UNDERSTANDING MOBILE LEARNING IN SUB-SAHARAN AFRICA: APPLYING AND EXTENDING THE TECHNOLOGY ACCEPTANCE MODEL

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Abstract

There is a proliferation of mobile technologies in developing countries whereby most students own mobile phones and other personal mobile technologies device that can offer more than sending long distance message. However schools, colleges and universities have not widely incorporated mobile devices in their teaching and learning practices. This paper explores the factors which influence students to adopt mobile technologies in education through the Technology Acceptance Model (TAM), an influential theory used to explore the adoption of information systems. This study introduces mobile readiness, perceived mobility value, perceived privacy and perceived trust as external variables that reflect the student's belief in mobile learning adoption. Data collected from respondents in Botswana were tested against a modified research model using structural equation modelling. The results indicated that perceived trust, mobile readiness, perceived privacy and perceived mobility value are crucial factors influencing students to adopt mLearning technologies. The findings provide in-depth knowledge derived from a theoretical model that assists in the successful adoption of mLearning. These findings imply that it is vital to teach students on the usefulness of these mLearning technologies before actual adoption as it helps to develop a positive attitude among the students. This work informs the development of an mLearning theory that comprehensively addresses the dimensions of mLearning.

Keywords: *mLearning, technology education, technology acceptance model, tertiary education, structural equation modelling, mixed method strategy*

Introduction

Worldwide growth in use of mobile technologies has fostered a change in the way education is delivered. Learning is no longer confined to traditional classroom environments but can be experienced anywhere and anytime through mobile technologies. Traditionally, the physical presence of students in classrooms in academic institutions was mandatory but with prevalence of mobile technologies, the norm is slowly shifting. Mobile technologies are promising to be suitable modes of learning, giving rise to the emergence of mobile learning widely known as mLearning. Mobile learning refers to a form of teaching and learning that occurs through mobile technologies taking advantage of affordability and portability (Alturki, 2013).

Mobile learning offers flexible and personalised learning approaches as students can access learning material anywhere and at any time. To date, considerable research on mLearning indicates that students prefer the flexibility of using mobile devices (Pollara and Broussard, 2011). The mLearning approaches are engaging to learners, shifting away from traditional passive learning to a more active learning approach. However, the key question regarding this change is whether students are ready for mobile learning now? (Corbeil and Corbeil, 2011). Mobile technologies will have a significant and promising role in education (Ally, 2013). Furthermore, Ally (2013) argues, "Mobile technologies will be the future of education whether one likes it or not: future generations of learner will demand that education should be delivered on mobile technologies". However, Alturki (2013) contends that students believe that these devices are meant only for entertainment and recreation, which complicates the potential behind mLearning. With such contradictory views, it is difficult to conclude on the readiness of mlearning among tertiary education students in Sub-Saharan Africa.

Botswana has one of the highest mobile penetration rates in Africa. Furthermore, mobile cellular subscription per 100 people is 144, which is one of the highest in the world (Telecommunications Research Site). Each person has more than one subscription. With the rapid growth of the utilization of mobile devices, a shift from eLearning to mLearning may be a welcome development in Botswana. Therefore with this high mobile penetration rates, it is important to explore the application of mobile technologies in the learning process. However, it has to be noted that although Botswana has high mobile penetration rates, this does not alone guarantee readiness to integrate mobile technologies in learning. Also limited knowledge exists on theoretical aspects of mLearning in an African context.

The problem this study explored is that there is an proliferation of mobile technology however in education these applications are not fully utilized. Limited research has been conducted concerning factors that influence adoption of mLearning in developing countries because the successful adoption of mLearning in one country does not necessarily apply to other countries due to the variance of environments (Almasri, 2014). Hence there is a need to assess factors which influence students to adopt mLearning, which is a dilemma faced by many tertiary education institutions (Trifonova, Georgieva, & Ronchetti, 2006; Almasri, 2014). The aim of this study is to apply and extend Technology Acceptance Model (TAM) as a theoretical framework to predict the determinants of mLearning adoption among tertiary education students.

Definitions of mobile learning

Mobile learning is a new and evolving concept. There is no consensus on the standard definition of mLearning. Most authors have defined mLearning based on their particular experiences, uses, and backgrounds (Winters, 2006). Traxler (2011) believes that mLearning is a new and emerging concept. Therefore, it is unclear and has no definite explanation. The existing definitions are diverse and sometimes contradictory.

