Exploring the Factors Driving M-Learning Adoption

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Exploring the Factors Driving M-Learning Adoption

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ABSTRACT
Mobile Learning (m-learning) is quickly spreading in many regions of the world. However, research addressing the driving factors for m-learning adoption is lacking. This study proposes a revised TAM by integrating perceived long-term usefulness and personal innovativeness. The adoption model was found to explain 60.8 percent of m-learning intentions based on 209 completed questionnaires. Perceived near-term/long-term usefulness and personal innovativeness are found to be significant motivators for m-learning adoption. The results in this study also suggest that, as most adoption theories are originated from a work-related context by employees, it is important to employ the construct of perceived long-term usefulness (the utility value) in adoption research when applied to education-related innovations.

Keywords
M-learning, mobile learning, mobile services, TAM, long-term usefulness, technology adoption.

INTRODUCTION
Along with a rapid proliferation of 3G mobile telephony, mobile learning (m-learning) has become a thriving research field. It is ushering us into a new era of training and learning. As Naismith et al. point out m-learning would enable a kind of ‘highly situated, personal, collaborative and long term; in other words, truly learner-centered learning’ (Naismith, Peter, Giasemi and Sharples, 2004, 36-36). In a similar way Sharma and Kitchens (2004) state, that the advent and subsequent development of mobile learning indicates a profound evolution from distance learning (d-learning) to electronic learning (e-learning) and then on to m-learning.

Nonetheless, recent research on m-learning reveals a new challenge as to how to promote the adoption of m-learning. In Attewell and Savill-Smith (2003, 2005), an important proportion of the learners did not show any preference for future use of m-learning at the end of the projects. A survey conducted by Corbeil and Valdes-Corbeil (2007) indicated that many students and education programs are still not ready for m-learning despite their familiarity with advanced mobile technologies. Based on a review of both current usability studies and two m-learning projects in UK, Kukulska-Hulme (2007) argued that m-learning activity continues to take place on devices which are not designed for educational use, and that usability issues are frequently reported. This is in line with the results of a series of large consumers studies (with a random sample of 1000 consumers and a response rate around 50%) of the use of mobile services carried out in Finland annually in 2002-2008 (cf. Bouwman, Carlsson and Walden (2008), Bouwman, Carlsson, Molina-Castillo and Walden (2007)). These studies show that consumers – as a general rule – do not use the technological features of advanced mobile phones but are satisfied with the traditional voice and SMS services. Maniar, Bennett, Hand and Allan (2008) suggest that there are many possible technological restrictions impeding m-learning adoption, such as small screen size, and poor screen resolution. However, research addressing the key motivators for m-learning acceptance is in short supply.

Further, as most of current IT adoption theories, such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), are originated in work-oriented innovations, an examination of the validity of TAM concerning educational innovations is necessary. In this study, we include both long-term usefulness and personal innovativeness in the TAM to explain learners’ intention to adopt m-learning. The rest of the paper is structured as follows: after a brief introduction of the current situation of m-learning development in the next section, a theoretical background and the research model are presented. This is followed by a detailed report on the results of the study and a discussion on a number of implications and possible conclusions. Finally, some limitations of this study are discussed.
OUTLINE OF M-LEARNING DEVELOPMENT

Currently, m-learning is quickly spreading in many regions of the world with the support from both government and business communities. As personal phones are to a large degree the only effective approach to access marginalized citizens, m-learning posits to be a good method to tackle some difficult social problems in Europe. For instance, a pan-European project — m-learning\(^1\) - funded by the European Commission has been run since 2001 for educationally disadvantaged young adults - such as dropouts and unemployed - to improve their literacy and numeracy skills. Many innovative m-learning applications have been implemented in European countries, in which a diversity of handhelds specially designed with m-learning functionalities have been offered in many tourist attractions locally, such as the Louvre Museum and the palace of Versailles. In the U.S., a recent report indicates that the tipping point for m-learning industry has been reached and that the market is growing fast (Adkins, 2008). According to the report from Ambient Insight (Adkins, 2008), despite the current economic crisis, the m-learning market reached $538 million in 2007 and it will continue to develop at a five-year compound annual growth rate (CAGR) of 21.7%. Mobile device manufacturers, such as Apple, have a significant influence on the m-learning market. By February 2009, over 100,000 educational audio and video files supporting mobile learning are already available in iTunes U.

