Students' Acceptance of Mobile Learning Technology

(Full Paper Submission)

Xiaoqing Li
Department of MIS
College of Business and Management
University of Illinois at Springfield
One University Plaza, MS UHB 4021
Springfield, Illinois 62703-5407, USA
xli1@uis.edu

ABSTRACT

With the recent development of telecommunications, mobile learning is rapidly appearing as a promising learning approach for students to learn anytime, anywhere. However, mobile learning is just at the beginning of its development and many key issues regarding the design and implementation of mobile learning are still unclear. With this research, we investigate factors leading to the acceptance of mobile learning based on student usage of Blackboard Mobile Learn. The research findings will not only help instructors to better design their courses for mobile users, but also help system developers to design mobile learning systems.

KEYWORDS: Mobile learning, Technology acceptance, Structural equation model

INTRODUCTION

Mobile learning is rapidly appearing as a new education format in addition to traditional face-to-face and computer based online learning. As a new format of education, mobile learning enables students to manage their time and learning pace flexibly. Now, increasingly more students are using their smartphones or tablets to access course materials at anytime and anywhere. Mobile learning shows great potential to enhance the effectiveness of education delivery. However, the development of mobile learning is still at the beginning. The course activities that students can accomplish through mobile are still very limited. Many students have not realized the advantages of mobile learning and are reluctant to access course materials from their mobile devices. Moreover, many instructors are not ready to prepare their course contents specifically for mobile learning.

With this study, we investigate key acceptance factors regarding mobile learning based on students’ experience of using Blackboard Mobile Learn, a specific mobile learning platform. The present paper is organized as follows. First, we review the background of mobile learning and related acceptance research activities. Next, we propose a research model and related hypotheses. Then, we describe the research methodology applied in this study and conduct data analysis. In the last section of this paper, we discuss implications to theory and practice and offer recommendations for future research.

MOBILE LEARNING

Mobile learning is a special kind of anytime anywhere e-learning approach enabled by the Internet, wireless networks and mobile devices (Motiwalla, 2007). In recent years, with the rapid
development of telecommunication and advanced mobile devices like smartphones and tablets, mobile learning has been gradually becoming a very promising approach in support of students’ learning activities (Martin et al., 2011). Although no one expects that it can completely replace other educational formats in the near future, mobile learning offers many unique values to students as a supplemental approach to classroom education and computer based online learning (Motiwalla, 2007; Liaw et al., 2010).

Researchers have already conducted some investigations on the acceptance issue of mobile learning in different scenarios. For example, Wang et al. (2009) investigated the determinants affecting the acceptance intention of mobile learning among students in Taiwan. Liu et al. (2010) investigated the determinants affecting the acceptance intention of mobile learning from students of mainland China. Cheon et al. (2012) conducted an acceptance study on students’ use intention of mobile learning in the US. Lin et al. (2013) investigated the acceptance of using podcasting, a specific tool, in mobile learning from perspectives of both teachers and students. However, these acceptance researches of mobile learning are mainly based on second hand knowledge, such as watching video and/or reading introduction materials (Wang et al., 2009; Liu et al., 2010; Cheon et al., 2012; Lin et al., 2013), rather than based on real hands-on experiences of conducting mobile learning. Therefore, these researches are about users’ behavior intentions of using mobile learning, rather than about actual usages of mobile learning.

The determinants of behavioral intention and actual usage are different, so there exists a gap between behavioral intention and actual usage of information technologies. That is, people with behavioral intentions may not actually use mobile learning due to technological, social or personal reasons. Therefore, in addition to studying key factors regarding behavioral intention like existing studies have done, further investigation on key determinants of actual usage of mobile learning is necessary. Based on the real experience of using mobile learning from college students, our research will not only study behavioral intention, but also the actual usage of mobile learning.

RESEARCH MODEL AND HYPOTHESES

As a widely used learning management system in the US, Blackboard (www.blackboard.com) can help instructors deliver course contents in online, on-ground, and blended classes. Using Blackboard, students can easily access their course materials, participate in online discussions, and take quizzes from their computers. This tool offers students great flexibility to study at their own schedule. More conveniently, its mobile version, Backboard Mobile Learn, enables students to perform many learning activities from smartphones or tablets just as they would on the computer based Blackboard system. In this paper, the research is based on students’ mobile learning experience using Blackboard Mobile Learn.

