Understanding the factors driving m-learning adoption: a literature review

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Abstract
Purpose – By surveying current literature, the purposes of this paper are twofold: to identify current situation of mobile learning (m-learning) adoption and specify the challenges and to identify the factors driving m-learning adoption.

Design/methodology/approach – The paper reviews literature related to: m-learning applications and challenging issues and adoption researches on m-learning and related topics. A reflection on the unique nature of m-learning adoption building upon the literature reviewed contributes to a new conceptual model.

Findings – Even if m-learning is fast evolving, the review of literature reveals a challenge as to how to promote m-learning adoption. In this light, the paper extends the scope of literature reviewed to the theories and factors relating to different roles m-learning users have into consideration, namely, technology user, consumer and learner, in an attempt to offer a more complete understanding of m-learning adoption. Insights are drawn from the proposed model.

Practical implications – A number of m-learning projects have been initiated worldwide while guidelines drawing from m-learning adoption research are in short supply. A research in this regard will contribute to a better understanding of developing acceptable m-learning service.

Originality/value – Based on a literature review, the paper not only specifies the current situation of m-learning adoption, but also develops factors influencing m-learning adoption to enrich our understanding of m-learning adoption – which help to facilitate and promote future empirical research.

Keywords Learning, Technology led strategy

Paper type General review

1. Introduction
Along with the popularity of mobile telephony, mobile learning (m-learning) presents to be a new education conduit helping people to acquire knowledge and skill in a ubiquitous manner with the support of mobile technologies. Over the past decade m-learning has grown from a minor research interest to be a thriving research field. It is increasingly used in workplaces, museums, schools, enabling a wide spectrum of new education possibilities. Naismith et al. (2004, p. 36) point out that m-learning would initiate a kind of “highly situated, personal, collaborative and long term; in other words, truly learner-centered learning”. Since nearly half of the world’s population are mobile phone owners and the figure will expand to 75 percent in 2011 (Portio Research, 2007),
m-learning enables citizens covering all social-economic levels to access training and education in a ubiquitous and even lifelong manner, using their personal devices.

Despite widespread enthusiasm, m-learning is still in an embryonic stage, and its theoretical underpinnings have not yet matured (Muyinda, 2007). In particular, the issues regarding how to promote learners’ acceptance of m-learning are largely unsolved. Research in this regard is in short supply. Note that even if mobile technology is one of the prerequisites of m-learning, the availability of mobile technology per se does not guarantee that its potential will be realized. First, recent reports show that whilst advanced phones along with 3G mobile telephony are increasingly diffused, advanced mobile services have not yet found their ways into the consumers’ everyday lives and consumers in general are still hesitant to use these services (Carlsson et al., 2005, 2006a; Walden et al., 2007). There is no reason why m-learning services should be an exception. Second, from the perspective of distance learning, a high dropout rate is frequently reported in for instance online courses, which can be as high as 50 percent in some cases (Sulcic and Sulcic, 2007). As m-learning is frequently described as a subset of technology-mediated distance learning, there is some concern whether a high dropout rate will also happen. For instance, in the research conducted by Attewell and Savill-Smith (2003), Attewell (2005), an important proportion of learners did not show any preference for future use of m-learning at the end of the projects. In order to deliver acceptable m-learning services and to retain the developing cost of service providers, it is important to investigate the learners’ adoption process of m-learning.

It is important to note that in m-learning contexts learners are trusted with great autonomy and that they are in charge of their own learning. Unlike learning in conventional formal contexts, the use of m-learning posits to be a new option rather than a compulsory responsibility. Hence, the key issues for the success of m-learning lies in an individual’s subjective willingness and cognitive engagement in m-learning activities. Based on previous researches on mobile information system (IS), we consider different roles m-learning users have when adopting m-learning services, namely technology user, consumer, and learner. Two theories, namely subjective task value and readiness for online learning, are integrated with technology acceptance model (TAM) in combination with two new ingredients – perceived quality and perceived mobility, in order to develop a sound conceptual model. The rest of paper is structured as follows. After a review of current m-learning research in Section 2, a conceptual model for m-learning adoption is proposed and elaborated in Section 3, followed by a brief conclusion of the study in Section 4.