Song (2008) reflected that most definitions are inclined to the mobility of the technology as opposed to other components. However, it was suggested that more emphasis should be on the mobility of learning (El- Hussein & Cronje, 2010). Similarly, Ahmadi and Noroozi, & Mohamadi (2013) emphasises that more focus should be on the learning process and the learner. Mehdipour and Zerehkafi (2013) believes that mLearning is specifically designing learning experiences that exploit opportunities that mobility can offer. Also,El Hussin and Cronje, (2010) highlighted that the word "mobile" in mLearning refers mainly to the mode of learning such as a mobile phone or tablet which serves merely as a tool to enhance learning. Thus more focus should be on the learning itself not on the technology.

More often mLearning is mistaken as eLearning, as they use the terms in a complementary way (Peng, Su, Chou, & Tsai, 2009). Mobile learning is not merely the conjunction of "mobile" and "learning" it means "mobile eLearning" (Mehdipour et al. 2013). It is a subset of eLearning. However, it is argued that mLearning is emerging as a new and distinct concept (Traxler, 2007; Oller, 2012; Song, 2008; Traxler, 2005). Oller (2012) highlighted that mLearning had shown a great potential to disrupt existing pedagogical infrastructure, including online education. This indicates that eLearning and mLearning are totally distinct. Additionally, Traxler (2005) believes that regarding mLearning as portable eLearning will ease its diffusion but slowly weaken its contribution.

Current debates on mobile learning

The use of mobile devices for learning purposes is still in its infancy stages in terms of both technology and pedagogy. Thus there is a disagreement on how mLearning should be defined or conceptualized. Firstly, it is acknowledged that there is no standard definition or conceptualization of mLearning. Technologists focus on the mobility of the technology, while educationalists focus on the mobility of the learning material or content, some on the mobility of the student and others on the students' experience of learning with mobile devices. Everyone defines mLearning according to their own particular experiences (Song, 2008; Ally, 2013). Similarly, El-Hussein and Cronje (2010) indicated that it is impossible to attribute one fixed meaning to the concept of mLearning because understanding mLearning is challenging.

There is currently a misconception on understanding the nature of mLearning. Some consider it as a new paradigm while others merely consider it as a subset of eLearning or distance learning. Similarly El-Hussein and Cronje (2010) indicated that mLearning opens the minds to the possibility of a new paradigm. It is noted that mLearning represents more than a mere extension of traditional forms of education but facilitates alternative learning processes and instructional methods that the theories of new learning identify as effective for learning (El-Hussein and Cronje, 2010).

It is difficult to make assumptions or conclusions on mLearning based on prior studies because there is no standardized theory on mLearning. This implies that it is not fit to generalize the findings of other theories in the context of mLearning. It is highlighted that as a result each author comes up with a different expectation about the scope and legitimacy of a theory in their work (El- Hussein and Cronje, 2010). Therefore El- Hussein and Cronje (2010) emphasized that there is need to place mLearning within the context of the theories' instructional design as well as understanding foundational assumptions of higher education.

Theoretical framework

The Technology acceptance model (TAM) is the most robust and widely used theory in Information Systems (Khanh & Gim, 2014). It has been widely applied in a variety of fields such as business, agriculture, and healthcare with success. The goal of TAM is to explain and predict factors which determine the acceptance of computer applications (Davis, 1985). It is evident from wide application of TAM that researchers not only want a model that can predict but also can explain why a particular Information System may be unacceptable and pursue appropriate corrective measures (Bagozzi. 1989).

Previous studies have been conducted in developed countries in institutions where there are policies and regulations governing the use of mLearning applications among tertiary students. However, limited knowledge exists on key factors influencing mLearning adoption in developing countries where tertiary institutions do not have policies for implementation of mLearning applications in teaching and learning. From previous studies, most of the studies on adoption of mLearning were entirely quantitative. However, there is a concern on IS research that mixed method approach in information systems is fading away (Venkatesh, Brown, & Bala, 2013). Venkatesh et al. (2013) also highlighted that mixed method approaches are essential since they build on a common scientific basis essential to advance and sustain the tradition of methodological diversity in information systems research and to create a cumulative body of knowledge.