In China, the concept of m-learning started to become popular in 2005. Device manufacturers played a central role in offering m-learning products and services. A series of new phone models are specifically designed for m-learning. At the end of 2005, a domestic mobile manufacturer—Bird Corp., launched a marketing campaign with the theme of ‘learning in mobiles’ for selling its new mobile phones with a powerful English learning function. Well-known material for English study were included in Bird’s mobile phone, and more learning material can be downloaded to a memory card from its cooperating partners\(^2\). Bird sold 15 million mobile phones in the Chinese market in 2006, and has become one of the leading domestic mobile manufacturers in China (Yesky news, 2007). In September 2007, Nokia announced that the widely adopted BBC English teaching material will be included in its English learning service termed ‘Trip of Pioneers’. Nokia further launched an online learning platform to offer services for its mobile users, including Real English, Take Away English, Quizzes, and BBC’s other classic courses. In addition, a variety of m-learning courses are provided by Nokia, such as courses in management, golf, cooking, Yoga, health preserving and so on. Many of these courses are sold with a price of RMB¥ 2 per course. Currently, almost all mobile manufacturers, including Amoi, Lenovo, LG, OKWAP and GIGANYTE, are offering m-learning services in some of their products. A number of mobile manufacturers are marketing their m-learning enabled phones through advertisements in various media channels, particularly in influential TV channels.

THEORETICAL BACKGROUND AND THE RESEARCH MODEL

Adoption of innovations has been intensively investigated by both researchers and practitioners of many disciplines, in which TAM appears to be one of the most widely applied models (Davis, 1989). The structures of TAM have been extended and examined in a diversity of mobile services, such as mobile chat (Nysveen, Pedersen and Thorbjørnsen, 2005), mobile credit card (Amin, 2007), mobile games (Ha, Yoon and Choi, 2007), mobile parking (Pedersen, 2005), B2C mobile commerce (Khalifa and Shen, 2008) and mobile ticketing (Mallat, Rossi, Tuunainen and Öörni, 2008). Concerning education, TAM has been used to investigate the antecedents affecting people’s behavioral intention in multimedia learning environments (Saadé, Nebebe and Tan, 2007) and e-learning (Lee, 2006; Ngai, Poomb and Chana, 2007). An extensive body of previous research has demonstrated the robustness and explanatory power of TAM in predicting the acceptance of various IT innovations.

TAM originates from the theory of reasoned action (TRA), and postulates that two beliefs (perceived ease of use and perceived usefulness) predict the attitudinal component of intention to use (Davis, 1989). User’s intention in turn is an effective predictor of the actual behavior itself. Perceived ease of use refers to the degree to which a user believes that using a particular service would be free of effort. Perceived usefulness is defined as the degree to which an individual perceives that using a particular system would enhance his or her job performance. Further, perceived usefulness is influenced by perceived ease of use.

Nonetheless TAM was met with some criticism as being a black box (Bouwman, Wijngaert and Vos, 2008), while the perceived usefulness construct suffers from being rather broadly based (Moree and Benbasat, 1991). Even if relative advantage is analogous to perceived usefulness, it has been criticized as being poorly explicated and measured (Tornatzky and Klein, 1982). Drawing from a review of IS and psychology literature, Chau (1996) argued that perceived usefulness in fact consists of two distinct aspects: near-term usefulness and long-term usefulness. He further found that both perceived

1 http://www.m-learning.org/
2 www.englishto.com
near-term and long-term usefulness have significant impacts on the intention to use IT. Thompson, Higgins and Howell (1991) adopted the concept of near-term/long-term usefulness to analyze the adoption of personal computers. They proposed a construct of job-fit and defined it as “the extent to which an individual believes that using a technology can enhance the performance of his or her job”, which is similar to the perceived usefulness in TAM (Thompson et al., 1991, pp: 129). Meanwhile, they defined long-term consequences of use as ‘outcomes that have a pay-off in the future’ (Thompson et al., 1991, pp: 129). In their study, significant impacts of both structures on personal computer utilization were found as well (Thompson, Higgins and Howell, 1994). Regarding adoption of Internet at work, Chang and Cheung (2001) found that perceived near-term consequences have a significant positive influence on long-term consequences. In addition, perceived long-term usefulness has been proposed or validated to be an important antecedent in studying a number of IS/IT innovations (e.g. Jiang, Hsu, Klein and Lin, 2000; Lu, Yu, and Yao, 2003).