2. Outline of m-learning researches and applications
Both for education and business, m-learning potentials and benefits abound. In addition to common students, learners “who were hard to reach, hard to engage, or hard to access – for example young offenders, traveler communities, disengaged teenagers and work-based learners in difficult contexts” appears to be a hot topic for m-learning research (Attewell, 2005; Stead, 2006, p. 1; Duncan-Howell and Lee, 2007). Funded by the European Commission, a pan-European project – m-learning for instance has been run since 2001 for educationally disadvantaged young adults, such as dropouts and unemployed, to improve their literacy and numeracy skills. Further, m-learning in many countries has been developed to be a sort of new education products, generating new sources of revenue for business communities. In the USA, Ambient Insight (2008)
reports that despite current economic crisis, m-learning market in USA is still growing. It reached $538 million in 2007 and will continue to develop at a five-year compound annual growth rate of 21.7 percent. “In the last 18 months”, stated Ambient Insight (2008, p. 5), “all the major educational publishers have launched mobile content” in the USA. Astonishingly, m-learning also attracts the interest of leading handheld device manufacturers, such as Nokia and Apple, to make a step into this growing market. For instance, in China market, almost all the mobile manufacturers have started to offer m-learning services in their products since 2007.

Despite aforementioned potentials, the uptake of m-learning services in general is much slower than expected. Patten et al. (2006) classify current m-learning services into seven distinct categories, namely administrative, referential, interactive, micro-world, data collection, location aware, and collaborative. They further conclude that much of the work presented across the categories has limited success “in the field” (Patten et al., 2006). By investigating the behavior of both teachers and students, Corbeil and Valdes-Corbeil (2007) state that familiarity with handheld devices and technologies does not ensure that teachers and students would like to use them in teaching and learning scenarios (Corbeil and Valdes-Corbeil, 2007). Pozzi (2007) points out that m-learning service in most cases is still used occasionally and in a supplemental manner in education settings. In fact, these research findings support the proposition made by Carlsson et al. (2005), who argue that the adoption of mobile technology and services is asynchronous and that the adoption of mobile technology per se does not guarantee the adoption of mobile services.

From a technology viewpoint, many scholars state that there are many technical restrictions that may impede m-learning adoption. Wang et al. (2009) note that technical challenges make the adaptation of existing e-learning services to m-learning difficult, and that users may not be inclined to accept m-learning. These restrictions, as discussed by Maniar and Bennett (2007), include following eight aspects:

1. small screen size and poor screen resolution;
2. lack of data input capability;
3. low storage;
4. low bandwidth;
5. limited processor speed;
6. short battery life;
7. software issues and interoperability; and
8. lack of standardization.

Based on two m-learning projects in the UK and a review of usability findings from the empirical studies of m-learning, Kukulska-Hulme (2007) points out that m-learning activity continues to take place on devices which are not designed for educational use, and that therefore usability issues are frequently reported. These issues may include physical attributes (e.g. size, weight, memory, and battery life), content and software applications (e.g. students seem to be more comfortable with built-in functions), network speed and reliability, and physical environment (e.g. use in rainy conditions, risk of loss and theft).
A handful of adoption studies are carried out to investigate learners’ m-learning activities. Phuangthong and Malisawan (2005) put forward an adoption model in their preliminary research on m-learning, and propose that perceived enjoyment would have a direct impact on people’s attitudes. Based on 245 completed questionnaires, Ju et al. (2007) indicate that perceived usefulness significantly affects users’ attitude, which further impact users’ intention to use m-learning. Building upon TAM, Huang et al. (2007) point out that individual differences significantly influence a user’s acceptance of m-learning in which the perceived enjoyment and perceived mobility predict users’ adoption intention. Through a study of 330 usable responses from five organizations, Wang et al. (2009) find that performance expectancy, effort expectancy, social influence, perceived playfulness, and self-management of learning are significant determinants of the behavioral intention to use m-learning. Despite these studies, it has to be noted that thus far m-learning has not yet had great impact on education context and the studies which address the adoption of mobile information and communications technologies in school settings are still lacking (Pozzi, 2007; Perry, 2002). Consequently, insufficient research on m-learning adoption results in a lack of a complete view of m-learning adoption. In light of this, we believe that in addition to current m-learning literature, a more extensive review to the relevant adoption literature is essential in order to extend the scope of our theoretical support and to identify the possible predictors of m-learning adoption.

