British Journal of Educational Technology *Vol 40 No 1 2009* 92–118
doi:10.1111/j.1467-8535.2007.00809.x

Investigating the determinants and age and gender differences in the acceptance of mobile learning

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Abstract

With the proliferation of mobile computing technology, mobile learning (m-learning) will play a vital role in the rapidly growing electronic learning market. M-learning is the delivery of learning to students anytime and anywhere through the use of wireless Internet and mobile devices. However, acceptance of m-learning by individuals is critical to the successful implementation of m-learning systems. Thus, there is a need to research the factors that affect user intention to use m-learning. Based on the unified theory of acceptance and use of technology (UTAUT), which integrates elements across eight models of information technology use, this study was to investigate the determinants of m-learning acceptance and to discover if there exist either age or gender differences in the acceptance of m-learning, or both. Data collected from 330 respondents in Taiwan were tested against the research model using the structural equation modelling approach. The results indicate that performance expectancy, effort expectancy, social influence, perceived playfulness, and self-management of learning were all significant determinants of behavioural intention to use m-learning. We also found that age differences moderate the effects of effort expectancy and social influence on m-learning use intention, and that gender differences moderate the effects of social influence and self-management of learning on m-learning use intention. These findings provide several important implications for m-learning acceptance, in terms of both research and practice.

Introduction

The use of information and communication technology (ICT) may improve learning, especially when coupled with more learner-centred instruction (Zhu & Kaplan, 2002). From notebook computers to wireless phones and handheld devices, the massive infusion of computing devices and rapidly improving Internet capabilities have altered the nature of higher education (Green, 2000). Mobile learning (m-learning) is the follow up of e-learning, which for its part originates from distance education.

M-learning refers to the delivery of learning to students anytime and anywhere through the use of wireless Internet and mobile devices, including mobile phones, personal digital assistants (PDAs), smart phones and digital audio players. Namely, m-learning users can interact with educational resources while away from their normal place of learning—the classroom or desktop computer. The place independence of mobile devices provides several benefits for e-learning environments, such as allowing students and instructors to utilise their spare time while traveling in trains or buses to finish their homework or lesson preparation (Virvou & Alepis, 2005). If e-learning took learning away from the classroom, then m-learning is taking learning away from a fixed location (Cmuk, 2007). Motiwalla (2007) contends that learning on mobile devices will never replace classroom or other e-learning approaches. Thus, m-learning is a complementary activity to both e-learning and traditional learning. However, Motiwalla (2007) also suggests that if leveraged properly, mobile technology can complement and add value to the existing learning models, such as the social constructive theory of learning with technology (Brown & Campione, 1996) and conversation theory (Pask, 1975). Thus, some believe that m-learning is becoming progressively more significant, and that it will play a vital role in the rapidly growing e-learning market.

Despite the tremendous growth and potential of the mobile devices and networks, wireless e-learning and m-learning are still in their infancy or embryonic stage (Motiwalla, 2007). While the opportunities provided by m-learning are new, there are several challenges facing m-learning, such as connectivity, small screen sizes, limited processing power and reduced input capabilities. Siau, Lim and Shen (2001) also note that mobile devices have '(1) small screens and small multifunction key pads; (2) less computational power, limited memory and disk capacity; (3) shorter battery life; (4) complicated text input mechanisms; (5) higher risk of data storage and transaction errors; (6) lower display resolution; (7) less surfability; (8) unfriendly user-interfaces; and (9) graphical limitations' (p. 6). Equipped with a small phone-style keyboard or a touch screen, users might require more time to search for some information on a page than they need to read it (Motiwalla, 2007). These challenges mean that adapting existing e-learning services to m-learning is not an easy work, and that users may be inclined to not accept m-learning. Thus, the success of m-learning may depend on whether or not users are willing to adopt the new technology that is different from what they have used in the past. While e-learning and mobile commerce/learning has received extensive attention (Concannon, Flynn & Campbell, 2005; Davies & Graff, 2005; Govindasamy, 2002; Harun, 2002; Ismail, 2002; Luarn & Lin, 2005; Mwanza & Engeström, 2005; Motiwalla, 2007; Pituch & Lee, 2006; Selim, 2007; Shee & Wang, in press; Ravenscroft & Matheson, 2002; Wang, 2003), thus far, little research has been conducted to investigate the factors affecting users' intentions to adopt m-learning, and to explore the age and gender differences in terms of the acceptance of m-learning. As Pedersen and Ling (2003) suggest, even though traditional Internet services and mobile services are expected to converge into mobile Internet services, few attempts have been made to apply traditional information technology (IT) adoption models to explain their potential adoption.

Consequently, the objective of this study was to investigate the determinants, as well as the age and gender differences, in the acceptance of m-learning based on the unified theory of acceptance and use of technology (UTAUT) proposed by Venkatesh, Morris, Davis and Davis (2003). The remainder of this paper is organised as follows. In the next section, we review the UTAUT and show our reasoning for adopting it as the theoretical framework of this study. This is followed by descriptions of the research model and methods. We then present the results of the data analysis and hypotheses testing. Finally, the implications and limitations of this study are discussed.

Unified Theory of Acceptance and Use of Technology

M-learning acceptance is the central theme of this study, and represents a fundamental managerial challenge in terms of m-learning implementation. A review of prior studies provided a theoretical foundation for hypotheses formulation. Based on eight prominent models in the field of IT acceptance research, Venkatesh *et al* (2003) proposed a unified model, called the unified theory of acceptance and use of technology (UTAUT), which integrates elements across the eight models. The eight models consist of the theory of reasoned action (TRA) (Fishbein & Ajzen, 1975), the technology acceptance model (TAM) (Davis, 1989), the motivational model (MM) (Davis, Bagozzi & Warshaw, 1992), the theory of planned behaviour (TPB) (Ajzen, 1991), the combined TAM and TPB (C-TAM-TPB) (Taylor & Todd, 1995a), the model of PC utilisation (MPCU) (Triandis, 1977; Thompson, Higgins & Howell, 1991), the innovation diffusion theory (IDT) (Rogers, 2003; Moore & Benbasat, 1991) and the social cognitive theory (SCT) (Bandura, 1986; Compeau & Higgins, 1995). Based on Venkatesh *et al*'s (2003) study, we briefly review the core constructs in each of the eight models, which have been theorised as the determinants of IT usage intention and/or behaviour.

First, TRA has been considered to be one of the most fundamental and influential theories on human behaviour. Attitudes toward behaviour and subjective norms are the two core constructs in TRA. Second, TAM was originally developed to predict IT acceptance and usage on the job, and has been extensively applied to various types of technologies and users. Perceived usefulness and perceived ease of use are the two main constructs mentioned in TAM. More recently, Venkatesh and Davis (2000) presented TAM2 by adding subjective norms to the TAM in the case of mandatory settings. Third, Davis *et al* (1992) employed motivation theory to understand new technology acceptance and usage, focusing on the primary constructs of extrinsic motivation and intrinsic motivation. Fourth, TPB extended TRA by including the construct of perceived behavioural control, and has been successfully applied to the understanding of individual acceptance and usage of various technologies (Harrison, Mykytyn & Riemenschneider, 1997; Mathieson, 1991; Taylor & Todd, 1995b). Fifth, C-TAM-TPB is a hybrid model that combines the predictors of TPB with perceived usefulness from TAM. Sixth, based on Triandis' (1977) theory of human behaviour, Thompson *et al* (1991) presented the MPCU and used this model to predict PC utilisation. MPCU consists of six constructs, including job fit, complexity, long-term consequences, affect towards use, social factors and facilitating conditions. Seventh, Moore and Benbasat (1991) adapted the properties of innovations posited by IDT and refined a set of constructs that could be used to explore individual technology acceptance. These constructs include relative advantage, ease of use, image, visibility, compatibility, results demonstrability and voluntariness of use. Finally, Compeau and Higgins (1995) applied and extended SCT to the context of computer utilisation (see also Compeau, Higgins & Huff, 1999). Their model consists of five core constructs: outcome expectations–performance, outcome expectations–personal, self-efficacy, affect and anxiety.

