Internet Research

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Received 5 October 2014
Revised 20 October 2014
26 January 2015
27 January 2015
Accepted 30 January 2015

Abstract

Purpose – Based on the literature on technology readiness, online learning readiness, and mobile computer anxiety, the purpose of this paper is to develop and validate a mobile learning readiness (MLR) scale which can be used to assess individuals' readiness to embrace m-learning systems.

Design/methodology/approach – Based on previous literature, this study conceptualizes the construct of MLR and generates an initial 55-item MLR scale. A total of 319 responses are collected from a three-month internet-based survey. Based on the sample data, this study provides an empirical validation of the MLR construct and its underlying dimensionality, and develops a generic MLR scale with desirable psychometric properties, including reliability, content validity, criterion-related validity, convergent validity, discriminant validity, and nomological validity.

Findings – This study develops and validates a 19-item MLR scale with three dimensions (i.e. m-learning self-efficacy, optimism, and self-directed learning). A tentative norm of the MLR scale is presented, and the scale's theoretical and practical applications are also discussed.

Originality/value – This study is a pioneering effort to develop and validate a MLR scale. The results of this study are helpful to researchers in building m-learning theories and to educators in assessing and promoting individuals' acceptance of m-learning systems.

Keywords M-learning readiness, Mobile computer anxiety, Online learning readiness, Technology readiness

Paper type Research paper

1. Introduction

With the advance of mobile technologies, users are able to access to multimedia materials on the devices such as mobile phone, tablet, and laptop in the present day (Lu and Su, 2009). The richness of information accessed via mobile technologies has altered people's lifestyles, and the means for people to learn have been diversified (Wang and Li, 2012). The portability of mobile devices enables learners to gain knowledge beyond the restrictions of time and space (Cheong and Park, 2005). With the ownership of mobile devices growing explosively and the prevalence of wireless networks (e.g. Wi-Fi and 3G),

This research was substantially supported by the Ministry of Science and Technology (MOST) of Taiwan under Grant No. MOST 101-2511-S-025-001-MY2. The authors would like to thank Yu-Ting Jiang for her assistance in collecting the sample data.

Internet Research
Vol. 26 No. 1, 2016
pp. 265-287

1066-2243
DOI 10.1108/IntR-10-2014-0241

mobile learning (m-learning) has been a popular trend and has played a supplementary role or even a primary role in formal and informal education (Huang and Chiu, 2014).

A review of studies on m-learning reveals that evaluation of m-learning effectiveness is the major research focus (Hung and Zhang, 2012; Wu *et al.*, 2012) with mixed results. There have been studies that demonstrated that m-learning itself can be an effective learning approach or even better than traditional face-to-face lecturing approaches (e.g. Shih *et al.*, 2010). Still, prior studies have also found negative or neutral results due to or moderated by learners' characteristics (Sha *et al.*, 2012).

For example, Doolittle and Mariano (2008) reported that learning in a mobile condition is much less effective in both recalling information and transferring knowledge than learning in a stationary condition because of divided attention: m-learning creates a condition that has more stimuli and thus more distractions, which divide learner' attention and affect learning performance. Similarly, Chu (2014) reported that m-learning ineffectiveness could be caused by the heavy cognitive load as a result of an improper learning design. Doolittle and Mariano (2008) further investigated the effect of learners' working memory capacity (WMC) which refers to the individual's ability to store and process information of a task concurrently, as an individual characteristic that could affect m-learning effectiveness. The m-learning achievement of learners with high WMC significantly outperformed those with low WMC in a mobile learning condition, but learners of high and low WMC performed equally in a stationary condition, because learners with high WMC could better handle the issue of divided attention as described earlier. Kim *et al.* (2012) found the influence of gender on solving numeracy problems with palmed device; mixed-gender groups showed better ability in answering math problems than girl groups. Individual differences, such as WMC, gender and others, may consolidate and/or enrich theory contentions. More research into the role of individual difference in m-learning effectiveness is imperative.

One of the important individual difference variables that affect individuals' acceptance and effectiveness of m-learning could be readiness. Readiness is derived from individual's action- or object-related experience (Teo, 2010), and has been verified to be strongly in relation to the occurrence of an action or the usage of an object. The object can be technology as in the context of readiness to adopt a technology (Parasuraman, 2000). The action can be change management as in the context of organizational readiness for changes resulting from implementation of an information system (Kwahk and Lee, 2008). The action can also be about learning, as in the context of readiness to learn (Hung *et al.*, 2010). The concept of mobile learning readiness (MLR) from a psychology perspective will be at the intersection of readiness to adopt a technology and readiness to learn. As m-learning is defined as incorporating mobile technology into learning activities (Motiwalla, 2007), MLR can be defined as individual's propensity to embrace and/or use mobile technology to execute formal and informal learning activities.

Prior studies have found that e-learning or online learning readiness (OLR) has substantial impacts on learning effectiveness. OLR of the students is a critical factor to e-learning success (Holsapple and Lee-Post, 2006) and e-learning satisfaction (Holsapple and Lee-Post, 2006). As m-learning is derived from e-learning (Ozuorcun and Tabak, 2012), it is very plausible that MLR, like e-learning readiness, could have similar effects on learning effectiveness and thus could be quite important to the success of m-learning programs.

But still, there are considerable differences between m-learning and e-learning. Siau *et al.* (2001) pointed out the differences between mobile computing and regular computing, including mobile computers having small screens, small multifunction key pads, less computational power, limited memory and disk capacity, complicated text input mechanisms, and unfriendly user interfaces, etc. The physical constraints of mobile computers can affect the ways in which the users ultimately use the mobile computers differently than regular computers.

Peng *et al.* (2009) further directly pointed out that the mobility and ubiquitousness characteristics are what set apart m-learning from e-learning, defining m-learning as mobile learners' use of ubiquitous computing technology to learn the right thing at the right time at the right place. Sha *et al.* (2012) augmented the same viewpoint. While e-learning has enabled distance learning, m-learning has facilitated situated learning (Laouris and Eteokleous, 2005); the differences can be characterized as a tethered, formal, and structural learning environment for e-learning, and an untethered, more private, situational, and unstructured learning environment for m-learning (Ozuorcun and Tabak, 2012). The features of mobility and situated learning in m-learning have also been empirically validated as the difference makers from e-learning (Jeng *et al.*, 2010).

