Electron Markets (2016) 26:323–338
DOI 10.1007/s12525-015-0214-x

RESEARCH PAPER

Factors propelling the adoption of m-learning among students in higher education

Jasmine A. L. Yeap[1] **· T. Ramayah**[1] **· Pedro Soto-Acosta**[2]

Received: 2 June 2015 / Accepted: 16 December 2015 / Published online: 14 January 2016

Abstract University students seem primed for mobile learning (m-learning) given their affinity with technology and the ubiquity of mobile computing devices on campuses. However such conditions do not necessarily guarantee their readiness for m-learning. For m-learning to thrive in higher education, it is crucial to understand the factors propelling its adoption. Accordingly this study uncovers factors that drive the adoption of m-learning among university students. Using a mobile learning readiness model based on the Theory of Planned Behavior, data was collected from 900 undergraduates in a local, public university in Malaysia. Partial least squares analysis revealed that all three constructs of attitude, subjective norm and perceived behavioral control significantly influenced students' intention to adopt m-learning. These three constructs were significantly predetermined by their respective external beliefs components. In fostering m-learning adoption among students, more emphasis should be expended to capitalize on subjective norm and improve perceived behavioral control.

Keywords Mobile learning readiness · Mobile learning acceptance · Mobile devices · Theory of planned behavior · Universities · Undergraduates

Responsible Editor: Ricardo Colomo-Palacios

✉ Pedro Soto-Acosta
psoto@um.es

T. Ramayah
ramayah@gmail.com

[1] School of Management, Universiti Sains Malaysia, 11800 USM, Penang, Malaysia

[2] Department of Management & Finance, University of Murcia, 30100 Espinardo, Murcia, Spain

Introduction

The proliferation of mobile technologies in recent years has ushered in a new paradigm in education, i.e., mobile learning or m-learning. Generally m-learning can be viewed as any form of learning that takes place when mediated through a mobile device (Winters 2006). It differs from electronic learning or e-learning in the sense that learning occurs using mobile computing devices such as smartphones and tablets over wireless transmissions rather than the conventional method of learning using desktop personal computers hooked up on wired connections (Tan et al. 2014). Thus, through m-learning, the acquisition of knowledge and skills is unrestricted to any time and place (Liu et al. 2010).

The popularity of this type of learning has been on the rise over the past few years (Donnelly 2009; Park et al. 2012) and is steadily gaining the attention of higher education institutions in various regions of the world. It has been said that m-learning can serve as a significant complement to the universities' existing e-learning systems by creating an additional channel of access for users of mobile devices (Gikas and Grant 2013). Furthermore, university students of this era seem primed for m-learning as they comprise largely of Millennials (Tapscott 1998) - the first generation to grow up with access to computers and the Internet, making them naturally adept at using various technological devices (Margaryan et al. 2011).

In spite of being hailed as an emergent, promising paradigm undergoing intense development, the adoption of m-learning technologies in universities has yet to achieve widespread adoption among students in higher education institutions (Herrington and Herrington 2007; Pozzi 2007). For those that have, whether the mobile devices are being used in pedagogically appropriate ways remains unclear (Herrington and Herrington 2007). In order for m-learning to thrive in higher education, students must actively and effectively weave technology into their lives for learning in greater diversity, both inside and outside classes. Nevertheless, current understanding of mobile technology adoption for learning from the students' perspective is still rather limited (Corrin et al. 2010; Liu et al. 2010).

At this juncture, there is a need for research on potential factors driving m-learning adoption (Viberg and Gronlung 2013) especially in the context of developing countries (Mohammadi 2015) such as Malaysia. Malaysia, for one, makes an interesting context of study as it is one of the fast-growing Internet nations among the developing countries. The country's technology-related statistics indicate the presence of untapped potential and a positive prospect for m-learning in Malaysia. As of Quarter 2 in 2015, Malaysia has broadband penetration rates of 91.7 (per 100 inhabitants) and 72.2 (per 100 households) (Malaysian Communications and Multimedia Commission 2015a). Recently there has been a impressive upsurge in the use of mobile Internet among Malaysians, rising from 22.0 % of user base in 2013 to 65.1 % in 2014 which can be largely attributed to increase of mobile gadgets like smartphones as the main device of Internet access (Malaysian Communications and Multimedia Commission 2015b). The percentage of smartphone ownership has risen from 55.9 % in 2013 to 74.3 % in 2014 while tablet ownership has also risen from 18.3 % in 2013 to 25.5 % in 2014 (Malaysian Communications and Multimedia Commission 2015b). On the contrary, the use of notebooks/ laptops/netbooks and personal computers as the mode to access the Internet in 2014 has took a downturn at 51.4 % and 35.3 % respectively (Malaysian Communications and Multimedia Commission 2015b). The largest percentage of Internet users in Malaysia comprise of the 20 to 24 year olds (24.2 %) followed by the 25 to 29 year olds (19.3 %) who are mainly college or university students and young working adults (Malaysian Communications and Multimedia Commission 2015b). Among the number of Internet users who are still studying, about 62.5 % are college or university students (Malaysian Communications and Multimedia Commission 2015b).

In terms of information structure readiness, Malaysia appears to be on the right track to embark on m-learning. In most of the local public universities, e-learning platforms have already been implemented and are widely used among the lecturers and students; therefore this could be further enhanced into mobile compatible platforms that serve as the basis for m-learning (Mohammad et al. 2012). Furthermore, internet access through wi-fi connections is available widely in campus. Table 1 shows the e-learning systems that are currently implemented in several public universities in Malaysia.

Given all these conditions, there seems to a high potential for the adoption of m-learning in higher education institutions of Malaysia. However, having such conditions present does not necessarily guarantee that students will use the mobile devices for academic purposes (Corbeil and Valdes-Corbeil 2007). In other words, supposed readiness does not indicate genuine readiness (Parkes et al. 2015). As of the present, m-learning has yet to reach a state of widespread adoption. Though previous studies on m-learning conducted in Malaysia explored the readiness of students in higher education institutions to adopt m-learning (e.g. Abas et al. 2009; Andaleeb et al. 2010), there is a need for a clearer understanding on the factors driving m-learning adoption in Malaysia (Tan et al. 2014). Thus in this study, we sought to uncover the answer to our primary research question: What are the factors that propel the adoption of m-learning among higher education students in Malaysia?

In investigating the factors that contribute to the adoption of m-learning among students, we applied and validated the model of mobile learning readiness by Cheon et al. (2012) developed based on the established Theory of Planned Behavior in our study. Replication studies play a vital part in the scientific research process (Burman et al. 2010; Easley et al. 2000) because they reflect one of the most important principles of the scientific method which is *reproducibility. Reproducibility is crucial because it helps to confirm the validity of the original authors' findings as well as expose any possible flaws in their work* (*Flaherty* 2015). Apart from the United States (USA) where it was first tested, to the best of our knowledge, Cheon et al.'s (2012) model of mobile learning readiness has yet to be tested in different contexts of study. This brings us to our secondary research question: Will the mobile learning readiness model based on TPB remain robust in the Malaysian context? While the structure of the model may remain robust across countries, the role and importance of the same variables in the model could differ in different contexts of study which are driven by distinct national cultures. For instance, the influence of others as represented by the variable subjective norm in TPB could exhibit a stronger effect in Asian countries which have a high collectivist culture whereas in other Western counterparts, this variable could exhibit a lesser impact.

For the most part, this study is important because it provides a true account of m-learning readiness in higher education from the perspective of the students themselves. This can assist higher education authorities in gauging the level of students' interest in this mode of learning, the essential factors that propel their intentions towards m-learning and these can then help them to strategize accordingly. Only by studying the factors that motivate users to adopt a particular technology can we be more certain of that technology being successfully adopted. In addition, this study is also a timely one given the age of digital devices that we are living in. Currently, sales for desktop and laptop computers have already slowed down. It has been forecasted that 87 % of the worldwide smart connected device market will be dominated by tablets and smartphones by 2017 (Milošević et al. 2015). This clearly

Table 1 E-learning systems in Malaysian public universities

Public Universities in Malaysia	E-learning management system	Wi-Fi in campus
Universiti Malaya	ADeC e-Learning	Yes
Universiti Sains Malaysia	e-Learn@USM	Yes
Universiti Kebangsaan Malaysia	LearningCare	Yes
Universiti Putra Malaysia	eSprint	Yes
Universiti Teknologi Malaysia	eLearning@UTM	Yes
Universiti Teknologi MARA	i-Learn	Yes
Universiti Utara Malaysia	LearningCare	Yes
Universiti Malaysia Sabah	LMS UMS	Yes
Universiti Malaysia Sarawak	MORPHEUS	Yes
Universiti Pendidikan Sultan Idris	MyGuru	Yes
Universiti Teknikal Malaysia Melaka	U-Learn	Yes
Universiti Malaysia Pahang	KALAM	Yes
Universiti Sains Islam Malaysia	G.O.A.L.S	

Source: Adapted from Mohammad et al. (2012)

shows that the use of mobile technologies have grown to such an extent over recent years that they now surpass the proliferation of personal computers in modern professional and social contexts. In short, this study contributes to the growing number of research efforts striving to understand the ways technology is changing the manner and means of human education and learning.

This paper is structured as follows: in the next section, we review some literature pertaining to m-learning followed by the theoretical background and research model and hypotheses of this study. Subsequently, we explain the methodology of the study followed by the results of the analyses conducted. Thereafter we discuss the findings in greater detail along with a number of implications. Finally, the paper ends with the limitations of this study and suggestions for future studies.