Note that constructs analogous to perceived long-term usefulness are widely used in education research. Cole, Bergin and Whittaker (2008, pp: 316) defined usefulness as ‘the student’s perception that the task will be useful to meet some future goal’. Concerning math, English, science and social study, their empirical study suggest that if students don’t recognize usefulness of the exam they are being asked to complete, both their effort and test score will suffer (Cole, Bergin and Whittaker, 2008). Originated from the expectancy-value theory, utility value is similarly defined as the extent to which individuals perceive the task to be useful in the future (Eccles and Wigfield, 1995). It is self-evident that learning activities do not necessarily bring an instant reward, but tend to benefit a learner in the long run. Eccles and Wigfield (2002) stated that students may adopt a learning activity since it facilitates important future goals, even if they are not interested in the learning activity itself. In this regard, utility value (perceived long-term usefulness) posits to be a kind of extrinsic motivation which exerts significant influence on students’ learning behaviors (Chiu and Wang, 2008). In previous studies, utility value was found to significantly relate to intentions to attend graduate school (Battle and Wigfield, 2003) as well as intentions to continue mathematical study (Brush, 1980). In recent studies conducted by Chiu, Sun, Sun and Ju (2007), and Chiu and Wang (2008) on web-based learning continuance, utility value is found to be a significant variable driving educational IS/IT adoption (Chiu et al., 2007; Chiu and Wang, 2008). In a longitudinal study on IS in education settings, Mendoza, Carroll and Stern (2008) found that students may discontinue the use of IT if they can not perceive long-term benefits or are unable to resolve persistent issues. These studies suggest that perceived long-term usefulness should be a significant construct in predicting educational IT innovation adoption.

As TAM is initiated in an organizational context by employees to test work-related IT (Davis, 1989), it is essential to include a construct of perceived long-term usefulness into the model to explain the adoption of education-oriented innovations. Instead of offering instant rewards, m-learning tends to benefit learners in the future and in the long term. Learners would be more willing to accept m-learning when it complies with their future goals. This should give rise to a positive feeling of near-term usefulness. Therefore, we propose that a positive belief in long-term usefulness will also induce a positive feeling of perceived near-term usefulness. Based on previous research on TAM and perceived near-term/long-term usefulness, we have constructed the following hypotheses:

**H1:** Perceived ease of use positively relates to perceived near-term usefulness of m-learning.

**H2:** Perceived ease of use positively relates to behavioral intention to use m-learning.

**H3:** Perceived near-term usefulness positively relates to behavioral intention to use m-learning.

**H4:** Perceived long-term usefulness positively relates to perceived near-term usefulness of m-learning.

**H5:** Perceived long-term usefulness positively relates to behavioral intention to use m-learning.

In IS research, personal innovativeness refers to the degree to which an individual is willing to try out any new information technology (Agarwal and Prasad, 1998). Individuals with higher levels of personal innovativeness are more likely to develop positive beliefs towards new information technology than users with lower levels (Lu, Yao and Yu, 2005). Innovative users tend to be more venturesome and daring. Therefore, there are more possibilities for innovative users to adopt a new technology innovation though there is a high level of uncertainty in new IT adoption. In many studies, personal innovativeness has been found to be an important construct in understanding new IS/IT diffusion and usage intentions. Specifically, personal innovativeness is a positive predictor for perceived ease of use (Lu et al., 2005; Yi, Jackson, Park and Probst, 2006; Serenko, 2008), and behavioral intentions (Taylor, 2007; Crespo and Rodriguez, 2008). Additionally, in our research, a more innovative user is expected to be more likely to develop positive beliefs on m-learning, such as perceived long-term usefulness, as shown in Figure 1. Based on the above discussion on personal innovativeness, we proposed the following hypotheses:

**H6:** Personal innovativeness positively relates to perceived ease of use of m-learning.
**H7:** Personal innovativeness positively relates to perceived long-term usefulness of m-learning.

**H8:** Personal innovativeness positively relates to behavioral intention to use m-learning.

![Figure 1. The Research Model](image)

**RESEARCH METHODOLOGY**

**Sample and Data Collection**

As a majority of current m-learning services are targeted at university students, they accordingly will be our target group of study. In this regard, a sample was collected from undergraduate students in Zhejiang Normal University in China in November 2008. Students were invited to participate and complete the questionnaire in computer rooms after a brief introduction of our research purposes. Major websites offering m-learning products and services were introduced and made available to the students either through computers or their personal mobile phones before filling in the questionnaire. A total of 220 responses were collected from 230 participants resulting in a response rate of 95.7%. However 11 questionnaires were discarded as they were partially incomplete. The respondents consisted of 65 males and 144 females ranging from 18 to 23 years old. The demographic information of the respondents is shown in Table 1. Among the respondents, 93.3% have already used mobile phones for more than one year, and most of them (64.6%) use advanced mobile services at least once per week.