Venkatesh *et al* (2003) conducted an empirical study to compare the eight competing models and then proposed a unified model, UTAUT, which contains four core determinants of IT use behaviour, and up to four moderators of key relationships (see Figure 1). UTAUT posits that performance expectancy, effort expectancy, social influence and facilitating conditions are determinants of behavioural intention or use behaviour, and that gender, age, experience and voluntariness of use have moderating effects in the

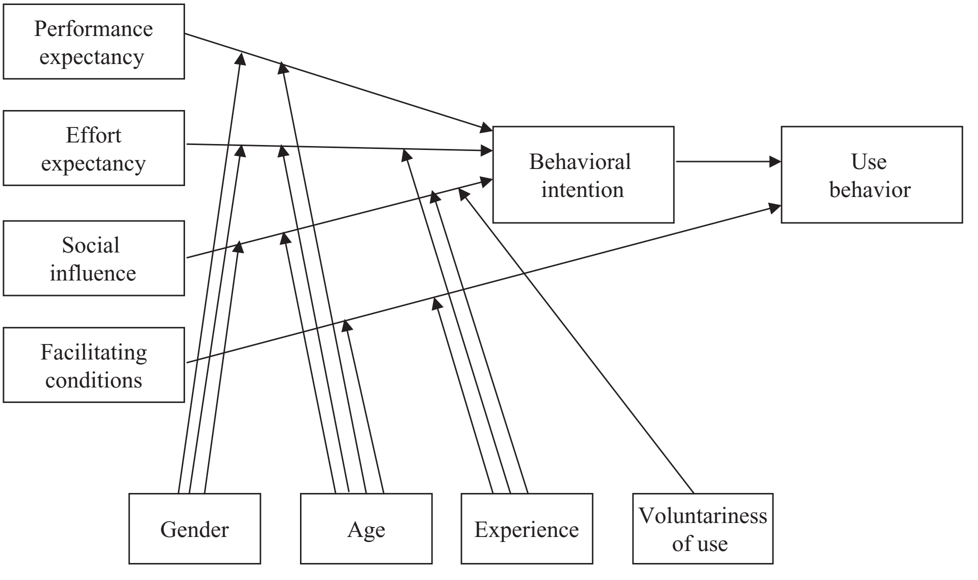

Figure 1: The UTAUT model
Source: Venkatesh et al (2003). UTAUT, unified theory of acceptance and use of technology.

acceptance of IT. Sun and Zhang (2006) also state that examining the potential moderating effects in user technology acceptance is a necessary step.

Research model and hypotheses

Research model

Within the m-learning context, mobile learners use the m-learning systems to conduct learning activities, making the m-learning system an IT phenomenon that lends itself to the UTAUT model. Venkatesh *et al* (2003) provided empirical evidence to demonstrate that IT use behaviour was well explained by the UTAUT, and encouraged others to continue validating and testing their model. The UTAUT model can also be applied to the implementation challenges of a new m-learning context. Accordingly, we adopted Venkatesh *et al*'s (2003) UTAUT as a primary theoretical framework to examine users' acceptance of m-learning.

However, since the m-learning context in some ways differs from the traditional IT context, the UTAUT's fundamental constructs do not fully reflect the specific influences of m-learning context factors that may alter user acceptance. Pedersen and Ling (2003) also suggest that the traditional adoption models in information systems research may be modified and extended when they are applied to study the adoption of mobile Internet services such as m-learning. After considering the m-learning context and user factors, we incorporated two additional constructs into the UTAUT in order to account for m-learning acceptance: perceived playfulness and self-management of learning. In fact, very few people have experience using m-learning, as it is still in its early infancy. To avoid any incorrect inferences, this study used behavioural intention as a dependent variable in the early stage of m-learning acceptance research. Thus, three constructs found in UTAUT, including use behaviour, facilitating conditions and experience, were omitted in this study. Further, as we investigated the acceptance of m-learning in a voluntary usage context, the moderator of voluntariness of use in UTAUT was also omitted.

The research model tested in this study is shown in Figure 2. In this model, performance expectancy (PE), effort expectancy (EE), social influence (SI), perceived playfulness (PP) and self-management of learning (SL) were hypothesised to be determinants of behavioural intention (BI) to use m-learning. We also hypothesised that age and gender differences would moderate the influence of these determinants on behavioural intention. The proposed constructs and hypotheses are supported by previous literature. The following sections elaborate on the theory base and derive the hypotheses.

Performance expectancy

Venkatesh *et al* (2003) define performance expectancy as the extent to which an individual believes that using an information system will help him or her to attain benefits in job performance. They also suggest that five constructs from the existing models capture the concept of performance expectancy: perceived usefulness (TAM/TAM2 and C-TAM-TAB), extrinsic motivation (MM), job-fit (MPCU), relative advantage (IDT) and outcome expectations (SCT). In addition, they have also demonstrated that perfor-

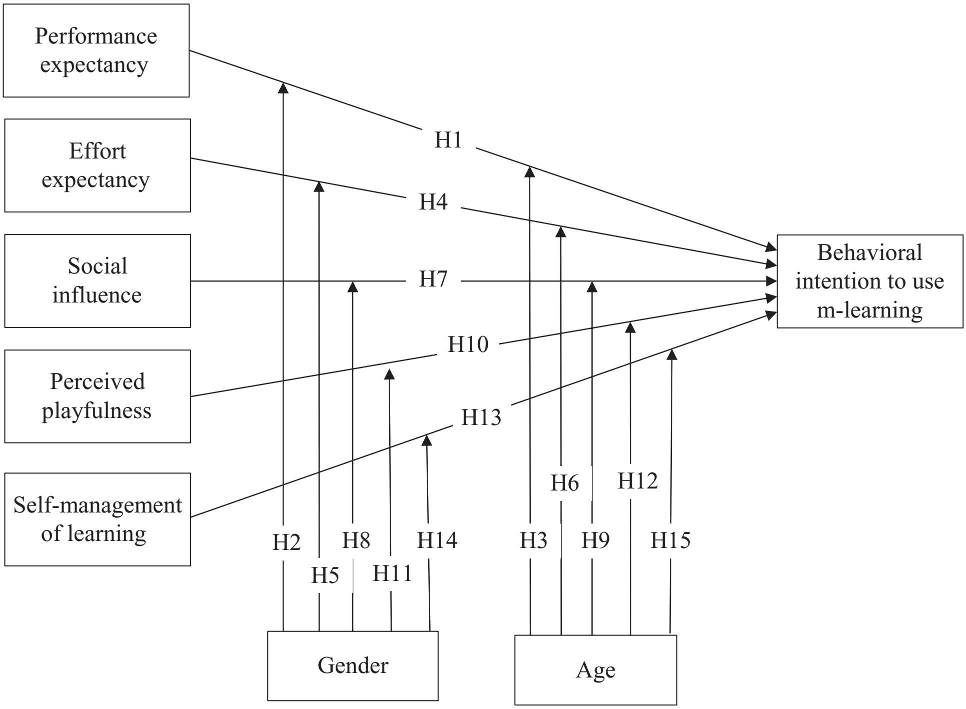

Figure 2: Research model
m-learning, mobile learning; H, hypothesis.

