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Predicting students' intention to adopt mobile learning

A combination of theory of reasoned action and technology acceptance model

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Abstract

Purpose – The purpose of this paper is to explore the ability of the integration of technology acceptance model (TAM) and theory of reasoned action (TRA) to predict and explain university students' intention to use m-learning in schools.

Design/methodology/approach – In total, 487 students participated in this study. A seven-likert scale survey questionnaire which comprised of 23 items was completed by the students. Structural equation modeling was used as the statistical technique to analyze the data.

Findings – The study found that the resulting model was fairly able to predict and explain behavioral intention (BI) among students in Ghana. In addition, this study found that attitudes toward use and subjective norm significantly influenced students' BI to use mobile learning. The model explained 23.0 percent of the variance in BI, 33.8 percent in perceived usefulness and 47.6 percent in attitudes toward use. Of all the three endogenous variables, attitude had the greatest effect on BI.

Originality/value – Although, the above-mentioned models have been adopted in many studies, few or none have combined TRA and TAM as a research framework to predict and explain students' intention to use m-learning since m-learning is fairly new in educational environments. Therefore, a model that combines all constructs from TRA and TAM was proposed in this study to explore university students' intention to use m-learning in schools.

Keywords Students, Attitude, Mobile learning, Technology acceptance model, Perceived ease of use, Perceived usefulness

Paper type Research paper

Introduction

The advancement of the internet and wireless technologies has provided a basis for the development of mobile learning (m-learning). M-learning refers to the delivery of learning to students anytime and anywhere via wireless mobile devices, such as mobile phones, personal digital devices (PDAs), smart phones and tablet personal computers (Wang, Wu and Wang, 2009). Despite, incredible development of networks and wireless technologies, the acceptance of m-learning in higher education is in its initial stage. According to Teo (2010) and Swanson (1988), understanding users' intention to use technology has become one of the most challenging concerns for information system researchers. Literature has shown that researchers' interests in information system studies were determination of factors that are related to the acceptance of technology (Legris *et al.*, 2003; King and He, 2006). As a result of this, information system researchers have developed intention models to help in predicting and explaining technology acceptance across a wide variety

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of domains. For instance, Ajzen and Fishbein (1980) developed theory for reasoned action (TRA) to predict and explain behavior across a wide variety of domains. TRA is very general, "designed to explain virtually any human behavior" (Ajzen and Fishbein, 1980, p. 4) and, thus, appropriate to determine users' intention to use technology. In addition, technology acceptance model (TAM) was developed from TRA by Davis (1986) with the aim of explaining technology usage behavior. TAM uses TRA as a theoretical foundation for identifying the basic relationship between two main beliefs: perceived usefulness and perceived ease of use, and users' attitudes, intentions and actual use of technology. TAM is less general than TRA to determine technology usage behavior. Since TAM has been applied in information system research for more than two decades, it is suitable for studying users' intention to use mobile technology.

TRA and TAM have been widely used to explain users' intention to use computer technology. Among the researchers who used these models were: Davis *et al.* (1989) used TRA and TAM to study users' acceptance of computer technology, Yuen and Ma (2008) adopted TAM to explore teacher acceptance of e-learning technology, and Teo and van Schaik (2012b) applied both TRA and TAM to examine student–teachers' intention to use computer technology. Despite the extensive application of TRA and TAM in research studies, few, if any, have explored an integration of TRA and TAM to predict and explain students' intention to use m-learning in developing countries since m-learning is fairly new in educational environments in these countries. Therefore, the goal of this study is to explore the ability of the integration of TRA and TAM to predict and explain university students' intention to use m-learning in schools.