Literature review

Millennials and technology

The university population at present is largely made up of the Millennial generation (Tapscott 1998). Millennials are the post 1980s generation, those who have have been exposed to computers and the Internet since young (Djamasbi et al. 2010) and as a result are inherently technology-savvy (Jones et al. 2010). Junco and Mastrodicasa (2007) found that the university student segment of Millennials use technology much more than any previous generational cohorts. Technological devices such smartphones, tablets, computers, mp3 players, digital cameras are ubiquitous among them and these group of people are extremely adept at multitasking with multiple devices (Taleb and Sohrabi 2012). They are constantly involved in online activities such as text messaging, social networking, blogging, podcasting and downloading. Almost all of them have created a profile on social networking sites such as Facebook while one-in-five have posted a video of themselves online on YouTube (Malikhao and Servaes 2010).

University students around the world carry their miniature computing and communication devices (i.e. smartphones and tablets) around during the university day, using them almost exclusively for personal purposes (Evans 2008). For them, a mobile phone is regarded as a 'necessity' and not a luxury (Barbosa and Geyer 2005). Empowered by the massive use of technology, they are a generation who not only absorb content on their technological devices but produce it both individually and in groups and share the content in their social networks (Ferreira et al. 2013; Palacios-Marqués et al. 2015a, b). In this manner, the use of mobile technologies in learning processes have the potential to generate great motivation among this generation, benefitting particularly those who are usually not engaged with the course or demonstrate a lack of performance (Goh et al. 2011, Mahat et al. 2012).

Concept of m-learning

The advent and of m-learning is alleged to have evolved from distance learning (d-learning) to electronic learning (e-learning) (Sharma and Kitchens 2004). The popularity of m-learning can be attributed to the development of iPad and tablets that operate based on wireless technology (Park et al. 2012). M-learning can be defined as the acquisition of any knowledge and skills through the use of mobile technology at anywhere and anytime of the day (Liu et al. 2010). In other words, m-learning refers to learning using mobile devices in the likes of smartphones, tablet computers, personal digital assistants (PDAs), MP3 and MP4 devices as well as other portable devices (Milošević et al. 2015, Tan et al. 2014). Such devices are handheld (suitable for holding in your hand and do not need to be installed on a desktop), easily portable (can be carried brought anywhere in one's bag or pocket and have their batteries charged anywhere) as well as light (devices do not weigh much) (Nordin et al. 2010). The development of social media with its free apps and tools that enable communication and enhance learning further intensifies the utilization of m-learning (Rodriguez 2011).

Uses of m-learning in higher education

The use of m-learning in higher education could range from simple applications to support traditional teaching to more sophisticated systems which are developed specifically for the m-learning educational modality (Ferreira et al. 2013). Patten et al. (2006) asserted that the use of mobile devices in higher education can generally be classified into three categories namely administration functions (e.g. calendaring and timetabling); reference functions (e.g. e-books and dictionaries) and interactive functions (response and feedback activities). There are many possible applications of mobile technologies for both formal and informal learning. As Kukulska-Hulme et al. (2011) have found, m-learning via cellphones, smartphones, PDAs and MP3 players are used being to create, collect and access useful resources to communicate inventively in multiple ways with other individuals and communities as well as to maximize their time wherever they happen to be. Some examples of m-learning practices are listed as follows:

- Using SMS to interact with classmates and teachers regarding class activities, notes of mixed nature, including delivery of essays, study meetings, doubts etc. This could also include participation in discussion forums or video classes through cell phones (Goh et al. 2011; Grönlund and Islam 2010; Hayati et al. 2012; Motiwalla 2007).
- Accessing learning management systems (which are specifically designed for mobile devices) to complete a course, interact with classmates and sharing knowledge with each other, search for or post materials anywhere or whenever (Beckmann 2010; Chen and Huang 2010; Saccol et al. 2011).
- Listening to podcasts of comments or lecture syntheses recorded by a teacher or classmate after a class (Beckmann 2010; Evans 2008).
- Answer a "quiz" through a cell phone containing questions to be answered after watching a video, listening to an audio track or accessing previously defined content in a mobile way (Gedik et al. 2012).
- Accessing mobile virtual worlds on mobile devices such as Third Dimension Virtual Worlds via Pocket Metaverse which provides mobile access to Second Life and Virtway (Ferreira et al. 2013).
- Learning using educational games designed for mobile devices (Brown et al. 2011; Liu et al. 2010)
- Accessing social networks such as Facebook and Twitter) on mobile devices to exchange information or engage in informal learning activities (Ferreira et al. 2013).

Benefits, drawbacks and challenges of m-learning in higher education

In his exploratory study on the effectiveness of m-learning in higher education, Evans (2008) found that m-learning in the form of podcast revision lectures had significant potential as an innovative learning tool for undergraduate students. As described by Milošević et al. (2015), some of the major benefits provided by m-learning include the following:

- Mobility and convenience - mobile devices are light enough to be carried around everywhere thus allowing students to learn anywhere, take notes or record sounds in class.
- Interactivity - facilitates faster interaction between students and their lecturers/instructors.
- Collaboration – facilitates easier cooperation among students.
- Environmental-friendly - reduces the cost of printing reading materials and other literature.
- Fun and engaging - appeals to a new generation of students who love using mobile devices.
- Flexibility - students are able to study at their own pace and capacity.
- Accessibility – assists students with disabilities in learning and also extends learning opportunities to a wider range of people in society.

In contrast, the disadvantages of m-learning cited by researchers such as Ibrahim et al. (2014) and Ally and Samaka (2013) are mostly related to the:

- Small screen size and keys, internet connection and battery life of the mobile devices.

Standards and operating systems which mobile devices do not support as there are difficulties to adapt existing content for e-learning to mobile devices.

- Price of devices whereby mobile devices with better features are typically expensive
- Mobile device market which evolves very fast, rendering the devices as obsolete very quickly.

In terms of the challenges associated with m-learning, the diffusion of m-learning in higher educational institutions is not a simple matter because it necessitates much cultural change. For one, the current teaching culture which in general is strongly marked by traditional (face-to-face) environments will have to change (Grönlund and Islam 2010). University lecturers or instructors would need to change their pedagogic practices and learn new technologies and teaching method with which they are unfamiliar with (Kukulska-Hulme et al. 2011).

Furthermore, not all courses are suitable for the m-learning environment (Keegan 2003). For instance, short courses which are mainly theory and information type of courses seem better suited for the m-learning environment. More importantly, Internet connection issues concerning bandwidth, speed, network coverage, security and the reliability of service provider warrant much attention in ensuring the smooth implementation of m-learning (Abachi and Muhammad 2014). There is also the issue of university lecturers or instructors being uncomfortable using technology given that they comprise of earlier generations such as the Boomers and GenXers who are less technology-savvy. Many of these university educators may also feel somewhat threatened by mobile devices knowing that their students are more technology-competent than they are themselves (Herrington and Herrington 2007).

Theoretical background

The Theory of Planned Behavior (TPB) explains various behaviors and behavioral intentions which are not under a person's volitional control (Ajzen 1991, 2001). It is an extension of the Theory of Reasoned Action (TRA) which states that individuals will be influenced by their own attitudes and what other people think they should or should not do (Ajzen and Fishbein 1980). In other words, behavioral intention is formed based on the attitude towards the behavior and subjective norm regarding the behavior. To deal with the criticism that TRA does not adequately explain circumstances when behavior is not under an individual's control condition, TPB was conceived by adding another variable, i.e., perceived behavioral control (PBC) as a third determinant. Thus, TPB is considered more realistic in terms of investigating behavioural phenomena such as the new technology acceptance process.

According to Ajzen (1991), the first determinant in TPB, attitude toward behavior is the degree to which performance of the behavior is positively or negatively valued; it is produced by behavioral beliefs about the likely consequences. The second determinant, subjective norm refers to the perceived social pressure of whether or not to engage in a behavior, as determined by normative beliefs or expectations of others (Hrubes et al. 2001). The more favorable the attitude towards the behavior and subjective norm are, the more likely the individual's intention to perform that specific behavior (Ajzen and Driver 1991; Miesen 2003).

The third determinant, perceived behavioral control concerns the degree to which a person has favorable or unfavorable evaluation or appraisal of the behavior in question. Perceived behavioral control predicts the probability of successful behavioral attempt when there is a realistic extent of resources (Ajzen 1985). It is determined by its set of control beliefs and has both direct and indirect effects on behaviour. The link from perceived behavioral control to intention indicates the perceived behavioral control's influence on behavior indirectly through intention whereas the direct path from perceived behavioral control to behavior is assumed to reflect the actual control an individual has over the performance of a behavior (Madden et al. 1992).

Research model and hypotheses

Cheon et al. (2012) investigated university students' intention to adopt m-learning in higher education institutions by developing a model of mobile learning readiness based on TPB. The model was tested among undergraduate students in a large, public-intensive university located in the Southwest region of USA. In constructing their framework, Cheon et al. (2012) were mindful of several points. First, the constructs of attitude, subjective norm and perceived behavioral control were posited to be determined by their respective sets of external beliefs. This is done in consideration of Ajzen and Fishbein's (1980) suggestion that researchers should identify beliefs for behavior from a specific population or contexts because salient beliefs are conditional to context. Attitude is determined by behavioral beliefs associating the behavior to various outcomes and other attributes; subjective norm is influenced by normative beliefs which are relevant others' beliefs about performing a particular behavior; and perceived behavioral control is affected by control beliefs about the presence of factors that may enable or hinder performance of the behavior.