In a meta-analysis of mobile commerce literature which covered several key publication sources from 2000 to 2006, AlHinai et al. (2007) extend the researching findings of Kim et al. (2007) and Pedersen et al. (2002), and contend that it is necessary to consider the threefold roles people played in adoption research, namely technology user, network member, and customer. They further conclude that researchers may need to consider and integrate theories concerning the different roles people play in other than ISs (AlHinai et al., 2007). Following this notion, we made an extensive review of literature from the perspective of both mobile services and consumer in general, and technology-mediated learning in particular. As m-learning is generally described as the intersection between mobile services and distance education, or as a natural extension of e-learning, the m-learning user in fact has a new role: learner. Concerning this, the topics reviewed and main findings are specified in Table I. However, as papers concerning m-learning adoption are limited but broadly distributed, our scope of review includes both conferences and journal papers, most of which are retrieved from Emerald and ScienceDirect database.

3. Factors driving m-learning adoption
In this section, we summarize the finding from reviewing the literature concerning three roles m-learning users play as aforementioned. Key theories and factors in relation to m-learning adoption are specified.

3.1. M-learning user as a technology user
3.1.1. Technology acceptance model. Adoption of innovations has been intensively investigated by researchers and practitioners of many disciplines, in which the TAM is one of the most widely accepted and applied models (Davis, 1989). TAM originates from the theory of reasoned action (TPA; Ajzen and Fishbein, 1975, 1980). TPA proposes that beliefs affect attitude, which influences intention, while intention in turn brings
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<tr>
<th>Authors</th>
<th>IS applications</th>
<th>Samples</th>
<th>Results</th>
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<tr>
<td>Ju et al. (2007)</td>
<td>M-learning</td>
<td>245 university students</td>
<td>Perceived self efficacy significantly influences perceived ease of use, which positively impacts perceived usefulness. Perceived usefulness significantly affects users’ attitude which further impacts the intention to use m-learning</td>
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<td>Huang et al. (2007)</td>
<td>M-learning</td>
<td>313 university students</td>
<td>Individual differences have a great impact on user acceptance in which the perceived enjoyment and PMV can predict users’ intention of using m-learning</td>
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<tr>
<td>Wang et al. (2009)</td>
<td>M-learning</td>
<td>330 useful responses from five organizations</td>
<td>Performance expectancy, effort expectancy, social influence, perceived playfulness, and self-management significantly impact behavioral intention</td>
</tr>
<tr>
<td>Liu (2008)</td>
<td>M-learning</td>
<td>A conceptual model</td>
<td>Based on the basic structures of UTAUT, a model is proposed with an integration of self-efficacy, mobility, attainment value, perceived enjoyment, and self-management of learning, to explain learners’ behavior intention</td>
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<tr>
<td>Phuangthong and Malisawan (2005)</td>
<td>M-learning</td>
<td>Preliminary research with 385 responses</td>
<td>In addition to basic constructs of TAM, perceived enjoyment was included to explain users’ behavior Perceptions of relative advantage and compatibility are significantly related to users’ intention to the use of e-learning; prior experience affects learners’ adoption of technology</td>
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<td>Liao and Lu (2008)</td>
<td>E-learning web sites</td>
<td>137 university students</td>
<td>Perceived self-efficacy is a critical factor affecting learners’ satisfaction while perceived usefulness and perceived satisfaction impact learners’ behavioral intention to use the e-learning system</td>
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<td>Liaw (2008)</td>
<td>Blackboard e-learning system</td>
<td>424 university students</td>
<td>TAM is found to be a solid theoretical model where its validity can be extended to multimedia and e-learning contexts (continued)</td>
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<td>Saadé et al. (2007)</td>
<td>Multimedia learning</td>
<td>362 students</td>
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<td>Authors</td>
<td>IS applications</td>
<td>Samples</td>
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<td>Shih (2008)</td>
<td>Web-based learning</td>
<td>350 part-time students</td>
<td>This study concludes that learners' efficacy control and efficacy expectations can be used to guide their adaptation learning behaviors on the web.</td>
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<tr>
<td>Chiu and Wang (2008)</td>
<td>Web-based learning</td>
<td>286 part-time students</td>