Despite that some researchers have posited the effect of MLR in theory (e.g. Mahat *et al.*, 2012), projecting the effectiveness of m-learning based on e-learning findings needs to be cautious, given the differences between e-learning and m-learning; similarly, applying existing e-learning readiness scales to m-learning studies should proceed with caution. The first step for developing m-learning theories should start with the investigation of the proper measurement of m-learning factors. As such, a better understanding of MLR is necessary for investigating m-learning effectiveness, and thus the purpose of this study is to develop an MLR scale. Much academic effort has been made in the scale development of individual's technology readiness (Parasuraman, 2000) and OLR (Hung *et al.*, 2010). However, these studies are not specific to m-learning context and may not fully capture the nature of learning in mobile platforms. A validated MLR scale is advantageous. First, for researchers, it will help constitute and testify theories regarding m-learning activities. Second, for educators, it will help design instruction strategies and materials for learners with varied MLR. Lastly, for managers, it will help develop marketing campaigns in order for segmented learners with distinct MLR score to accept or continuously use m-learning systems (Lin *et al.*, 2007).

The rest of this paper is organized as follows. In the subsequent section, we first conceptualize the construct of MLR based on the literature concerning technology readiness and OLR (MacKenzie *et al.*, 2011). As Parasuraman (2000) argue that the factors which inhibit an individual's technology readiness should be included in the development of a technology readiness scale, mobile computer anxiety (MCA) (Wang, 2007) which represents an individual's negative responses to use mobile computer devices is considered in this study to broaden the initial item pool of the proposed MLR scale. Next, we describe the procedure of the MLR scale development, including item generation, sampling survey, item purification, identification of factor structure of MLR, reliability test, and validity test (i.e. content validity, criterion-related validity, convergent validity, discriminant validity, and nomological validity). After these tests indicate that the scale requirements are satisfied, a tentative norm for the MLR scale is proposed. Finally, implications for research and practice are discussed. It concludes with the research limitations and the avenues for future research.

2. Literature review

2.1 Technology readiness

The most accepted definition of technology readiness is offered by Parasuraman (2000), which is "people's propensity to embrace and use new technologies for accomplishing goals in home life and at work." It is an individual's psychological state indicating how prepared an individual is for the acceptance of new technologies.

Technology readiness has been operationalized as a multidimentional construct. Postulating that technology readiness is determined by a collection of facilitators and inhibitors, Parasuraman (2000) developed a 36-item technology readiness index (TRI) with four distinct dimensions as optimism (ten items), innovativeness (seven items), discomfort (ten items), and insecurity (nine items). Optimism and innovativeness positively contribute to technology readiness while discomfort and insecurity are the two factors to hinder individual's readiness to accept new technologies. Optimism refers to a positive belief that technology can improve life quality in the light of increased control, flexibility, and efficiency (Parasuraman, 2000). Individual with optimism will concentrate on the benefits of technology rather than loss (Son and Han, 2011). Innovativeness means the inclination to test a variety of new technology to gain fantastic experience regardless of the possible outcomes are positive or negative (Liu *et al.*, 2010a, b; Parasuraman, 2000). Individual with higher innovativeness will generally be the early adopter or thought leader (Thakur and Srivastava, 2014). Oppositely, it is agreed that discomfort denotes a negative feeling deriving from "a perceived lack of control and a sense of being overwhelmed by technology" (Walczuch *et al.*, 2007), and insecurity relates to "the distrust of technology for security and privacy reasons" (Son and Han, 2011).

A deeper exploration of the essence of technology readiness with the four dimensions (Parasuraman, 2000) will result in a more fruitful understanding of technology acceptance. For example, Lam *et al.* (2008) examined the effect of the four dimensions on the consumer's internet adoption time and the variety of the internet use, demonstrating that optimism, innovativeness, and insecurity significantly impact the two behavioral-dependent variables in an expected direction. They further claimed that the effect of innovativeness on internet usage is relatively less than that of optimism and insecurity. More specifically, Lam *et al.* (2008) identified innovativeness as a personality trait (i.e. an individual difference characteristic) which is stable over time and the other three dimensions as generalized beliefs and affects which may change with increased knowledge and experience. This contention refines Parasuraman's (2000) definition of technology readiness which is viewed as an individual trait. In addition, Son and Han (2011) inquired the relationship between the four technology readiness dimensions and the usage patterns of IPTV (i.e. the usage rate of basic functions, the usage rate of innovative functions, and the variety of uses of innovative functions). Their results found that the two drivers of technology readiness, optimism, and innovativeness, may have a greater influence on the use of innovative functions in frequency and variety. On the contrary, discomfort may result in a greater use of basic functions.

Readiness is a belief construct while technology adoption intention is a behavioral intention construct (Cheon *et al.*, 2012). The beliefs, attitudes, intentions, and behavior constructs have causal relations and have been explored by many rich theories and studies in social, organizational, and consumer behavior (e.g. Ajzen, 2012). In studying technology adoption, the technology acceptance model (TAM) (Venkatesh and Davis, 2000) often is used as a theoretical foundation. TAM includes two belief constructs as antecedents to technology adoption intention: perceived usefulness (PU) and perceived ease of use (PEOU), suggesting that a technology which is highly evaluated in terms of performance (i.e. PU and PEOU) will be adopted/used with greater possibility. Though TAM is predictable and parsimonious, it neglects the effect of individual factors, which are the basis of evaluation of PU and PEOU (Lin *et al.*, 2007). A TRAM model which integrates technology readiness into TAM offers better insights into technology acceptance. The findings of Lin *et al.* (2007) supported that the effect of technology readiness on use intention will be mediated by PU and PEOU in an e-service context, functioning in a causality path of technology readiness →PEOU→PU→use intention. Following the conclusion of Lin *et al.* (2007), Walczuch *et al.* (2007) modeled the four dimensions as the antecedents of PU and PEOU and analyzed the direct and indirect effect of the four antecedents on PU. Most of the hypotheses were supported with empirical evidence except that innovativeness negatively associates with PU. It was explained that innovative individuals may be serious critics, and thus their requirement for PU is harder to satisfy.

2.2 OLR

E-learning utilizes technology that is free-standing or based on either local networks or the internet (Cheng, 2012). The extent to which e-learning assists or replaces other learning and teaching approaches ranges on a continuum from none to fully online distance learning (Bates and Poole, 2003). As the web continues to be a popular means for sharing information and communication, online learning has become a common synonym for e-learning. For example, Holsapple and Lee-Post (2006) freely interchanged e-learning with online learning.

