TECHNOLOGY ACCEPTANCE AND ACTUAL USE WITH MOBILE LEARNING: FIRST STAGE FOR STUDYING THE INFLUENCE OF LEARNING STYLES ON THE BEHAVIORAL INTENTION

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TECHNOLOGY ACCEPTANCE AND ACTUAL USE WITH MOBILE LEARNING: FIRST STAGE FOR STUDYING THE INFLUENCE OF LEARNING STYLES ON THE BEHAVIORAL INTENTION

Complete Research
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Abstract
Technology and mobile devices have been successfully integrated in peoples’ everyday activities. Educational institutions around the world are increasing their interest to create mobile learning (ML) environments considering the advantage of connectivity, situated learning, individualized learning, social interactivity, portability, affordability and more widely ubiquity. Even with the fast development of ML environments, there is however a lack of understanding about the factors that influence ML adoption. This paper proposes a framework for ML adoption integrating a modified Unified Theory of Acceptance and Use of Technology (UTAUT) with constructs from the Expectation Confirmation Theory (ECT). Since the goal for education is learning, this research will include individual attributes such as learning styles (LS) and experience to understand how they moderate ML adoption and actual use. For this reason, the framework brings together the adoption theory for initial use and the constructs of continuance intention for actual and habitual use as an outcome of learning. The framework is divided in two stages, acceptance and actual use. The purpose of this paper is to test the first stage: ML acceptance through the structural equation modeling statistical technique. The data was collected from students that already are experiencing ML. Findings demonstrate that performance and effort expectation constructs are significant predictors of ML and there is some influence of LS and experience as moderators for ML adoption. The practical implication in educational services is to incorporate LS influence when designing strategies for learning enhanced by mobile devices.

Keywords: mobile learning, UTAUT, Expectation-Confirmation Theory, acceptance, continuance use.

1 Introduction

Considering the benefits that mobile devices provide for students, instructors and universities, mobile learning (ML) has become a viable alternative adopted by educational institutions worldwide to produce new educational practices (Liu, Han, et al. 2010). Actual research shows the increasing use of mobile devices in educational fields (Fozdar and Kumar 2007; James 2011) enhanced by advances in mobile technology, students are able to bring with them their personally owned devices.

Mobile adoption in commerce and services has been growing successfully. However, educational services as ML practices are in early stages and they should bring educational strategies that ensure collaboration and meaningful learning to be adopted in educational contexts. Thus, we need to understand the capabilities of mobile technology and its challenges within universities to offer materials that teacher can experience in their classrooms and students can take advantage of them.
In technology there is a big challenge for designers to understand how and why people adopt or do not adopt specific innovation. There is a lack of understanding about the factors that encourage or inhibit consumers/users to adopt and use mobile devices (Sarker and Wells 2003). Carlsson et al. (2005) pointed out that it is important to make a distinction between the acceptance of mobile devices, the technology by itself, and mobile services. It seems that technology is not enough reason to use services so they should be value-adding to make the user change the everyday routine.

The understanding of individual acceptance and use of information technology is one of the most mature areas in management information systems (MIS) research. Different theoretical models have been employed to explain technology acceptance and use. Among various adoption models, UTAUT (Carlsson et al. 2006; Zhou et al. 2010) and ECT (Bhattacherjee 2001; Lin et al. 2005) are widely adopted to explain factors for technology acceptance and consumer behavior respectively. UTAUT was originally developed to explain employee technology acceptance and use; it will be critical to examine how it can be extended to the context of education. ECT is widely used in the consumer behavior literature to study consumer satisfaction, post-purchase behavior (e.g. repurchase, complaining), and service marketing in general (Bhattacherjee and Premkumar 2004).