Second, Cheon et al. (2012) distinguished perceived behavioral control from attitude conceptually because personal behavioral control refers to a subjective degree of control over performance of a behavior but does not imply the likelihood that performing a behavior will deliver a given outcome (Ajzen 2002). Third, behavioral intention was used as a final dependent variable instead of actual behavior as it was assumed to be the immediate antecedent of actual behavior. Suffice to say, behavioural intention is one of the most accurate predictors available for an individual's future, actual behaviour (Davis 1989; Davis et al. 1989; Sheppard et al. 1988; Venkatesh and Davis 2000; Venkatesh et al. 2000). The stronger the intention to perform a behavior, the more likely the individual will perform the behavior in question (Cheon et al. 2012). The strength of Cheon et al.'s (2012) framework lies in the fact that it sought to measure m-learning adoption from a multi-faceted perspective that is grounded in a time-honored theory. For this reason, we applied this framework as the model of our study (see Fig. 1). Referring to Fig. 1, we posit that external beliefs (behavioral beliefs, normative beliefs and control beliefs) influence attitude, subjective norm and perceived behavioral control of which these three constructs are then posited to affect the adoption of m-learning.

Behavioral beliefs and attitude towards m-learning

Researchers have consistently proven the significant, positive relationship between attitudinal beliefs and attitude towards behavior (Ajjan and Hartshorne 2008; Chang and Chang 2009; Davis 1989; Marler and Dulebohn 2005; Riquelme and Rios 2010; Venkatesh and Davis 2000; Yang et al. 2012). In this study perceived ease of use and perceived usefulness were conceptualized as the variables of behavioral beliefs which serve as the antecedents of attitude towards m-learning. Derived from the Technology Acceptance Model (TAM) (Davis1989), perceived usefulness is defined as the degree to which a person believes that using a particular system would enhance his or her job performance whereas perceived ease of use is defined as the degree to which a person believes that using a particular system would be free of effort. Students are more likely to use m-learning if they perceive it to be relatively uncomplicated, easy to use and also if it is brings improvements to their academic development and performance. For this reason, we hypothesize that:

H1: University students' perceived ease of use of m-learning has a positive effect on their attitude towards m-learning.

H2: University students' perceived usefulness of m-learning has a positive effect on their attitude toward m-learning.

Normative beliefs and subjective norm

Subjective norm refers to an individual's perception of social norms or his or her peers' beliefs about a behavior. According to Taylor and Todd (1995), subjective norm relates to how an individual's behavior is swayed by the desire to act according to how salient referents think they should act. It has been said to be determined by the accessible normative beliefs that account for the expectations of other people (Ajzen 1991). Previous studies have shown the positive influence of referent groups towards subjective norm for technologies (Ajjan and Hartshorne 2008; Baylor and Ritchie 2002; Ertmer et al. 2012; Hamat et al. 2012). In this study, salient referents for the adoption of m-learning are the instructors and students' peers. Thus, we propose the normative beliefs of instructors and other students as antecedents of subjective norm. The more instructors and students' peers are in favor of the students using mobile devices for their courses, the higher the likelihood of the students doing so. Thus, the hypotheses formulated are as such:

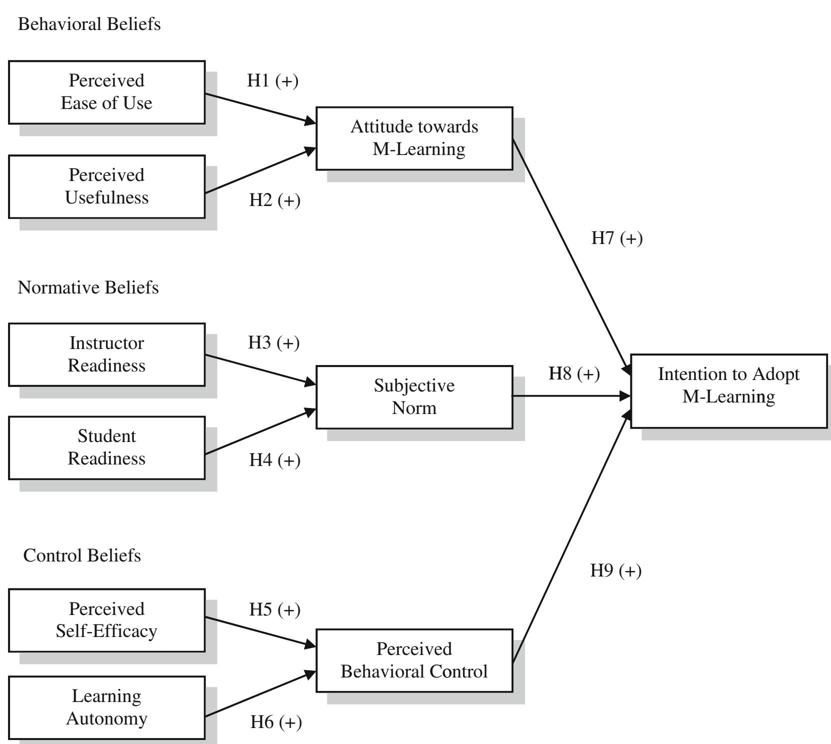


Fig. 1 Research model of this study. Source: adopted from Cheon et al. (2012)

H3: Perceived instructor readiness for m-learning has a positive effect on subjective norm for m-learning.
H4: Perceived peer student readiness for m-learning has a positive effect on subjective norm for m-learning.

Control beliefs and perceived behavioral control

Control beliefs refer to the factors that may facilitate or impede performance of a behavior and contribute to perceived behavioral control (Ajzen 1991). Two constructs, perceived self-efficacy and learning autonomy comprise control beliefs that are proposed to have an impact on perceived behavioral control. Perceived self-efficacy can be defined as an individual's belief that he or she has the capability to perform a particular behavior (Bandura 1986). Individuals are more likely to undertake a particular behavior if they believe that they can master a certain skill or valued outcomes. For instance, higher levels of perceived self-efficacy in the use of computing technology were found to lead to higher levels of usage intention for that technology (Compeau and Higgins 1995; Gist et al. 1989; Lim 2001; Torkzadeh and Van Dyke 2001, 2002). On the other hand, learning autonomy, in the context of m-learning, refers to the extent to which students have sufficient control and are in charge of their learning process using mobile devices. Liaw et al.'s (2007) study on instructors and learners' attitude towards e-learning showed that effective learner autonomy is a major factor for e-learning system acceptance. Considering the role of both perceived self-efficacy and learning autonomy in the adoption of m-learning, we assert that:

H5: University students' perceived self-efficacy towards m-learning has a positive effect on their behavioral control with m-learning.
H6: University students' perceived learning autonomy towards m-learning has a positive effect on their behavioral control with m-learning.

Predictors of intention to adopt m-learning

Attitude towards m-learning refers to the degree to which a person has a favorable or unfavorable feeling about using mobile devices for learning. Previous studies have found that attitude strongly affected the behavioral intention to adopt new technologies (Ajzen 1991; Chang and Chang 2009; Jairak et al., 2009; Taylor and Todd 1995). Subjective norm is the perceived social pressure to engage or not in a behavior (Ajzen 1991). As described by Venkatesh and Davis (2000), salient referents' opinions such as friends or family members are persuasive enough to shape an individual's intention to use new technologies. Perceived behavioral control pertains to an individual's perception of his or her control over a particular behavior. Individuals' perception of behavioral control increases and positively affects behavioral intention to use a technology when they perceive that they have sufficient resources and confidence to overcome the obstacles of using a particular technology (Ajzen 1985; Ajzen and Madden 1986; Lee and Kozar 2005; Lim and Dubinsky 2005; Madden et al. 1992). Accordingly we develop the following hypotheses:

H7: University students' attitude toward m-learning has a positive influence on their behavioral intention to adopt m-learning.
H8: University students' subjective norm towards m-learning has a positive effect on their behavioral intention to adopt m-learning.
H9: University students' perceived behavioral control towards m-learning has a positive effect on their behavioral intention to adopt m-learning.

Methodology

Sample and data collection

As this study concerns m-learning in higher education institutions, the sample consists of university students. In particular, the undergraduates were the targeted respondents given their high affinity with technology as they fall under the Millennial generation. To decide on the sample size of the respondents for this study, we first used the Gpower software to calculate the minimum sample size required. Since the model had a maximum of 3 predictors (for the outcome variable Intention to Adopt M-Learning), we set the effect size as small (0.02) and power needed as 0.95. The sample size required was 863. Hence we set out to collect data which was equal to or slightly larger than the required number.

Using an intercept survey method, 900 responses were collected from undergraduates of an established public university which is designated as a Research University in Malaysia. The students were from both the Arts and Sciences and they have exposure to the use of an e-learning portal established by the university. Since all the students were actually accessing the same platform, the issue of differences in system was not an issue. Generally the students have a common understanding of m-learning as the e-learning portal allows multiple device access. The students comprised of different years of study from year 1 to year 4. Their participation in the study was on voluntary basis.

Measures

Data was collected using a structured questionnaire. Although the students have a common understanding of what m-learning is, a definition of m-learning was provided at the beginning of the questionnaire just in case the students need to confirm that they have interpreted the meaning of m-learning correctly. They were then asked to answer questions pertaining to their demographics, usage of technology and their perceptions about m-learning. Perceptions about m-learning pertained to the variables Perceived Ease of Use, Perceived Usefulness, Attitude towards M-Learning, Instructor Readiness, Student Readiness, Subjective Norm, Perceived Self-Efficacy, Learning Autonomy, Perceived Behavioral Control and Intention to Adopt M-Learning. The items or measures for all these variables were adapted from Cheon et al. (2012) anchored on a 7-point Likert scale (1 = strongly disagree to 7 = strongly agree) and are listed out in the Appendix.