mance expectancy is the strongest predictor of behavioural intention to use IT. Adapting performance expectancy to an m-learning context suggests that m-learners will find m-learning useful because it enables learners to accomplish learning activities more quickly and flexibly, or even helps increase their learning effectiveness. Based on the UTAUT and previous literature (Morris & Venkatesh, 2000; Venkatesh & Morris, 2000), gender and age are theorised to play a moderating role on the influence of performance expectancy on behavioural intention. That is, the influence of performance expectancy on behavioural intention will be moderated by gender and age, such that the effect will be stronger for men and particularly for younger men (Venkatesh *et al*, 2003). Therefore, this study tested the following hypotheses:

Hypothesis 1: Performance expectancy has a positive effect on behavioural intention to use m-learning.

Hypothesis 2: Performance expectancy influences behavioural intention to use m-learning more strongly for men than for women.

Hypothesis 3: Performance expectancy influences behavioural intention to use m-learning more strongly for younger than for older people.

Effort expectancy

Venkatesh *et al* (2003) define effort expectancy as the degree of ease associated with the use of the information system. The three constructs from the different models that relate to effort expectancy are perceived ease of use (TAM/TAM2), complexity (MPCU) and ease of use (IDT) (Venkatesh *et al*, 2003). Prior studies suggest that constructs associated with effort expectancy will be stronger determinants of individuals' intention for women (Venkatesh & Morris, 2000; Venkatesh, Morris & Ackerman, 2000) and for older workers (Morris & Venkatesh, 2000). In addition, an effort-oriented construct is expected to be more salient in the early stages of a new behaviour (Davis *et al*, 1989; Szajna, 1996; Venkatesh, 1999). Since m-learning is still in its early infancy, it is believed that effort expectancy will be a critical determinant of behavioural intention to use m-learning. Accordingly, based on the UTAUT, we expect that individual acceptance of m-learning will depend on whether or not the m-learning system is easy to use, and that the influence of effort expectancy on behavioural intention will be moderated by gender and age, such that the effect will be stronger for women, particularly for older women (Venkatesh *et al*, 2003). Thus, we tested the following hypotheses:

Hypothesis 4: Effort expectancy has a positive effect on behavioural intention to use m-learning.

Hypothesis 5: Effort expectancy influences behavioural intention to use m-learning more strongly for women than for men.

Hypothesis 6: Effort expectancy influences behavioural intention to use m-learning more strongly for older than for younger people.

Social influence

Venkatesh *et al* (2003) define social influence as the extent to which a person perceives that important others believe he or she should use a new information system. Three constructs from the existing models capture the concept of social influence: subjective norm (TRA, TAM2, TPB and C-TAM-TPB), social factors (MPCU) and image (IDT) (Venkatesh *et al*, 2003). Prior studies suggest that social influence is significant in shaping an individual's intention to use new technology (Harrison *et al*, 1997; Mathieson, 1991; Moore & Benbasat, 1991; Thompson *et al*, 1991; Venkatesh & Davis, 2000). This study incorporates social influence to the research model in order to explore the moderating effect of age and gender differences on the relationships between social influence and behavioural intention. Based on the UTAUT and previous literature (e.g., Miller, 1976; Morris & Venkatesh, 2000; Venkatesh *et al*, 2000; Venkatesh *et al*, 2003), we expect that social influence is a significant determinant of behavioural intention to use m-learning, and that the effect of social influence on behavioural intention will be moderated by gender and age, such that the effect will be stronger for women, particularly older women. Thus, the following hypotheses were tested:

Hypothesis 7: Social influence has a positive effect on behavioural intention to use m-learning.

Hypothesis 8: Social influence influences behavioural intention to use m-learning more strongly for women than for men.

Hypothesis 9: Social influence influences behavioural intention to use m-learning more strongly for older than for younger people.

Perceived playfulness

Perceived playfulness can be considered to be either a state of mind (Moon & Kim, 2001) or an individual trait (Webster & Martocchio, 1992). Traits refer to comparatively stable characteristics of individuals that tend to be relatively invariant to situational stimuli. A state of mind, however, refers to affective or cognitive episodes that are experienced in the short run and fluctuate over time. Webster and Martocchio (1992) examined playfulness as an individual trait rather than a state, and defined microcomputer playfulness as the degree of cognitive spontaneity in microcomputer interactions, with a high level of cognitive spontaneity indicating a high degree of playfulness, and a low level of cognitive spontaneity indicating a low degree of playfulness. While the trait-based approach focuses on playfulness as the individual's characteristic, the state-based approach emphasises playfulness as the individual's subjective experience of human-computer interaction (Moon & Kim, 2001). Based on Moon and Kim's definition, perceived playfulness in this study is defined as a state of mind that includes three dimensions: the extent to which the individual (1) perceives that his or her attention is focused on the interaction with the m-learning (ie, concentration); (2) is curious during the interaction (ie, curiosity); and (3) finds the interaction intrinsically enjoyable or interesting (ie, enjoyment).

Based on Liebermain's (1977) pioneering works, Barnett's (1990, 1991) studies and Csikszentmihalyi's (1975) flow theory, Moon and Kim (2001) extended and empirically validated the TAM for the Web context by adding an intrinsic motivation factor, perceived playfulness, to the TAM. They found that perceived playfulness has a significant positive influence on behavioural intention to use the Web. In fact, an m-learning system can be considered as a kind of wireless website. Past studies have also suggested that the use of IT is influenced by perceived playfulness-related constructs (Agarwal & Karahanna, 2000; Chung & Tan, 2004; Davis *et al*, 1992; Igbaria, Schiffman & Wieckowshi, 1994). The rationale is that individuals who experience pleasure or enjoyment from using an information system are more likely to intend to use it extensively than those who do not (Igbaria, Parasuraman & Baroudi, 1996; Venkatesh, 2000). Kiili (2005) emphasises the importance of playful and hedonic characteristics in the design of digital learning systems. Van der Heijden (2004) contends that for hedonic systems, perceived enjoyment (a dimension of perceived playfulness) is a stronger predictor of behavioural intention to use than is perceived usefulness. Based on the above discussion, we suggest that an individual's intention to use m-learning systems will be influenced by his or her perceptions regarding the playfulness of the systems.

According to our definition, m-learning content is received through wireless Internet and palm-sized computers, and thus m-learning usage can be considered to be a natural extension of computer use. Prior research suggests that there are significant gender differences in attitudes towards computers (Durndell & Thomson, 1997; Mitra *et al*, 2000; Whitely, 1997), with males scoring higher than females. It is therefore expected that perceived playfulness of m-learning systems will influence behavioural intention to use m-learning more saliently for men than for women. In addition, prior studies investigating computer use among adults reveal that the older the individual, the less interest they are likely to have (Billipp, 2001; Czaja & Lee, 2001; DeOllos & Morris, 1999; Ellis & Allaire, 1999; White & Weatherall, 2000). Thus, we expect that the influence of perceived playfulness on behavioural intention will be moderated by gender and age, such that the effect will be stronger for men, particularly younger men. The following hypotheses were tested:

Hypothesis 10: Perceived playfulness has a positive effect on behavioural intention to use m-learning.