Literature review

Theory of Reasoned Action (TRA)

TRA is an extensively used theory which explains the determinants of consciously intended behaviors (Ajzen and Fishbein, 1980; Fishbein and Ajzen, 1975). The theory hypothesizes that a "person's performance of a specific behavior is determined by his/her behavioral intention (BI) and BI is in turn influenced by the person's attitude and subjective norm (SN) concerning the behavior in question" (Davis *et al.*, 1989, p. 983). BI measures one's intention to perform a specified behavior (Fishbein and Ajzen, 1975, p. 288). Attitude is defined as an individual's positive or negative feelings (evaluative affect) about performing the target behavior (Fishbein and Ajzen, 1975, p. 216). Subjective norm refers to "the person's perception that most people who are important to him think he should or should not perform the behavior in question" (Fishbein and Ajzen, 1975, p. 302). TRA asserts that "one's attitude toward a behavior is determined by his or her salient beliefs (b_i) about the consequences of performing the behavior multiplied by the evaluation (e_i) of those consequences" (Davis *et al.*, 1989, p. 984). Beliefs refer to "the individual's subjective probability that performing the target behavior will result in consequence$_i$" (Davis *et al.*, 1989, p. 984). Subjective norm is "determined by the multiplication of one's normative beliefs (nb_i) and his or her motivation to comply (mc_i) with these beliefs" (Davis *et al.*, 1989, p. 984).

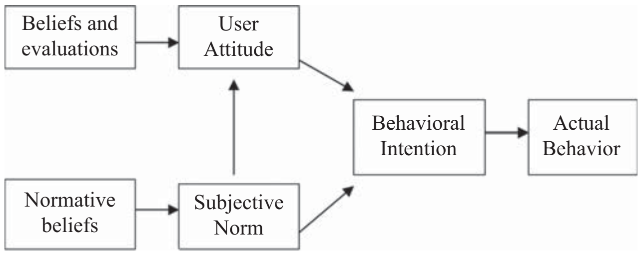
Over the years, TRA has been used as a theoretical framework to study human behaviors related to the use of information and communication technology. Attitude and subjective norm have been found to be the most important determinants of the intention to use technology (Yuen and Ma, 2008). Figure 1 shows the theory of reasoned action (TRA). Despite being useful in predicting social behaviors, TRA has been criticized as not sufficiently explaining when behavior is not under an individual's control (Chan and Lu, 2004).

Technology Acceptance Model (TAM)

Davis (1989) developed TAM from the TRA (Ajzen and Fishbein, 1980). Davis (1989) used TAM to explain the determinants of user acceptance of a broad spectrum of end-user computing.

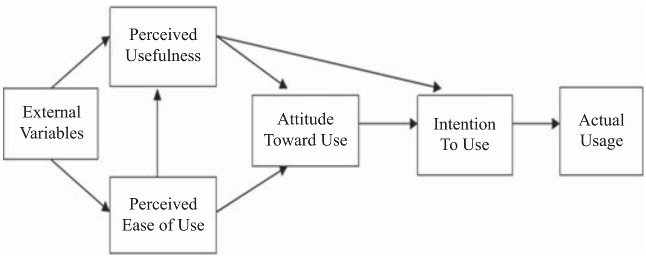
In TAM, two belief constructs, perceived usefulness and perceived ease of use influence users' intention to use technology. Perceived usefulness is "the extent to which a person believes that using a particular system would enhance his or her job performance" (Davis, 1989, p. 320). In contrast, perceived ease of use is "the extent to which a person believes that using a particular system would be free of effort" (Davis, 1989, p. 320). While it is likely that users may perceive a technology to be useful, at the same time, they may perceive its use to be difficult. In other words, the performance benefits of the technology outweigh the efforts of adopting it (Davis, 1989). Perceived ease of use was theorized to have a direct impact on perceived usefulness (Davis *et al.*, 1989). Both perceived usefulness and perceived ease of use were hypothesized to be determined by external variables (Davis *et al.*, 1989). For example, Holden and Rada (2011) found that integration of perceived usability (external variable) into the TAM explained more variance and was more influential to TAM elements than its absence, thereby supporting the importance, positive influence and necessity of evaluating usability when investigating educational technology acceptance and usage behavior. Over the years, TAM has been used in several studies in different contexts including school teachers (Pynoo *et al.*, 2011), virtual learning environment (Rienties *et al.*, 2016), pre-service teachers (Teo, 2010), e-learning (Yuen and Ma, 2008) and perceived usability and self-efficacy on teachers' technology acceptance (Holden and Rada, 2011). Although it was initially developed to explore technology acceptance in business and commercial settings, it was found to be a parsimonious model for use in educational environments (Drennan *et al.*, 2005). Figure 2 shows the TAM.