OLR indicates learners' belief in access to materials (e.g. text, video, or animation) and communication with others in a computer-mediated environment over the internet (Blankenship and Atkinson, 2010). Compared with the face-to-face lecture, which is teacher-centered and proceeds in a synchronous way, online learning is a new paradigm and is learner centered (Hung *et al.*, 2010). Learners have greater autonomy in the material selection, presentation mode, and learning pace in such an asynchronous learning approach. In this vein, learner characteristics (e.g. attitude and computer self-efficacy) are obviously crucial determinants influencing the effectiveness of online learning systems (Keramati *et al.*, 2011).

OLR was initially proposed by Warner *et al.* (1998). They suggested that the definition of OLR includes learners' preference for a flexible instruction, competence, and confidence in the use of electronic communication, and autonomous learning. Given OLR is recognized to positively impact learners' achievement and satisfaction (Ho *et al.*, 2010), a gathering of studies have attempted to probe readiness for online learning and develop different versions of OLR scale. McVay's (2000, 2001) works are the pioneering one of these studies. She found OLR can be measured with 13 items and is structured with two underlying dimensions. First, self-management of learning, also called as self-directed learning, indicates that learners are able to manage/control their own learning in terms of content and pace (Smith, 2005). On the other hand, comfort with e-learning purports that learners feel comfortable while using electronic means to learn over internet. In brief, self-management of learning may be related to learners' learning style while comfort with e-learning associates with learners' technology capability. Later studies like Blankenship and Atkinson (2010), Dray *et al.* (2011), Smith *et al.* (2003), and Smith (2005) had similar findings that the OLR is comprised by these two dimensions.

Some studies revealed that OLR is a more complex construct and consists of more dimensions. Parnell and Carraher (2003) discovered that technological mastery, flexibility of course delivery, and anticipated quality of course are the three dimensions of OLR. Similarly, Teo (2010) found that three dimensions as tutor quality, PU, and facilitating conditions are underlay in OLR. In the study of Bernard *et al.* (2004), OLR is conceptualized with four dimensions as confidence in prerequisite skills, general beliefs about online learning, self-direction and initiative, and desire for interaction with others. Identified as a five-dimension construct in the study of Kerr *et al.* (2006), OLR is constituted by computer skills, independent learning, dependent learning, need for online delivery, and academic skills. Also, Hung *et al.* (2010) confirmed that OLR is formed with five dimensions, including self-directed learning, motivation for learning, learner control, computer and internet self-efficacy, and online communication self-efficacy. Finally, Watkins *et al.* (2004) contended that technology access, online skills and relationships, motivation, online audio/video, internet discussions, and importance to the success are the implicit dimensions of OLR. A scrutiny of these studies showed that the common dimensions of OLR seem to include learning style, perceived technology self-efficacy, and perceived benefits of online learning systems (e.g. anticipated quality of course, and general beliefs about online learning).

Additionally, e-learning or OLR has been studied not only at individual level but at organizational level as well. Different dimensions of readiness have also been identified in an organizational e-learning context as opposed to an individual one. Keramati *et al.* (2011) suggested that e-learning readiness can include three factors: technical, organizational, and social. Technical factors include the availability of hardware, software, content, internet access, bandwidth, and school's space. Organizational factors include the support of experts, organizational rules, organizational culture, and management permanence. Social factors include society's conception of e-learning, governmental rules, and administrative instructions. Chapnick (2000) identified eight readiness factors in organizations that implement e-learning, including psychological readiness, sociological readiness (i.e. the interpersonal aspects of the environment in which the e-learning program will be implemented), environmental readiness (i.e. the large-scale forces operating on the stakeholders both inside and outside the organization), human resource readiness (i.e. the availability and design of the human-support system), financial readiness (i.e. the budget size and allocation process), technological skill/aptitude readiness (i.e. observable and measurable individual technical competencies), equipment readiness (i.e. proper equipment possession), and content readiness (i.e. the subject matter and goals of the instruction). Holsapple and Lee-Post (2006) studied four e-learning readiness measures: academic preparedness (e.g. academic standing, GPA, course loads, etc.), technical competence (i.e. computer setup and technical literacy), lifestyle aptitude (i.e. study habits and communication patterns), and learning preference toward e-learning (i.e. learning styles and values). Taking a further look at these studies reveals that the nature of e-learning readiness is more diverse at organizational level than at individual level. The latter tends to focus on psychological states of the learners, while the former addresses a greater variety of factors, including what organizations can afford and constrain individuals in e-learning, such as finance, equipment, etc. This study is looking to investigate MLR at the individual level, specifically, psychological states of the individuals.

2.3 MLR

The above-mentioned OLR measures were developed for stationary computer or internet-based technology. A specific exploration for the evolving mobile technology and m-learning systems is especially necessary. As said earlier, MLR is defined as individual's propensity to embrace and/or use mobile technology to execute formal and informal learning activities. Such a conceptual definition for MLR is consistent with the literature on technology readiness and online learning or e-learning readiness.

In the context of m-learning, Hussin *et al.* (2012) enlisted MLR as basic readiness (i.e. usage of mobile technology features), skill readiness (i.e. efficacy in using mobile technology features), psychologyical readiness (i.e. perception about applying mobile technology for m-learning), and budget readiness (i.e. financial ability to pay for incurred expenses). Mahat *et al.* (2012) also adopted the definition of psychological readiness by Hussin *et al.* (2012) to study readiness for m-learning. But both Hussin *et al.* (2012) and Mahat *et al.* (2012) provided neither the relibility analysis of the MLR scale nor the causal relationships of such a measure with other constructs. Thus, this study elected to focus mainly on empirical development of the psychological readiness in the individual level as opposed to the organizational level.

Many researches that have studied the effect of MLR on technology acceptance have followed the lead of technology readiness researches by using TAM as the theoretical foundation. In studying factors driving the adoption of m-learning, Liu *et al.* (2010a, b) examined the causal relationships among core constructs in TAM but differentiated PU as near-term usefulness vs long-term usefulness. The only true construct about psychological learning readiness in this study was personal innovativeness, which was a dimension in technology readiness (Parasuraman, 2000). Park *et al.* (2012) also used TAM to study m-learning adoption, including m-learning self-efficacy, a dimension of OLR (Hung *et al.*, 2010), as an antecedent to PEOU. Cheon *et al.* (2012) posited PEOU and PU as attitudinal beliefs, readiness as normative beliefs, and perceived self-efficacy and learning autonomy as control beliefs, but readiness or normative beliefs were conceptually defined as "participants' perceptions toward the extent to which other people are in favor of using mobile devices in their courses," which actually resemble more about subjective norms than about the conceptual definition of MLR in this paper.