For ML teachers and course designers, the challenge is how they might use mobile devices in the learning process and how they can create opportunities and environments that enhance learning (Singh 2010). A good moderator for learning performance is commonly related with learning styles (LS) identification (Huang et al. 2012). Since everybody learns in different ways, technology can be an enabler to enhance a personalized approach to learning. “The impact on learning when just-right information is flowing to the right place, person, and time cannot be overstated” (Hodgins 2006 p. 76). While there have been studies to explain the LS influence on technology mediated learning environments, there is a lack of an integrative view that considers ML adoption influenced by LS as an accurate predictor of adoption. Moreover, there is a need to consider if LS can further explain continuance usage as a result of learning.

This paper presents the first stage results from an integrated model using UTAUT in an education context with constructs from the ECT model. These two models were considered because UTAUT explains usage behavior as a consequence of user intentions moderated by individual differences; however it lacks to explain further use as a result of effectiveness. In this integrated model the individual differences are represented by experience and LS. In order to understand continuance use, the ECT model is incorporated to investigate the use of mobile devices as a result of learning confirmed by satisfaction and performance.

Hence, the objective of the study is to develop an integrated framework to understand the influence of LS in ML acceptance and actual use, the question raised in this paper is “How learning style has an effect on the acceptance and use of Mobile Learning in higher education? Bringing an answer to this question would allow universities and professors to introduce mobile devices and to explore learning opportunities. The aim of this study is to shed light on this research question, and to formulate a starting point for ML acceptance and use.

The remainder of the paper is organized as follows. In section 2, we will introduce the relationship among LS, ML and technology adoption models. In section 3, we will describe the two stages research model. The research method will be detailed in Section 4 and in Section 5 we will examine the methodology and results for the first stage. In Section 6, 7 and 8 we present the discussion, study limitations and contributions. Finally, we conclude in section 9.
2 Background

2.1 Learning Styles

Learning is influenced by student attributes, which interact in the learning process with an instructional activity in a specific learning environment. LS have been considered as a key attribute in learning and the research community has some findings about their influence. LS denote the set of preferences that students have for perceiving, assimilating, and interpreting or processing incoming information (Felder and Silverman 1988; Kolb 1984). Collinson (2000) describes LS as a combination of cognitive, affective, and physiological factors. Different authors on diverse theoretical models have researched the preferred way in which an individual learns.

LS provide information about individual differences to suggest instructional design to support learning preferences (Akdemir and Koszalka 2008). LS have been under research and the amount of LS models has increased over the years proposing each one a description and classification of LS. In a study conducted by Coffield et al. (2004), were found valuable only 71 over 100 existing learning models. The number and diversity of models explains how researchers consider LS identification as an important factor to predict students’ preferences for learning. Examples of these models are Gregorc (1979), Kolb (1981), Felder and Silverman (1988), Dunn and Dunn (1992), Honey and Mumford (1992) and Sternberg (1999). Among the models, the Felder and Silverman LS model has been identified as an appropriated model for engineering and IT education (Zywno 2003). Franzoni et al. (2008) conducted a research to explain how learning process could be enhanced adapting electronic resources with different LS through an appropriate teaching strategy. This study was tested using the Felder and Silverman Model. The present research will be based on Franzoni’s work addressing the ability to predict students’ use of ML considering the LS as an influencing factor.

Kolb developed the Learning Style Model that was built using two-dimensional scales depending in how a person perceives and process information classifying individuals in four types on the basis of their position along these two dimensions. Thus, how a person process the information was classified as active experimentation (AE) or reflective observation (RO) and how a person perceives information was classified as concrete experience (CE) or abstract conceptualization (AC). This model will situate a person in one of the quadrants such as an accommodator, diverger, converger or assimilator.

2.2 Mobile Learning

There are different ML perspectives in the literature. While mobility has different connotations and literally means movement; this capability creates a variety of conceptualizations of mobile education where students are be able to learn while they are traveling, driving, sitting, or walking with or without an electronic device (Traxler, 2007). For this reason, is important to define ML for this research as a kind of learning model allowing learners to obtain learning materials anywhere and anytime using mobile technologies and Internet (Lan and Sie 2010).