Respondents' profile

The demographics of the respondents are tabulated in Table 2. Females (58.2 %) were slightly more than the males (41.8 %) in this study which somewhat reflects the gender ratio of undergraduates for public universities in Malaysia. Generally there are more women pursuing tertiary education in universities and colleges compared with men (Izwan 2014). Majority of the respondents were of Chinese ethnicity (52.1 %). This is due to the meritocracy policy employed by the university in the last few years. About 45 % of students used the Internet for 1–5 h daily while 50.3 % used the Internet for 6 h and more daily. More than 90 % owned smartphones while 42.6 % owned tablets.

Table 2 Profile of respondents

Profile	Frequency	Percentage
Gender		
Male	376	41.8
Female	524	58.2
Ethnicity		
Malay	336	37.3
Chinese	469	52.1
Indian	75	8.3
Others	20	2.2
Time spent on the Internet daily		
Almost never	15	1.7
< 1 h	28	3.1
1–5 h	405	45.0
6–10 h	266	29.6
11–15 h	106	11.8
16–20 h	53	5.9
More than 20 h	27	3.0
Own smartphone		
Yes	831	92.3
No	69	7.7
Own tablet		
Yes	383	42.6
No	517	57.4

Results

To analyze the research model we employed the Partial Least Squares (PLS) analysis technique using the SmartPLS 3.0 software (Ringle et al. 2015). Following the recommended two-stage analytical procedures by Anderson and Gerbing (1988), we tested the measurement model (validity and reliability of the measures) followed by an examination of the structural model (testing the hypothesized relationships) (see Hair et al. 2014; Ramayah et al. 2011, 2013). To test the significance of the path coefficients and the loadings, a bootstrapping method was used (Hair et al. 2014).

Measurement model evaluation

To assess the measurement model 2 types of validity were examined, the first being convergent validity and the second being discriminant validity. Convergent validity of the measurement model is usually ascertained by examining the loadings, average variance extracted (AVE) and also the composite reliability (Gholami et al. 2013). The loadings were all higher than 0.7, the composite reliabilities were all higher than 0.7 and the AVE values were also higher than 0.5 as suggested by Hair et al. (2014) (see Table 3).

The discriminant validity of the measures (the degree to which items differentiate among constructs or measure distinct concepts) was examined by following the Fornell and Larcker (1981) criterion of comparing the correlations between constructs and the square root of the AVE for that construct (see Table 4). Referring to Table 4, the square root of the AVEs as represented by the bolded values on the diagonals were greater than the corresponding row and column values (correlations between constructs) indicating the measures were discriminant. In sum, both convergent and discriminant validity of the measures in this study were established.

Structural model evaluation

Assessing the structural model involves evaluating R^2, beta and the corresponding t-values (Hair et al. 2014). To obtain the t-values, a bootstrapping procedure with 5000 resamples was applied. In addition to these basic measures researchers should also report predictive relevance (Q^2) and effect sizes (f^2) (Hair et al. 2014; Soto-Acosta et al. 2015).

First we looked at the antecedents to Attitude, Subjective Norm and Perceived Behavioral Control. Perceived Ease of Use ($\beta = 0.156$, $p < 0.01$) and Perceived

Table 3 Convergent validity of measurement model

Construct	Item	Loadings	AVE[a]	CR[b]
Attitude towards M-Learning	ATT1	0.893	0.825	0.934
	ATT2	0.930		
	ATT3	0.902		
Intention to Adopt M-Learning	INT1	0.925	0.856	0.947
	INT2	0.931		
	INT3	0.920		
Instructor Readiness	IR1	0.898	0.810	0.928
	IR2	0.922		
	IR3	0.880		
Learning Autonomy	LA1	0.893	0.814	0.929
	LA2	0.910		
	LA3	0.904		
Perceived Behavioral Control	PBC1	0.893	0.833	0.937
	PBC2	0.930		
	PBC3	0.914		
Perceived Ease of Use	PEU1	0.869	0.789	0.918
	PEU2	0.907		
	PEU3	0.888		
Perceived Self Efficacy	PSE1	0.912	0.826	0.934
	PSE2	0.894		
	PSE3	0.919		
Perceived Usefulness	PU1	0.881	0.790	0.919
	PU2	0.887		
	PU3	0.898		
Subjective Norm	SN1	0.901	0.817	0.931
	SN2	0.897		
	SN3	0.914		
Student Readiness	SR1	0.896	0.801	0.924
	SR2	0.916		
	SR3	0.873		

[a] AVE = (summation of squared factor loadings)/(summation of squared factor loadings) (summation of error variances)

[b] Composite reliability = (square of the summation of the factor loadings)/[(square of the summation of the factor loadings) + (square of the summation of the error variances)]

Usefulness (β = 0.637, $p < 0.01$) were positively related to Attitude explaining 57.2 % of the variance in Attitude. Instructor Readiness (β = 0.365, $p < 0.01$) and Student Readiness (β = 0.523, $p < 0.01$) were also positively related to Subjective Norm explaining 69.6 % of the variance in Subjective Norm. Perceived Self-Efficacy (β = 0.298, $p < 0.01$) and Learning Autonomy (β = 0.571, $p < 0.01$) were also positively related to Perceived Behavioral Control explaining 69.3 % of the variance in Perceived Behavioral Control. Thus H1, H2, H3, H4, H5 and H6 were supported. The R^2 values were all above the 0.35 value as suggested by Cohen (1988) indicating a substantial model.

Next we looked at the predictors of Intention to Adopt M-Learning. Attitude (β = 0.188, $p < 0.01$), Subjective Norm (β = 0.421, $p < 0.01$) and Perceived Behavioral Control (β = 0.320, $p < 0.01$) were all positively related to Intenion explaining 71.6 % of the variance in Intention. Surprisingly Subjective Norm was the strongest predictor followed by Perceived Behavioral Control with Attitude being a weak predictor of Intention. These results gave support for H7, H8 and H9 of this study. The R^2 value of 0.716 was higher than the 0.35 (substantial) value suggested by Cohen (1988). Table 5 summarizes the results of the structural model analysis (hypotheses testing).

We also assessed effect sizes (f^2). As asserted by Sullivan and Feinn (2012), "While a *P* value can inform the reader whether an effect exists, the *P* value will not reveal the size of the effect. In reporting and interpreting studies, both the *substantive significance* (effect size) and *statistical significance* (*P* value) are essential results to be reported" (p.279). In assessing effect sizes, Hair et al. (2014) suggested that the change in the R^2 value should also be examined. The method suggested is to examine the R^2 change when a specified exogenous construct is omitted from the model. This is to evaluate whether the omitted construct has a substantive impact on the endogenous construct. To measure the magnitude of the effect size we used Cohen's (1988) guideline which is 0.02, 0.15, and 0.35, representing small, medium, and large effects respectively. Looking at the f^2 values in Table 5, it can be observed that all the relationships showed substantive impact whereby there were 4 relationships with small effect sizes, 2 with medium effect sizes and 3 with large effect sizes.

Further to that we also assessed the predictive relevance of the model by using the blindfolding procedure. Blindfolding is a sample reuse technique that omits every *d*th data point in the endogenous construct's indicators and estimates the parameters with the remaining data points (Chin 1998; Henseler et al. 2009; Tenenhaus et al. 2005). Hair et al. (2014) suggested that the blindfolding procedure should only be applied to endogenous constructs that have a reflective measurement (multiple items or single item). If the Q^2 value is larger than 0 the model has predictive relevance for a certain endogenous construct and otherwise if the value is less than 0 (Hair et al. 2014; Fornell and Cha 1994). From Table 5 we can see that all the Q^2 values are more than 0 ranging from 0.471 to 0.612 suggesting that the model has sufficient predictive relevance. Hair et al. (2014) also stated that as a relative measure of predictive relevance, values of 0.02, 0.15, and 0.35 indicate that an exogenous construct has a small, medium, or large predictive relevance for a certain endogenous construct.

Importance performance matrix analysis

As an extension to the results of the study, we ran a post-hoc importance-performance matrix analysis (IPMA) using Intention to Adopt M-Learning as the target construct or

Table 4 Discriminant validity of measurement model

	ATT	PEU	IR	INT	LA	PBC	SN	PSE	SR	PU
ATT	**0.908**									
PEU	0.617	**0.888**								
IR	0.767	0.585	**0.900**							
INT	0.724	0.633	0.727	**0.925**						
LA	0.742	0.646	0.751	0.809	**0.902**					
PBC	0.703	0.612	0.698	0.766	0.815	**0.912**				
SN	0.738	0.651	0.762	0.798	0.789	0.745	**0.904**			
PSE	0.757	0.659	0.759	0.817	0.819	0.766	0.814	**0.909**		
SR	0.740	0.660	0.759	0.722	0.746	0.707	0.800	0.734	**0.895**	
PU	0.750	0.725	0.693	0.715	0.732	0.694	0.713	0.735	0.728	**0.889**

Diagonals (bolded) represent the square root of the average variance extracted while the off-diagonals are correlations among constructs. Diagonal elements should be larger than off-diagonal elements in order to establish discriminant validity

ATT Attitude towards M-Learning, *PEU* Perceived Ease of Use, *IR* Instructor Readiness, *INT* Intention to Adopt M-Learning, *LA* Learning Autonomy, *PBC* Perceived Behavioral Control, *SN* Subjective Norm, *PSE* Perceived Self-Efficacy, *SR* Student Readiness, *PU* Perceived Usefulness.

outcome variable. The IPMA builds on the PLS estimates of the structural model relationships (importance of each latent variable) and includes an additional dimension to the analysis that considers the latent variables' average values (performance) (Hair et al. 2014). The importance scores were derived from the total effects of the estimated relationships in the structural model for explaining the variance of the endogenous target construct or outcome variable (Völckner et al. 2010). On the other hand, the computation of the performance scores or index values were carried out by rescaling the latent variables scores to range from 0 (lowest performance) to 100 (highest performance) (Hair et al. 2014). Table 6 presents the results of total effects (importance) and index values (performance) used for the IPMA.