Reviewing the literature, Liu *et al.* (2010a, b) summarized the factors driving m-learning adoption by classifying m-learning users in terms of roles played: technology user, consumer, and learner. When playing the role of technology user, m-learning technology users' intention to adopt the technology is driven by their perceptions of their interaction with the technology, which can be best characterized by the antecedent variables to behavioral intention in TAM: PEOU and PU, as well as by perceived mobility, the most significant feature of mobile services (Mallat *et al.*, 2009). With the role of consumer, m-learning technology users' intention to adopt the technology is driven by their perception of technology quality, which can be best characterized dimensions of information systems quality in the Information System Success Model by DeLone and McLean (1992), system quality vs content quality. With the role of learner, m-learning technology users' intention to adopt the technology is determined by subjective task value of expectancy-value theory (including allainment value, intrinsic value, utility value, and cost) and readiness for m-learning (including self-management of learning, comfort with m-learning). Of all the drivers for m-technology adoption by Liu *et al.* (2010a, b), the last factor is the most relevant to our study and can be charactized by the OLR dimensions as described previously. And MLR can be further contruded as learner's propensity to embrace and/or use mobile technology to execute formal and informal learning activities, as opposed to being in the roles of technology user or consumer.

A construct relevant to individual psychlogical MLR in the literature is MCA. According to Wang (2007), MCA represents a negative feeling an individual perceives while using a mobile device. Wang (2007) developed the MCA scale specific to the use of mobile device based on more generic scales on computer anxiety and internet anxiety. Computer anxiety is defined as emotional fear, apprehension, and phobia felt by individuals toward interactions with computers or toward the thought of using computers (Powell, 2013). Similarly, internet anxiety has been defined as the fear or apprehension that individuals experience when using the internet (Thatcher *et al.*, 2007). Internet anxiety is closely related to computer anxiety, but the concepts are distinct (Thatcher and Perrewe, 2002). Thatcher *et al.* (2007) only found a very moderate correlation between the two. Thatcher *et al.* (2007)

explained "While computer anxiety reflects a lifetime of experience with computers, Internet anxiety reflects current encounters with IT involving the Internet." By the same token, it could be very plausible that MCA likely can be considered a distinct concept from computer anxiety and internet anxiety, despite that they likely are all closely related.

To develop the MCA scale, Wang (2007) reviewed the literature on computer anxiety and internet anxiety to generate the scale items, and then conducted experience surveys and personal interviews regarding MCA to help revise the initial scale items and to expand with new items. He then distributed the survey to potential users of mobile computers across different organizations. To purify the items, he subjected the items to an overall construct reliability test before running exploratory factor analysis to find dimensions/factor. For each factor, further factor reliability and validity analysis were conducted. Finally, Wang (2007) concluded that MCA consists of 38 items and seven factors, including learning to use basic function of mobile computer (e.g. multimedia or calendar), internet use of mobile computer (e.g. search or download/upload), equipment limitation (e.g. limited memory or battery power), job replacement after adopting mobile computer, computer use (e.g. data loss or error message), computer configuration (assemble/disassemble mobile device), and internet stability (bad internet status).

The concept of anxiety with a computer product has been an active research stream. Conducting the latest meta analysis on computer anxiety researches in the last two decades, Powell (2013) summarized the antecedents, correlates, and outcomes of computer anxiety. Antecedents negatively related to computer anxiety include openness to new experiences, which is one of the big five personality traits as in Leen and Lang (2013), amount of education, ownership, training, and experience/use, while antecedents positively related to computer anxiety are neuroticism, which is another big five personality trait, and other anxieties. As to correlates, PEOU, computer self-efficacy and attitudes toward computers were consistently found to be in a negative correlation to computer anxiety, but PU and satisfaction were found to be in negative association only by about two-thirds of the studies. Two outcomes variables to computer anxiety that have been studied frequently are regarding performance of using and intention to use a computer product. Performance can be operationalized in a variety of ways, including level of learning and retention, course grades and withdrawal behavior, test results, and productivity, etc. But only half of the 35 articles examining performance as a consequence of computer anxiety found relationship between the two. Intention to use, which likely is operationalized more or less the same manner, as a consequence of computer anxiety, was found to be directly affected by computer anxiety in 60 percent of the 23 articles.

The application of MCA in mobile computing research is still young. For example, Wang (2007) further confirmed that the MCA scale negatively correlates with individual's self-efficacy and intention to use a mobile computing device. In agreement with Parasuraman's (2000) suggestion that technology readiness may contain negative elements such as discomfort and insecurity, we argued that individual's anxiety toward mobile computer (i.e. mobile device), which may deter individual's readiness for m-learning, should be included into the consideration for the MLR scale development.

3. Development of the MLR Scale

3.1 Methods

The way how the scale was developed for technology readiness, OLR, MCA, and our research focus on MLR has been pretty much consistent with Churchill's (1979) paradigm for developing scales. The initial step for technology readiness was a bit different, mainly because it was not developed based on other similar concepts. To come up with initial items, the technology readiness scale started with focus groups, while the other scales relevant to MLR started with literature review. Quantitative analysis methods to finalize the scale and item inventory, including factor analysis and reliability and validity analysis, are more or less the same in all these related scales.

3.2 Item generation

The development of the MLR scale begins with item generation. Both technology readiness and OLR are more of a general readiness instrument that is not specific to m-learning context and may not fully capture the nature of learning in mobile platforms to predict individuals' learning behavior and effectiveness. Although MCA is concerning a psychological state associated with mobile computing, it is not specific about m-learning. Thus, we adapted all the candidate items into m-learning context, and incorporated the characteristics of m-learning in the wording (Cheon *et al.*, 2012; Evans, 2008; Martin *et al.*, 2011; Ozdamli and Cavus, 2011; Sha *et al.*, 2012).

Liu *et al.* (2010a, b) defined MLR from the perspective of learner, not from technology user or consumer. According to Lin *et al.*'s (2007) suggestion that technology readiness is an individual-specific and system-independent construct, this study emphasized individual's personal psychological state while developing the MLR scale. Thus, the system-specific factors (e.g. PEOU and PU) or social factors (e.g. subjective norm) which may influence the acceptance of m-learning systems, were excluded (Cheon *et al.*, 2012; Liu *et al.*, 2010a, b).