Mobile devices, such as laptops, notebooks, tablets and smartphones are defined as communicators, multimedia entertainment and business processing devices designed to be transported by individuals (Poslad 2009). They have emerged because of the mobility feature but also new devices are introduced in the market continuously with enhanced features such as powerful processors, abundant memory, larger screens and open operating systems. Moreover, the actual trend is toward the convergence of applications, the ubiquitousness of mobile phones, and the continuing demand for smaller and smarter devices (Shin et al. 2011).

Mobile networks enhancements, in terms of speed and reliability, have enabled telecommunication and service providers to offer mobile services (m-services). M-services are data services provided in mobile devices as well if they were performed in a web page with the opportunities of location,
ubiquity, flexibility, personalization, dissemination and interactivity. Everyday these services are gaining popularity becoming a trend topic in the information systems and marketing community (Yi-Shun Wang et al. 2006). Advanced mobiles services enable communication, information, transaction and entertainment to provide banking, commerce, gaming, help desk, health care, advertising and educational services (López-Nicolás et al. 2008).

The changes on the mobile economy, technology advancements and lower costs, allowed people to own powerful and affordable mobile devices. This phenomenon is known as Bring Your Own Device (BYOD) and emerged in the business field but now this phenomenon has been extended to schools and universities.

With the acceptance of technology in education, universities provided new learning environments such as distance learning and e-learning. Now universities are launching new projects on ML encouraging classroom participation through mobile application in learning activities and developing learning resources such as recorded lectures and interactive activities on mobile platforms (Meister 2011). The ML has been considered as a subset of e-learning while ML uses electronic devices that are not fixed at home or office. The use of ML is due largely to the main learning capabilities offered by mobile devices such as portability and availability enabling the development of engaging activities that can be applied anytime and anywhere.

2.3 Technology Adoption

Technology is evolving and with this a big challenge for designers and managers to understand how and why people adopt or do not adopt new technology. In the mobile context there is a lack of understanding about the factors that encourage or inhibit consumers/users to adopt and use mobile devices (Sarker and Wells 2003).

2.3.1 Adoption Theory

The Theory of Reasoned Action (Fishbein and Ajzen 1975) and the Theory of Planned Behavior (Ajzen 1991) have been used successfully to assess technology adoption. TRA states that there are four constructs that a user has in actual behavior since the behavioral intention is positively influenced by beliefs, attitude, normative beliefs and subjective norm. TPB states that the attitude toward the behavior, subjective norm, and perceived behavioral control determine behavior intention and in consequence behavior. Technology Acceptance Model (TAM) is an adaptation of TRA and proposes that the acceptance of a technology in the workplace is influenced by the perceived usefulness and ease of use for the technology use (Davis 1989). Researchers have also confirmed that these models are useful explaining technology adoption by teachers and students in educational contexts (Lai et al. 2012; Sun et al. 2008).

Some researchers have considered that technology acceptance should be studied considering more variables, for this reasons two more models emerged: Technology Readiness and Acceptance Model (TRAM) and Unified Theory of Acceptance and Use of Technology (UTAUT). TRAM includes individual beliefs to understand how people embrace and use new technologies for home and work measured by optimism, innovativeness, discomfort and insecurity (Parasuraman 2000). UTAUT provides a model to assess the likelihood of adoption for a new technology; it emerged from eight different technology acceptance models (Venkatesh et al. 2003). It was formulated with four core determinants of intention and usage (performance expectancy, effort expectancy, social influence and facilitating conditions) and four moderators of key relationships (age, gender, experience and voluntariness of use). This model explains better the ML acceptance compared with TAM since it considers individual variables that influence adoption. UTAUT has been used to investigate different mobile adoptions such as tablet PC (Anderson et al. 2006; El-Gayar and Moran 2006), ML (Jairak et
al. 2009), smartphones (Pitchayadejanant 2011; Shin et al. 2011) and mobile services, (Carlsson et al. 2006).