<table>
<thead>
<tr>
<th>Demographic profile</th>
<th>Frequency</th>
<th>Percent (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>65</td>
<td>31.1</td>
</tr>
<tr>
<td>Female</td>
<td>144</td>
<td>68.9</td>
</tr>
<tr>
<td>Total</td>
<td>209</td>
<td>100</td>
</tr>
<tr>
<td>Length of time using a smartphone (years)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Less than 0.5</td>
<td>4</td>
<td>1.9</td>
</tr>
<tr>
<td>0.5-1</td>
<td>10</td>
<td>4.8</td>
</tr>
<tr>
<td>1-1.5</td>
<td>65</td>
<td>31.1</td>
</tr>
<tr>
<td>More than 2</td>
<td>130</td>
<td>62.2</td>
</tr>
<tr>
<td>Total</td>
<td>209</td>
<td>100</td>
</tr>
<tr>
<td>Frequency of using advanced mobile services</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(times per week)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Never</td>
<td>74</td>
<td>35.4</td>
</tr>
<tr>
<td>1-5</td>
<td>71</td>
<td>34</td>
</tr>
<tr>
<td>5-10</td>
<td>44</td>
<td>21</td>
</tr>
<tr>
<td>More than 10</td>
<td>20</td>
<td>9.6</td>
</tr>
<tr>
<td>Total</td>
<td>209</td>
<td>100</td>
</tr>
</tbody>
</table>

Table 1. Demographic Information of Participants

**Survey Instrument**

The questionnaire was developed largely based on the scope and structure of previous researche. A seven-point Likert-scale ranging from strongly disagree (1) to strongly agree (7) was used to measure each item. The scales for measuring perceived near-term usefulness (PNTU), perceived ease of use (PEOU) and behavioral intention (BI) were built on the instrument developed by Davis’ (1989) and Chau’s (1996), which have been widely validated in prior TAM research. The items for personal innovativeness (PI) came from that developed by Agarwal and Prasad (1998), while the items for perceived long-term usefulness (PLTU) were adapted from that developed by Chau (1996) and Eccles et al. (1983). Some modifications and rewording of the survey instrument were made to meet the requirements of the present study.
Data Analysis

At first, principal components extraction with varimax rotation was performed to extract five factors with SPSS 15.0. The results indicate that all items fit their respective factors quite well. Also all the factor loadings are above the cutoff value (0.5) (Hair, Black, Babin, Anderson and Tatham, 2006). The Cronbach’s alpha values ranged from 0.798 and 0.909, and all of them are over the 0.7 level, as described in Table 2. Then AMOS 7.0 were used to conduct confirmative factor analysis. The values of composite reliability (CR) and average extracted variance (AVE) satisfy the cutoff value 0.6 and 0.5 respectively, thereby demonstrating good internal consistency (Fornell and Larcker, 1981). The square root of AVE of all constructs are greater then the correlation estimate with the other constructs (see Table 3). This shows that each construct is more closely related to its own measures than to those of other constructs, and discriminant validity is supported (Fornell and Larcker 1981).