We plotted the index values and total effects scores out in a priority map as shown in Fig. 2. Based on Fig. 2, it can be observed that Subjective Norm and Perceived Behavioral Control are very important factors in determining a student's intention to adopt m-learning due to their relatively higher importance values compared to the rest of the variables. However the performance of these two important factors lagged behind Attitude. Though variables such as Perceived Ease of Use scored relatively high in performance, it has little relevance in influencing students' intention to adopt m-learning. With respect to the predecessors of Subjective Norm and Perceived Behavioral Control, the constructs Student Readiness and Learning Autonomy exhibited intermediate importance and performance compared with the other constructs. In sum, managerial activities to improve students' acceptance of m-learning should focus on improving the performance of Subjective Norm and Perceived Behavioral Control. Attention should also be given to build up the importance and performance of Student Readiness and Learning Autonomy as these two constructs function as precursors to Subjective Norm and Perceived Behavioral Control.

Table 5 Results of the Structural Model Analysis (Hypotheses Testing)

Hypo-thesis	Relationship	Std Beta	Std Error	t-value	Decision	R^2	f^2	Q^2
H1	PEU → ATT	0.156	0.044	3.570**	Supported	0.572	0.027	0.471
H2	PU → ATT	0.637	0.037	17.156**	Supported		0.451	
H3	IR → SN	0.365	0.044	8.312**	Supported	0.696	0.186	0.567
H4	SR → SN	0.523	0.045	11.641**	Supported		0.382	
H5	PSE → PBC	0.298	0.040	7.463**	Supported	0.693	0.095	0.577
H6	LA → PBC	0.571	0.039	14.619**	Supported		0.351	
H7	ATT → INT	0.188	0.044	4.304**	Supported	0.716	0.050	0.612
H8	SN → INT	0.421	0.039	10.820**	Supported		0.222	
H9	PBC → INT	0.320	0.047	6.799**	Supported		0.143	

**$p < 0.01$

ATT Attitude towards M-Learning, *PEU* Perceived Ease of Use, *IR* Instructor Readiness, *INT* Intention to Adopt M-Learning, *LA* Learning Autonomy, *PBC* Perceived Behavioral Control, *SN* Subjective Norm, *PSE* Perceived Self-Efficacy, *SR* Student Readiness, *PU* Perceived Usefulness.

Table 6 Index values and total effects

Latent Variable	Total effect of the latent variable Intention to Adopt M-Learning (Importance)	Index values (Performance)
Attitude towards M-Learning	0.188	79.273
Perceived Ease of Use	0.029	75.203
Instructor Readiness	0.154	67.561
Learning Autonomy	0.183	68.690
Perceived Behavioral Control	0.320	68.218
Subjective Norm	0.421	69.567
Perceived Self-Efficacy	0.095	69.085
Student Readiness	0.220	69.703
Perceived Usefulness	0.119	71.260

Discussion and conclusions

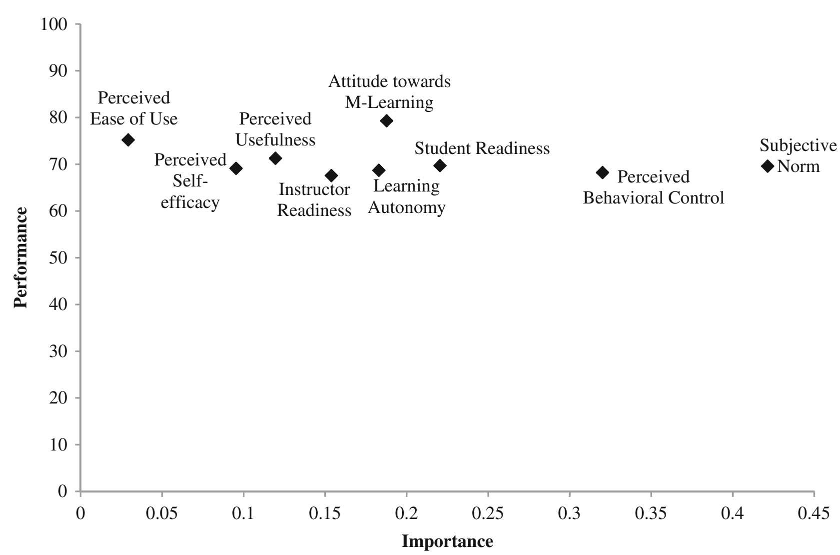
Summary of findings

In this study, we set out to ascertain the factors that would propel m-learning adoption among university students. We replicated the research framework developed by Cheon et al. (2012) which was grounded on the Theory of Planned Behavior in the context of Malaysian university students. As predicted, all three constructs of attitude, subjective norm and perceived behavioral control had a significant and positive influence on intention to adopt m-learning. Subjective norm had the strongest impact followed by perceived behavioural control and finally attitude. This is in contrast to the findings of Cheon et al. (2012) who found that perceived behavioral control has the strongest impact on intention followed by attitude and lastly subjective norm. The findings in our study imply that the readiness of students in adopting m-learning is driven primarily by the perceptions of their own ability and confidence in mastering a new mode of learning as well as the opinion and influence of others.

Scholars (e.g. Cheung et al. 2011; Hsu and Lu 2004; Karahanna and Straub 1999; Liker and Sindi 1997; Sledgianowski and Kulviwat 2009) have contended that social influences profoundly affect an individual's behaviour. Throughout history, the adoption of a new technology is observed to reach popular consumption when the technology in question experiences an accelerated adoption to the point of mass acceptance and when there is an exertion of normative pressure from current users to potential others. In fact, innovation diffusion studies have suggested that apart from the characteristics of the technology, user adoption decisions are influenced by a social system beyond an individual's decision style (Hsu and Lu 2004). Furthermore, conformity theories have posited that group members tend to comply with the group norm, and these in turn influence the perceptions and behavior of members (Lascu and Zinkhan 1999).

All external belief components also positively influenced their intended constructs - perceived ease of use and perceived usefulness positively affected attitude towards m- learning; instructor readiness and student readiness positively affected subjective norm and perceived self-efficacy and learning autonomy positively affected perceived behavioural control. These results were consistent with the ones found by Cheon et al. (2012) except for the relationship between student readiness and subjective norm of which student readiness demonstrated no effect on subjective norm. Although all the external belief components positively influenced their intended constructs, the impact of the beliefs component was rather lopsided. Perceived usefulness was clearly more instrumental in determining attitude towards m-learning instead of perceived ease of use given that the generation of university students today is technology-savvy. Students will view m-learning

Fig. 2 IPMA (Priority Map) for M-Learning Readiness Among Undergraduates



favourably when they are convinced of it helping them in their learning and productivity thereby explaining the higher weightage found for the impact of perceived usefulness. To foster faster m-learning adoption, students must be shown the usefulness aspects of m-learning such as helping them to improve the quality of interaction among themselves and their peers, enhance their learning process as well as offering the convenience of accessing information at any time of the day (Tan et al. 2014). Apart from enhancing the learning process, support services that facilitate the students' academic life experience can be introduced as a way to further highlight the usefulness of m-learning. For instance, m-learning can also include other aspects that help complement the campus learning experience such as retrieval of exam results, course registration, calendar, schedule services, library services, campus facilities etc. (Alzaza and Yaakub 2010).

Students rather than instructors were the more influential referent group that influences subjective norm for m-learning. Students' peers play an important role in the context of their campus life. Peers not only serve as course mates, but also as friends and rivals in their studies. Hence, peers' approval of adopting m-learning matters much to the students. Nevertheless, the role of the instructor should not be dismissed as unimportant. Instructors must lead effective ways to implement devices in learning (Gikas and Grant 2013) such as by designing learning activities that combine both formal and informal learning and also learning that continues on throughout a day or days, tolerating pauses and disruptions (Ng et al. 2010). Apart from that, learning autonomy assumed a more dominant role in predicting perceived behavioral control instead of perceived self-efficacy. While students may not be that perturbed about their ability in using mobile devices for their courses, the extent to which they have control over the process and pace of learning is crucial in deciding whether they will be able to adopt m-learning successfully. Students are more likely to adopt technology for learning when the use of that particular technology aligns with their learning approaches and when they perceive the compatibility between technology use and their learning style and needs (Lai et al. 2012). In this manner, the provision of student training programmes on m-learning should emphasize on the two criteria mentioned.