Hypothesis 11: Perceived playfulness influences behavioural intention to use m-learning more strongly for men than for women.

Hypothesis 12: Perceived playfulness influences behavioural intention to use m-learning more strongly for younger than for older people.

Self-management of learning

The notion of readiness for online learning was proposed by Warner, Christie and Choy (1998). McVay (2000, 2001) developed a 13-item instrument for measuring readiness for online learning. The items in the McVay instrument relate strongly to the characteristics of readiness for flexible learning identified by Smith (2001), and described within his two-factor space of learner preferences for resource-based learning (Smith, 2000). As Smith, Murphy and Mahoney (2003) suggest, the McVay instrument appears to have considerable potential congruence with broader research literature on the readiness of learners for resource-based distance education and flexible learning. Based on the McVay readiness for online learning questionnaire, Smith *et al* (2003) conducted an exploratory study to identify factors underlying readiness for online learning, and yielded a two-factor structure, 'comfort with e-learning' and 'self-management of learning', which is readily interpretable and strongly resonant with other research findings from the broader flexible learning literature. Smith *et al* (2003) also suggested that the two dimensions identified in the McVay instrument are similar to those identified by Smith (2000) and Sadler-Smith and Riding (1999): comfort with the learning resources available in a sequence learning and degree of self-direction.

After confirming that the McVay readiness for online learning instrument exhibits good psychometric properties in terms of reliability and factorability, Smith *et al* (2003) suggest that further work needs to be done to establish the predictive validity of the instrument, as well as its value and applications. The McVay instrument describes a readiness for engagement with the particular form of resource-based learning delivery that is online, making the two aspects identified in the instrument become potential factors affecting mobile learning acceptance. Since the 'comfort with e-learning' factor associates comfort with the instructional delivery and resources, which is conceptually similar to the effort expectancy construct, we chose to neglect it in this study. Self-management of learning is defined as the extent to which an individual feels he or she is self-disciplined and can engage in autonomous learning (Smith *et al*, 2003). Indeed, the need for self-direction, or self-management of learning, runs clearly throughout the distance education and resource-based flexible learning literature (Evans, 2000; Smith *et al*, 2003; Warner *et al*, 1998). Since m-learning can be considered as a kind of e-learning via mobile devices, it is expected that a person's level of self-management of learning will have a positive influence on his or her behavioural intention to use m-learning. Furthermore, there is evidence to support the notion that men are more likely to display autonomous personality traits than women (Beck, 1983), and, in general, the older an individual, the better self-management he or she is likely to display. Consequently, we expect that the effect of self-management of learning on m-learning acceptance will be moderated by gender and age, such that the effect will be stronger for men, particularly older men. We tested the following hypotheses:

Hypothesis 13: Self-management of learning has a positive effect on behavioural intention to use m-learning.

Hypothesis 14: Self-management of learning influences behavioural intention to use m-learning more strongly for men than for women.

Hypothesis 15: Self-management of learning influences behavioural intention to use m-learning more strongly for older than for younger people.

Research methodology

Measures

To ensure the content validity of the scales, the items selected must represent the concept about which generalisations are to be made. Therefore, the items used to measure performance expectancy, effort expectancy, social influence and behavioural intention were adapted from Venkatesh *et al* (2003). The items for the perceived playfulness construct were adapted from Moon and Kim (2001). Finally, four items selected from Smith *et al* (2003) were used to measure self-management of learning. The items were modified to make them relevant to the m-learning context. Pretesting of the measures was conducted by users and experts selected from the m-learning field. Accordingly, the items were further adjusted to make their wording as precise as possible. Likert scales (1–7), with anchors ranging from 'strongly disagree' to 'strongly agree', were used for all construct items. Appendix lists the original items used in this study.

Subjects

Because of the lack of a reliable sampling frame, it is difficult to conduct a random sampling for all the potential m-learning users in Taiwan. Thus, this study adopted a nonrandom sampling technique (ie, convenience sampling) to collect the sample data. To make the results generalisable, we gathered sample data from five organisations in Taiwan: Aerospace Industrial Development Corporation (AIDC), IBM Taiwan, National Changhua University of Education, Chung Chou Institute of Technology and Yuanlin

Table 1: Characteristics of the respondents

Characteristic	*Number*	*Percentage*
Gender		
Female	128	38.8
Male	202	61.2
Age		
<20	43	13.0
21–30	148	44.9
31–40	44	13.3
41–50	59	17.9
>51	36	10.9
Education		
Elementary school	4	1.2
Junior high school	10	3.0
Senior high school	16	4.8
Junior college	98	29.7
Bachelor	181	54.8
Master	21	6.4
Industry		
Manufacturing	117	35.5
Service	35	10.6
Education and research	124	37.6
Government agencies	17	5.2
Others	37	11.2

Community University. Respondents were asked to participate in a survey. The willing respondents were first introduced to the definition of m-learning. This declaration made respondents exactly understand the meaning of the term 'm-learning' in the questionnaire. Respondents then self-administered the questionnaire and were asked to circle the response which best described their level of agreement with the statements. On this basis, a sample of 330 usable responses was obtained from a variety of respondents with different levels of computer or Internet experience. The respondents had an average of 8.15 years of computer experience (standard deviation [*SD*] = 5.53) and 5.55 years of Internet experience (*SD* = 3.44). The characteristics of the respondents are shown in Table 1.

Data analysis and results

Assessment of measurement model

A confirmatory factor analysis using AMOS 4.0 was conducted to test the measurement model. Six common model-fit measures were used to assess the model's overall goodness of fit: the ratio of χ^2 to degrees of freedom (*df*), goodness-of-fit index (GFI), adjusted goodness-of-fit index (AGFI), normalised fit index (NFI), comparative fit index (CFI) and root mean square residual (RMSR). After examining the modification indices, three items, including item PP1, PP2 and SL1 (see Appendix) were eliminated due to cross-factor loadings.

Table 2: Fit indices for measurement and structural models

Goodness-of-fit measure	*Recommended value*	*Measurement model*	*Structural model*
χ^2/df	≤3.00	1.891	1.891
GFI	≥0.90	0.916	0.916
AGFI	≥0.80	0.886	0.886
NFI	≥0.90	0.959	0.959
CFI	≥0.90	0.980	0.980
RMSR	≤0.10	0.065	0.065

df, degrees of freedom; GFI, goodness-of-fit index; AGFI, adjusted goodness-of-fit index; NFI, normalised fit index; CFI, comparative fit index; RMSR, root mean square residual.

Table 3: Reliability, average variance extracted and discriminant validity

Factor	*CR*	*1*	*2*	*3*	*4*	*5*	*6*
1. Performance expectancy	0.947	0.818					
2. Effort expectancy	0.949	0.306	0.824				
3. Social influence	0.938	0.288	0.112	0.791			
4. Perceived playfulness	0.931	0.392	0.210	0.208	0.818		
5. Self-management of learning	0.956	0.196	0.186	0.173	0.157	0.880	
6. Intention to use m-learning	0.954	0.420	0.325	0.249	0.348	0.291	0.874

Diagonal elements are the average variance extracted. Off-diagonal elements are the shared variance.
CR, composite reliability; m-learning, mobile learning.