Compared with acceptance studies about computer based online learning systems such as moodle (Sánchez & Hueros, 2010), the acceptance of mobile learning involves different factors when explaining usage intention and actual usage. In the present research, the United Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) model is adapted to the acceptance analysis of mobile learning. In order to identify more factors in this new application context, we introduce several new constructs to UTAUT in our research model. Next, we discuss the included factors and related hypotheses. See figure 1.
Figure 1: Research model

- **Performance Expectancy**

Performance expectancy means "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" (Venkatesh et al., 2003, p447). Specifically, the performance expectancy of mobile learning means to what extent students can conduct course activities using Blackboard Mobile Learn. Consistent with the UTAUT model (Venkatesh et al., 2003), we expect that higher performance expectancy will lead to higher usage intention for mobile learning. Thus,

**H1**: Performance expectancy has a positive effect on the usage intention of mobile learning.

- **M-learning Effort Expectancy**

Effort expectancy means "the degree of ease associated with the use of the system" (Venkatesh et al., 2003, p450). An easy-to-use mobile learning system will encourage students to perform course activities from mobile devices. Consistent with the original UTAUT model (Venkatesh et al., 2003), we expect that the effort expectancy will positively affect the usage intention of mobile learning. Thus,

**H2**: Effort expectancy has a positive effect on the usage intention of mobile learning.

- **Learning Autonomy**

Mobile learning autonomy means "the extent to which students are responsible and have control over the process of learning with mobile devices" (Cheon et al., 2012, pp 1057). With the anytime, anywhere access of online materials through Blackboard Mobile Learn, students can have better control of their learning pace. We expect that learning autonomy will positively affect the usage intention to mobile learning. Thus,

**H3**: Learning autonomy has a positive effect on the usage intention of mobile learning.
Students’ Acceptance of Mobile Learning Technology

● Social Influence

Social influence means “the degree to which an individual perceives that important others believe he or she should use the new system” (Venkatesh et al., 2003, pp. 451). Different from computer-based online learning, in which students usually have no choice in whether or not to use it, the use of mobile learning is up to students. Many students will not use or are not even aware of the existence of a mobile learning system without influence from instructors, classmates, or friends. We expect that the social influence will positively affect the usage intention of mobile learning. Thus,

H4: Social influence has a positive effect on the usage intention of mobile learning.

● Personal Innovativeness in Information Technology

Personal innovativeness in information technology means “the willingness of an individual to try out any new information technology” (Agarwal & Prasad, 1998, pp 206). As indicated in existing acceptance studies, users with higher personal innovativeness would more likely try different kinds of new technologies. Therefore, we expect that users with higher innovativeness will also have higher intention to try out mobile learning when possible. Thus,

H5: Personal innovativeness in information technology has a positive effect on the usage intention of mobile learning.

● Behavioral Intention

If it is possible, users’ usage intention will normally lead to actual usage of technology. Consistent with the original UTAUT model (Venkatesh et al., 2003), we expect that users with high usage intention will actually use more mobile learning. Thus,

H6: Behavioral intention has a positive effect on the usage of mobile learning.

● Mobile Learning Compatibility

As in computer-based online learning, the course structure and design should be compatible with students’ learning activities (Chen, 2011; Escobar-Rodriguez & Monge-Lozano, 2012). Moreover, the compatibility issue is even more critical to mobile learning than in a computer-based online learning. Obviously, students will not use mobile learning if they are unable to find compatible course activities to do on their smartphones, no matter whether or not they have use intention. Due to limitations of mobile devices, not all course activities are suitable for mobile learning (Molina et al., 2014). Mobile learning, in particular smartphone-based mobile learning, is more suitable for activities involving lower cognitive load compared with a computer-based online learning (Molina et al., 2014).