TAM as compared to its counterparts is a generic model simplified to suit the varying contexts of information systems, for instance from file based systems, electronic and mobile applications. However, the main limitation of TAM as reflected by earlier studies is its inability to reveal determinants of PU and PEOU. Thus a significant number of scholars has criticized TAM that it is not a suitable theory since it can account for only 40% of behavioral intention to use a certain technology (Bagozzi, 1989; Venkatesh et al, 2013). The determinants of PU and PEOU vary according to context hence the simplicity of TAM favour its application in different contexts as opposed to its predecessors.

Mobile learning is still in the early stages of introduction and needs more studies focusing on the implementation of mLearning in the educational context in order to validate the findings. It is emphasized by previous studies that there is a need for testing in various educational settings and populations so that generalizations can be based on empirical data and not on assumptions only.

Frequent use of mobile devices did not translate into readiness for mobile teaching and learning. Although studies on readiness have been conducted, it mostly focuses on readiness in developed countries were facilities and technologies which support mLearning are easily and readily available. Therefore there is a need to determine mLearning readiness in developing countries were there are limited facilities which support mLearning. This will help in providing better and clearer insights into the issue of readiness of using mLearning approaches in developing countries. There is an argument or disagreement on previous scholars on the key determinants which influence students to adopt mLearning. Hence there is a need explore TAM to find out the key determinants of mLearning adoption among tertiary students.

Most of the studies conducted on mLearning adoption lack theoretical foundation in information systems. Limited studies were found which used information systems theories or models to provide a theoretical background for their studies. Therefore it raises arguments on the suitability and applicability of such studies in the field of information systems. Thus it is necessary to explore the suitability and applicability of various technologies basing on existing information system theories, models and frameworks.

Methodology

Research approach

The study utilized a deductive approach and followed a mixed method strategy. Both quantitative and qualitative data were collected. Qualitative data was used during the preliminary stages of the study to identify and understand the factors which influence adoption of mLearning among tertiary students. Quantitative data analysis was employed at the late stages of the study to examine the relationships amongst external variables, key determinants and behavioral intention to use mLearning.

Population and sample

Stratified random sampling was adopted for the research. The population comprised of public and private TEI in Botswana, namely University of Botswana (UB), Botswana International University of Science and Technology (BIUST), Botho University and Limkokwing University of Creative Technology.

Data analysis using Structural Equation Modelling (SEM) qualifies a sample size of 50 as very poor, 100 as poor, 200 as fair, 300 as good and 500 as very good (Kline, 2011). As indicated before SEM requires a large sample size, due to the assumptions made or not made about the data (Kline, 2011). Therefore the sample size for the study was 480, distributed proportionally to each stratum.

Instrument and pilot study

A pilot study was conducted with 15 students to test for reliability of the measurement instrument. The reliability assumptions were satisfied. Cronbach's alpha was used to measure the internal consistency of the measurement instrument. The range of values for Cronbach's alpha is from 0.00 to 1.0; 0.00 indicates no consistency in measurement and 1.0 indicates perfect consistency. For acceptable results, Cronbach's alpha is recommended to be greater than 0.7 meaning that 70% of the variance in the scores is reliable variance.

Operationalisation of variables

External variables were operationalised by using validated items from previous research. Items on Perceived Usefulness (PU) were adapted from Davis (1985) and Davis et al. (1989) studies, items on Perceived Ease of Use (PEOU) from Davis, Bagozzi and Warshaw (1989) study, items on attitude, behavioral intention and perceived mobility value from Huang et al. (2007), items on mobile experience were adopted from Alenezi et al. (2010), Pituch et al. (2006) and items on mobile readiness from Huang et al. (2006). The questions were also modified where appropriate to suit the context of mLearning. Perceived privacy and perceived trust were operationalised based on the comments made by students during group interviews.

Data analysis

Quantitative data analysis

Descriptive analysis was conducted using SPSS. The model fitness was tested through SEM by using LISREL (student version).

Response rate

A total of 480 questionnaires were issued to respondents (120 questionnaires per tertiary institution) and only 403 were obtained. Thus the overall response rate was 84% (403/480).

Data screening

There were missing items in the data. The missing items were replaced with mean values for each specific variable. From the data set, 9 cases with outliers were detected using Mahalanobis distance. The cases with outliers were cross-checked against data on the questionnaires. It was found that the outliers are a result of true results indicated by the respondents. However, a decision to remove the outliers on the dataset was reached. Normality, linearity and homoscedasticity tests were conducted and they satisfied requirements for multi variet analysis.