As shown in Table 2, all the model-fit indices exceeded their respective common acceptance levels suggested by previous research, thus demonstrating that the measurement model exhibited a fairly good fit with the data collected. We could therefore proceed to evaluate the psychometric properties of the measurement model in terms of reliability, convergent validity and discriminant validity.

Reliability and convergent validity of the factors were estimated by composite reliability[1] and average variance extracted (see Table 3). The interpretation of the composite reliability is similar to that of Cronbach's alpha, except that it also takes into account the actual factor loadings rather than assuming that each item is equally weighted in the composite load determination.

Composite reliability for all the factors in our measurement model was above 0.90. The average extracted variances were all above the recommended 0.50 level (Hair, Anderson, Tatham & Black, 1992), which means that more than one-half of the variance

[1]Composite reliability = (Σ standardised loading)^2/([Σ standardised loading]^2 + $\Sigma\varepsilon_j$) where the standardised loadings are obtained directly from the program output, and ε_j is the measurement error for each indicator.

Table 4: Factor loadings and squared multiple correlations of items

	Factor loadings	*Squared multiple correlations*
Performance expectancy		
PE1	0.851	0.724
PE2	0.934	0.873
PE3	0.939	0.882
PE4	0.890	0.792
Effort expectancy		
EE1	0.861	0.741
EE2	0.925	0.856
EE3	0.942	0.888
EE4	0.900	0.810
Social influence		
SI1	0.904	0.817
SI2	0.931	0.867
SI3	0.898	0.806
SI4	0.820	0.673
Perceived playfulness		
PP3	0.834	0.695
PP4	0.943	0.888
PP5	0.933	0.871
Self-management of learning		
SL2	0.932	0.868
SL3	0.952	0.907
SL4	0.930	0.864
Behavioural intention		
BI1	0.918	0.842
BI2	0.959	0.920
BI3	0.927	0.860

PE, performance expectancy; EE, effort expectancy; SI, social influence; PP, perceived playfulness; SL, self-management of learning; BI, behavioural intention.

observed in the items was accounted for by their hypothesised factors. Convergent validity can also be evaluated by examining the factor loadings and squared multiple correlations from the confirmatory factor analysis (see Table 4). Following the recommendation made by Hair *et al* (1992), a factor loading greater than 0.50 was considered to be very significant. All of the factor loadings of the items in the research model were greater than 0.80. Also, squared multiple correlations between the individual items and their a priori factors were high. Thus, all factors in the measurement model had adequate reliability and convergent validity.

To examine discriminant validity, this study compared the shared variance between factors with the average variance extracted of the individual factors (Fornell & Larcker, 1981). This analysis showed that the shared variances between factors were lower than the average variance extracted of the individual factors, thus confirming discriminant validity (see Table 3). In summary, the measurement model demonstrated adequate reliability, convergent validity and discriminant validity.

Structural model and hypotheses testing
A similar set of model-fit indices was used to examine the structural model (see Table 2). Coincidentally, the six common model-fit measures of the structural model were the same as those of the measurement model. This provided firm evidence of a good model-data fit. Thus, we could proceed to investigate the determinants, and age and gender differences in the acceptance of m-learning.

Standardised path coefficients in the hypothesised model are shown in Figure 3. As expected, Hypotheses 1, 4, 7, 10 and 13 were supported, in that performance expectancy, effort expectancy, social influence, perceived playfulness and self-management of learning all had a significant positive effect on behavioural intention to use m-learning ($\gamma = 0.26$, $\gamma = 0.21$, $\gamma = 0.12$, $\gamma = 0.21$ and $\gamma = 0.20$ respectively). Altogether, the model accounted for 58% of the variance in behavioural intention, with performance expectancy contributing more to intention than the other constructs.

We continued to explore the gender differences. For the male group, the model accounted for 53% of the variance in behavioural intention. As indicated in Figure 4, the path coefficients for the PE–BI, EE–BI, SI–BI, PP–BI and SL–BI links in the model were all significant for the male group. On the other hand, for the female group, the model accounted for 68% of the variance in behavioural intention, and the path coef-

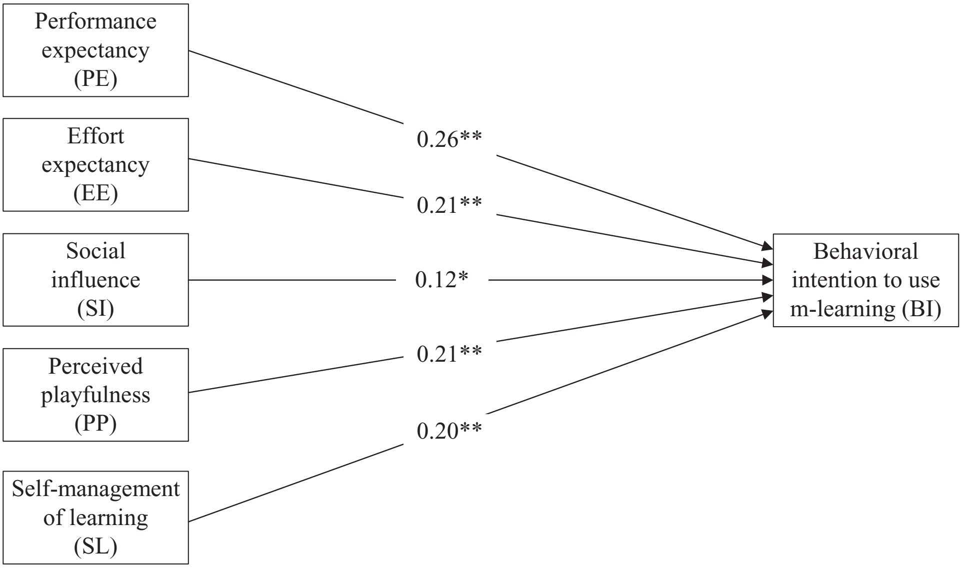

Figure 3: Standardised path coefficients for all respondents
*$p < 0.05$; **$p < 0.01$.

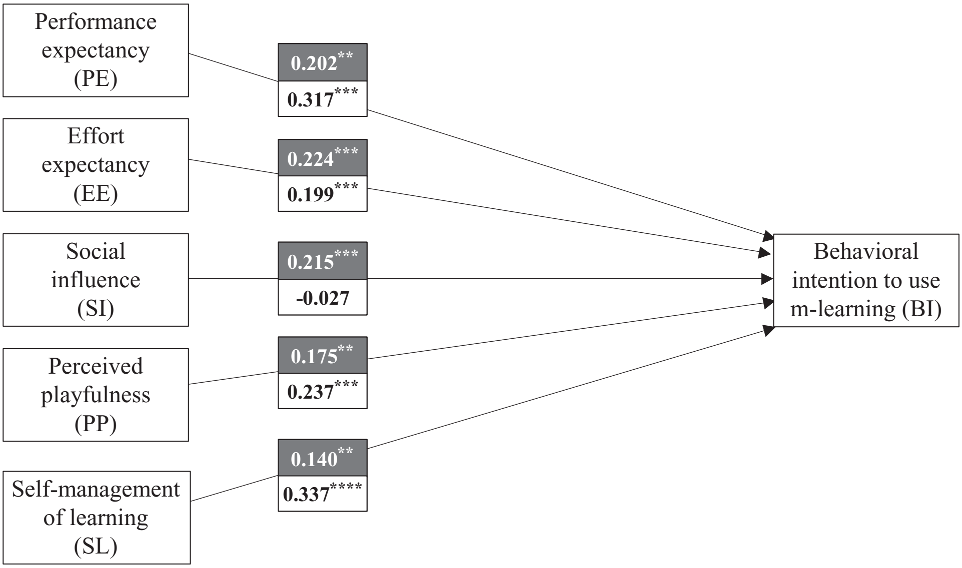

Figure 4: Standardised path coefficients[a] for males and females
[a]*Coefficients for males are in the shaded boxes.* $^{**}p < 0.05$; $^{***}p < 0.01$; $^{****}p < 0.001$.

ficients for the PE–BI, EE–BI, SI–BI, PP–BI and SL–BI links in the model were all significant (see Figure 4). However, the effect of social influence on behavioural intention was not significant for the female group.