However, mobile learning compatibility is not a pure objective issue. For the same course activity, one student might think it can be done on the mobile, but another student might not think it is compatible with mobile learning due to differences in learning styles, time pressures, time management skills, and smartphone capabilities. Students normally have high adaptability to a learning environment. As a supplemental learning tool, the compatibility heavily depends on a user’s intention to use mobile learning. If it is necessary, students can manipulate the platform
to complete certain difficult tasks on mobile. Therefore, we expect that higher intention of using mobile learning can motivate students to find more compatible activities on the mobile. Thus,

**H7:** Usage intention has a positive effect on mobile learning compatibility.

As soon as one student has found compatible activities on the mobile, the student is able to regularly conduct these activities in the study. We expect that compatibility will positively affect the actual usage of mobile learning. Thus,

**H8:** Mobile learning compatibility has a positive effect on the usage of mobile learning.

### Facilitation Conditions

Facilitating conditions means “the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system” (Venkatesh et al., 2003, pp. 453). According to the diffusion of innovations theory, the population can be classified into five categories: innovators, early adopters, early majority, late majority, and laggards (Roger, 1995). Except for a few innovative students, many students will not try mobile learning even when they perceive the usefulness, ease of use, and other obvious advantages of it. Therefore, external promotion and support are necessary for many students to use mobile learning. In order to target each specific support in future teaching efforts, we classify facilitation conditions into three categories: instructor support, peer support, and professional support.

Different from other educational technologies, mobile learning implementation is mainly a student driven effort (Gikas & Grant, 2013). With the rapid adoption of smartphones in recent years, many students can easily learn how to use various mobile apps. When facing technical difficulties, students can often find solutions from their peers. Peer support is an important source of facilitation in using mobile learning. When taking online courses, students naturally consider instructors as a direct and important support resource although there are many other supports available. Instructors inform students the existence of mobile learning, explain the advantages of mobile learning, and if possible, help to resolve technical issues in installing and using mobile learning. Therefore, instructor support is important to the successful acceptance of mobile learning. Of course, professional support from the technical support staff is also important for students when they cannot solve difficult problems using the two aforementioned ways.

Based on the above discussions, we expect that the three facilitation conditions have positive effects on the actual usage of mobile learning respectively. Thus,

**H9:** Instructor support has a positive effect on the usage of mobile learning.
**H10:** Peer support has a positive effect on the usage of mobile learning.
**H11:** Professional support has a positive effect on the usage of mobile learning.

### RESEARCH METHODOLOGY

#### Instrument Development

The first part of the questionnaire collects users’ demographic information, including age, gender, usage, and devices for conducting mobile learning (i.e., smartphones and tablets). The second part of the questionnaire collects data on users’ perceptions based on the proposed
research model. At the end of the survey, we request users to give open comments about using Blackboard Mobile Learn. See appendix.

- **Subjects and Data Collection**

  The data collection was conducted from students in two campuses of a public university in the Midwest of the United States. The survey was distributed through daily campus announcements and classified advertisements for two months. The survey is anonymous and voluntary. This survey reflects students’ perception of mobile learning in a real education scenario. The survey asks respondents’ perceptions of mobile learning on a specific mobile learning tool, i.e., Blackboard Mobile Learn. In total, we received 114 responses. To ensure the quality of analysis, we eliminated 3 straight lining responses. Thus, our data analysis was conducted based on the remaining 111 valid responses, consisting of 45 male students and 66 female students. The validity rate of this survey is 97.4%. There is no missing value among 111 valid responses. In this survey, the average age of participants is 31.1 years old (STD=12.1). Among 111 valid responses, 68 are from undergraduate students; 41 are from master students; and 2 are from doctoral students. In this survey, the average usage of mobile learning is 3.9 hours (STD=3.6) per week.

**DATA ANALYSIS**

Data analysis was conducted using SmartPLS 2.0 (M3) Beta (www.smartpls.de). According to Barclay et al. (1995), the PLS sample size should be at least 10 times the maximum number of predictors (formative indicators or antecedent constructs) of a construct in the PLS path model. In this research, the usage behavioral intention has the maximum number of predictors: five, so the smallest sample size is fifty. Thus, the 111 valid responses satisfy the sample size requirement very adequately. When applying the PLS-SEM calculation, the parameter settings follow the suggestion from Hair et al. (2014). We choose “Path Weighting Scheme” for “Weighting Scheme”, “Mean 0, Var 1” for “Data Metric”, 300 for “Maximum Iterations”, 1 for “Initial Weights”, 1.0E-5 for “Abortion Criterion”. Table 1 lists the mean values and standard deviations of constructs in this research.