<td>Performance expectancy, effort expectancy, computer self-efficacy, attainment value, utility value, and intrinsic value were significant predictors of individuals' intentions to continue the use of web-based learning, while anxiety had a negative effect.</td>
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<tr>
<td>Chiu et al. (2007)</td>
<td>Web-based learning</td>
<td>221 students of a web-based learning program</td>
<td>Attainment value, utility value, intrinsic value, distributive fairness, and interactional fairness are predictors for learners' satisfaction, while utility value and satisfaction exhibited significant positive effects in shaping learners' intention to continue using web-based learning.</td>
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<tr>
<td>Chiu et al. (2005)</td>
<td>E-learning</td>
<td>189 students using e-learning services</td>
<td>The result suggest that perceived usability, perceived quality, perceived value, and usability disconfirmation impact perceived satisfaction while perceived satisfaction determine users' continuance intention to use e-learning.</td>
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<td>Eom and Wen (2006)</td>
<td>Online education</td>
<td>397 students enrolled in web-based courses</td>
<td>The research found that course structure, self-motivation, learning styles, instructor knowledge and facilitation, interaction, and instructor feedback significantly influenced students' satisfaction.</td>
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<td>López-Nicolás et al. (2008)</td>
<td>Advanced mobile services</td>
<td>542 valid questionnaires by households</td>
<td>Social factor is found to have an important impact on people's decision to adopt advanced mobile services. The results also suggest that both ease of use and perceived usefulness can be linked to diffusion-related variables, such as social influence and perceived benefits.</td>
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<td>Koivumaki et al. (2008)</td>
<td>Mobile services</td>
<td>243 service users</td>
<td>Whilst duration of the use does not effect consumers' perceptions of mobile services, the familiarity of the device and user skills have an impact on the perceptions of the services.</td>
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<th>Authors</th>
<th>IS applications</th>
<th>Samples</th>
<th>Results</th>
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<tr>
<td>Kargin and Basoglu (2007)</td>
<td>Mobile services</td>
<td>A qualitative research with 12 interviewees</td>
<td>Ease of use and usefulness are the most significant factors in mobile service adoption. Content and mobility are dominant factors from a service perspective while social influence is also important.</td>
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<td>Carlsson et al. (2006b)</td>
<td>Mobile services</td>
<td>300 Finnish consumers</td>
<td>Performance and effort expectancies are found as predictors for behavioral intention, but the social influence cannot be used as predictor.</td>
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<td>Shin (2007)</td>
<td>Mobile internet</td>
<td>986 adult Koreans</td>
<td>Perceived quality and perceived availability are found to have significant influence on users’ extrinsic and intrinsic motivation to use mobile internet in Korea.</td>
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<td>Cheong and Park (2005)</td>
<td>Mobile internet</td>
<td>1,279 replies from an online survey</td>
<td>The research identified the positive impact of perceived playfulness and the negative impact of perceived price level in forming the attitude and adoption intention. Perceived content and system quality are positively affecting the perceived usefulness. In addition, there is a causal relationship between internet experience and perceived ease of use.</td>
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<tr>
<td>Lu et al. (2005)</td>
<td>Wireless internet services</td>
<td>357 MBA students</td>
<td>The research revealed strong relationships between personal innovativeness and social influences and the perceptual beliefs – usefulness and ease of use, which further affect intentions to adopt innovation.</td>
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<tr>
<td>Lu et al. (2008)</td>
<td>Wireless mobile data services</td>
<td>1,432 individuals living in five cities in China</td>
<td>The research revealed the importance of perceived usefulness, ease of use, personal innovativeness in IT and mobile trust belief in affecting individuals’ intention to use wireless mobile data service.</td>
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about behaviors. TAM adapts this belief-attitude-intention-behavior relationship and further postulates that two beliefs (perceived ease of use and perceived usefulness) are the key beliefs leading to user acceptance of information technology (IT). Perceived ease of use refers to the degree to which a user believes that using a particular service would be free of effort while perceived usefulness is defined as the degree to which an individual perceives that using a particular system would enhance his or her job performance (Davis, 1989). Further, perceived ease of use is supposed to influence perceived usefulness, which directly affects both attitude and intention (Davis, 1989).