To explore the age differences, we divided the survey respondents into two groups: the older group with ages greater than 30 years and the younger group with ages less than or equal to 30 years. For the older group, the research model accounted for 53% of the variance in behavioural intention, and the path coefficients for the PE–BI, EE–BI, SI–BI, PP–BI and SL–BI links in the model were all significant (see Figure 5). Similarly, for the younger group, the proposed model explained 62% of the variance in behavioural intention, and the path coefficients for the PE–BI, PP–BI and SL–BI links in the model were significant. Nevertheless, the path coefficients for the EE–BI and SI–BI links were not significant for the younger group (see Figure 5). Next, we proceeded to examine how gender and age differences moderated the effects of performance expectancy, effort expectancy, social influence, perceived playfulness and self-management of learning on behavioural intention.

We conducted two multisample tests to examine the gender and age differences in the strength of the path coefficients respectively. In each of the two analyses, one path coefficient was constrained to be equal across the two gender groups or age groups. Using a χ^2 difference test, the resulting model fit was then compared to a base model, in which all path coefficients were freely estimated.

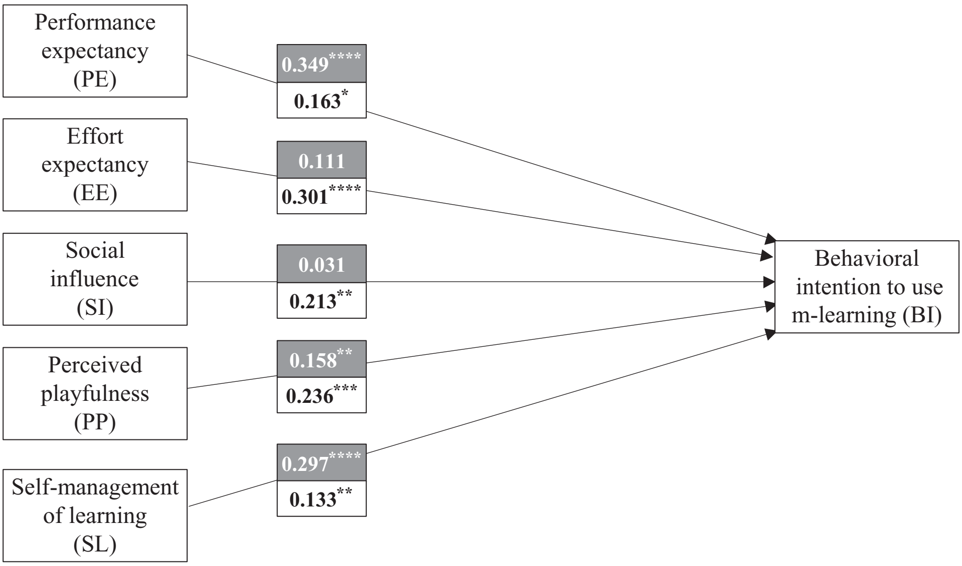

Figure 5: Standardised path coefficients[a] for younger and older people
[a]Coefficients for younger people are in the shaded boxes. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$; ****$p < 0.001$.

Table 5: Multisample comparison of paths for women and men

	χ^2	df	*$\Delta\chi^2$ from base model*
Unconstrained base model[a]	526.950	342	
Constrained paths[b]			
PE–BI	528.002		1.052[ns]
EE–BI	527.018		0.068[ns]
SI–BI	532.799		5.849**
PP–BI	527.543		0.593[ns]
SL–BI	531.989		5.039**

[a]Paths for the two gender groups were allowed to be freely estimated.
[b]The path specified was constrained to be equal across the two gender groups.
[ns]Not significant.
**$p < 0.05$.
df, degrees of freedom; PE, performance expectancy; EE, effort expectancy; SI, social influence; PP, perceived playfulness; SL, self-management of learning; BI, behavioural intention.

The results of the analyses of gender and age differences are shown in Tables 5 and 6 respectively. The path coefficients for the PE–BI, EE–BI and PP–BI links did not differ between the male and female groups. Thus, Hypotheses 2, 5 and 11 were not supported. Unexpectedly, social influence was found to be a stronger predictor of

Table 6: Multisample comparison of paths for older and younger people

	χ^2	df	$\Delta\chi^2$ from base model
Unconstrained base model[a]	572.505	342	
Constrained paths[b]			
PE–BI	573.567		1.062[ns]
EE–BI	575.538		3.033*
SI–BI	575.497		2.992*
PP–BI	573.523		1.018[ns]
SL–BI	574.192		1.687[ns]

[a]Paths for the two age groups were allowed to be freely estimated.
[b]The path specified was constrained to be equal across the two age groups.
[ns]Not significant.
*$p < 0.1$.
df, degrees of freedom; PE, performance expectancy; EE, effort expectancy; SI, social influence; PP, perceived playfulness; SL, self-management of learning; BI, behavioural intention.

behavioural intention for men than for women ($\Delta\chi^2 = 5.849$, $p < 0.05$), and self-management of learning influenced behavioural intention more strongly for women than for men ($\Delta\chi^2 = 5.039$, $p < 0.05$). Therefore, Hypotheses 8 and 14 were not supported. As expected, both effort expectancy and social influence were found to be stronger predictors of behavioural intention for older users than for younger users ($\Delta\chi^2 = 3.033$, $p < 0.1$ and $\Delta\chi^2 = 2.992$, $p < 0.1$ respectively). However, the two *p*-values were only significant at the 0.1 level, and the effects of the two constructs on intention were not significant for younger users. Thus, Hypotheses 6 and 9 were partially supported. In addition, the path coefficients for the PE–BI, PP–BI and SL–BI links did not differ between the older and younger groups. Thus, Hypotheses 3, 12 and 15 were not supported. Table 7 summarises the results of the hypotheses testing.