The assessment of measurement model

Exploratory factor analysis yielded lower factor loadings on five items from the mobile experience construct thus these items were deleted from the measurement instrument. Results from the remaining measurement indicators were used for the study.

Structural model analysis

Bivariate correlations were performed using Pearson correlations analysis to depict statistically significant relationships on the proposed model. Based on the correlations performed the proposed model was revised and analyzed using multiple regression and LISREL.

Path analysis using multiple regression

Multiple regressions were conducted to test for the significant paths in the model. Table 4:4 shows the different paths tested on the model.

The assessment of model

The fitness of the model was analysed to ensure that the hypothesised model is consistent with the actual data. Therefore several Goodness of Fit (GOF) measures were used to analyse the model to estimate the measurement model fit. GOF refers to how well the data fits into the statistical model Hair et al., (2010). The entire model fit was assessed, which determined whether to accept the structural model Kline (2011). Model fit indices that were explored and analysed in the study involves: goodness of fit (GFI), adjusted goodness of fit (AGFI), Normalized fit index (NFI), Comparative fit index (CFI), Root mean square residual

(RMSR), Root mean square error of approximation (RMSEA), Root mean squared residual (RMR) and Critical N (CN).

Qualitative data analysis

Interviews were conducted with 7 students in BIUST and Botho during the preliminary stages of the study mainly to understand individual factors that influence students to adopt mLearning applications. Non-verbal cues of participants were observed during the interview sessions. An audio recording of sessions was also conducted in order to aid during qualitative data analysis. According to Markle (2011) audio tapes are the primary source of data for data analysis. Similarly, it is emphasized that the use of audio tapes in qualitative research is a significant advancement in research in general (Markle, 2011). Also, a diary of reflective notes was kept to keep track of time, place and key points of the interview session.

The audio-recorded interviews were transcribed immediately after each interview session. The audio records were played multiple times before actual transcription process. Rapley (2007) indicated that the process of making detailed transcripts of actual recorded data immediately after the interview process enables the researcher to become familiar with the subject matter or content. Rapley (2007) also emphasized that interesting themes may also emerge as people interact during the process of recording.

Summary of transcribed data was conducted in order to identify key points or themes emerging from the transcripts. Data transcription basically entails transforming the audio file into written words. The meaningful categories relating to the data were developed. The categories aided in the development of factors deployed in the development of the model for predicting mLearning adoption. The categories were used as the initial platform for quantitative study. The categories were derived from the data based on actual terms or emerging themes from the participants.

Finally, the data was unitized, that is reducing and re-arranging data into a manageable and comprehensible form. The data was attached to the identified categories to ensure that each and every piece of data is represented in the identified categories.

Results

Quantitative data results

Through the Pearson correlation analysis, it was depicted that perceived usefulness had a statistically significant correlation with perceived ease of use ($r = .377$), attitude ($r = .298$), perceived mobility value ($r = .215$), mobile readiness ($r = .343$), behavioral intention ($r = .533$) and statistically significant correlations with perceived trust ($r = -0.336$) and perceived privacy ($r = -0.166$) were found.

Perceived ease of use had a statistically significant correlation with attitude ($r = .304$), perceived mobility value ($r = .175$), mobile readiness ($r = .361$), behavioral intention ($r = .396$). Statistically significant negative correlations were found between perceived ease of use and perceived trust ($r = -0.193$) as well as between perceived ease of use and perceived privacy ($r = -0.121$).

Attitude had a statistically significant correlation with perceived mobility value (r = 132), mobile readiness (r = 192), and BI (r = .309). However, ATT did not have a statistically significant correlation with PT and PP.

Perceived mobility value had a statistically significant positive correlations with mobile readiness (r = .269) and behavioral intention (r = .259) and a statistically negative correlation with perceived trust (r = -0.137). However, perceived mobility value did not have any statistically significant correlation with perceived privacy.

Mobile readiness had a statistically significant correlation with behavioral intention (r =.437) and a statistically significant negative correlations with perceived trust (r= -0.348) and perceived privacy (r = -0.164). Perceived trust had a statistically significant positive correlation with perceived privacy (r = .457) and a statistically significant negative correlation with behavioral intention (r = -.333). However, no correlations were found between perceived trust and attitude. Perceived privacy had a statistically significant negative correlations with the behavioral intention (r= -0.122). However, no correlation was found between perceived privacy and attitude nor was it found between perceived privacy and perceived mobility value.