Despite the extensive use of TAM, many shortcomings have been found by meta-analyses of TAM studies. Bagozzi (2007) criticized TAM of being oversimplified. Also, regardless of the credit given to TAM for its ability to explain users' intention to use technology, Dishaw and Strong (1999) indicated that it is important to conduct more research in order to increase external validity of the TAM. Another critical limitation of the TAM is its lack of emphasis on the system characteristics, which may influence user acceptance, as in usability evaluations



Source: Adapted from Davis *et al*. (1989)

Figure 1.
Theory of reasoned action



Source: Adapted from Davis *et al*. (1989)

Figure 2.
Technology acceptance model

(Holden and Rada, 2011). As stated by Holden and Rada (2011), "TAM was developed prior to increase in demand for technology usability assessments and, therefore, does not include essential measures relating to users' perceived usability of the technology" (p. 345). Also, TAM does not include subjective norm as a determinant of BI (Davis, 1989). According to Davis, "it is difficult to disentangle direct effects of subjective norm on behavioral intention from indirect effects via attitude" (p. 986). Legris, Ingham and Collerette (2003) concluded "TAM is a useful model, but has to be integrated into a broader one which would include variables related to both human and social change processes, and to the adoption of the innovation model" (p. 191). Therefore, while TAM was used as a main framework in this study, suitable human and social construct from TRA such as subjective norm was considered in formulating the integrated model. Therefore, this study contributes to literature by utilizing TAM and TRA to investigate the factors that influence students' intention to use m-learning in higher education in developing countries.

Hypotheses development

Perceived usefulness

The TAM has been widely used as a powerful and parsimonious research model for understanding users' acceptance of technology (Davis *et al.*, 1989). TAM is used in this study for its ability to predict and explain users' intention to use technology (Davis *et al.*, 1989; Teo, 2012a; Yuen and Ma, 2008). TAM asserts that perceived usefulness and perceived ease of use are relevant for technology acceptance belief. Perceived usefulness is the "degree to which the individual believes that using a technology would enhance his or her job performance" (Davis *et al.*, 1989, p. 985). It is clear that users would use a system which they believe would increase their job performance. On the contrary, users would decline to use a system which they believe would decrease their job performance. Teo (2010) conducted a study on pre-service teachers' attitudes toward computer use. The results indicated that perceived ease of use significantly influenced both perceived usefulness and attitude. In addition, Teo (2010) found that perceived usefulness significantly affected attitude (Teo, 2012a). Also, Lee *et al.* (2013) revealed that attitude significantly influenced BI. Based on the above results, the following hypotheses were developed:

H1. Perceived usefulness would have a significant effect on attitudes toward use.

H2. Attitudes toward use would have a significant effect on BI.

Perceived ease of use

Davis *et al.* (1989) defined users' perceived ease of use as "the extent to which the potential user believes the system or technology would be free of effort" (p. 985). According to Davis *et al.* (1989), if prospective users believe that a system or technology is beneficial, they may, at the same time, believe that the system or technology is too hard to use. Thus, perceived usefulness is hypothesized to be influenced by perceived ease of use. In addition, Abramson, Dawson and Stevens (2015) conducted a study to examine the use of e-learning within an extended TAM and the factors that influence the BI of users to use m-learning. They found that perceived ease of use significantly influenced attitudes toward use. Based on the above findings, the following hypotheses were formulated:

H3. Perceived ease of use would have a significant effect on perceived usefulness.