<table>
<thead>
<tr>
<th>Items</th>
<th>Factors extracted</th>
<th>Cronbach’s alpha</th>
<th>Standardized Factor Loading</th>
<th>CR</th>
<th>AVE</th>
</tr>
</thead>
<tbody>
<tr>
<td>PNTU1</td>
<td>0.306</td>
<td>.730</td>
<td>.031</td>
<td>.144</td>
<td>.290</td>
</tr>
<tr>
<td>PNTU2</td>
<td>.235</td>
<td>.825</td>
<td>.141</td>
<td>.030</td>
<td>.224</td>
</tr>
<tr>
<td>PNTU3</td>
<td>.301</td>
<td>.855</td>
<td>.070</td>
<td>.134</td>
<td>.045</td>
</tr>
<tr>
<td>PEOU1</td>
<td>.163</td>
<td>-.010</td>
<td>.819</td>
<td>.075</td>
<td>.213</td>
</tr>
<tr>
<td>PEOU2</td>
<td>.122</td>
<td>.106</td>
<td>.873</td>
<td>.215</td>
<td>.026</td>
</tr>
<tr>
<td>PEOU3</td>
<td>.090</td>
<td>.140</td>
<td>.856</td>
<td>.234</td>
<td>.043</td>
</tr>
<tr>
<td>PLTU1</td>
<td>.788</td>
<td>.374</td>
<td>.044</td>
<td>.212</td>
<td>.079</td>
</tr>
<tr>
<td>PLTU2</td>
<td>.792</td>
<td>.219</td>
<td>.208</td>
<td>.103</td>
<td>.196</td>
</tr>
<tr>
<td>PLTU3</td>
<td>.815</td>
<td>.314</td>
<td>.082</td>
<td>.141</td>
<td>.201</td>
</tr>
<tr>
<td>PLTU4</td>
<td>.818</td>
<td>.158</td>
<td>.194</td>
<td>.073</td>
<td>.258</td>
</tr>
<tr>
<td>PI1</td>
<td>.273</td>
<td>.012</td>
<td>.315</td>
<td>.709</td>
<td>.243</td>
</tr>
<tr>
<td>PI2</td>
<td>.218</td>
<td>.119</td>
<td>.208</td>
<td>.819</td>
<td>.257</td>
</tr>
<tr>
<td>PI3</td>
<td>.003</td>
<td>.134</td>
<td>.114</td>
<td>.827</td>
<td>.033</td>
</tr>
<tr>
<td>BI1</td>
<td>.282</td>
<td>.367</td>
<td>.187</td>
<td>.129</td>
<td>.778</td>
</tr>
<tr>
<td>BI2</td>
<td>.361</td>
<td>.213</td>
<td>.126</td>
<td>.252</td>
<td>.780</td>
</tr>
</tbody>
</table>

Table 2. The Measurement Model

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean</th>
<th>SD</th>
<th>PNTU</th>
<th>PEOU</th>
<th>PLTU</th>
<th>PI</th>
<th>INT</th>
</tr>
</thead>
<tbody>
<tr>
<td>PNTU</td>
<td>4.63</td>
<td>1.33</td>
<td>0.825</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PEOU</td>
<td>5.32</td>
<td>1.24</td>
<td>0.254</td>
<td>0.829</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PLTU</td>
<td>4.68</td>
<td>1.27</td>
<td>0.627</td>
<td>0.351</td>
<td>0.847</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PI</td>
<td>4.64</td>
<td>1.31</td>
<td>0.324</td>
<td>0.463</td>
<td>0.405</td>
<td>0.794</td>
<td></td>
</tr>
<tr>
<td>BI</td>
<td>4.80</td>
<td>1.37</td>
<td>0.585</td>
<td>0.368</td>
<td>0.635</td>
<td>0.455</td>
<td>0.875</td>
</tr>
</tbody>
</table>

Table 3. Correlation Matrix and Discriminant Assessment

(The bold items on the diagonal represent the square roots of the AVE, off-diagonal elements are the correlation estimates.)

Results

The chi-square value for this model is significant ($\chi^2$ of 165.605 with 82 degrees of freedom, $p < 0.001$). In addition, five different fit statistics are measured, including the root mean square error of approximation (RMSEA), the goodness-of-fit index (GFI), the adjusted GFI (AGFI), the normed fit index (NFI), Tucker–Lewis index (TLI) and the comparative fit index (CFI). These model fit indices (GFI of 0.905, AGFI of 0.860, NFI of 0.922, CFI of 0.959, TLI of 0.948 RMSEA of 0.7) all satisfy the recommended guidelines, and suggest that our research model presents a good fit to the data, as shown in Table 4.

<table>
<thead>
<tr>
<th>Model Fit Indices</th>
<th>$\chi^2$/df</th>
<th>GFI</th>
<th>AGFI</th>
<th>NFI</th>
<th>CFI</th>
<th>TLI</th>
<th>RMSEA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Recommended value</td>
<td>&lt; 3</td>
<td>&gt; 0.9</td>
<td>&gt; 0.9</td>
<td>&gt; 0.9</td>
<td>&gt; 0.9</td>
<td>&gt; 0.9</td>
<td>&lt; 0.8</td>
</tr>
<tr>
<td>Obtained</td>
<td>2.020</td>
<td>0.905</td>
<td>0.860</td>
<td>0.922</td>
<td>0.959</td>
<td>0.948</td>
<td>0.700</td>
</tr>
</tbody>
</table>