Based on the correlations performed the proposed model was revised and analyzed using multiple regression. The following table indicates the paths tested on the model.

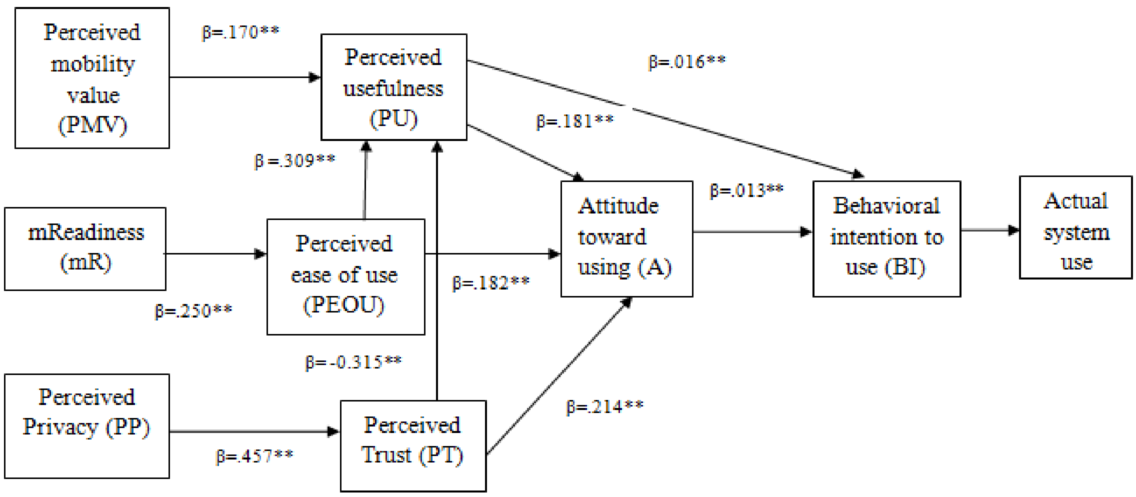
Table 4:1 Path Analyses using multiple regressions

Paths	Exogenous variables	Endogenous Variables
Regression Path 1	Perceived Ease of Use, Perceived Mobility Value,Mobile Readiness, Perceived Privacy	Perceived Usefulness
Regression Path 2	Perceived Mobility Value, Mobile Readiness, Perceived Privacy	Perceived Ease of Use
Regression Path 3	Perceived Usefulness, Perceived Ease of Use, Perceived Trust	Attitude
Regression Path 4	Perceived Usefulness Attitude	Behavioral Intention
Regression Path 5	Perceived Privacy	Perceived Trust

Results from path analysis indicated that path coefficients from PEOU to PU were statistically significant (β=.309, ρ=.000). The path from PMV to PU was statistically significant (β=.170, ρ=.031). The path from PT to PU was statistically significant (β= -0.315, ρ=.000). The path coefficients from MR to PU were not statistically significant (β=.134, ρ=.05). The path from PP to PU was not statistically significant (β= -0.013, ρ=.862). The path coefficients from MR to PEOU were statistically significant (β=.250, ρ=.000) whilst path coefficients from PMV, PT, PP to PEOU were not statistically significant (β=.119, ρ=.093), (β= -0.65, ρ=.347) and (β= -0.054, ρ=.411) respectively.

Path analysis depicted that path coefficients from PU to ATT were statistically significant (β=.181, ρ=.000). Similarly, paths from PEOU to ATT were statistically significant (β=182, ρ=.000). Also, path coefficients from PT to ATT were statistically significant (β=.214, ρ=.000). Path coefficients from PU to BI were statistically significant (β=.016, ρ=.000). Paths from ATT to BI were also statistically significant (β=.013, ρ=.000). Finally, path coefficients from PP to PT were also statistically significant (β=.457, ρ=.000). Figure depict statistically significant paths after multiple regression analysis of the model.

Figure 4:1 Multiple Regression analysis of significant path coefficients



**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

Based on the statistical tests performed to test for the relationships among the variables and significance path coefficients a list of supported and unsupported hypothesis was compiled. Table 4:4 below shows a list of supported and unsupported paths on the proposed model.