The diversity of models for individual technology acceptance suggests the maturity of this topic on IS research. While these approaches have been used to measure initial user adoption for technologies using pre-usage variables, the prediction for the post-adoption behaviors have been researched with continuance use models. Together, both approaches could enrich the measurement of the initial adoption and ongoing use for the same technology. Acceptance models have been used in work context where the use of technology is mandatory. Among the technology adoption models, UTAUT was used to test acceptance in different time periods considering work and non-work contexts (Venkatesh, Thong, Chan, et al., 2011). To understand the consumer use on technology an extension of the original version generated the UTAUT2 model (Venkatesh and Thong 2012). While UTAUT implicitly deals with the continuance use including experience as a moderator (Shin et al., 2011) we consider appropriate to extend the model to build this research.

2.3.2 Expectation Confirmation Theory

The ECT developed a model to explain continuance intention that explains why a user continues using a service in the post-acceptance stage (Oliver 1980). ECT proposes that expectation and perceived performance affect confirmation, which consequently impacts on satisfaction and continuance intention (Bhattacherjee 2001). The levels for confirmation will influence successive behaviors. This theory has been widely used to research consumer behavior as well as marketing services. Its predictive ability was applied to predict usage on information technology (Bhattacherjee and Premkumar 2004), mobile devices in u-learning (Shin et al., 2011) and mobile services (Zhou 2011).

3 Research conceptual framework

There are two theoretical perspectives relevant to our conceptual model; it has therefore been divided in two stages. The first, UTAUT model, focuses on the determinants that influence behavioral intention. The second, ECT model, explores continuance intention determined by satisfaction. The model is shown in Figure 1. In the acceptance stage, performance expectancy (PE), effort expectancy (EE) and social influence (SI) where hypothesized to be core determinants of behavioral intention (BI) to use ML. Experience (E) and learning styles (LS) would moderate the influence for the core determinants on behavioral intention, which will influence the use behavior (UB). For actual use stage, we hypothesized that once individual accepted to use, this experience will have an effect on satisfaction (S) and performance (P) each of them affecting use continuance (UC). The framework also includes two more relationships where LS have an effect in satisfaction and performance. Facilitating conditions construct was not considered in this study because in presence of performance expectancy and effort expectancy constructs it becomes non-significant to predict intention (Venkatesh et al. 2003). Age and gender were not included as moderators; age because the study will be conducted in undergraduate programs where the ages are not quite different and gender because actual research shows that under learning environments it is not significant (McElroy et al. 2007). The model is appropriate to reflect the nature of ML because it addresses the use acceptance in ML environments and how this experience will lead to a successive use while they have a subjective or objective confirmation that they are learning.
Figure 1. Integrated Framework.

Acceptance

Performance Expectancy
Performance expectancy is defined as 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).

H1: Performance expectancy has a positive effect on behavioral intention.

Effort Expectancy
Effort expectancy is defined as the degree of ease associated with the use of the system (Venkatesh et al. 2003).

H2: Effort expectancy has a positive effect on behavioral intention.

Social Influence
Social influence is defined as the degree to which an individual perceives that important others believe he or she should use the new system. In mandatory settings, social influence appears to be important only in the early stages of individual experience with the technology, with its role eroding over time and eventually becoming non-significant (Venkatesh et al. 2003).

H3: Social influence has a positive effect on behavioral intention.

Behavioral Intention
According to Theory of Planned Behavior, an individual’s behavior can be explained by his or her behavioral intention that refers to the individual’s decision to perform a specific behavior in the future (Chatzoglou et al., 2009). In our model and consistent with the adoption theory, we expect that behavior intention would have a significant influence on ML usage.
Moderators

Experience
Considering that ML is still in infancy and consequently, very few activities have been implemented in the classrooms therefore, students experience for learning activities have not being measured. Thus, is relevant to study how students perceive their experiences using mobile devices for non-learning activities and how these skills can be transferred in the learning environment. Venkatesh (2013) argues that experience can moderate the effect on behavioral intention and consequently in the continuance use or habit.