H4. Perceived ease of use would have a significant effect on attitudes toward use.

Subjective norm

Subjective norm is defined as an individual's perception that most people who are important to him or her think that he or she should or should not perform the behavior in question

(Ajzen and Fishbein, 1980). A person sees that the more important others think that he or she should perform a behavior, the more he or she would aim to perform so. Literature has shown that subjective norm significantly influenced perceived usefulness (Teo, 2010; Yuen, and Ma, 2008). Also, studies conducted by Abramson *et al.* (2015), Park (2009), and Teo (2012a) have found that subjective norm significantly affected attitudes toward use and BI. Therefore, the following hypotheses were formulated:

H5. Subjective norm would significantly influence perceived usefulness.

H6. Subjective norm would significantly influence attitudes toward use.

H7. Subjective norm would significantly influence BI.

Methodology

Participants and data collection methods

Participants were 487 students from two universities located in the southern Ghana. Participation was voluntary. The participants were told of the goal of this study before completing the questionnaires and were also assured of confidentiality of any information provided. Among them, 56.9 percent were males, 42.3 percent were between 21 and 24 years and 70.6 percent had more than five years computer technology experience.

Instrumentation

A survey instrument was developed using items that were validated from previous studies and used with participants in educational settings. The questionnaires were distributed to 487 students. Participants who took part in the survey gave their demographic information and completed the 18 statements on the five constructs. The constructs were perceived usefulness (four items), perceived ease of use (five items), attitudes toward use (three items), subjective norm (three items) and BI (three items). The items on perceived usefulness, perceived ease of use and BI were adapted from (Davis, 1989). The items on attitudes toward use were adapted from Compeau and Higgins (1995) and Thompson and Higgins (1991). Subjective norm was adapted from Taylor and Todd (1995). Each item was measured on a seven-point scale ranging from 1 (strongly disagree) to 7 (strongly agree) (see Appendix). On average, each respondent used at least 20 min to complete the questionnaire.

Data analysis

In this study, data were analyzed using the partial least square (PLS) approach to structural equation modeling (SEM). The advantages of SEM include: its capability to explore a series of dependent relationships concurrently, especially where there are direct and indirect effects among the constructs within the model (Hair *et al.*, 2010); analyze relationships between latent and observed variables; model random errors in the observed variables thus providing more precise measurements; and measure latent variables using multiple indicators and testing hypotheses at the construct instead of item level (Hoyle, 2011). Applying two-step approach to SEM (Schumacker and Lomax, 2010), the first step measures the measurement model which describes how well the observed indicators (survey items) measure the unobserved (latent) constructs. The second step, the structural part of the SEM measures the relationships among the exogenous and endogenous latent variables. Smart PLS 3 was used to analyze the models.

Results

Convergent validity

This part describes details on the reliability and validity of the data collected in this study. To measure convergent validity, Fornell and Larcker (1981) suggested three methods to examine the convergent validity. These include: item reliability, composite reliability (CR) and average variance extracted (AVE). The item reliability is assessed by indicator factor loading of an item. Hair *et al.* (2006) indicated that an item is adequate if its factor loading exceeds 0.5. From Table I, the factor loadings (in bold) of individual items ranged from 0.63 to 0.91 which exceeded the value suggested by Hair *et al.* (2006). For CR to be satisfactory, values between 0.7 and 0.9 were proposed by Nunnally and Bernstein (1994). As shown in Table I, the CR of an item ranged from 0.84 to 0.90. A third measure of convergent validity, AVE is defined as "the grand mean value of the squared loadings of the indicators associated with the construct" (Hair *et al.*, 2014). Convergent validity is adequate when AVE equals or greater than 0.5 (Fornell and Larcker, 1981). The internal consistency of items was assessed using Cronbach's α (CA). Hair *et al.* (2014) recommended that CA values above 0.60 and 0.70 are considered appropriate. As shown in Table I, CA values exceeded the acceptable level of 0.7. Also AVEs exceeded acceptable level of 0.5. From Table I, the convergent validity for the proposed constructs is satisfactory.