Theoretical implications

In this study, we replicated and validated Cheon et al.'s (2012) model of m-learning readiness based on TPB using a larger sample. We have successfully proven that their model holds true at a different time, place, researchers and subjects of study that is Malaysia. Replication is pivotal in providing support to any worthwhile theory and in our case the theory in question was the TPB. Our findings have shown that intention to adopt m-learning is affected by a combination of attitudinal factors which are central in the TPB; in particular, attitude, subjective norm and perceived behavioral control. Also the external belief components which expanded the TPB contributed relevantly to the prediction of attitude, subjective norm and perceived behavioral control. With the exception of the relationship between student readiness and subjective norm, our findings mirror the findings of Cheon et al. (2012), thus confirming that what we found reflects the true state of affairs in the university student population. In addition, we have also extended the analysis of this study to include more diagnostics such as effect sizes, predictive relevance and the IPMA which were all not done in the original article (i.e. Cheon et al. 2012).

Practical implications

Though our findings indicate that all the variables in the m-learning readiness model have their roles to play in affecting students' intention to adopt m-learning, there are some factors which higher education authorities or other decision-makers should emphasize in fostering students' involvement in and use of m-learning. The IPMA conducted revealed which variables were particularly important in order to prioritize managerial actions; it enables researchers as well as decision makers to focus on improving the performance of those variables that are highly important in explaining a certain target variable but at the same time have a relatively low performance. As the IPMA findings show, students already seemed to have an open and favourable attitude towards the idea of adopting m-learning in their studies. However the elements that will impel them to adopt m-learning are perceived behavioral control and subjective norm.

As students are prone to the influence of their peers and friends, social media should be capitalized on to advocate the benefits of m-learning. Efforts should be expended to convey using mobile devices in lessons and coursework as a 'cool' and wise idea consistent with today's digitized way of living. This may spark off some conversations online and lead the students to share their anticipation or excitement with their network of friends and peers on social media. At this juncture, higher education authorities or other decision-makers should seize the opportunity to encourage and foster sharing and discussions among students on their experience of m-learning to get students motivated about m-learning. When students hear of their peers and/or coursemates' stories on successful learning experience with m-learning, they are more likely to adopt technologies for learning.

To build up students' ability and confidence in using m-learning, lecturers can try incorporating simple aspects of m-learning in their lessons. In addition, they can demonstrate how using mobile devices for learning actually empowers the students to take control of their learning pace and help them in their academic development and productivity. Once students become familiarized with the mobile environment, more advanced functions of m-learning can then be introduced in their courses.

Limitations and future research directions

The findings of this study should be interpreted in light of its limitations. First, only the perceptions of the students were surveyed in this study. The perspectives of the instructors/lecturers or other parties of interest were not taken into account thus this could result in a potential bias in the study despite the fact that care was taken to ensure that students from all faculties (sciences to the arts) were surveyed. Therefore, it would be helpful if future researchers examine perspectives of not only the students but the lecturers/instructors as well to compare if there are any discrepancies in the readiness to adopt m-learning. Second, the sample of this study was restricted to a single university thus generalization of this study's findings to the whole population of undergraduates and other age group of students may be limited. In future, this study can be further replicated in both public and private universities so as to obtain a more representative state of higher education institutions in Malaysia. Third, this study captured only students' intention to adopt m-learning in lieu of actual behavior of adoption although intention is regarded as a reasonable proxy for actual behavior (Davis 1989; Davis et al. 1989; Sheppard et al. 1988; Venkatesh and Davis 2000). At the point of investigation, most universities have yet to develop m-learning platforms that complement their e-learning systems. In future, should m-learning be implemented across universities, it would be interesting to examine whether students' evaluations of m-learning remain consistent through time (i.e. pre-use and post-use).

Appendix

Attitude towards M-Learning.

I would like my coursework more if I used m-learning (ATT1).

Using m-learning in my coursework would be a pleasant experience (ATT2).

Using m-learning in my coursework would be a wise idea (ATT3).

Intention to Adopt M-Learning.

I predict I would use a mobile device for my courses (INT1).

I plan to use a mobile device if a course has mobile learning functions (INT2).

I intend to adopt a mobile device for university courses (INT3).

Instructor Readiness.

I think instructors (i.e. lecturers, tutors) would approve of utilizing m-learning for their courses (IR1).

I think instructors (i.e. lecturers, tutors) would believe that a mobile device could be a useful educational tool in their courses (IR2).

I think instructors (i.e. lecturers, tutors) would have adequate technical skills to use a mobile device in their teaching (IR3).

Learning Autonomy.

I would be able to actively access coursework material with a mobile device (LA1).

I would have more opportunities to create knowledge in my coursework with a mobile device (LA2).

I would be able to control the pace (speed) of learning in my classes with a mobile device (LA3).

Perceived Behavioral Control.

I have sufficient extent of knowledge to use m-learning (PBC1).

I have sufficient extent of control to make a decision to adopt m-learning (PBC2).

I have sufficient extent of self-confidence to make a decision to adopt m-learning (PBC3).

Perceived Ease of Use.

I believe that mobile devices would be easy to use (PEU1).

I believe it would be easy to access course material with my mobile device (PEU2).

I believe that mobile devices would be easy to operate (PEU3).

Perceived Self-Efficacy.

I am confident about using a mobile device for my courses (PSE1).

Using a mobile device for my courses would not be a challenge for me (PSE2).

I would feel comfortable using a mobile device in my courses (PSE3).

Perceived Usefulness.

I believe that using mobile devices would improve my ability to learn (PU1).

I believe that mobile devices would allow me to get my work done more quickly (PU2).

I believe that mobile devices would be useful for my learning (PU3).

Subjective Norm.

Most people who are important to me think that it would be fine to use a mobile device for university courses (SN1).

I think other students in my classes would be willing to adopt a mobile device for learning (SN2).

Most people who are important to me would approve of using a mobile device for university courses (SN3).

Student Readiness.

I think other students would approve of utilizing m-learning in their coursework (SR1).

I think other students would believe that a mobile device could be a useful educational tool in their coursework (SR2).

I think other students would have adequate technical skills to use a mobile device in their coursework (SR3).

References

Abachi, H. R., & Muhammad, G. (2014). The impact of m-learning technology on students and educators. *Computers in Human Behavior*, *30*(January), 491–496.

Abas, Z.W., Chng, L.P., & Mansor, N. (2009). A study on learner readiness for mobile learning at Open University Malaysia. *IADIS International Conference Mobile Learning 2009* (pp. 151–157).

Ajjan, H., & Hartshorne, R. (2008). Investigating faculty decisions to adopt Web 2.0 technologies: Theory and empirical tests. *The Internet and Higher Education*, *11*(2), 71–80.

Ajzen, I. (1985). From intentions to actions: A theory of planned behavior. In J. Kuhl, & J. Beckmann (Eds.), *Action control: From cognition to behavior* (pp. 11–39). Berlin, Heidelberg, New York: Springer-Verlag.

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211.

Ajzen, I. (2001). Nature and operation of attitudes. *Annual Review of Psychology*, *52*, 27–58.

Ajzen, I. (2002). Perceived behavioral control, self-efficacy, locus of control, and the theory of planned behavior. *Journal of Applied Social Psychology*, *32*(4), 665–683.

Ajzen, I., & Driver, B. L. (1991). Prediction of Leisure Participation from Behavioral, Normative, and Control Beliefs: An Application of the Theory of Planned Behavior. *Leisure Sciences*, *13*(3), 185–204.

Ajzen, I., & Fishbein, M. (1980). *Understanding attitudes and predicting social behavior*. Englewood Cliffs, New Jersey: Prentice-Hall.

Ajzen, I., & Madden, T. J. (1986). Prediction of Goal-Directed Behavior: Attitudes, Intentions, and Perceived Behavioral Control. *Journal of Experimental Social Psychology*, *22*(5), 453–474.

Ally, M., & Samaka, M. (2013). Open Education Resources and Mobile Technology to Narrow the Learning Divide. *The International Review of Research in Open and Distance Learning*, *14*(2), 14–27.

Alzaza, N. S., & Yaakub, A. R. (2010). Students' awareness and requirements of mobile learning services among Malaysian students in the higher education environment. In *Proceedings of the knowledge management 5th international conference*. Malaysia: Universiti Utara.

Andaleeb, A. A., Idrus, R. M., Ismail, I., & Mokaram, A. K. (2010). Technology Readiness Index (TRI) Among USM Distance Education Students According to age. *International Journal of Human and Social Sciences*, *5*(3), 189–192.

Anderson, J. C., & Gerbing, D. W. (1988). Structural Equation Modeling in Practice: A Review and Recommended two-Step Approach. *Psychological Bulletin*, *103*(May), 411–423.

Bandura, A. (1986). *Social foundations of thought and action*: *A social cognitive theory*. In *Englewood cliffs*. NJ: Prentice-Hall.

Barbosa, D., & Geyer, C. (2005). Pervasive personal pedagogical agent: A mobile agent shall always be with a learner. *Proceedings of the IADIS International Conference Mobile Learning 2005* (pp. 281–285).

Baylor, A. L., & Ritchie, D. (2002). What Factors Facilitate Teacher Skill, Teacher Morale, and Perceived Student Learning in Technology-Using Classrooms? *Computers & Education*, *39*(4), 395–414.

Beckmann, E. (2010). Learners on the Move: Mobile Modalities in Development Studies. *Distance Education*, *31*(2), 159–173.

Brown, D. J., McHugh, D., Standen, P., Evett, L., Shopland, N., & Battersby, S. (2011). Designing Location-Based Learning Experiences for People with Intellectual Disabilities and Additional Sensory Impairments. *Computers & Education*, *56*(1), 11–20.