H4: The influence of performance expectancy on behavioral intention will be moderated by experience on ML.

H5: The influence of effort expectancy on behavioral intention will be moderated by experience on ML.

H6: The influence of social influence on behavioral intention will be moderated by experience on ML.

Learning Styles
Because LS influence learning, we consider it as a possible moderator.

H7: The influence of performance expectancy on behavioral intention will be moderated by LS.

H8: The influence of effort expectancy on behavioral intention will be moderated by LS.

H9: The influence of social influence on behavioral intention will be moderated by LS.

4 Research Method

4.1 Measurement
Two instruments were conducted to collect the data, the learning style measured with the Kolb instrument and a second instrument to measure technology acceptance.

The participants responded the Kolb instrument and they were categorized as Convergers, Divergers, Assimilators or Accommodators. This instrument contains 12-items in the form of two-choice questions (polar scale) to assess learning. According to Kayes (2005) the Kolb Learning Style Inventory (KLSI) has remained as one of the most influential instruments used to measure individual learning preference. This instrument is available in a Spanish version.

Measurement items used for technology adoption were adapted from literature wherever possible. The scales for the UTAUT constructs were adapted from Vankatesh et al. (2003). New items were developed from information in the literature (Lai et al. 2012; Venkatesh and Thong 2012). The questionnaire was written in English and to ensure clearness and completeness, a pre-test session was conducted with 2 experts to assess logical consistency and easy of understanding. This session produced several suggestions that were discussed and changed in the instrument. For all the measures, a seven-point Likert type scale was adopted with anchors ranging from unlikely extremely (1) to likely extremely (7).

4.2 Sample and procedures
The target population was undergraduate full time students that are enrolled in a business major. The study was conducted in Mexico City in the context of learning experience with mobile devices on two accounting courses for the semester of Fall 2013. Mobile devices support a diversity of tools such as tablets, smartphones, and laptops. These devices enables people to collaborate participate, while they
are at the classrooms or outside them. In this BYOD context, the use of mobile devices is optional. Both instruments were distributed to the students during the class time. We conducted the study in two phases: 1) in the beginning of the semester to collect the LS data and 2) in the middle of the semester to collect technology acceptance data after the ML experience.

We received 42 LS instruments and a total of 39 technology acceptance instruments were returned. The study only used the sample for 39 with both instruments. Among the respondents, 38% were female and 62% male. On average, the participants were 21 years old and spend on the phone 74 minutes per day for calls and SMS, 59 on mobile apps, 20 on emailing, 20 on video games and 69 on social networking platforms.

In the beginning of the semester the students were communicated about the new learning activities using mobile devices. The groups are small and the students were asked to sign a mobile policy to participate in the study, this policy allows the use of mobile devices in the classroom for academic purposes. The IT department was consulted to have support in mobile networks. One email was sent to the students to download the applications required (Google Docs and Nearpod). The learning activities included quizzes, videos and rubrics that were used with mobile devices.

4.3 Data Analysis Technique

Data analysis was undertaken using partial least squares (PLS). PLS has the capacity to estimate simultaneously the measurement component and the structural component (Chin 1998b). In this research, PLS becomes relevant while it does not require a large sample size and is more convenient in causal predictive testing. The software used was SmartPLS version 2.0 to analyze the data.

5 Results

The procedure to analyze the data followed a two-steps procedure. The first step included the assessment of the measurement model and the second step tested the structural model. The results are reported in the following sections.

5.1 Measurement model

The accuracy of the measurement model was assessed on the criteria of reliability, convergent and discriminant validity. First, we measured reliability using composite reliability to see whether all items exceeded the recommended cut-off of 0.7 (Chin 1998b). The convergent validity of the measurement model was assured looking first at the cross-factor loadings. The loadings for that particular construct should be higher than the other indicators used to measure the other constructs and exceed 0.70 (Chin 1998b). For a satisfactory discriminant validity the square root of the average variance extraction (AVE) for a particular construct should be larger than the correlations between it and the other constructs (Chin 1998b).