An extensive body of research has demonstrated the robustness and validity of TAM in predicting the acceptance of various IT innovations. Regarding advanced mobile services, TAM have been widely examined in for instance mobile chat (Nysveen et al., 2005a, b), mobile credit card (Amin, 2007), mobile games (Ha et al., 2007), mobile parking (Pedersen, 2005), business-to-consumer mobile commerce (Khalifa and Shen, 2008), and mobile ticketing (Mallat et al., 2008). Concerning educational innovations, TAM offers a concrete theoretical background to investigate learners’ adoption intention in multimedia learning environments (Saadé et al., 2007) and e-learning (Lee, 2006; Ngai et al., 2007). As TAM is developed to be a parsimonious model (Davis, 1989), many scholars seek to increase its explanatory power by integrating related theories, like flow theory (Liu et al., 2009; Lu et al., 2009), media richness theory (Liu et al., 2009) and task technology fit theory (Dishaw and Strong, 1999). In light of this, the basic structures of TAM therefore are adopted as the key foundation for our research model.

3.1.2. Unique nature of mobile services: perceived mobility. Mobility is perceived to be the most significant feature of mobile services (Mallat et al., 2006). According to Kakihara and Sørensen (2001), the concept of mobility consists of three distinct dimensions of human interaction, namely spatial, temporal, and contextual mobility. As mobile technology conforms to the increasingly mobile nature of people’s lifestyle, mobility is accordingly perceived as the critical advantage of m-learning that makes it distinct from traditional education approaches, such as computer-based learning. Using mobile technology, learners can access education without the restrictions of place and time. Also, to tolerate the small screen of mobile phones, learners’ perception of the benefits from increased flexibility and mobility is important. The research by Kaigin and Basoglu (2006), and Mallat et al. (2008), provide clear evidence that perceived mobility can affect individuals’ decision to adopt particular mobile services. Huang et al. (2007) state that perceived mobility value (PMV) has a significant influence on user intentions of using m-learning. Hence, we propose that perceived mobility is an important variable impacting m-learning adoption.

3.2. M-learning user as a consumer: perceived quality. Currently, m-learning courses and products are mostly sold as a kind of education products, such as in USA and China. M-learning users therefore gain a role as consumers as well. For customers perceived quality of products or services impacts customer’s intentions to use them. Perceived quality is defined by Zeithaml (1988) as “the consumer’s judgment about a product’s overall excellence or superiority”. Quality research tends to be most important stream of services research. Specifically, many researches tend to divide perceived quality into different dimensions regarding different research subjects (Parasuraman et al., 1985, 1988), due to the fact that perceived quality is product-related (Chu and Lu, 2007). Concerning IS, a number of scholars...
suggest that the quality of both technology infrastructure and service delivered would impact perceived overall quality, which further affects users’ acceptance intention. Delone and McLean (1992) propose the notion of information quality and suggest that information quality plays an important role in building successful ISs. Cheong and Park (2005) show that perceived system quality and perceived content quality are positively related to users’ perceived usefulness of the mobile internet. Lin and Lu (2000) employ information quality as a part of IS quality, and argue that information quality is an important determinant of perceived usefulness. From a knowledge management viewpoint, Dai et al. (2007) suggest that content quality is one of the significant determinants of perceived usefulness of online social information services. Further, many scholars tend to study perceived quality of IS in a global view. Yang et al. (2005) outline six dimensions of quality and further find a positive causal relationship between the perceived overall service quality and a user’s satisfaction towards a web portable. Measuring both the system issues and content issues, Chiu et al. (2005) and Liaw (2008) found that perceived quality is a significant predictor of perceived satisfaction with e-learning. Since m-learning can also be perceived as a kind of advanced information service, it stands to reason to use perceived quality as an important component of our model. Also, based on prior studies, the quality perceived in our research model includes both two dimensions: perceived content quality and perceived system quality.