Based on the m-learning evolutionary history and its definition mentioned earlier, technology readiness (Parasuraman, 2000), readiness for online learning (Smith *et al.*, 2003), OLR (Hung *et al.*, 2010), and MCA (Wang, 2007) were regarded as the item base for the MLR scale. A research panel composed of three m-learning experts, five graduate students majoring in information systems, and two m-learning users was organized to select the initial items for measuring MLR by evaluating the comprehensiveness and appropriateness of the items from the four studies. During the research panel's discussion, the items which earned all penal members' agreement were selected. After the panel's discussion and selection, a total of 55 initial items for measuring the concept of MLR yielded (see the Appendix). To have a better item quality, all the candidate items were adapted into m-learning context, and the characteristics of m-learning were taken into consideration in the wording as the research panel suggested (Cheon *et al.*, 2012; Evans, 2008; Martin *et al.*, 2011; Ozdamli and Cavus, 2011; Sha *et al.*, 2012). The items were scaled in Likert format anchoring from 1 ("strongly disagree") to 7 ("strongly agree") for the follow-up analyses.

Additionally, two items measuring generic readiness for m-learning were developed to examine the criterion validity of the MLR scale (Wang, 2007) while the other two items measuring intention to use a m-learning system were developed for testing the scale's nomological validity (Cheon *et al.*, 2012). Similarly, the four items were formatted in a seven-point Likert scale. The Appendix presented all the items measured in this study. In the formal questionnaire, the demographics of respondents were also inquired.

3.3 Sample

To purify and validate the MLR scale, an internet-based survey was conducted to gather information (Kohls *et al.*, 2009). A professional online survey website was chosen to host the questionnaire. An invitation to join this study was posted on the main community websites and BBSs in Taiwan. If web surfers were interested in the study, they were able to reach the questionnaire easily through a link directing to the survey page. All of the respondents were first introduced the meaning of m-learning systems prior to their answering of the survey questionnaire. After three months, a sample of 319 usable responses was obtained. Table I summarizes the profile of the respondents. Nearly 60 percent respondents were male. The mean age of the sample was 24.66, and 85.27 percent respondents aged between 21 and 30 years. Most respondents had high education (98.44 percent). Specifically, three-fifths respondents were students, which is "similar to" Wu *et al.*'s (2012) findings that students are major mobile learners (65.64 percent). Compared with prior studies that validated learning-related scales with a student sample (Dray *et al.*, 2011; Hung *et al.*, 2010; McVay, 2000, 2001; Smith, 2005; Teo, 2010), m-learning activities may occur in the daily life of mobile device holders and the sample source should be diversified (Wang *et al.*, 2012). Thus, our online convenience sample may be helpful for the generalization of the MLR scale. In general, the average response time was 10-15 minutes.

3.4 Scale purification

While the generated items were initially adapted from the previous MLR-related scales, not all of the previous scale items were selected by the research panel. Thus, we did not know exactly what final dimensions would be generated without a further data analysis. To obtain a condensed factor structure of the MLR scale, reliability test and principal

Characteristic	Number	%
Gender		
Male	190	59.56
Female	129	40.44
Age		
Below 20	29	9.09
21-30	272	85.27
31-40	18	5.64
Education		
High school or less	10	3.13
2-year college	5	1.57
4-year college	174	54.55
Graduate	135	42.32
Occupation		
Student	198	62.07
Service	25	7.84
Manufacturing	19	5.96
Computer and telecommunication	19	5.96
Government agencies	13	4.08
Education and research	7	2.19
Trade	7	2.19
Healthcare	7	2.19
Finance	6	1.88
Electric and electronics	6	1.88
Real estate	2	0.63
Others	10	3.13

Note: $n = 319$

Table I. Profile of the respondents

factor analysis were repeatedly and iteratively performed on the initial MLR scale for scale purification and dimension identification. Cronbach's coefficient α measuring the internal consistency of items was employed to examine scale reliability (DeVellis, 2003). The α value which exceeds 0.7 is acceptable (Hair *et al.*, 2010). The corrected item-to-total correlation which indicates the extent to which a given item correlates with the summation of the rest items was considered as well. It is suggested that the value of corrected item-to-total correlation should be greater than 0.5 (Hair *et al.*, 2010). To explore the dimension structure of the MLR scale, the principal factor analysis with varimax orthogonal rotation method was conducted. The Kaiser's measure of sampling adequacy ($MSA > 0.5$) and the Bartlett's test of sphericity (significant χ^2 value) were first examined to verify the feasibility of factor analysis (Hair *et al.*, 2010). The factors were then successfully extracted based on following criterion (Hair *et al.*, 2010): first, the eigenvalue of factor should be larger than 1; second, the factor loading of each item on its corresponding factor should be greater than 0.6; and third, each factor contains five to ten items. Based on ten iterations of reliability test and factor analysis, 36 items were excluded and a 19-item MLR scale was obtained. Three dimensions were identified and accounted for 68.40 percent variance totally. The three dimensions are named as m-learning self-efficacy, optimism, and self-directed learning according to their measuring items and previous literature. All the derived items were expressed in a positive tone instead of a negative tone. The results were shown in Table II.

3.5 *Reliability test*

The value of Cronbach's α of the 19-item MLR scale was 0.9386 and was much higher than the minimum requirement suggested (see Table II). The MLR scale presented a high reliability and the items were internally consistent. Three dimensions of MLR were also observed to be reliable, with a value of 0.9086 for m-learning self-efficacy, 0.9131 for optimism, and 0.9132 for self-directed learning. The corrected item-to-total correlations were above 0.5, ranging from 0.5741 to 0.7403. As a whole, the strong reliability of the MLR scale indicated that the necessary condition of construct validity was satisfactory (Hair *et al.*, 2010). To further validate the construct validity, five validity tests including content validity, criterion-related validity, convergent validity, discriminant validity, and nomological validity were investigated (Nunnally, 1978).

3.6 *Content validity*

Content validity or face validity is a qualitative criterion for the evaluation of construct validity (Hair *et al.*, 2010). Churchill (1979) advocated that content validity refers to the extent to which the domains of construct are comprehensively specified and the items of construct are exhaustedly generated and rigorously purified. Similarly, MacKenzie *et al.* (2011) posited that content validity indicates the extent to which the chosen items represent the corresponding dimension of the construct (i.e. adequacy of sampled items). As the MLR was well conceptualized and all the items were strictly adapted from literature and purified, the 19-item MLR scale satisfies the requirement of content validity.