After examining our first run of the model, we discovered that two items, SI3 and SI4, (Appendix) were not explaining the construct in the cross-factor loadings showing a lower value compared with other items under social influence construct. In order to assess the validity of the model we decided to exclude SI3 and SI4 items from the model and to rerun it.

The results from the measurement model analysis are shown in Table 1 and Table 2 that reveal that the measures in our model have adequate reliability, convergent and discriminant validity. First, the reliability, assessed with the composite scale reliability, they were above the recommended threshold of 0.7 showing values above .92. Second, the convergent validity was measured with a factor loading (Table 2), according to Hair et al. (1992) a factor loading greater than 0.50 was considered to be significant, no measurement item loaded more highly on a construct other than the construct intended to measure, all of the factor loadings of the items in the research model were greater than 0.85,
providing evidence of acceptable item convergence. Third, the discriminant validity of the factors was satisfied when the square root of the AVE from a construct exceeded the respective constructs’ correlation with any other variable in the model (Fornell & Larcker, 1981). In summary, this analysis implies that this study exhibits reliability, convergent and discriminant validity.

<table>
<thead>
<tr>
<th></th>
<th>C-R</th>
<th>AVE</th>
<th>PE</th>
<th>EE</th>
<th>SI</th>
<th>BI</th>
</tr>
</thead>
<tbody>
<tr>
<td>PE</td>
<td>0.94</td>
<td>0.80</td>
<td>0.89</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>EE</td>
<td>0.93</td>
<td>0.77</td>
<td>0.61</td>
<td>0.88</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SI</td>
<td>0.96</td>
<td>0.92</td>
<td>0.60</td>
<td>0.25</td>
<td>0.96</td>
<td></td>
</tr>
<tr>
<td>BI</td>
<td>0.92</td>
<td>0.75</td>
<td>0.77</td>
<td>0.71</td>
<td>0.40</td>
<td>0.87</td>
</tr>
</tbody>
</table>

C-R: Composite Reliability; PE: Performance Expectancy; EE: Effort Expectancy; SI: Social Influence; BI: Behavioral Intention

Diagonal elements (bold) are the square root of the average variance extracted (AVE). Off-diagonal elements are the correlations among constructs. For discriminant validity, diagonal elements should be larger than off-diagonal elements.

Table 1. Result of Measurement Model.

<table>
<thead>
<tr>
<th></th>
<th>1. PE</th>
<th>2. EE</th>
<th>3. SI</th>
<th>4. BI</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. PE1</td>
<td>0.85</td>
<td></td>
<td>0.53</td>
<td>0.74</td>
</tr>
<tr>
<td>1. PE2</td>
<td>0.91</td>
<td>0.51</td>
<td>0.56</td>
<td>0.70</td>
</tr>
<tr>
<td>1. PE3</td>
<td>0.93</td>
<td>0.55</td>
<td>0.49</td>
<td>0.66</td>
</tr>
<tr>
<td>1. PE4</td>
<td>0.88</td>
<td>0.40</td>
<td>0.56</td>
<td>0.64</td>
</tr>
<tr>
<td>2. EE1</td>
<td>0.57</td>
<td></td>
<td>0.21</td>
<td>0.60</td>
</tr>
<tr>
<td>2. EE2</td>
<td>0.47</td>
<td>0.85</td>
<td>0.26</td>
<td>0.56</td>
</tr>
<tr>
<td>2. EE3</td>
<td>0.60</td>
<td></td>
<td>0.26</td>
<td>0.69</td>
</tr>
<tr>
<td>2. EE4</td>
<td>0.51</td>
<td></td>
<td>0.16</td>
<td>0.64</td>
</tr>
<tr>
<td>3. SI1</td>
<td>0.60</td>
<td>0.29</td>
<td></td>
<td>0.97</td>
</tr>
<tr>
<td>3. SI2</td>
<td>0.55</td>
<td>0.19</td>
<td></td>
<td>0.95</td>
</tr>
<tr>
<td>4. BI1</td>
<td>0.71</td>
<td>0.63</td>
<td>0.34</td>
<td></td>
</tr>
<tr>
<td>4. BI2</td>
<td>0.66</td>
<td>0.75</td>
<td>0.30</td>
<td>0.34</td>
</tr>
<tr>
<td>4. BI3</td>
<td>0.67</td>
<td>0.73</td>
<td>0.33</td>
<td>0.92</td>
</tr>
<tr>
<td>4. BI4</td>
<td>0.63</td>
<td>0.33</td>
<td>0.44</td>
<td>0.76</td>
</tr>
</tbody>
</table>