Discussion

Determinants of m-learning acceptance

Based on the UTAUT and prior studies, this study proposed an extended UTAUT to explore the factors affecting users' acceptance of m-learning by adding two constructs to the model: perceived playfulness and self-management of learning. This study is a pioneering effort in applying UTAUT to the newly emerging context of m-learning, which has only recently become available. The results indicate that performance expectancy, effort expectancy, social influence, perceived playfulness and self-management of learning were all significant determinants of behavioural intention to use m-learning. It is worth noting that the two newly proposed constructs, perceived playfulness and self-management of learning, were significant for all respondents ($\gamma = 0.21$, $p < 0.01$ and $\gamma = 0.20$, $p < 0.01$ respectively). Thus, this study has successfully extended the applicability of the UTAUT in an m-learning context by adding

Table 7: Summary of testing results

	Relationship	*Hypothesis*	*Testing result*
Main effect			
H1	PE–BI	Positive	Supported
H4	EE–BI	Positive	Supported
H7	SI–BI	Positive	Supported
H10	PP–BI	Positive	Supported
H13	SL–BI	Positive	Supported
Gender difference			
H2	PE–BI	Men > women	Not supported
H5	EE–BI	Women > men	Not supported
H8	SI–BI	Women > men	Not supported, Men > women found
H11	PP–BI	Men > women	Not supported
H14	SL–BI	Men > women	Not supported, Women > men found
Age difference			
H3	PE–BI	Younger > older	Not supported
H6	EE–BI	Older > younger	Partially supported
H9	SI–BI	Older > younger	Partially supported
H12	PP–BI	Younger > older	Not supported
H15	SL–BI	Older > younger	Not supported

H, hypothesis; PE, performance expectancy; EE, effort expectancy; SI, social influence; PP, perceived playfulness; SL, self-management of learning; BI, behavioural intention.

perceived playfulness and self-management of learning to the UTAUT, with careful attention being given to placing these constructs in UTAUT's existing nomological structure. The findings of this study provide several important implications for m-learning research and practice.

Consistent with Venkatesh *et al* (2003), the three constructs derived from UTAUT (performance expectancy, effort expectancy and social influence) had a significant, positive influence on behavioural intention to use m-learning. Performance expectancy was shown to be the strongest predictor of behavioural intention to use m-learning. It is therefore believed that an individual with high performance expectancy is more likely to adopt m-learning than an individual with lower performance expectancy. In order to promote the perceived usefulness and usage of m-learning, m-learning systems designers should focus on the development of valuable functions and content of m-learning systems for potential users. Based on Wang's (2003) suggestions on improving user satisfaction in e-learning contexts, m-learning systems should provide sufficient, up-to-date contents that can exactly fit users' needs. In addition, m-learning systems should enable users to choose what they want to learn, control their learning progress, and record their learning progress and performance. On the other hand, m-learning designers should pay attention to the importance of content presentation standards and communication standards, thus making their content portable to diverse types of mobile devices. It is also important for m-learning educators to increase users' performance expectancy of using m-learning systems. M-learning educators should take advantage of the value-adding characteristics of m-learning in promoting performance expectancy. For example, it seems to be a good strategy to emphasise that m-learning can help individuals get timely knowledge, make quick responses or decisions, and increase their competitive advantage in learning and business.

The results indicate that effort expectancy had a significant influence on individual intention to use m-learning. This means that the majority of users think m-learning systems should be easy to use. As Siau *et al* (2001) suggest, mobile devices have '(1) small screens and small multifunction key pads; (2) less computational power, limited memory and disk capacity; (3) shorter battery life; (4) complicated text input mechanisms; (5) higher risk of data storage and transaction errors; (6) lower display resolution; (7) less surfability; (8) unfriendly user-interfaces; and (9) graphical limitations' (p. 6). These limitations might make it difficult for users to figure out how to use m-learning systems. Thus, m-learning providers should improve the user friendliness and ease of use of m-learning systems in order to attract more users to use m-learning. For example, m-learning system designers should provide easier-to-use user interfaces hiding the complexity and details of the hardware and software involved, including touch screen menus, light pen data entry, handwriting recognition, natural language processing, etc. M-learning system designers can also develop personalised user interfaces, such as a one-touch key to make the operation of m-learning systems easier to learn and use for learners. These kinds of highly intuitive data entry capabilities could render m-learning systems more suitable for novices.

Social influence was found to have a significant effect on usage intention of m-learning. M-learning practitioners and educators should be aware of the importance of social influences. Once users start using and become familiar with an m-learning system, they may begin to persuade their colleagues and friends to adopt it. Thus, m-learning educators can promote m-learning to potential early adopters who tend to have a higher level of personal innovation in IT than do others (Agarwal & Prasad, 1998). When the number of m-learning users reaches a critical mass point, the number of later m-learning adopters is likely to grow rapidly (Rogers, 2003).

We also found that the two newly added constructs, perceived playfulness and self-management of learning, had a stronger influence on behavioural intention than the traditional UTAUT variable, social influence in the context of m-learning. Consistent with prior research (Lin, Wu & Tsai, 2005; Moon & Kim, 2001), this study also confirmed that perceived playfulness has a significant effect on behavioural intention to use Internet-based information systems. Given that the usage of m-learning is fully voluntary and that the target user group consists of a large number of people with very diversified backgrounds, making an m-learning system playful and enjoyable to interact with is crucial for attracting more users to the m-learning system. Chung and Tan (2004) conducted an exploratory study to investigate the antecedents of perceived playfulness, and proposed several antecedent categories of the construct, including cognitive aspects, website characteristics and motivation for searching. M-learning designers could refer to Chung and Tan's framework in developing playful m-learning systems.

Self-management of learning was also found to play a critical role in predicting m-learning acceptance. That is, an individual with a highly autonomous learning ability will be more likely to use m-learning than will an individual with a lower autonomous learning ability. This result establishes the predictive validity of the self-management of learning instrument proposed by Smith *et al* (2003) in predicting the behavioural intention to use m-learning. This finding can also help m-learning practitioners target the early adopters of m-learning systems and promote the advanced IT to them. For m-learning system developers, they can design m-learning systems with functions of time management, learning content hierarchy control and learning progress control to attract those who have highly autonomous learning abilities. On the other hand, pedagogical policy makers could program corresponding curriculums that can inspire and boost learners' capability of self-management of learning. Educators should diligently deliver these curriculums to cultivate students' habit of continuous self-learning and lifelong learning, which will in turn increase the number of users of m-learning systems in the near future.

Age and gender differences

Overall, the results indicate that the proposed determinants of m-learning acceptance exhibit an adequate ability to predict and explain an individual's behavioural intention to use m-learning. This study further investigated if any gender or age differences existed in the effect of these determinants on behavioural intention. For both gender groups, all determinants of behavioural intention, except social influence for the female group, were significant. Also, for both age groups (ie, the older group with ages >30 years and the younger group with ages ≤30 years), all determinants of behavioural intention, other than effort expectancy and social influence for the younger group, were significant.

We found that the effects of performance expectancy and perceived playfulness on behavioural intention were significant, but no gender or age differences were found to exist. That is, no matter what gender or age group an individual belonged to, those with high performance expectancy and playfulness perception towards using m-learning had a higher intention to use m-learning than those with lower performance expectancy and playfulness perception. Based on the findings, a universally accepted strategy for promoting m-learning usage is to make potential users perceive m-learning systems as playful and beneficial to them. Previous researchers suggest that an individual likes to encounter challenges and experiences the greatest perceived playfulness when challenges and skills are matched (eg, Csikszentmihalyi, 1975; Kiili, 2005; Woszczynski, Roth & Segars, 2002). If the challenge rendered by an m-learning system is significantly lower than the user's knowledge level, the user may feel bored. In contrast, if the challenge is significantly greater than the user's knowledge level, he or she may become frustrated. Thus, m-learning developers, game designers and educators can cooperate with each other to program mobile game-based learning systems capable of providing challenges that are closely matched to users' knowledge level, as well as contents that can exactly fit users' needs. For pedagogical policy makers, they can establish a highly motivational and rewarding environment to encourage the cooperation between m-learning researchers, educators and developers.