3.7 *Criterion-related validity*

Criterion-related validity was performed to examine whether the 19-item MLR scale was highly correlated with the criterion variables (DeVellis, 2003). Two generic measures of readiness for m-learning were developed as criterion variables and had a reliability value (Cronbach's α) of 0.8393. They were expected to have a highly positive correlation with

Table II.
Results of scale purification

Dimension and item New item code/original item code/item description			Reliability	Corrected item-to-total correlation	Factor loading
Factor 1: m-learning self-efficacy			0.9086		
L1	Q51	I feel confident in performing the basic functions of mobile learning systems		0.6651	0.7802
L2	Q52	I feel confident in my knowledge and skills of mobile learning systems		0.6919	0.7573
L3	Q54	I feel confident in using mobile learning systems to effectively communicate with others		0.6445	0.7532
L4	Q53	I feel confident in using the internet (Google, Yahoo) to find or gather information for mobile learning		0.6903	0.7462
L5	Q11	I feel confident in studying to operate mobile learning systems		0.5839	0.7324
L6	Q12	I feel confident in knowing all the special keys and functions contained in a mobile learning system		0.6000	0.7200
L7	Q10	I feel confident in knowing how a mobile learning system works		0.6812	0.7137
Factor 2: optimism			0.9131		
E1	Q3	I like studying via mobile learning systems because I am able to study anytime		0.6679	0.8094
E2	Q6	Mobile learning systems make me more efficient in my studying		0.6802	0.7916
E3	Q5	I like mobile learning systems that allow me to tailor things to fit my own needs		0.6916	0.7903
E4	Q4	I like mobile learning systems		0.7403	0.7584
E5	Q1	Mobile learning systems give people more control over their studying time		0.5741	0.7133
E6	Q2	The newest mobile learning system is much more convenient to use		0.6148	0.6965
E7	Q7	Mobile learning systems give me more freedom of studying		0.6270	0.6693
Factor 3: self-directed learning			0.9132		
S1	Q45	I can direct my own learning progress		0.5762	0.8696
S2	Q41	I carry out my own study plan		0.6195	0.8159
S3	Q40	In my studies, I set goals and have a high degree of initiative		0.6897	0.7865
S4	Q43	I manage time well		0.6101	0.7857
S5	Q39	In my learning, studying, or working, I am self-disciplined and find it easy to set aside learning time		0.6259	0.7733

the MLR scale if the MLR scale successfully captured the nature of MLR. Since two criterion variables were assessed with the MLR scale in one questionnaire at the same time, the criterion-related validity was also referred to as concurrent validity. The results of Pearson correlation presented that the MLR scale is significantly correlated to the summation of two criterion variables ($\gamma = 0.7454$, $p < 0.0001$) and exceeds the recommended value of 0.6 (Johnson, 1998). The criterion-related validity was validated.

3.8 Convergent and discriminant validity

In the classical model of validity, construct validity is one of three main types of validity evidence, alongside content validity and criterion validity (Brown, 1996). Convergent and discriminant validity are the two subtypes of validity that make up construct validity. Convergent validity signifies that items "share a high proportion of variance in common" (Hair *et al.*, 2010), and factor analysis is often used to verify convergent validity. Factor loading which is higher than 0.7 indicates half of the variance of an item is explained by its corresponding dimension, and the convergent validity is sustained when the factor loadings of the items of a given dimension meet the requirement (Hair *et al.*, 2010). The results of factor analysis in Table II provide strong evidence that all items successfully converge on the corresponding dimensions. All but two items have an excellent loadings higher than 0.7, while the minimum loading is 0.6693.

Discriminant validity examines the distinction among dimensions of the MLR scale. Following the recommendations of Anderson and Gerbing (1988), the confidence interval of the correlations among dimensions/factors was calculated with two standard deviation. The discriminant validity is determined if these confidence intervals do not contain one. The 95 percent confidence interval of the $\gamma_{M\text{-}O}$ ranged from 0.4407 to 0.7231, $\gamma_{M\text{-}S}$ from 0.3466 to 0.6655, and $\gamma_{O\text{-}S}$ from 0.3415 to 0.6622. These results validated the discrimination of dimensions, and no paired dimensions were perfectly correlated. Table III showed the correlation matrix of dimensions. Though the three dimensions were significantly discriminant, the high correlations indicated that the MLR scale governed the three dimensions.

3.9 Nomological validity

Nomological validity denotes that whether the MLR scale has a strong predictability on the relevant constructs theoretically. Its main objective is to confirm the usefulness of the MLR scale instead of testing a proposed hypothesis (Wang, 2007). In this study, respondents' intention to use m-learning systems which was assessed with two items (Cronbach's $\alpha = 0.9087$) was proposed as the consequence of MLR. Similar to the effect of technology readiness on technology acceptance (Lam *et al.*, 2008) and the effect of learners' readiness on e-learning system usage (Rahimi and Katal, 2012), MLR is expected to positively influence on intention to use m-learning systems. Individual who scores highly in MLR scale shows greater possibility to learn by mobile devices and systems than those with a low MLR scale (Cheon *et al.*, 2012; Rahimi and Katal, 2012). The results of Pearson correlation satisfies the cut-off value of 0.6 (Johnson, 1998) and MLR was significantly associated with intention to use m-learning systems ($\gamma = 0.7255$, $p < 0.0001$). The nomological validity of the MLR scale is supported.

3.10 The norm of the MLR scale

With the reliability and various validity examinations satisfied, the final stage in the scale development is to establish norms of the scale (MacKenzie *et al.*, 2011). The norms are helpful to identify where an individual is situated in the distribution of the population for a specific construct. In this vein, the development of scale norms would help practitioners assess the relative standing of an individual in comparison to others

	M-learning self-efficacy	Optimism	Self-directed learning
M-learning self-efficacy	1		
Optimism	0.6003	1	
Self-directed learning	0.5242	0.5199	1

Table III. Correlation matrix of dimensions on the targeted scale (Wang, 2007). This would offer much more strategic thoughts than just knowing an individual's scale scores.

Consequently, while the proposed MLR scale can be used to evaluate the extent of an individual's MLR. However, a better way of assessing individual MLR is to compare individual readiness levels with the norm – the total distribution of the readiness levels rated by other people. The diversity property of the sample data used in this study makes it appropriate for the development of a tentative norm. The percentile scores of the 19-item MLR scale were shown in Table IV. Some main statistics of the MLR scale were summarized as followed: minimum = 46; maximum = 133; mean = 103.5235; median = 104; mode = 114; standard deviation = 14.4405; skewness = −0.5366; and kurtosis = 0.4707.