Burman, L. E., Reed, W. R., & Alm, J. (2010). A Call for Replication Studies. *Public Finance Review*, *38*(6), 787–779.

Chang, K. C., & Chang, C. C. (2009). Library Self-Service: Predicting User Intentions Related to Self-Issue and Return Systems. *Electronic Library*, *27*(6), 938–949.

Chen, H., & Huang, H. (2010). User Acceptance of Mobile Knowledge Management Learning System: Design and Analysis. *Educational Technology & Society*, *13*(3), 70–77.

Cheon, J., Lee, S., Crooks, S. M., & Song, J. (2012). An Investigation of Mobile Learning Readiness in Higher Education Based on the Theory of Planned Behavior. *Computers & Education*, *59*(3), 1054–1064.

Cheung, C. M. K., Chiu, P., & Lee, M. K. O. (2011). Online Social Networks: Why do Students use Facebook? *Computers in Human Behavior*, *27*(4), 1337–1343.

Chin, W. W. (1998). The partial least squares approach to structural equation modeling. In G. A. Marcoulides (Ed.), *Modern methods for business research* (pp. 295–358). Mahwah, New Jersey: Lawrence Erlbaum.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences*. Mahwah, New Jersey: Lawrence Erlbaum.

Compeau, D. R., & Higgins, C. A. (1995). Computer Self-Efficacy: Development of a Measure and Initial Test. *MIS Quarterly*, *19*(2), 189–211.

Corbeil, J. R., & Valdes-Corbeil, M. E. (2007). Are you Ready for Mobile Learning? *Educause Quarterly*, *30*(2), 51–58.

Corrin, L., Lockyer, L., & Bennett, S. (2010). Technological diversity: An investigation of students' technology use in everyday life and academic study. *Learning, Media and Technology*, *35*(4), 387–401.

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of use, and User Acceptance of Information Technology. *MIS Quarterly*, *13*(3), 319–340.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User Acceptance of Computer Technology: A Comparison of two Theoretical Models. *Management Science*, *35*(8), 982–1003.

Djamasbi, S., Siegel, M., & Tullis, T. (2010). Generation Y, web Design, and eye Tracking. *International Journal of Human-Computer Studies*, *68*(5), 307–323.

Donnelly, K. (2009). Learning on the Move: How m-Learning Could Transform Training and Development. *Development and Learning in Organisations*, *23*(4), 8–11.

Easley, R. W., Madden, C. S., & Dunn, M. G. (2000). Conducting Marketing Science: The Role of Replication in the Research Process. *Journal of Business Research*, *48*, 83–92.

Ertmer, P. A., Ottenbreit-Leftwich, A. T., Sadik, O., Sendurur, E., & Sendurur, P. (2012). Teacher Beliefs and Technology Integration Practices: A Critical Relationship. *Computers & Education*, *59*(2), 423–435.

Evans, C. (2008). The Effectiveness of m-Learning in the Form of Podcast Revision Lecturers in High Education. *Computers & Education*, *50*(2), 491–498.

Ferreira, F., Dias, F., Braz, J., Santos, R., Nascimento, R., Ferreira, C., & Martinho, R. (2013). Protege: a mobile health application for the elder-caregiver monitoring paradigm. *Procedia Technology*, *9*, 1361–1371.

Flaherty, C. (2015). Why replication matters. Inside Higher Ed. Retrieved from https://www.insidehighered.com/news/2015/08/28/landmark-study-suggests -most-psychology-studies-dont-yield-reproducible-results

Fornell, C., & Cha, J. (1994). Partial least squares. In R. P. Bagozzi (Ed.), *Advanced methods in marketing research* (pp. 52–78). Cambridge: Blackwell.

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, *18*(1), 39–50.

Gedik, N., Hanci-Karademirci, A., Kursun, E., & Cagiltay, K. (2012). Key Instructional Design Issues in a Cellular Phone-Based Mobile Learning Project. *Computers & Education*, *58*(4), 1149–1159.

Gholami, R., Sulaiman, A. B., Ramayah, T., & Molla, A. (2013). Senior Managers' Perception on Green Information Systems (IS) Adoption and Environmental Performance: Results from a Field Survey. *Information Management*, *50*(7), 431–438.

Gikas, J. G., & Grant, M. M. (2013). Mobile Computing Devices in Higher Education: Student Perspectives on Learning with Cellphones, Smartphones & Social Media. *The Internet and Higher Education*, *19*(October), 18–26.

Gist, M. E., Schwoerer, C., & Rosen, B. (1989). Effects of Alternative Training Methods on Self-Efficacy and Performance in Computer Software Training. *Journal of Applied Psychology*, *74*(6), 884–891.

Goh, T., Seet, B., & Chen, N. (2011). The Impact of Persuasive SMS on Students' Self-Regulated Learning. *British Journal of Educational Technology*, *43*, 624–640.

Grönlund, Å., & Islam, Y. M. (2010). A Mobile e-Learning Environment for Developing Countries: The Bangladesh Virtual Interactive Classroom. *Information Technology for Development*, *16*(4), 244–259.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2014). *A primer on partial least squares structural equation modeling (PLS-SEM)*. Los Angeles: Sage Publication.

Hamat, A., Embi, M. A., & Hassan, H. A. (2012). Mobile Learning Readiness Among UKM Lecturers. *Procedia - Social and Behavioral Sciences*, *59*, 406–410.

Hayati, A., Jalilifar, A., & Mashhadi, A. (2012). Using short message service (SMS) to teach English idioms to EFL students. *British Journal of Educational Technology*, *44*(*1*), 66–81.

Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). The use of Partial Least Squares Path Modeling in International Marketing. *Advances in International Marketing*, *20*, 277–320.

Herrington, A., & Herrington, J. (2007). Authentic mobile learning in higher education. Retrieved from http://www.aare.edu.au/data/publications/2007/her07131.pdf

Hrubes, D., Ajzen, I., & Daigle, J. (2001). Predicting Hunting Intentions and Behavior: An Application of the Theory of Planned Behavior. *Leisure Sciences*, *23*(3), 165–178.

Hsu, C.,& Lu, H. (2004). Why do People Play on-Line Games? An Extended TAM with Social Influences and Flow Experience. *Information Management*, 41, 853–868.

Ibrahim, N. A., Salisu, M., Popoola, A. A., & Ibrahim, T. I. (2014). Use of Smartphones Among Medical Students in the Clinical Years at a Medical School in Sub-Sahara Africa: A Pilot Study. *Journal of Mobile Technology in Medicine*, *3*(2), 28–34.

Izwan, M. (2014). Gender Imbalance in Universities and Colleges Worrying, Says Pak Lah. Malaysian Insider. Retrieved from http://www.themalaysianinsider.com/malaysia/article/gender-imbalance-in-universities-and-colleges-worrying-says-pak-lah

Jairak, K., Praneetpolgrang, P., & Mekhabunchakij, K. (2009, December). An acceptance of mobile learning for higher education students in Thailand. *In Sixth International Conference on eLearning for Knowledge-Based Society, Thailand, 17,*(18), 361–368.

Jones, C., Ramanau, R., Cross, S., & Healing, G. (2010). Net Generation or Digital Natives: Is There a Distinct new Generation Entering University? *Computers & Education*, *54*(3), 722–732.

Junco, R., & Mastrodicasa, J. M. (2007). *Connecting to the Net generation: What higher education professionals need to know about today's students*. Washington, DC: NASPA.

Karahanna, E., & Straub, D. (1999). The Psychological Origins of Perceived Usefulness and Ease-of-use. *Information Management*, *35*, 237–250.

Keegan, D. (2003). *The future of learning: From e-learning to m-learning. Institute for research into distance education*. Hagen, Germany: Fern Universitat Retrieved from http://files.eric.ed.gov/fulltext/ED472435.pdf.

Kukulska-Hulme, A., Sharples, M., Milrad, M., Arnedillo-Sanchez, I., & Vavoula, G. (2011). The genesis and development of mobile learning in Europe. In D. Parsons (Ed.), *Combining e-learning and m-learning: New applications of blended educational resources* (pp. 151–177). Hershey, PA: IGI Global.

Lai, C., Wang, Q., & Lei, J. (2012). What Factors Predict Undergraduate Students' use of Technology for Learning? *Computers & Education*, *59*(2), 569–579.

Lascu, D., & Zinkhan, G. (1999). Consumer Conformity: Review and Applications for Marketing Theory and Practice. *Journal of Marketing Theory and Practice*, *7*, 1–12.

Lee, Y., & Kozar, K. A. (2005). Investigating Factors Affecting the Adoption of Anti-Spyware Systems. *Communications of the ACM*, *48*(8), 72–77.

Liaw, S.-S., Huang, H.-M., & Chen, G.-D. (2007). Surveying Instructor and Learner Attitudes Toward e-Learning. *Computers & Education*, *49*(4), 1066–1080.

Liker, J., & Sindi, A. (1997). User Acceptance of Expert Systems: A Test of the Theory of Reasoned Action. *Journal of Engineering and Technology Management*, *14*, 147–173.

Lim, C. K. (2001). Computer Self-Efficacy, Academic Self-Concept, and Other Predictors of Satisfaction and Future Participation of Adult Distance Learners. *American Journal of Distance Education*, *15*(2), 41–51.

Lim, H., & Dubinsky, A. J. (2005). The Theory of Planned Behavior in e-Commerce: Making a Case for Interdependencies Between Salient Beliefs. *Psychology and Marketing*, *22*(10), 833–855.