<table>
<thead>
<tr>
<th>Constructs</th>
<th>Number of Items</th>
<th>Mean</th>
<th>Standard Deviation</th>
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</thead>
<tbody>
<tr>
<td>Instructor Support</td>
<td>3</td>
<td>4.15</td>
<td>1.66</td>
</tr>
<tr>
<td>Learning Autonomy</td>
<td>3</td>
<td>5.56</td>
<td>1.29</td>
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<tr>
<td>M-learning Compatibility</td>
<td>4</td>
<td>5.04</td>
<td>1.57</td>
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<tr>
<td>M-learning Effort expectancy</td>
<td>4</td>
<td>5.83</td>
<td>1.28</td>
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<tr>
<td>Peer Support</td>
<td>3</td>
<td>4.26</td>
<td>1.49</td>
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<tr>
<td>Performance Exptantancy</td>
<td>4</td>
<td>5.23</td>
<td>1.37</td>
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<tr>
<td>Personal Innovativeness</td>
<td>3</td>
<td>5.68</td>
<td>1.26</td>
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<tr>
<td>Professional Support</td>
<td>3</td>
<td>4.87</td>
<td>1.40</td>
</tr>
<tr>
<td>Social influence</td>
<td>4</td>
<td>4.19</td>
<td>1.27</td>
</tr>
<tr>
<td>Usage</td>
<td>1</td>
<td>3.92</td>
<td>3.62</td>
</tr>
<tr>
<td>Use Intention</td>
<td>4</td>
<td>6.00</td>
<td>1.41</td>
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</table>

5.1 **Measurement Model Results**
For the reflective measurement model, we need to evaluate four criteria: 1) internal consistency reliability; 2) individual indicator reliability; 3) convergent validity; and 4) discriminant validity (Hair et al., 2014). Specifically, we assess the internal consistency reliability by checking the composite reliability. In our research, the minimum composite reliability value is 0.91 (see Table 2), which is higher than the lowest acceptable value of 0.70 (Nunnally, 1978). As a criterion of indicator reliability, the minimum value of all outer loadings in this model is 0.7664 (Table 3: SI4 of social influence). Therefore, all values of outer loadings in this model are higher than 0.707 (Chin, 1998). We assess the convergent validity by checking AVE (average variance extracted) (See Table 2). The AVE of each construct should be at least .50 (Fornell & Larcker, 1981). In present research, all AVE values are greater than 0.74. The indicators of all constructs are internally consistent and reliable, and all constructs are convergent.

Discriminant validity is the extent that a construct is different from other constructs (Hair et al., 2014). The cross loadings are used to check the discriminant validity. As indicated in Table 3, the values of outer loadings of one construct are much higher than that of all cross loadings. The Fornell-Larcker criterion is the second criterion to assess the discriminant validity (Hair et al., 2014). That is, the AVE of each construct should be greater than its highest squared correlation with any of other constructs (Chin, 1998). In our model, all AVE values are much greater than the corresponding listed squared correlations (see Table 2). Considering that all constructs’ measurement items are adapted from other existing research, the results from our research proved the effectiveness of applying these existing measurements of constructs in mobile learning.

5.2 Structural Model Results

The above analysis indicates that the measurements used in the proposed model are valid and reliable. In this part, we evaluate the structural model results. That is, we will check whether or not the collected data support the proposed theory.

- Coefficient of Determination (R² Values)

The proposed model explains 61.7% of the variance (R²) of users’ behavioral intention, 43.8% of the variance (R²) of learning compatibility, and 7.7% of the variance (R²) of actual usage of mobile learning. See figure 2. The results indicate that the proposed model can explain the behavioral intention very well (substantial level: 0.75 (Hair et. al., 2014)), and also explain the mobile learning compatibility close to the moderate level (moderate level: 0.5 (Hair et al., 2014)).
However, the degree in explaining the actual mobile learning usage is very weak (weak level: 0.25 (Hair et al., 2014)). This tells us that actual usage of mobile learning is a complicated issue affected by many unidentified factors in practice.