Discriminant validity

Discriminant validity is the extent to which a construct is truly distinct from other constructs by empirical standards. To assess discriminant validity, two proposed procedures were used: the Fornell–Larcker criterion, which states that the square root of AVE of each latent construct should be greater than the highest squared correlations between any other construct (Fornell and Larcker, 1981); and the loadings of each indicator should be greater than all its cross loadings (Chin, 1998). From Table I, it is revealed that all indicators load their highest on their respective construct and that no indicator loads higher on other constructs than on its intended construct. As indicated in Table II, the square root of the AVEs (in italic) for each construct is greater than the cross correlation with other constructs. Discriminant validity appears satisfactory at the construct level in the case of all constructs.

	ATT	BI	PEU	PU	SN	CA	CR	AVE
ATT1	*0.819*	0.375	0.523	0.454	0.386	*0.731*	*0.849*	*0.652*
ATT2	*0.854*	0.386	0.522	0.404	0.303			
ATT3	*0.746*	0.363	0.449	0.44	0.373			
BI1	0.431	*0.825*	0.358	0.287	0.212	*0.829*	*0.898*	*0.747*
BI2	0.404	*0.913*	0.299	0.321	0.273			
BI3	0.366	*0.853*	0.275	0.28	0.322			
PEU1	0.469	0.221	*0.718*	0.548	0.232	*0.757*	*0.835*	*0.504*
PEU2	0.307	0.267	*0.628*	0.282	0.181			
PEU3	0.475	0.331	*0.755*	0.356	0.295			
PEU4	0.368	0.223	*0.726*	0.333	0.264			
PEU5	0.528	0.25	*0.717*	0.309	0.227			
PU1	0.454	0.318	0.444	*0.828*	0.261	*0.834*	*0.890*	*0.668*
PU2	0.413	0.233	0.423	*0.803*	0.358			
PU3	0.433	0.332	0.463	*0.846*	0.387			
PU4	0.453	0.234	0.409	*0.793*	0.303			
SN1	0.331	0.231	0.241	0.285	*0.750*	*0.751*	*0.858*	*0.669*
SN2	0.375	0.288	0.295	0.305	*0.852*			
SN3	0.369	0.243	0.293	0.389	*0.847*			

Notes: Diagonal values indicate the square root of average variance extracted from observed variables and the off-diagonal values indicate correlations between constructs. ATT, attitude toward use; BI, behavioral intention; PEU, perceived use of ease; PU, perceived usefulness; SN, subjective norm

Table I. Convergent validity for the measurement model

Hypotheses testing

To determine the path coefficients and also testing the hypotheses, a standard bootstrapping method was adopted with 5,000 resamples drawn with replacement. As shown in Table III, attitude was predicted by perceived usefulness ($\beta = 0.227$, $p = 0.001$), supporting *H1*, and attitudes toward use was found to be significant in influencing intention to use ($\beta = 0.407$, $p = 0.000$) supporting *H2*. Also, perceived ease of use significantly influenced both perceived usefulness ($\beta = 0.447$, $p = 0.00$) and attitudes toward use ($\beta = 0.429$, $p = 0.000$), confirming *H3* and *H4*. Moreover, subjective norm was found to significantly influence perceived usefulness ($\beta = 0.249$, $p = 0.000$), attitudes toward use ($\beta = 0.202$, $p = 0.000$) and BI ($\beta = 0.132$, $p = 0.032$), supporting *H5–H7*. The predictive power of the model was determined using the coefficient of determination, R^2. The model explained 23.0 percent of the variance in BI, 33.8 percent in perceived usefulness and 47.6 percent in attitudes toward use. All hypotheses were supported.