3.3. M-learning user as a learner

3.3.1. Subjective task value of expectancy-value theory. Expectancy-value theory of achievement motivation is proposed by Eccles et al. (1983) based on the work of Atkinson (1964). According to the theory, achievement behavior is predicted by two structures: expectancy for success in a given task and the value an individual places on the task. With the same belief of behavioral outcome, people may hold different evaluations of the attractiveness of that outcome (Bandura, 1997). The one who values the outcome will be more motivated to attain the outcome, which may compensate for low probabilities of success as well as the monetary and nonmonetary cost perceived. In contrast, even when individuals feel competent that they can successfully accomplish a task, they may not choose to participate if the task value perceived is low (Cole et al., 2008). Eccles and Wigfield (1995) outline four motivation components of subjective task value:

1. attainment value;
2. intrinsic value;
3. utility value; and
4. cost.

Attainment value is personal importance of doing well with regard to self-schema and core personal values, such as achievement (Chiu and Wang, 2008; Mori and Gobel, 2006). Wigfield and Eccles (1992) argue that tasks will have higher attainment value to the extent that they allow the individual to confirm salient aspects of a learner’s self-schema. A positive relationship between attainment value and continuance intention has been identified in, for instance, Mathematics, English studies as well as web-based courses studies (Meece et al., 1990; Mori and Gobel, 2006; Chiu and Wang, 2008). Utility value is the extent to which individuals perceive the task relates to their current and future goals.
It is self-evident that learning activities on a large-scale do not bring an instant reward, but more frequently, benefit the learner in the long run. In this regard, utility value posits to be a kind of extrinsic motivation which also has a major influence on students’ learning behaviors (Chiu and Wang, 2008). Intrinsic value is the extent to which an activity is perceived to be enjoyable in its own right, apart from any performance consequences that may be anticipated (Davis et al., 1992). Intrinsic value is closely related to perceived entertainment, perceived enjoyment and perceived playfulness, and is widely applied to investigate people’s perception of education innovation (Wang et al., 2009; Chiu and Wang, 2008). As the process of learning may also bring a sense of pressure, it is necessary to make learning activities more enjoyable in order to be accepted. It is also reported that when the process is novel, interesting, enjoyable, exciting, and optimally challenging, students will be intrinsically motivated to pursue the learning activities. Cost refers to how the decision to engage in a learning activity limits access to other activities (e.g. playing a mobile game or talking to friends) (Wigfield and Eccles, 2000). It may also include emotional cost needed to accomplish the activity, such as fear of failure. A sense of isolation, anxiety, lack of personal contact, delay in responses and risk of arbitrary learning may contribute to the cost of distance learning based on the studies of Fozdar and Kumar (2007) and Chiu and Wang (2008). This theory has already been widely used in explaining learners’ educational motivation and academic achievement in a number of studies (Eccles et al., 1984; Eccles, 1987; Meece et al., 1990; Mori and Gobel, 2006; Cole et al., 2008). Eccles et al. (1983) and Wigfield and Eccles (1989) found that the components of the subjective task value can be used to predict students’ intentions to carry out mathematics and English studies in traditional classroom education contexts. Testing the subjective task value of expectancy-value theory in web-based learning, Chiu et al. (2007) found that attainment value, utility value, and intrinsic value are significant variables to predict a learner’s satisfaction and these variables further influence a learner’s continuance intentions.