Table 2. Loadings and Cross-loadings.

5.2 Structural model

After confirmed the measurement model, the following step is to assess the explanatory power of the entire model on the ML acceptance, as well as the predictive power of the independent variables and mediating variables. The R-square value given for the endogenous constructs were used to assess the productiveness of the model. The statistical significance for each path was calculated with a PLS bootstrapping method using 5000 subsamples to get standard errors estimates and t-values (Chin 1998a). The statistical significance of each path coefficient permits the assessment for the supported hypothesis. The results of the PLS analysis are shown in Figure 2.
The results indicated that the structural model explained 81.8% of the variance on behavioral intention. The R-square indicated the predictive power of this model, and suggested that there is a significant combined effect of all independent and mediating variables on the dependent variable. The values obtained for performance expectancy ($\beta=.60, t=5.50$) and effort expectancy ($\beta=.78, t=3.25$) help to support H1 and H2. The social influence had no significant impact on behavioral intention, leading to the rejection of H3. The coefficient for experience as a moderator for performance expectancy was significant and positive ($\beta=.235, t=2.144$), providing support for hypotheses H4. However the results for the moderating effect for effort expectancy and social influence on performance expectancy had no significant impact ($\beta=-1.314, t=1.909$) and ($\beta=1.14, t=1.337$). Thus, H5 and H6 are not supported. The moderating effect of LS on performance expectancy and social influence were not significant ($\beta=-2.57, t=1.27$) and ($\beta=.508, t=1.206$). These results lead to the H7 and H9 rejection. However the moderating effect on effort expectancy ($\beta=.443, t=1.849$) was found significant, supporting H8.

6 Discussion

The UTAUT model proposed by Venkatesh et al. (2003) explained 70% of behavioral intention, this study explained 81%. Using UTAUT as a baseline, this study proposed a modified model to explore the factors affecting student’s ML acceptance and use. First we conducted a study to measure behavioral intention adding two moderators: experience and learning style. This study is an innovative effort on the research on the ML introducing the learning style as a moderator. Literature review show that other factors are considered measuring the acceptance of ML such as gender and age (Wang, Wu & Wang, 2009). The results indicate that performance expectancy and effort expectancy were significant determinants of behavioral intention to use ML.

Considering that performance expectancy, the degree to which a student believes that using the ML will help him or her to attain gains in academic performance, is the most important variable in
behavior intention, is relevant the introduction for learning strategies that requires great attention for professors while they are introducing mobile activities. If students believe that a mobile technology will help them to have a better performance it could be inferred that they will accept to use and therefore a continuance use can be studied. Effort Expectancy (EE) was significant with ML. It appears that students are willing to invest the time to learn and use ML strategies while they think that the use of mobile device does not require a big effort for them.

Social Influence (SI) was not significant in introducing ML. This could be attributed to the fact that the technology is not required in the classrooms or even promoted. In some classes, is forbidden the use of mobile devices inside the classroom. Two items were excluded from the study, SI3 and SI4, because they were not explaining the construct. It seems that professors and university as promoters for ML are conditions that should be studied. Considering that the ML study was conducted under a BYOD context, where the students bring their own devices to the university.