Liu, Y., Li, H., & Carlsson, C. (2010). Factors Driving the Adoption of m-Learning: An Empirical Study. *Computers & Education*, *55*(3), 1211–1219.

Madden, T. J., Ellen, P. S., & Ajzen, I. (1992). A Comparison of the Theory of Planned Behavior and the Theory of Reasoned Action. *Personality and Social Psychology Bulletin*, *18*(1), 3–9.

Mahat, J., Ayub, A. F. M., & Wong, S. L. (2012). An assessment of students' mobile self-efficacy, readiness and personal innovativeness towards mobile learning in higher education in Malaysia. *Procedia – Social and Behavioral Sciences*, *64*, 284–290.

Malaysian Communications and Multimedia Commission (2015a). *Communications and Multimedia*: *Pocket Book of Statistics Q2 2015*. Retrieved from http://www.skmm.gov.my/skmmgovmy/media/General/pdf/C-M-Q2-2015.pdf

Malaysian Communications and Multimedia Commission (2015b). *Internet Users Survey 2014*. Retrieved from http://www.skmm.gov.my/skmmgovmy/media/General/pdf/Internet-Users-Survey-2014.pdf

Malikhao, P., & Servaes, J. (2010). The Media use of American Youngsters in the age of Narcissism: Surviving in a 24/7 Media Shock and awe - Distracted by Everything. *Telematics and Informatics*, *28*(2), 66–76.

Margaryan, A., Littlejohn, A., & Vojt, G. (2011). Are Digital Natives a Myth or Reality? University Students' use of Digital Technologies. *Computers & Education*, *56*(2), 429–440.

Marler, J. H., & Dulebohn, J. H. (2005). A model of employee self-service technology acceptance. In J. J. Martocchio (Ed.), *Research in personnel and human resources management, volume 24 (pp. 137–180)*. Emerald Group Publishing Limited.

Miesen, H. W. J. M. (2003). Predicting and Explaining Literary Reading: An Application of the Theory of Planned Behavior. *Poetics*, *31*(3–4), 189–212.

Milošević, I., Živković, D., Manasijević, D., & Nikolić, D. (2015). The effects of the intended behaviour of students in the use of m-learning. *Computers in Human Behavior*, *51*(Part A), 207–215.

Mohammad, N. M. N., Mamat, M. N., & Isa, P. M. (2012). M-learning in Malaysia: Challenges and strategies. *Procedia – Social and Behavioral Sciences*, *67*, 393–401.

Mohammadi, H. (2015). Social and Individual Antecedents of m-Learning Adoption in Iran. *Computers in Human Behavior*, *49*, 191–207.

Motiwalla, L. (2007). Mobile Learning: A Framework and Evaluation. *Computers & Education*, *49*(3), 581–596.

Ng, W., Howard, N., Loke, S., & Torabi, T. (2010). Designing effective pedagogical systems for teaching and learning with mobile and ubiquitous devices. *Multiplatform e-learning systems and technologies*: *Mobile devices for uniquitous ICT-based education* (pp. 42–56), Hershey: PA: IGI Global Publishing.

Nordin, N., Embi, M. A., & Yunus, M. M. (2010). Mobile Learning Framework for Lifelong Learning. *Procedia -Social and Behavioral Sciences*, *7*, 130–138.

Park, S. Y., Nam, M.-W., & Cha, S.-B. (2012). University Students' Behavioral Intention to use Mobile Learning: Evaluating the Technology Acceptance Model. *British Journal of Educational Technology*, *43*(4), 592–605.

Palacios-Marqués, D., Merigó, J. M., & Soto-Acosta, P. (2015a). Online social networks as an enabler of innovation in organizations. *Management Decision*, *53*(9), 1906–1920.

Palacios-Marqués, D., Soto-Acosta, P., & Merigó, J. M. (2015b). Analyzing the effects of technological, organizational and competition factors on Web knowledge exchange in SMEs. *Telematics and Informatics*, *32*(1), 23–32.

Parkes, M., Stein, S., & Reading, C. (2015). Student Preparedness for University e-Learning Environments. *The Internet and Higher Education*, *25*(April), 1–10.

Patten, B., Sanchez, I. A., & Tangney, B. (2006). Designing Collaborative, Constructionist and Contextual Applications for Handheld Devices. *Computers in Education*, *46*, 294–308.

Pozzi, A. (2007). The Impact of m-Learning in School Contexts: An "Inclusive" Perspective. *Lecture Notes in Computer Science*, *4556*, 748–755.

Ramayah, T., Lee, J. W. C., & Boey, J. C. I. (2011). Network Collaboration and Performance in the Tourism Sector. *Service Business*, *5*(4), 411–428.

Ramayah, T., Yeap, J. A. L., & Ignatius, J. (2013). An Empirical Inquiry on Knowledge Sharing Among Academicians in Higher Learning Institutions. *Minerva: A Review of Science, Learning and Policy*, *51*(2), 131–154.

Ringle, C. M., Wende, S., & Becker, J.-M. (2015). *SmartPLS 3*. Hamburg: SmartPLS Retrieved from http://www.smartpls.com.

Riquelme, H. E., & Rios, R. E. (2010). The Moderating Effect of Gender in the Adoption of Mobile Banking. *The International Journal of Bank Marketing*, *28*(5), 328–341.

Rodriguez, J.E. (2011). Social media use in higher education: Key areas to consider for educators. *MERLOT Journal of Online Learning and Teaching*, *7*(4). Retrieved from http://jolt.merlot.org/vol7no4/rodriguez_ 1211.htm

Saccol, A., Barbosa, J., Schlemmer, E., & Reinhard, N. (2011). Mobile Learning in Organizations: Lessons Learned from two Case Studies. *International Journal of Information and Communication Technology Education*, *7*, 11–24.

Sharma, S. K., & Kitchens, F. L. (2004). Web Services Architecture for m-Learning. *Journal of e-Learning*, *2*(1), 203–216.

Sheppard, B. H., Hatrwick, J., & Warshaw, P. R. (1988). The Theory of Reasoned Action: A Meta-Analysis of past Research with Recommendations for Modifications and Future Research. *Journal of Consumer Research*, *15*(3), 325–343.

Sledgianowski, D., & Kulviwat, S. (2009). Using Social Network Sites: The Effects of Playfulness, Critical Mass and Trust in a Hedonic Context. *Journal of Computer Information Systems, Summer*, *74-83*.

Soto-Acosta, P., Popa, S., & Palacios-Marqués, D. (2015). E-business, organizational innovation and firm performance in manufacturing SMEs: an empirical study in Spain. *Technological and Economic Development of Economy*, doi:10.3846/20294913.2015.1074126.

Sullivan, G. M., & Feinn, R. (2012). Using Effect Size - or why the *p* Value is not Enough. *Journal of Graduate Medical Education*, *4*(3), 279–282.

Taleb, Z., & Sohrabi, A. (2012). Learning on the move: The use of mobile technology to support learning for university students. *Procedia – Social and Behavioral Sciences*, *69*, 1102–1109.

Tan, G. W.-H., Ooi, K.-B., Leong, L.-Y., & Lin, B. (2014). Predicting the Drivers of Behavioural Intention to use Mobile Learning: A Hybrid SEM-Neural Networks Approach. *Computers in Human Behavior*, *36*(July), 198–213.

Tapscott, D. (1998). *Growing up digital: The rise of the net generation*. New York: McGraw-Hill.

Taylor, S., & Todd, P. (1995). Decomposition and Crossover Effects in the Theory of Planned Behavior: A Study of Consumer Adoption Intentions. *International Journal of Research in Marketing*, *12*(2), 137–155.

Tenenhaus, M., Esposito Vinzi, V., Chatelin, Y.-M., & Lauro, C. (2005). PLS Path Modeling. *Computational Statistics and Data Analysis*, *48*, 159–205.

Torkzadeh, G., & Van Dyke, T. P. (2001). Development and Validation of an Internet Self-Efficacy Scale. *Behaviour & Information Technology*, *20*(4), 275–280.

Torkzadeh, G., & Van Dyke, T. P. (2002). Effects of Training on Internet Self-Efficacy and Computer User Attitudes. *Computers in Human Behavior*, *18*(5), 479–494.

Venkatesh, V., & Davis, F. D. (2000). A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. *Management Science*, *46*(2), 186–204.

Venkatesh, V., Morris, M. G., & Ackerman, P. L. (2000). A Longitudinal Field Investigation of Gender Differences in Individual Technology Adoption Decision-Making Processes. *Organizational Behavior and Human Decision Processes*, *83*(1), 33–60.

Viberg, O., & Gronlung, A. (2013). Cross-Cultural Analysis of Users' Attitude Toward the use of Mobile Devices in Second and Foreign Language Learning in Higher Education: A Case from Sweden and China. *Computers & Education*, *69*, 169–180.

Völckner, F., Sattler, H., Hennig-Thurau, T., & Ringle, C. M. (2010). The Role of Parent Brand Quality for Service Brand Extension Success. *Journal of Service Research*, *13*(4), 379–396.

Winters, N. (2006). What is mobile learning? In M. Sharples (Ed.), *Big issues in mobile learning*. Retrieved from http://matchsz.inf.elte.hu/tt/docs/Sharples-20062.pdf

Yang, H. C., Liu, H., & Zhou, L. (2012). Predicting Young Chinese Consumers' Mobile Viral Attitudes, Intents and Behavior. *Asia Pacific Journal of Marketing and Logistics*, *24*(1), 59–77.