Table 3: Loadings and cross-loadings for the measurement model

<table>
<thead>
<tr>
<th>Factor</th>
<th>SI4</th>
<th>SI3</th>
<th>SI2</th>
<th>SI1</th>
<th>SI5</th>
<th>SI6</th>
<th>SI7</th>
<th>SI8</th>
<th>SI9</th>
<th>SI10</th>
<th>SI11</th>
<th>SI12</th>
<th>SI13</th>
<th>SI14</th>
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<tr>
<td>Intrinsic Support</td>
<td>0.3256</td>
<td>0.598</td>
<td>0.239</td>
<td>0.227</td>
<td>0.245</td>
<td>0.180</td>
<td>0.153</td>
<td>0.119</td>
<td>0.227</td>
<td>0.300</td>
<td>0.319</td>
<td>0.269</td>
<td>0.284</td>
<td>0.284</td>
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<tr>
<td>Learning Autonomy</td>
<td>0.515</td>
<td>0.627</td>
<td>0.633</td>
<td>0.634</td>
<td>0.869</td>
<td>0.299</td>
<td>0.277</td>
<td>0.246</td>
<td>0.315</td>
<td>0.342</td>
<td>0.312</td>
<td>0.314</td>
<td>0.308</td>
<td>0.193</td>
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<td>M-learning Compatibility</td>
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<td>Social Influence</td>
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<td>Mobile Learning Usage</td>
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<tr>
<td>M-learning Compatibility R² = 43.8%</td>
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Figure 2: Structural model path coefficients

- **Instructor Support**
  - H1: 0.315; T=2.6382***
  - H2: 0.2877; T=2.4639***
  - H3: 0.2377; T=1.7595*
  - H4: -0.0666; T=1.0042
  - H5: 0.1369; T=1.4507
  - H6: 0.662; T=1.1539***
  - H7: 0.1747; T=1.7398*
  - H8: 0.1648; T=1.5579

- **Personal Innovativeness**
  - H9: -0.025; T=0.2199
  - H10: 0.0311; T=0.3295

- **Learning Autonomy**
  - H11: 0.1618; T=1.5579

- **Performance Expectancy**
  - H12: 0.0518; T=0.3311

- **M-learning effort expectancy**
  - H13: 0.239; T=1.3568

- **Behavioral Intention R² = 61.7%**
  - H14: 0.1747; T=1.7398*

- **M-learning Compatibility R² = 43.8%**
  - H15: 0.2877; T=2.4639***
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- Structural Model Path Coefficients

Path coefficients and corresponding T Values are listed in Figure 2 and Table 4. T values were calculated using bootstrapping (Sign Changes = No Sign Changes; Cases = 111; Sample = 5000).

Table 4: Structural model path coefficients

<table>
<thead>
<tr>
<th>Path Coefficients</th>
<th>t Values</th>
<th>Significant levels</th>
</tr>
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<tbody>
<tr>
<td>Instructor Support -&gt; Usage</td>
<td>0.1648</td>
<td>1.5579</td>
</tr>
<tr>
<td>Learning Autonomy -&gt; Use Intention</td>
<td>0.2377</td>
<td>1.7595</td>
</tr>
<tr>
<td>M-learning Compatibility -&gt; Use Intention</td>
<td>0.1747</td>
<td>1.7398</td>
</tr>
<tr>
<td>M-learning Effort expectancy -&gt; Use Intention</td>
<td>0.2877</td>
<td>2.4639</td>
</tr>
<tr>
<td>Peer Support -&gt; Usage</td>
<td>0.0311</td>
<td>0.3294</td>
</tr>
<tr>
<td>Performance Expectancy -&gt; Use Intention</td>
<td>0.315</td>
<td>2.6382</td>
</tr>
<tr>
<td>Personal Innovativeness -&gt; Use Intention</td>
<td>0.1369</td>
<td>1.4507</td>
</tr>
<tr>
<td>Professional Support -&gt; Use Intention</td>
<td>-0.025</td>
<td>0.2199</td>
</tr>
<tr>
<td>Social influence -&gt; Use Intention</td>
<td>-0.0666</td>
<td>1.0042</td>
</tr>
<tr>
<td>Use Intention -&gt; M-learning Compatibility</td>
<td>0.662</td>
<td>11.5394</td>
</tr>
<tr>
<td>Use Intention -&gt; Usage</td>
<td>-0.0302</td>
<td>0.3066</td>
</tr>
</tbody>
</table>