Table 4 Model Fit Indices

The findings provide significant support for all the hypotheses, except for H1 (PEOU→BI, $\beta = 0.063$, $p > 0.5$) and H2 (PEOU→PNTU, $\beta = 0.054$, $p > 0.5$). Perceived long-term usefulness is the most influential factor motivating m-learning acceptance ($\beta = 0.356$, $p < 0.001$). Perceived near-term usefulness is the second important variable causing m-learning
adoption ($\beta = 0.306, p < 0.001$). Personal innovativeness significantly affects behavioral intention ($\beta = 0.233, p < 0.01$), perceived long-term usefulness ($\beta = 0.501, p < 0.001$) as well as perceived ease of use ($\beta = 0.537, p < 0.001$). Additionally, perceived long-term usefulness significantly impacts the perceived near-term usefulness ($\beta = 0.694, p < 0.001$). The proposed adoption model explains 60.8% of adoption intention, while perceived long-term usefulness account for 50.5% of perceived near-term usefulness. In addition, personal innovativeness interprets 28.8% and 25.1% of perceived ease of use and perceived long-term usefulness respectively. The results are shown in Figure 2.

**Figure 2. The Results**

**IMPLICATIONS AND CONCLUSION**

The results from our study indicate that the adoption of m-learning is different from that of traditional IS/IT. For learners, the usefulness of m-learning in improving their learning performance is strongly related to their expectation on the future. It is crucial to convince learners that adopting m-learning would reward them in the long run or in the future. Even if perceived near-term usefulness also significantly relates to behavioral intention, 50.5 percent of the perceived near-term usefulness can still be explained by the perceived long-term usefulness. It can be concluded that, perceived near-term usefulness is largely originated from a positive perception of long-term usefulness. Hence, it is suggested that an improvement of perceived long-term usefulness is the key to the success of m-learning, as it will promote the near-term usefulness perceived as well as the intention to use.

In consistence with previous research on perceived innovativeness, a learner who is more innovative will more possibly adopt m-learning. Additionally, personal innovativeness accounts for 28.8 percent of perceived ease of use and 25.1 percent of perceived long-term usefulness. These indicate that personal traits influence learners’ decisions on m-learning acceptance. Innovative learners tend to be the early adopters of m-learning. Consequently, it would be more effective to push m-learning services to innovative users at early stages of the diffusion of m-learning methods and technology.

The perception of ease of use doesn’t motivate the use of m-learning. The results of the study indicate, that among all the latent variables measured, the value of perceived ease of use is much higher than other variables (PEOU= 5.32), as shown in Table 3. It somewhat indicates a general perception that m-learning is easy to use. In contrast to previous research, technology restrictions seem not to induce significant usability problems impeding m-learning adoption. It should largely be attributed to the efforts from both mobile manufacturers and learning content designers. In the Chinese market, a number of phone models are specially designed for m-learning purposes, therefore the passive influence of technological restrictions, such as a small screen size and cumbersome input routines, can to a great extent be alleviated. In addition there are widespread efforts to design learning software and materials suitable for handheld usage. As a result, the ease of use factor is widely accepted among students in which shows up in the study as an insignificant impact on the intention to use m-learning. To some extent, the results also suggest that an inclusion of mobile device manufacturers in the provision of m-learning products is a practical and flexible method to build a prospering m-learning market, and it will help to tackle possible technological restrictions in relation to perceived ease of use.

Traditional TAM constructs, including PEOU and PNTU, were not found as important as they were in previous TAM research. Specifically, there are no significant paths from PEOU to PNTU, and neither the path from PEOU to BI. Also,
PNTU is not the most important motivator compared with PLTU. The study indicates that adoption of IS/IT for education purposes is quite different from the adoption of IS/IT for business purposes. As TAM is initiated from studying work-related innovations, extra attention is required when it is applied to educational IS/IT contexts. More research in this regard is needed.

Taking the previous studies on education adoption research into account, perceived long-term usefulness (the utility value) should be an important construct in predicting educational IS/IT adoption. The validity of this structure has been validated in both traditional classroom based learning and technology-mediated learning, such as e-learning and m-learning. In this light, it is proposed that, in future research on IS/IT for education purposes, scholars should pay enough attention to the impact of perceived long-term usefulness.

LIMITATIONS

As all research, there are some limitations in this study that should be considered. First, the study only measures the intention to use m-learning, and actual usage is not included. Second, this study focused on education-oriented m-learning products, therefore the results should not be generalized to the m-learning systems for communication or administration purposes. Third, as the sample was collected from undergraduate students in China, this should be taken into consideration when the results are applied to m-learning users in different age groups or with other cultural backgrounds.

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REFERENCES