These statistics will be useful in more precisely evaluating a student's MLR. As the concise MLR scale with good reliability and validity is periodically administered to a representative set of students, m-learning planners can use this MLR scale to enhance their understanding of students' MLR and to take necessary actions to improve them.

4. Discussions

4.1 Implications for research

The results of this study provide some theoretical implications for m-learning. First, the MLR scale is empirically tested as a three-dimension construct, including m-learning self-efficacy, optimism, and self-directed learning. Based on the social cognitive theory (Bandura, 2012), m-learning self-efficacy can be construed as an individual's self-perceived capability to not only master the functions of systems and mobile devices, but also to learn well via m-learning systems. Optimism, as with Parasuraman's (2000) argument, represents the extent to which the advantages of m-learning systems are appreciated. Higher optimism means m-learning systems are positively evaluated (i.e. usefulness) and leads to a greater acceptance possibility (Lam *et al.*, 2008). Self-directed learning, contrary to dependent learning, is a personality trait reflecting that an individual is self-motivated and responsible for his/her learning activities. By integrating all the resource accessed possibly, an individual is able to actively develop and implement his/her learning plans (Lin and Hsieh, 2001). The inclusion of self-directed learning in MLR scale was in line with Huang *et al.* (2012) and Smith's (2005) argument that self-directed learning is the core of technology-mediated distance education, and thus the derived MLR scale is effective and of good prediction.

Table IV.
Norms of the MLR scale: percentile scores

Percentile	Value
100	133
90	121
80	115
70	113
60	109
50	104
40	100
30	96
20	93
10	84

Second, taking a further examination of the nature of MLR suggests that MLR is manifested in individuals' perceived technology efficacy (i.e. self-efficacy), perceived advantages of m-learning systems (i.e. optimism), and learning style (i.e. self-directed learning). While the three dimensions of the MLR scale are separately included in different scales, such as Hung *et al.*'s (2010) OLR scale and Parasuraman's (2000) TRI, the proposed MLR scale is new because not all of the dimensions and items in the previous generic technology readiness scales and specific e-learning readiness scales are appropriate to measure MLR construct. More importantly, as Lam *et al.*'s (2008) study on the dimensions of technology readiness recognized that innovativeness is a psychological trait which does not involve in the evaluation of technology and the other three dimensions (i.e. optimism, discomfort, and insecurity) are generalized beliefs and affects involving in the evaluation of technology, the m-learning self-efficacy and optimism in MLR scale can be regarded as beliefs specific to m-learning systems, whereas self-directed learning is a personality trait.

Third, compared with the four-dimension technology readiness (Parasuraman, 2000), optimism was the only dimension kept in the MLR scale, while innovativeness, discomfort, and insecurity were not. The finding agrees with the perspective of Lam *et al.* (2008) that the four dimensions have their own importance and may not be manifestation of a common factor. Specifically, the inclusion of optimism in both TRI and MLR scales implies that perceived advantages of a technology/m-learning system are prerequisite and critical for an individual to embrace the system. Previous studies have also recognized the importance of optimism (i.e. perceived advantages) in measuring OLR (e.g. Bernard *et al.*, 2004; Parnell and Carraher, 2003; Teo, 2010).

Finally, the MLR scale may help researchers build m-learning theories. Based on the theory of reasoned action (Ajzen, 2012), external stimuli indirectly affect an individual's attitude toward a certain behavior by affecting his or her salient beliefs about the consequences of performing the behavior. Further, individual differences are important external stimuli for beliefs about using IT (e.g. Agarwal and Prasad, 1999). Individual differences include user factors such as demographic variables (e.g. gender and age difference), personality traits, computer self-efficacy, personal innovation in IT, and situational variables that account for circumstance-based differences such as experience and training (Agarwal and Prasad, 1999). Thus, MLR can be considered as an individual difference variable, which is suitable to explain and predict individual behavior. MLR is an important theoretical construct because of its potential for helping us develop theoretical relationships that are critical to the m-learning research community. Given the importance of MLR, future studies could also examine the relationship between MLR and other m-learning-related variables, such as learners' achievement and m-learning acceptance by not only treating MLR as an overall construct but also including its three distinct dimensions as well (Lam *et al.*, 2008; Son and Han, 2011). It may also yield more insightful findings by considering MLR as an antecedent or as a moderator variable in explaining the variations in m-learning effectiveness, similar to the effect of e-learning readiness on e-learning effectiveness (Keramati *et al.*, 2011).

4.2 Implications for practice

Our empirical findings provide several important implications for m-learning practices. First, educators can use the overall MLR scale to differentiate learners and design appropriate or customized teaching strategies for different learners. As a learner who has a higher MLR score is more ready to take advantage of m-learning systems, m-learning is expected to significantly enhance high MLR learners' learning achievement. Furthermore, m-learning is suggested to be a supplementary teaching strategy and should not be used as a primary evaluation of achievement for low MLR learners. For developers and marketers of m-learning systems, the MLR scale can also be employed to identify the high MLR users who are generally seen to be the innovators and the early adopters while marketing m-learning products (Shih and Venkatesh, 2004; Son and Han, 2011). The ability to segment users based on MLR will help educators and/or marketers develop strategies for new m-learning systems promotion.

More specifically, the dimensions of the MLR scale may aid in clustering learners/users, and thus appropriate teaching and marketing activities can be designed to attract distinct groups. Taking the Devolder *et al.* (2012) study as an example, the nursing staff were classified into five subgroups based on the four dimensions of TRI: explorers (high in optimism and innovativeness), paranoids (high in optimism), skeptics (low in all four dimensions), laggards (high in discomfort and insecurity), and pioneers (high in insecurity). It was further reported that the attitude toward a new technology (i.e. electronic patient record system) of explorers and pioneers was determined by performance expectancy, while that of skeptics and paranoids was driven by effort expectancy. Likewise, our MLRS with three dimensions is expected to be a good framework for m-learner classification by k-means cluster analysis technique. For example, individuals who primarily have high scores in the dimension of self-directed learning could be grouped as autonomous learners. Thus, the richness of learning content and the flexibility of learning pace and time could easily elicit autonomous learners to adopt m-learning system (Hung *et al.*, 2010). By contrast, for skillful learners who are primarily high in the dimension of m-learning self-efficacy, the challenging learning goals may be on motivating them to engage in the m-learning systems (Johnson, 2005).

