage in mobile learning. Theoretically, this result further strengthens UTAUT in predicting mobile learning adoption. The scale used for measuring performance expectancy focused on increased performance, productivity and effectiveness. From the practical viewpoint, the findings send a strong message on the importance for increasing student performance expectancy. Educators and administrators could perhaps play a role by promoting the benefits and usefulness of mobile learning to their students and encourage them to use their mobile devices for information searching, engaging in online group discussions or completing other learning activities.

Just as performance expectancy, effort expectancy which is derived from UTAUT was also found to be a significant predictor of mobile learning adoption (b = 0.164, p<0.01). The result is in tandem with past studies[22,23,25-27,29] which means that, the more students perceive that mobile learning is easy to use for learning, the more likely they are to engage in mobile learning. Effort expectancy construct is similar with perceived ease of use, which is defined as the degree to which a person believes that the use of a particular system would be free of effort[14]. The items used for measuring effort expectancy focused on the degree of difficulty on using mobile learning. Today, among students of Malaysian universities, the use of mobile devices, especially smart phones is very common. Perhaps, due to the fact that using a mobile device appears to be routine for most of these students; therefore, they may perceive using it will not require much of their efforts as it is just similar to using it for other tasks. Nevertheless, this finding has provided additional support for UTAUT in predicting mobile learning. The implication to practitioner is that, when developing mobile learning applications, serious attention should be given to user-friendliness aspects.

The third hypothesis of this study is between self management of learning and intention to adopt mobile learning. Compared to the constructs of UTAUT, this variable is not very extensively studied in the context of mobile learning. The result of this study has showed that this construct is indeed applicable in determining intention to adopt mobile learning (b = 0.146, p<0.01). This result is in line with the previous finding[22]. This finding implies that individual with a highly autonomous learning ability will be more likely to use mobile learning than will an individual with a lower autonomous learning ability. Given this finding, mobile learning developers should respond by developing mobile learning applications that are equipped with features that are suitable for those who are highly independent in their learning processes. On the other hand, educators and administrator can also play a role by grooming their students to be more independent and adapt themselves to be more self learning.

The results of this study also recognized that perceived playfulness as a significant predictor of intention to adopt mobile learning (b = 0.184, p<0.01). This finding further supports previous studies[22,27]. The result implies that the more students enjoy the mobile learning, the more they will be motivated to engage in mobile learning activities. Given that the use of mobile learning is fully voluntary and that the target user group consists of a large number of people with very diversified backgrounds, making mobile learning system playful and enjoyable to interact with, is crucial for attracting more users to the mobile learning system[22]. Therefore, mobile learning developers should react to this finding by enriching their mobile learning applications with enjoyable and entertaining features.

Consistent with past studies[25,28], this study had also found that facilitating condition as an essential predictor of intention to adopt mobile learning (b = 0.184, p<0.01). This finding suggests that student will not be attracted to adopt mobile learning in the absence of facilitating conditions. In the context of Malaysia, all university students are entitled to a special voucher for purchasing smart phones. On top of that, the free wireless networks, available in the universities as well as in other public places such as bistros, restaurants and public libraries provide convenient internet access to the students. Nonetheless, this finding should alert the authorities concerned with the importance of the continuous update and upgrade of the infrastructure or facilities required for the implementation of mobile learning.

The last construct being studied is social influence, which is also drawn from UTAUT. The results confirmed that social influence is a significant predictor of intention to adopt mobile learning (b = 0.265, p<0.01). In fact, in this study, social influence is found to be the strongest predictors compared to other constructs. This result is also consistent with earlier studies[22,27,28].

CONCLUSION

Based on the result, it can be concluded that the more students perceive faculty, peers and other individuals important to them believe they should use mobile learning, the more likely they are to engage in mobile learning. Given this finding, it is crucial that people who have a strong connection with the students such as the lecturers, colleagues or even family members, should persistently encourage the student to engage in mobile learning. The purpose of this study has been to explore factors that influence the intention of users to adopt mobile learning. To achieve this purpose, an empirical based framework drawn from UTAUT and previous empirical studies has been developed. The results of the analysis of the collected data significantly verified the established hypotheses. The results suggest that performance expectancy, effort expectancy, social factors, facilitating conditions, perceived playfulness and self management of learning are strong determinants of intention to adopt mobile learning.

Essentially, the present study provides both a theoretical and practical contributions to understanding the predictors of intention to adopt mobile learning and should be of interest to both researchers and practitioners. As for the researcher, the framework used in the study can be tested in other setting involving different types of population. As for the practitioner, this study has sent a strong message on the importance of technological features such as performance expectancy and effort expectancy that need to be addressed when developing mobile learning applications.

Just like in any other study, there are several limitations associated with the conduct of this study. Firstly, is the choice of students that was confined to one university only. Future study should consider extending the scope of population by taking students of other universities. Secondly, besides the six independent variables, there are other variables that could be examined. Other potential variables that could be explored are individual or environmental factors.

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