NS not significant * p<0.1 ** p<0.05 *** p<0.01

Based on the results of path coefficients and T values in Figure 2 and Table 4, H1, H2, H3, H7 and H8 are supported. H4, H5, H6, H9, H10, and H11 are not supported. This result indicates that effort expectancy, performance expectancy, and learning autonomy all have a significant positive impact on the behavioral intention of using mobile learning. Social influence does not play a significant role in use intention. The use of m-learning is voluntary and supplemental to the computer based online learning; our result is consistent with the finding from Venkatesh et al. (2003) when the scenario is voluntary use. Personal innovativeness does not play any significant role in use intention. The use intention does not play a significant role in the actual usage of mobile learning directly (i.e., H6). This is in contrast to what many others believe in acceptance studies (Venkatesh et al., 2003), but this result is consistent with another research regarding mobile health information acceptance (Lim et al., 2011). The use intention has a positive impact on the mobile learning compatibility (i.e., H7), and the mobile learning compatibility has a positive impact on the actual usage of mobile learning (H8). As indicated by Lim et al. (2011), the compatibility issues (i.e., text size, graphics and amount of information) do affect users’ actual usage of mobile application. This result indicates that users with higher use intention can find more compatible activities on mobile devices, and that the higher compatibility leads to higher usage of mobile learning. According to Hair et al. (2014), we checked the significance of the direct effect between use intention and actual usage behavior when the m-learning compatibility is not included. The path coefficient is 0.072; T value is 0.89. When the m-learning compatibility is included, the T value of the indirect effect between use intention and usage behavior is 1.62. This indicates that there is no mediating impact from the mobile learning compatibility to the link between use behavioral intention and actual usage of mobile learning. Finally, different from findings from Venkatesh et al. (2003), all three facilitations do not play any significant role in the usage of mobile learning (H9, H10, and H11).

DISCUSSION AND IMPLICATIONS
Compared with computer based online learning, mobile learning has many unique issues regarding users’ acceptance. Many previously proved constructs and casual relationships in technology acceptance studies need to be re-examined in this new scenario. To this end, the present research investigated the determinants of both the use behavioral intention and the actual usage of mobile learning based on students’ experience of using Blackboard Mobile Learn.

**Research and Practical Implications**

In addition to effort expectancy and performance expectancy in the baseline model (Venkatesh et al., 2003), learning autonomy is proved to be an important determinant of users’ behavioral intention. However, different from what many people believe that there usually exists a default causal relationship between use intention and the actual usage in technology acceptance studies (Venkatesh et al., 2003; Wang et al., 2009), this relationship is not significant in a mobile learning scenario. This finding is consistent with another acceptance study regarding mobile application (Lim et al., 2011). Therefore, future researchers should be very careful in addressing the casual relationship between use intention and actual usage when dealing with mobile applications. Most importantly, our research finding indicates that there exists another path from use intention to actual usage of mobile learning via mobile learning compatibility.

**Limitations and Future Research**

The major limitation of present research is using self-reported data to measure the actual usage of Blackboard Mobile Learn. The self-reported data is susceptible to recall errors due to variations of use from week to week. If possible, more precise measurement needs to be developed in a future study.

The use of mobile learning is in its infancy. From students’ responses in this survey, the activities conducted on the Blackboard Mobile Learn are mainly focused on relatively simple course activities. Very often, when a student has intention to conduct mobile learning, he or she has very limited activities to choose from. In the future, we expect instructors to develop and customize more compatible contents and activities for mobile learning.

In this present research, the R square of actual usage behavior is 7.7%. This means that there is plenty of room for further research on the actual usage of mobile learning. Therefore, future research about the acceptance of mobile applications should focus more on the actual usage.