More importantly, the results indicate that there exist some significant gender and age differences in terms of the effects of the determinants on behavioural intention. First, we found that age differences moderate the effects of effort expectancy and social influence on behavioural intention, and this result partially supported prior research that has found that effort expectancy and social influence are stronger predictors of IT usage intention for older people than for younger people (Venkatesh *et al*, 2003). However, inconsistent with the UTAUT, both of these effects were only significant for older users, but insignificant for younger users. This may be due to the fact that younger people tend to have higher computer self-efficacy, and thus effort expectancy does not influence their decision making in terms of m-learning adoption. Besides, younger people appear to have higher levels of self-worth than older people, and thus tend to decide for themselves whether to adopt an advanced m-learning system without being influenced by those around them. However, justifying and validating our explanations/propositions need further investigations in future studies. According to our findings, in order to increase the use of m-learning among older people, m-learning system developers should improve the user friendliness of the user interface through touch screen, light pen data entry, handwriting recognition and even voice recognition mechanism. This will make older people perceive m-learning systems as easier to use and thus more likely to adopt them in the future. As some of the older people become familiar with the operation of m-learning systems, they would persuade their colleagues and friends into using the systems. Besides, policy makers and educators promoting the usage of m-learning can program and deliver some education and training courses in various mobile computing technologies to build older people's confidence in using mobile computers, PDAs and other mobile devices. Even if these courses are not directly related to m-learning, they can still help older people develop positive ease-of-use beliefs, which can in turn influence their behavioural intention to use m-learning.

Second, an unexpected vital and interesting finding from this study was that the effect of social influence on behavioural intention was significant for men, but insignificant for women, and this finding was contrary to prior research (Morris & Venkatesh, 2000; Venkatesh *et al*, 2000; Venkatesh *et al*, 2003), which has found that social influence is a stronger determinant of IT usage intention for women than for men. This may be due to women being more unfamiliar with relatively advanced and complex m-learning technology, making them less likely to be influenced by their close friends in the early stages of m-learning development. However, justifying and validating our explanations/propositions need further investigations in future studies. Based on our findings, m-learning developers and policy makers can first target the male group in promoting the newly developed m-learning systems. M-learning developers and educators can also cooperate with each other to develop some learning contents suitable and attractive to male users, such as mobile learning games, to make them become early adopters of m-learning. Once they decide to adopt m-learning, they can use their social influence to encourage their peers to use m-learning, thus facilitating the diffusion of m-learning.

Finally, self-management of learning was also unexpectedly found to be a stronger determinant of intention for women than for men, and this finding seemed to be opposite to the viewpoint proposed by Beck (1983), who suggested that men are more likely to display self-autonomous traits than women. With the increase in female employment in Taiwan, women have strengthened their capabilities in terms of self-management of learning in order to increase their competitive advantage in business. This may be why the effect of self-management of learning on m-learning usage intention was stronger for women than for men. Nevertheless, due to the unique feature of female employment in Taiwan, this finding may not be replicable in other cultures.

Limitations and future research

Although rigorous research procedures were employed, this study has some limitations that could be addressed in future studies. First, the findings and their implications discussed in this paper were based on one study that examined a particular technology and targeted a specific user group in Taiwan. The sampling method has potential bias, as a sample of willing respondents (ie, convenience sample) may not be generalisable. If future researchers wish to make generalisations from the data, they should randomise their sample to include other nationalities and geographical areas outside of Taiwan. Additional research is needed to make the findings of this study generalisable.

Second, the use of self-report scales to measure study variables suggests the possibility of a common method bias for some of the results. Future research should employ both objective and subjective measures, and examine the correspondence (or lack thereof) between them.

Third, the model is cross-sectional, in that it measures perceptions and intentions at a single point in time. However, perceptions change over time as individuals gain experience (Mathieson *et al*, 2001; Venkatesh & Davis, 1996; Venkatesh *et al*, 2003). This change has implications for researchers and practitioners interested in predicting m-learning usage over time. Additional research is needed to evaluate the validity of the investigated model and our findings. A dynamic model or longitudinal evidence would not only help predict beliefs and behaviour over time, but also enhance our understanding of the causality and the interrelationships between variables that are important to the acceptance of m-learning by individuals.

Finally, as m-learning is still in its infancy, we did not incorporate actual usage behaviour in the proposed model. This is not a serious limitation, as there exists substantial empirical support for the causal link between intention and behaviour (Taylor & Todd, 1995a; Venkatesh & Davis, 2000; Venkatesh & Morris, 2000). However, behavioural intentions are only partially useful, as their correlation with actual behaviour is low and mediated by many other variables. Thus, continued research is needed to investigate this more thoroughly by adding use behaviour, facilitating conditions and experience into the model. Although there are limitations, this study has value anyways as the findings provide several important implications for pedagogical policy makers, educators and m-learning system developers.

Conclusions

Based on the UTAUT and previous literature, this study investigated the determinants of m-learning usage intention and explored how gender and age differences moderate the influence of these determinants on usage intention. The contributions of this study to m-learning acceptance research are fivefold. First, in the spirit of exploration, it has extended and validated the UTAUT for the Taiwan m-learning context by adding perceived playfulness and self-management of learning to the UTAUT's nomological structure. Second, the results indicate that the effects of performance expectancy and perceived playfulness on behavioural intention were significant, but no gender or age differences were found to exist. Third, the effect of effort expectancy on intention was moderated by age, such that it was significant for older users but insignificant for younger users. Fourth, the effect of social influence on usage intention was moderated by gender and age, such that it was significant for men and older users, but insignificant for women and younger users. Finally, the effect of self-management of learning on intention was significant across all groups, but it was moderated by gender such that it was more significant for women than for men. The findings of this research will not only help m-learning practitioners develop better user-accepted m-learning systems and promote this new IT to potential users, but also provide insights into research on m-learning acceptance.

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Appendix: original survey items used in the study

Performance expectancy

PE1: I would find m-learning useful in my learning.
PE2: Using m-learning enables me to accomplish learning activities more quickly.
PE3: Using m-learning increases my learning productivity.
PE4: If I use m-learning, I will increase my chances of getting a promotion.

Effort expectancy

EE1: My interaction with m-learning would be clear and understandable.
EE2: It would be easy for me to become skilful at using m-learning.
EE3: I would find m-learning easy to use.
EE4: Learning to operate m-learning is easy for me.

Social influence

SI1: People who influence my behaviour will think that I should use m-learning.
SI2: People who are important to me will think that I should use m-learning.
SI3: The seniors in my organisation have been helpful in the use of m-learning.
SI4: In general, my organisation has supported the use of m-learning.

Perceived playfulness

PP1: When using m-learning, I will not realise the time elapsed.
PP2: When using m-learning, I will forget the work I must do.
PP3: Using m-learning will give enjoyment to me for my learning.
PP4: Using m-learning will stimulate my curiosity.
PP5: Using m-learning will lead to my exploration.

Self-management of learning

SL1: When it comes to learning and studying, I am a self-directed person.
SL2: In my studies, I am self-disciplined and find it easy to set aside reading and homework time.
SL3: I am able to manage my study time effectively and easily complete assignments on time.
SL4: In my studies, I set goals and have a high degree of initiative.

Behavioural intention to use m-learning

BI1: I intend to use m-learning in the future.
BI2: I predict I would use m-learning in the future.
BI3: I plan to use m-learning in the future.