The overall model fit was assessed using the standardized root mean square residual (SRMR) composite model. Hu and Bentler (1999) proposed that SRMR values less than 0.08 shows a good model fit. The SRMR value for the integrated model in this study was 0.054, an indication of a good model fit. Figure 3 shows the result of structural model testing.

Path analysis

Table IV shows the direct effect, indirect effect and total effect on BI to use. A coefficient connecting one determinant to another in the path analysis describes the direct effect of an independent variable on a dependent variable. An indirect effect is a sequence of relationships with at least one intervening construct involved. The total effect is the sum of direct and indirect effects. Cohen's (1988) criteria were used to explain the effect sizes. According to Cohen (1988), effect sizes of 0.02, 0.15 and 0.35 denotes small, medium and large effects respectively. The effects of one determinant on another determine the strength of the correlation between determinants under study.

	ATT	BI	PEU	PU	SN
ATT	*0.808*				
BI	0.464	*0.864*			
PEU	0.618	0.361	*0.712*		
PU	0.536	0.343	0.532	*0.817*	
SN	0.439	0.31	0.339	0.401	*0.818*

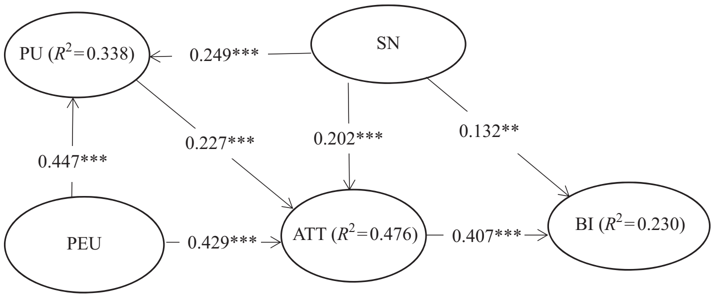
Notes: Diagonal values indicate the square root of average variance extracted from observed variables and the off-diagonal values indicate correlations between constructs. ATT, attitude toward use; BI, behavioral intention; PEU, perceived use of ease; PU, perceived usefulness; SN, subjective norm

Table II. Discriminant validity for the measurement model

Hypotheses	Path	Path coefficient	*T*-statistic	*p*-value	Results
H1	PU → ATT	0.227	3.295	0.001***	Supported
H2	ATT → BI	0.407	4.657	0.000***	Supported
H3	PEU → PU	0.447	7.090	0.000***	Supported
H4	PEU → ATT	0.429	7.717	0.000***	Supported
H5	SN → PU	0.249	4.887	0.000***	Supported
H6	SN → ATT	0.202	3.942	0.000***	Supported
H7	SN → BI	0.132	2.149	0.032**	Supported

Notes: ATT, attitude toward use; BI, behavioral intention; PEU, perceived use of ease; PU, perceived usefulness; SN, subjective norm. SRMR = 0.054. $^{**}p < 0.005$; $^{***}p < 0.001$

Table III. Results of hypothesis testing



Notes: ATT, attitude toward use; BI, behavioral intention; PEU, perceived use of ease; PU, perceived usefulness; SN, subjective norm. $^{**}p<0.005$; $^{***}p<0.001$

Figure 3. PLS results for structural model

Table IV. Direct, indirect and total effects of the research model

Endogenous variables	Coefficient of determination (R^2)	Determinant	Direct effect	Indirect effect	Total effect
Behavioral intention	0.230	ATT	0.41	–	0.41
		PU	–	0.09	0.09
		PEU	–	0.22	0.22
		SN	0.13	0.11	0.24
Attitude toward use	0.476	PU	0.23	–	0.23
		PEU	0.43	0.10	0.53
		SN	0.20	0.06	0.26
Perceived usefulness	0.338	PEU	0.45	–	0.45
		SN	0.25	–	0.25