	Path	**Path coefficient**	**β**	**Significance level**	**Result**
1	Perceived Mobility value --- Perceived Usefulness	.215	.170	.000	Supported
2	Perceived Mobility Value --- Perceived Ease Of Use	.175	.119	.093	Not supported
3	Mobile Readiness --- Perceived Usefulness	.343	.134	.05	Not supported
4	Mobile Readiness --- Perceived Ease Of Use	.361	.250	.000	Supported
6	Perceived Privacy --- Perceived Ease Of Use	.121	-0.054	.411	Not supported
7	Perceived Privacy --- Perceived Usefulness	.166	-0.013	.862	Not Supported
8	Perceived Privacy --- Perceived Trust	.457	.457	.000	Supported
9	Perceived Trust --- Perceived Ease Of Use	.193	-0.65	.347	Not Supported
10	Perceived Trust --- Perceived Usefulness	.182	-0.135	.000	Supported
11	Perceived Trust --- Attitude	.644	.214	.000	Supported
12	Perceived Ease Of Use --- Perceived Usefulness	.377	.309	.000	Supported
13	Perceived Ease Of Use --- Attitude	.304	.182	.000	Supported
14	Perceived Usefulness --- Attitude	.657	.181	.000	Supported

15	Perceived Usefulness --- Behavioral Intention	.533	.016	.000	Supported

Qualitative data results

The following snippets indicate how majority of students responded during the focus group interview.

Positive and negative points towards mlearning

positive	negative
We have been using mobile devices for so long, we know how to operate them, therefore, it will be easy for us to engage in mLearning."	*Some of us will spend more time familiarizing ourselves with how to use this mLearning for educational purposes which could have been spent on learning."*
we have programs such as WhatsApp, we have calendars, reminders in our phones. Therefore using these phones for learning purposes will be a welcome development, either for direct or indirect learning purposes."	*"For us it is late to incorporate technology in education since we are used to the traditional approaches. Maybe if this could be introduced at grassroots level it will be better that way perhaps it could yield fruitful. Mobile learning will be highly beneficial to young learners at primary or secondary schools not us at this stage."*
The timetables for the semesters can be part of the apps so that they remind us when we have lessons, tests or examinations, mLearning can be so helpful especially to us students. Through this, it will be easy for us to track our daily activities	*As long as we can get access to learning material anywhere and anytime then mLearning is useful. It is better to carry a single tablet loaded with course materials than carry a bag full of text books that you rarely read due to their heaviness, at the end of the day they will make your shoulders and back painful*
The mobile devices can help especially during deadlines or submission of assignments as one may have the access to submit their work even from home	*Technology is unreliable; we do not trust these applications. Who will be responsible for loading course content? Are the developers aware of what we study in school?"*
	We cannot risk our studies by using unreliable sources of information. We do not want to fail and fall into the fail and discontinue trap due to silly mistakes."
	As long as our instructors/lecturers can recommend the use of these mLearning applications then that's when we can use them
	"*In Africa, we copy from western cultures; do we really think mLearning can work for us?"*
	We need to consider context specific approaches which are relevant to our continent and culture. We do not have enough internet connections in our phones. The internet bundles are very expensive we cannot afford them."
	Some of us our mobile phones will not support advanced features needed by mLearning

	applications as we use bo sedi-lame (mainly for calling and texting) as a result this will bring the digital divide to our communities
	Even if we have the devices it seems like it is rude to use a phone during class even when you would want to refer to the devices during the class it may seem as bad manners."
	Provided the institutions come up with a fair way of ensuring that each and every student has access to these applications through their phones then it will be applicable.

Discussions of results and implications

The majority of the students are ready for mLearning in terms of technology ownership, skills and budget readiness. However, a significant number of respondents were reluctant to incur additional costs in order to engage in mLearning activities. The issue of budget when considering deployment of mLearning should be emphasized. These findings are consistent with Adedoja et al. (2013) and Hussin et al. (2012) that in terms of financial costs students are reluctant to spend extra costs on mLearning activities. Koch and Van Brakel (2012) suggested that the use of non-paying mobile services should be adopted including readily available mobile applications such as SMS and Bluetooth to cover for the concern on additional costs. Similarly, tertiary education institutions should liaise with network providers to provide free data packages so that they can access the educational content via mobile devices (Adedoja et al., 2013). This can be beneficial as students are not willing to incur additional costs on mLearning.