3.3.2. Readiness for online learning. The notion of readiness for online learning is first proposed by Warner et al. (1998). The theory focuses on the differences of personal attributes in influencing learners’ academic performance and learning behaviors in online learning contexts. The theory is further developed and empirically studied by McVay (2000) and Smith et al. (2003), who yield two-factor structures to explain the personal attributes. According to their studies, the factors for understanding readiness for online learning include the “comfort with e-learning” and “self-management of learning”. Self-management of learning refers to the degree to which an individual perceives he/she is self-disciplined and able to engage in autonomous learning (Smith et al., 2003). When away from pre-designed learning environment which help to guide learners on their learning activities, a capability and willingness to take control of and self-manage their own learning is especially important for the success in distance settings. Indeed, the need for self-direction, or self-management of learning, runs clearly across the distance education and resource-based flexible learning literature (Smith et al., 2003). Similarly, in m-learning contexts, learners are frequently socially and physically separated from both teachers and peer students, where learners themselves become in charge of their own learning. This initiates a strong requirement for learners to be able to self-manage their personal learning issues. McFarlane et al. (2007) point out that, the increased learner autonomy from m-learning posits a heightened requirement for appropriate capabilities of locating and evaluating resources, critical thinking,
and reflecting on their own learning. The research of Wang et al. (2009) found that learners with a higher level of self-management capability would more likely engage in m-learning activities. Also, self-directed learning is widely found to be a strong factor for predicting learners’ academic success in a traditional classroom as well as in online learning contexts (Long, 1991; Hanna et al., 2000).

The conceptual model is shown in Figure 1.

4. Conclusion
Indeed, there has to date seldom any communication equipment used as popular as a mobile phone. It comes as no surprise that people are eager to find ways to apply these portable and personal handhelds for education purposes. Currently, m-learning has not reached its maximum potential and the gap between what is offered and what is used is apparent. Whilst digital learning materials of different formats are generally available, very limited use of it has been made by learners via mobile phones. Owing to the limited screen size and input difficulties, individuals may be reluctant to adopt this new education approach. Therefore, technology alone does not bring about m-learning, and the key success factor is to understand the concerns of learners and to identify the determinants which lead to learners’ willingness to adopt m-learning.

However, it is a challenge to apply traditional adoption models in an m-learning context. For instance, Carlsson et al. (2006b, p. 8) argue that, TAM and unified theory of acceptance and use of technology (UTAUT) were developed to describe and explain IT innovation adoption in organizational contexts, “but the mobile technology adoption is more individual, more personalized and focused on the services made available by the technology”. In addition, an m-learning user behaves as a learner instead of employee, and on the other hand, m-learning is a kind of education services, which is different from traditional services. Based on an extensive review of researches on m-learning, technology-mediated learning as well as mobile services, this paper offers a comprehensive, yet parsimonious model. It contributes to the growing literature on m-learning by grounding new theories and variables into well-established model (TAM)

Figure 1.
and applying them to a new context of m-learning. It fills a gap by extending TAM to social contexts when technology user gains a new role – learner. Also, the paper provides several preliminary insights into the adoption of m-learning. It highlights the fact that the familiarity with and the adoption of mobile technologies per se does not guarantee the adoption of m-learning. To ensure a continuous and effective use of m-learning, promoting user’s self-management capability of learning is essential, since it is learners themselves who are in charge of their own learning issues. Further, unlike most mobile services, m-learning does not always bring an immediate sense of gratification, but probably rewards a learner in the long term, hence the use of m-learning will depend on how learners value their education tasks. In addition, as mobile technologies and devices are used as a conduit to transmit training and education to the learner, the quality of learning materials delivered would affect the perceived quality of services as a whole. Hence, it is essential to increase the relevancy, timeliness, adequacy, and uniqueness of learning materials that are delivered. The proposed model provides a coherent framework for further empirical research. An empirical testing of the conceptual model would extend the boundaries of current theoretical foundations, and enrich our understanding of m-learning. This in turn would offer a set of possible guidelines for practitioners to promote the diffusion of m-learning.

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**Further reading**


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