Notes: ATT, attitude toward use; BI, behavioral intention; PEU, perceived use of ease; PU, perceived usefulness; SN, subjective norm

From Table IV, attitude toward use was found to have the most dominant direct effect on BI, with a total effect of 0.41. This was followed by subjective norm which had a direct medium effect of 0.24 on BI. For attitudes toward use, perceived ease of use had the highest total effect of 0.53. This was followed by perceived usefulness and subjective norm with medium effects of 0.20 and 0.23, respectively. However, perceived usefulness had a small indirect effect of 0.09 on intention to use. As for perceived usefulness, perceived ease of use was the dominant determinant with a total effect of 0.45. Of all the three endogenous variables, attitude toward use had the highest amount of variance account by its determinants, at approximately 47.6 percent. This amount is as a result of effects contributed by perceived ease of use and subjective norm.

Discussion

This study aimed to explore the ability of the integration of TAM and TRA to predict and explain university students' intention to use m-learning in classrooms. From the resulting model in Figure 3, attitude was found to have the greatest significant effect on BI. In the case of perceived usefulness, it had indirect effect on BI. On the whole, the variables: attitude toward use of m-learning, subjective norm, perceived usefulness and perceived ease of use were able to explain 23 percent of the variances observed in students' intention to use m-learning. This suggests that the resulting model was fairly able to predict and explain BI among students in Ghana.

In addition, attitude was found to be the most important determinant of intention to use m-learning. The path coefficient from attitude to BI was the highest among all path coefficients to BI in the model. This stresses the point that users' development of positive attitude toward technology use is important.

Perceived usefulness had a small indirect effect on intention through attitudes toward use. This suggests that students' would be willing to use m-learning if they know it would be beneficial to them. Also, perceived usefulness was found to be a significant determinant of attitude. This finding is in line with previous studies (Teo and van Schaik, 2012b). Again, perceived ease of use strongly influenced perceived usefulness. This implies that students would be unwilling to use a technology regardless how useful the system would be, if they perceive it to be difficult to use. According to Sime and Priestley (2003), student–teachers were unwilling to apply a system that appeared to be complicated to use.

In the integrated model, subjective norm was found significant in predicting perceived usefulness. This shows that students' perception of the usefulness of m-learning would be highly influenced by "important others." In school context, "important others" include teachers, school leaders and colleagues. Furthermore, subjective norm significantly affected BI to use m-learning, implying that users' decisions regarding the use of technology would be impacted by "important others". This study contributes to recent studies that found subjective norm to be a determinant of BI (Park, 2009; Tan *et al.*, 2012; Yuen and Ma, 2008).

Implications for practice

The study found that attitude was dominant determinant of intention to use. Thus, it appears important to develop students' positive attitudes toward the use of technology. According to Luan *et al.* (2005) users who possess positive attitude toward technology are likely to use it. Moreover, perceived ease of use strongly influenced perceived usefulness. No matter how usefulness a technology is, students would refuse to use it if they perceive that the technology is difficult to use. Therefore, school authorities should create a learning environment that allows students to experience m-learning. For example, enhancing faculty technology training and supporting students with mentoring role would contribute to teachers' and students' use of mobile technology in their classrooms. Chen (2010) suggests that technology training directly influence students' self-confidence and value beliefs, which in turn impact their student-centered technology use. Also, school authorities should provide facilities such as reliable internet connection and constant supply of electricity to help teachers' and students' use of mobile technology in their classrooms. This would help both the teachers and students to familiarize themselves with the functionalities of mobile devices use for m-learning, so that these devices become easy to use. Familiarizing themselves with mobile technology would not only increase their knowledge of how to use the technology, but would increase their confidence in performing such behaviors.