Findings also indicated that mobile device ownership amongst tertiary education students stood at 99.5%. As such the mobile device ownership showed that students are ready for mLearning. However, the fact that some portion of the student community does not have mobile devices should not be overlooked when implementing mLearning technologies, such ignorance has potential to bring a digital divide between the students who own mobile devices and those ones who do not own mobile devices. This can widen the gap between the have and have not. These findings are consistent with Laouris et al. (2005) that mLearning is a potential actor in the digital divide.

The mathematical representations below show relationships among external variables, key determinants, and behavioural intention.

BI = A + PU
A = PEOU + PU + PT
PU = PMV + PEOU + PT
PEOU = mR

In this study, it was found out that behavioral intention was measured from measures of attitude and perceived usefulness. This means that behavioral intention to adopt mLearning is influenced or affected by attitude and perceived usefulness only. Findings as such confirm previous literature on TAM that behavioral intention can be predicted by attitude and perceived usefulness only (Bagozzi et al., 1989; Davis, 1985; Huang et al., 2006). This implies that educators need to develop a positive attitude on students as well as sensitize them with the usefulness of mLearning to help increase acceptance of these technologies. The findings indicate that attitude is a key factor in influencing behavioral intention. In the same way, Park et al., (2012) and Huang et al. (2006) found that attitude is a key factor in influencing behavioral intention. Conversely, Fadare (2011) argued that attitude is a less determinant of behavioral intention to use mLearning applications.

The results indicate that attitude is determined by perceived ease of use, perceived usefulness and perceived trust. The implications of the findings are that if mLearning technologies are easy to use students may develop a positive attitude towards using mLearning technologies. Similarly if students perceive mLearning technologies as useful they may develop a positive attitude as well.

In this study, it was found that perceived trust has a significant contribution to attitude as compared to perceived usefulness and perceived ease of use. This means that if students trust the content in these mLearning applications they may develop a positive attitude towards using them. This denotes that in order for students to develop a positive attitude to mLearning the issue of trust has to be considered during the processing of developing and rolling out of technologies. These findings are consistent with existing literature that trust plays a significant impact on behavioral intention to adopt a certain information system (Gefen et al., 2003; Arpaci, 2016). Gefen et al. (2003) found that trust in TAM model is as important as perceived usefulness and perceived ease of use, emphasizing that together these variables set explain a considerable proportion of variance in intended behavior. Although the context was online shopping, the findings are as well consistent in the mLearning context as depicted in this study. Therefore the mLearning applications need to be trustworthy so that students can develop a behavioral intention to adopt these technologies. As a result to increase mLearning acceptance there is a need to develop trust for mLearning applications amongst the student community. In addition, the results indicate that trust in mLearning technologies is more important than perceived usefulness and perceived ease of use. Therefore educators should develop the trust of students about applications in order to increase intention to use. Trust can be established by encouraging mLearning developers to develop reliable and trustworthy applications that can protect users' confidential data.

In the same way, perceived ease of use determined attitude with a higher degree as opposed to perceived usefulness. The findings are similar to what was found by Liu et al., (2010). This implies that policy makers and developers have to develop mLearning technologies that are easy to use in order to enable students to accept them. As such, the findings of this study contradicts the results found by Khanh et al. (2014) that perceived ease of use has no significant effect on attitude, emphasizing that mLearning technologies are not easy to use attributing this to technology restrictions such as small screen size.

In this study, a new significant relationship between perceived usefulness and perceived mobility value was found. It therefore means that if students recognize the mobility value of mLearning technologies they may, in turn, perceive them as useful. Hence students need to be reminded about the importance of the mobile aspect of mLearning technologies continuously as it would help in increasing acceptance as they would consider them useful. Also, Huang et al. (2006) emphasized that PMV is a crucial factor in predicting behavioral intention to adopt mLearning. Conversely, Khanh et al. (2014) argued that perceived mobility value does not affect perceived usefulness in any way. Khanh et al. (2014) emphasized the fact that awareness of mobility for usefulness is a truism because users are always aware that mobility is useful in most cases including mLearning.

The predictors of perceived usefulness were perceived mobility value, perceived ease of use and perceived trust. The external variables mobile readiness and perceived privacy did not have a direct effect on perceived usefulness. This brings an interesting argument as it was theorized in the original TAM that the external variables have a direct and indirect effect on perceived usefulness (Davis, 1985). Mobile readiness influenced perceived usefulness indirectly through perceived ease of use. Similarly, perceived privacy influenced perceived usefulness indirectly through PT. These results are inconsistent with what was found by Davis (1985) that external variables affect perceived usefulness directly and indirectly through perceived ease of use.