**APPENDIX: Survey Questionnaire**

**Part A: Demographic Information**

**Age** (subjects must be at least 18 years old): ___________

**Gender:** Male Female

**Education:** 1. Bachelor 2. Master 3. Doctorate

**Total number of courses using Blackboard Mobile Learn:** 0 course 1 course 2 courses 3 courses 4 courses 5 courses More than 5 courses
Total hours of using Blackboard Mobile Learn/week: __________ (e.g., 2 hours/week)

Which kind of mobile device that you use to access Blackboard Mobile Learn:
1. Smartphone
2. Tablet

Please list your major activities using Blackboard Mobile Learn: _______________

Part B: List of model construction and items for users

Performance expectancy (adapted from Venkatesh et al., 2003)
PE1: I would find the Blackboard Mobile Learn useful in my learning.
PE2: Using the Blackboard Mobile Learn enables me to accomplish learning tasks more quickly.
PE3: Using the Blackboard Mobile Learn increases my learning productivity.
PE4: If I use the Blackboard Mobile Learn, I will increase my chances of getting more competence.

M-learning effort expectancy (adapted from Venkatesh et al., 2003)
MEE1: My interaction with the Blackboard Mobile Learn would be clear and understandable.
MEE2: It would be easy for me to become skillful at using the Blackboard Mobile Learn.
MEE3: I would find the Blackboard Mobile Learn easy to use.
MEE4: Learning to operate the Blackboard Mobile Learn is easy for me.

Social influence (adapted from Venkatesh et al., 2003)
SI1: People who influence my learning behavior think that I should use the Blackboard Mobile Learn.
SI2: People who are important to me think that I should use the Blackboard Mobile Learn.
SI3: People who are superior to me have been helpful in the use of the Blackboard Mobile Learn.
SI4: In general, the University has supported the use of the Blackboard Mobile Learn.

Personal Innovativeness (adapted from Agarwal & Prasad, 1998)
PI1: I like to experiment with new information technologies.
PI2: If I heard about a new information technology, I would look for ways to experiment with it.
PI3: Among my peers, I am usually the first to try out new information technologies.

Learning Autonomy (adapted from Cheon et al., 2012)
LA1: I would be able to actively access coursework material with the Blackboard Mobile Learn.
LA2: I would have more opportunities to study my coursework with the Blackboard Mobile Learn.
LA3: I would be able to control the pace of learning in my courses with the Blackboard Mobile Learn.

M-learning Compatibility (adapted from Chen, 2011)
MC1: Using the Blackboard Mobile Learn is compatible with all aspects of my learning.
MC2: Using the Blackboard Mobile Learn is completely compatible with my current learning situation.
MC3: I think using the Blackboard Mobile Learn fits well with the way I like to conduct learning activities.
MC4: Using the Blackboard Mobile Learn fits into my learning style.

Instructor Support (adapted from Venkatesh et al., 2003)
IS1: Instructors offer the resources necessary to use the Blackboard Mobile Learn.
IS2: Instructors offer the knowledge necessary to use the Blackboard Mobile Learn.
IS3: Instructors are available for assistance with difficulties of using the Blackboard Mobile Learn.

Peer Support (adapted from Venkatesh et al., 2003)
PS1: My peers offer the resources necessary to use the Blackboard Mobile Learn.
PS2: My peers offer the knowledge necessary to use the Blackboard Mobile Learn.
PS3: My peers are available for assistance with difficulties of using the Blackboard Mobile Learn.

Professional Support (adapted from Venkatesh et al., 2003)
PS1: Professional Technical Support offers the resources necessary to use the Blackboard Mobile Learn.
PS2: Professional Technical Support offers the knowledge necessary to use the Blackboard Mobile Learn.
PS3: Professional Technical Support is available for assistance with difficulties of using the Blackboard Mobile Learn difficulties.

Mobile Learning Usage Intention (adapted from Chen, 2011)
MLUI1: I intend to use the Blackboard Mobile Learn in the future.
MLUI2: I predict I would use the Blackboard Mobile Learn in the future.
MLUI3: I plan to use the Blackboard Mobile Learn in the future.
MLUI4: I intend to use the Blackboard Mobile Learn for learning as often as needed.

Comments about Using Blackboard Mobile Learn:

* Measured using a 7-point, Likert-type scale, ranging from 1 (strongly disagree) to 7 (strongly agree).

REFERENCES