Also, subjective norm significantly influenced perceived usefulness. It is imperative that "important others" (e.g. teachers) demonstrate the usefulness of m-learning in their classrooms by blending traditional teaching with mobile technology in their classroom. This would inform the students that "important others" of the school would want them to utilize technology. Thus, the subject norm expressed by "important others" may help influence students' beliefs and practices with regard to mobile technology use. Finally, subjective norm significantly affected both BI and attitude toward m-learning. Therefore, it is important for the university to stress more on m-learning by persuading faculty to develop instructional contents that are more mobile friendly and promoting the benefits of m-learning to attract students.

Limitations and future research

First, this study was limited to university students. Future studies may consider changing participants, sampling procedure or data collection used to compare results from other academic institutions. The second limitation relates to the data collection method. Self-reported instrument was used to collect data. This may affect the validity of the result. Together, attitude toward m-learning, subjective norm, perceived usefulness and perceived ease of use accounted for 23.0 percent variances in students' intention to use m-learning, leaving 77 percent unexplained. To address this unexplained difference, future research should test the model with additional determinants that may influence intention to use.

The current study used the cross-sectional approach to collect data. Longitudinal studies could be investigated to determine key determinants that influence intention to use over time. Finally, because this sample was collected in Ghana, there are limitations in generalizing the results to other countries due to differences in culture in terms of technology usage.

Conclusion

The integration of TRA and TAM model adopted in this study to investigate students' intention to use m-learning has helped to understand the key determinants that influence students' adoption of technology. The model also helped to explain the relationship between the endogenous and exogenous variables. Also, this study contributes to existing body of knowledge on intention to use m-learning technology by applying structural equation model method for the analysis of data instead of general linear model. This is because structural equation model measures direct and indirect effects among the endogenous and exogenous variables compared to general linear model that examines only direct correlation between dependent and independent variables. Unlike multiple regression, structural equation model takes into account measurement errors, correlated residuals, modeling of interactions, nonlinearities and correlated independence.

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Further reading

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(The Appendix follows overleaf.)

Appendix

SURVEY INSTRUMENT

This survey is for academic purpose only. All information that is collected in this study will be treated confidentially. At no time will the name of any school or individual be identified.Please use a writing pen to write your answers

Instruction: Please indicate your response to the following questions by ticking appropriate letter

Part I: Demographic Information

1. Gender:
a. Male b. Female

2. Your current school status:
a. Morning b. Evening (c) Weekend

3. Your age is between:
a. 17–20 b. 21–24 c. Above 24

4. Including the current year, how many years have you been using computers?
a. 0–2 b. 3–5 c. Over 5

5. What is your current level of study?
(a) Level 100 (b) Level 200 (c) Level 300 (d) Level 400

Part II: Your Views on mobile learning technology

Construct	Strongly Disagree	Moderately Disagree	Slightly Disagree	Neutral	Slightly Agree	Moderately Agree	Strongly Agree
Perceived usefulness							
6. Using mobile learning enables me to accomplish tasks more quickly							
7. Using mobile learning improves my performance							
8. Using mobile learning will increase my productivity							
9. Using mobile learning enhances my effectiveness							
Perceived ease of use							
10. I find it easy to use mobile learningto do what I want to do							
11. My interaction with mobile learning does not require much effort							
12. It is easy for me to become skillful at using mobile learning technology							
13. I have control over mobile learning technology							
14. I have the knowledge necessary to use mobile learning technology							

Attitude							
15. I look forward to those aspects of my job that require me to use mobile learning technology							
16. I like working with mobile learning technology							
17. I have positive feelings towards the use of mobile learning technology							
Subjective norm							
18. People who influence my behavior think that I should use mobile learning technology							
19. People who are important to me will support me to usemobile Learning technology							
20. People whose views I respect support the use of mobile learning technology							
Behavioral intention							
21. I intend to continue to use mobile learning technology in future							
22. I expect that I would use mobile learning in future							
23. I plan to use mobile learning technology in future							

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