Perceived trust was found to be the influential predictor of perceived usefulness, although the influence was negative. This clearly indicates that if students consider mLearning technologies trustworthy they would, in turn, consider them useful to their learning process. This implies that educators need to ensure that the mLearning technologies are best suited to the needs of the students and will help them to improve their learning or academic performance. Sensitizing students as well about these applications may help students to develop some trust in these technologies and thus, in turn, consider them useful in their day to day learning activities.

The findings indicate that perceived ease of use was influenced by mobile readiness only. From the original theorized TAM it was indicated that the external variables influenced perceived ease of use directly as well. However, it was found that the only variable that influenced perceived ease of using mLearning technologies directly was mobile readiness. This finding challenges what was found in the previous literature. As a matter of fact, it implies that if students are ready in terms of having relevant technologies, skills and money to engage in mLearning they would perceive mLearning technologies easy to use. Therefore various tertiary institutions should ensure that the students are ready to engage in mLearning before actual implementation of mLearning technologies.

On the question of variable most influential in predicting intention to use mLearning, findings depicted that the key determinants in explaining behavioral intention to adopt mLearning are attitude and perceived usefulness. This means that if students understand the importance and need of mLearning technologies they may intend to use those applications to support their day to day learning activities and needs. Moreover, if students embrace a positive attitude towards mLearning technologies they may as well use those technologies fruitfully in their educational advance. Similarly, Park et al. (2012) and Huang et al. (2006) confirm that attitude is a key variable in predicting behavioral intention to adopt mLearning technologies. This is indicative that to increase adoption of mLearning technologies amongst students' community, a positive attitude towards mLearning needs to be encouraged and developed on the students. Likewise, more effort is needed towards sensitization of students on the usefulness and importance of mLearning. It is clear that the more students recognise the usefulness of mLearning technologies the more they are likely to adopt such technologies.

Conversely, Fadare et al., (2011) argued that attitude is a least determinant in predicting behavioral intention to adopt mLearning technologies. This finding is dissimilar with the current findings. The implications of Fadare et al., (2011) are that even if students do not hold a positive attitude towards mLearning they can still adopt mLearning technologies. This may be applicable in an environment where the usage of mLearning technologies is mandatory amongst the student body, meaning that non-compliance may disadvantage students somehow.

Directions for future studies

Different tertiary institutions should liaise with network providers to provide packages to students to allow access to mLearning technologies at a free or reasonable cost. Also various tertiary institutions should collaborate and develop an mLearning lab that would help in the development of course-specific mLearning applications or technologies.

The findings indicate self-reported usage of mLearning hence there is a need to validate with actual mLearning applications. Future studies should also determine the pedagogical implications of mLearning to the students in order to identify the approaches/subjects best suited for mLearning. There is a need to develop a mobile learning theory that incorporates all the aspects and dimensions of mLearning because mLearning encompasses a broad field of educational technology. Finally, the effect of institutional policies and infrastructure on adoption of mLearning should be assessed and examined as it provides a supporting environment for students.

Conclusion

The results from qualitative study showed that the external variables or factors which influence tertiary education students to adopt mLearning technologies are mainly mobile readiness, perceived privacy, perceived trust, perceived security, mobile experience and perceived mobility value. Both qualitative and quantitative studies found that perceived privacy, mobile readiness, perceived trust and perceived mobility value are essential variables in influencing behavioral intention to adopt mLearning technologies. The findings from both studies complemented each other. However, quantitative analysis indicated that perceived security and mobile experience does not influence tertiary education students to adopt mLearning technologies. The findings from the quantitative instruments contradict findings from the qualitative. Venkatesh et al., (2013) indicated that when conducting mixed method approach it is familiar that a researcher may find different (contradictory and complementary) conclusions from the quantitative and qualitative approaches. The divergent findings in mixed method approaches are valuable in that they enrich understanding of a phenomena as they open new avenues and questions for future research Venkatesh et al., (2013).

This implies that it is vital to sensitize students on the usefulness of these mLearning technologies before actual adoption. This can also help students to develop a positive attitude towards adopting these mLearning technologies and have an ownership of the initiative. Perceived trust was also found to be a crucial indicator of attitude, implying that developers or tertiary institutions should consider the issue of trust when developing mLearning applications to be used by students.

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