5. Conclusion and limitations

With the enhancement of computing capability and the augmentation of the embedded equipment (Jeng *et al.*, 2010; Wang, 2007), portable mobile devices have become important communication media for delivering rich contents, contributing to the development of m-learning. While learning via mobile devices is on an emerging tide, the factors which determine the effectiveness of m-learning are the concerns for both researchers and practitioners. One major factor which positively relates to m-learning effectiveness is the learners' readiness for m-learning. To our knowledge, however, the nature of MLR has never been explored carefully and this void may deter the development of m-learning theory and practice. Therefore, this study aims to develop a generic measurement of individuals' psychological readiness for m-learning. The results showed that MLR can be parsimoniously measured with 19 items and is structured with three dimensions as m-learning self-efficacy, optimism, and self-directed learning. All the desired psychometric properties of the MLR scale were satisfied.

Despite that the MLR scale was developed and validated through rigorous procedures of scale development, there are some limitations which future research need to take into consideration. First, the measured items generated from literature and personal interviews were processed in Chinese throughout the entire scale development procedure. Though the wording of items were examined and polished by experienced researchers, the participation of bilingual translator and the use of back-translation method would have been more beneficial to developing an English-based MLR scale and increasing the quality of this study (Choe, 2004). The derived MLR scale can be the base for comparisons of cross-cultural studies.

Second, the MLR scale in this study was validated based on an online survey in Taiwan. Even though the recruited respondents were voluntary, they were not sampled in a random manner and the generalizability of our finding should be made with caution. Future studies need to consider a more strict sampling method which is conducted in terms of the demographic distribution such as age, gender, or education (Fowler, 2002). A representative sample will reduce the bias and increase the external validity.

Finally, the scale reliability can be validated by means of internal consistency and temporal stability of measured items (DeVellis, 2003). While Cronbach's coefficient α was mainly employed to understand the extent to which the items in the MLR scale are highly consistent, whether these items and dimensions are able to successfully capture the concept the m-learning over time (i.e. temporal stability) should be addressed in the future. A test-retest examination is thus needed to check the correlation of the MLR scale measured at different time points to ensure more solid scale reliability.

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Appendix. The initial measurement of the MLR scale

Q1. Mobile learning systems give people more control over their studying time.*
Q2. The newest mobile learning system is much more convenient to use.*
Q3. I like studying via mobile learning systems because I am able to study anytime.*
Q4. I like mobile learning systems.*
Q5. I like mobile learning systems that allow me to tailor things to fit my own needs.*
Q6. Mobile learning systems make me more efficient in my studying.*
Q7. Mobile learning systems give me more freedom of studying.*
Q8. I feel confident that mobile learning systems will allow me to achieve expected effectiveness.
Q9. I feel confident in attending a class or studying via mobile learning systems.
Q10. I feel confident in studying to operate mobile learning systems.*
Q11. I feel confident in knowing all the special keys and functions contained in a mobile learning system.*
Q12. I feel confident in knowing how a mobile learning system works.*
Q13. Mobile learning systems are helpful for me.
Q14. Mobile learning systems are designed for use by ordinary people.
Q15. It is not embarrassing for me when I have trouble with a mobile learning system while people are watching.
Q16. I do not worry about a mobile learning system that may breakdown or get disconnected.
Q17. I am able to easily access mobile learning systems as needed for my studies.
Q18. I am comfortable using mobile learning systems to study.
Q19. I am willing to actively communicate with my friend, classmates, and instructors by a mobile learning system.
Q20. Mobile learning systems are of at least equal quality to traditional classroom learning.
Q21. My background and experience will be beneficial to my use of mobile learning systems.
Q22. I am comfortable with the communication of studying by a mobile learning system.
Q23. When it comes to studying or working, I am a self-directed person.

Q24. Other people may come to me for advice on new mobile learning systems while encountering difficulties.
Q25. I understand more about mobile learning systems than my friends.
Q26. I have fewer problems than other people in using mobile learning systems.
Q27. I consider it safe giving out my personal information over mobile learning systems.
Q28. I consider it safe to do any kind of business (e.g. buying a mobile learning product with a mobile vehicle) over mobile learning systems.
Q29. I do not worry about that information I send over mobile learning systems will be seen by other people.
Q30. I prefer a mobile learning system to a traditional learning manner.
Q31. If I provide information to a mobile vehicle and send it over wireless internet, I am sure it really gets to the right place.
Q32. I do not worry that mobile learning will replace traditional learning.
Q33. I do not worry that it is necessary to use an mobile learning system in my learning.
Q34. I feel confident in receiving and sending studying information over the internet using mobile learning systems.
Q35. I feel confident in getting software and data from remote websites using mobile learning systems.
Q36. I feel confident in posting an article or other information onto the Bulletin Board System (BBS) using mobile learning systems.
Q37. I feel confident in using a specific mobile learning system I never used before.
Q38. I believe looking back on what I have learned will help me to remember it better.
Q39. In my learning, studying, or working, I am self-disciplined and find it easy to set aside learning time.*
Q40. In my studies, I set goals and have a high degree of initiative.*
Q41. I carry out my own study plan.*
Q42. I seek assistance when facing learning problems.
Q43. I manage time well.*
Q44. I have higher expectations for my learning performance.
Q45. I can direct my own learning progress.*
Q46. I am not distracted by other factors (e.g. instant messages, internet surfing, and games on mobile vehicles) when using mobile learning system.
Q47. I am open to new ideas.
Q48. I have motivation to learn.
Q49. I improve from my mistakes.
Q50. I like to share my ideas with others.
Q51. I feel confident in performing the basic functions of mobile learning systems.*
Q52. I feel confident in my knowledge and skills of mobile learning systems.*
Q53. I feel confident in using the internet (Google, Yahoo) to find or gather information for mobile learning.*
Q54. I feel confident in using mobile learning systems to effectively communicate with others.*
Q55. I feel confident in expressing myself (emotions and humor) through text on mobile learning systems.

Criterion or overall mobile learning readiness

Q56. As a whole, I am ready to use mobile learning systems.
Q57. As a whole, I am not afraid of using mobile learning systems.

Intention to use a mobile learning system

Q58. Assuming I had a mobile learning system, I intend to use it.
Q59. I intend to increase my use of mobile learning systems in the future.

Note: These questions comprise the Technology Readiness Index 2.0 which is copyrighted by A. Parasuraman and Rockbridge Associates Inc., 2014. This scale may be duplicated only with written permission from the authors. Items with an asterisk at the end are included during the development process.

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