The experience moderator had a positive effect on the performance expectancy for behavioral intention. This could imply that, as more experienced are the students the more they can perform and will accept the ML. More analysis should be performed in order to understand why experience is not moderating the effort expectancy and social influence.

Considering the introduction of LS as a new moderator in the UTAUT model. The rejection of the moderating effect on performance expectancy and social influence and the supported effect on effort expectancy could imply that more studies should be performed to understand these relationships.

7 Implications

The research implications in this study are three. First, the performances and effort expectancy where confirmed for technology acceptance use. However social influence should be tested again in order to determine the influence in the model. Second, the BYOD context is becoming more frequent in the universities so this fact should be researched to determine the effect on social influence or in other constructs. Finally, the results of this study demonstrate that the UTAUT model can be incorporated in the integrated model to understand ML acceptance and use.

This study addresses some practical implications. First, since students are willing to use the mobile devices it should be noted that most of the learning strategies are not prepared or fitted for mobile devices use. Currently, most learning activities are prepared for traditional environments. The new mobile pedagogy will emerge with changes in instructional design. Second, university policies about mobile devices should be modified to take advantage of learning promises with mobile devices. If they are modified to promote ML use, then institutional support will be required to enhance facilities with powerful mobile networks. Finally, while social influence is a factor that is not explaining behavior intention, it seems that faculty should be trained to take advantage of mobile strategies.

8 Limitations and future studies

Considering the size and the sample of this study there are several limitations. The study only considered students on business majors and a limited number of students in one particular university. Future studies should expand to different universities and should examine additional academic fields.

The results for the pre-usage beliefs could differ from undergraduate students to other context such as adults, workers or graduate students. This study could be enhanced comparing the result in other universities, countries and contexts increasing the sample and the results.

Furthermore, future studies should also examine the BYOD environment while the conditions in the universities will evolve and the students will be allowed to bring their own devices. More findings should be addressed under this condition.
9 Conclusions

This study has successfully identified factors that affect the intention to use ML using the UTAUT model. The findings of this study are consistent with previous studies and are useful to promote the use of mobile devices for learning. Although this study was conducted in one private university in Mexico, the learning context is similar to many others countries. The results also suggest that students are accepting the use of mobile devices, however to understand the student’s perception of ML, the second stage of this study should be conducted to understand how satisfaction and performance are measured when they discovered that they are or are not learning. While the objective is learning, it should be confirmed that the students are performing better and that they will continue to use mobile strategies not because they are entertained but because they are learning.

New opportunities are now arising to build mobile skills with faculty and students on how to incorporate mobile devices into daily learning as effective learning strategies that enhance the learning process. Faculty should be encouraged to understand how to take advantage of ML strategies. In this point, the administrators play an important role so they can start initiatives to voluntarily use them in class. The issue in this initiative is that as early adopters, they will face institutional, pedagogical and psychological limitations.
References


Carlsson, C. et al. (2006). Adoption of Mobile Devices/Services – Searching for Answers with the UTAUT. In Island of Hawaii, USA.


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## Appendix: Technology Adoption Instrument

| PE1: I would find mobile learning useful in my learning. | Performance Expectancy (PE) (Venkatesh et al. 2003) |
| PE2: Using mobile learning enables me to accomplish learning activities more quickly. |  |
| PE3: Using mobile learning increases my learning productivity. |  |
| PE4: If I use mobile learning, I will increase my chances of getting a good grade. |  |
| EE1: My interaction with mobile learning would be clear and understandable. | Effort Expectancy (Venkatesh et al. 2003) |
| EE2: It would be easy for me to become skilful at using mobile learning. |  |
| EE3: I would find mobile learning easy to use. |  |
| EE4: Learning to operate mobile learning is easy for me. |  |
| SI1: People who influence my behavior will think that I should use mobile learning. | Social influence (Venkatesh et al. 2003) |
| SI2: People who are important to me will think that I should use mobile learning. |  |
| SI3: The professors in my university have been helpful in the use of mobile learning. |  |
| SI4: In general, my university has supported the use of mobile learning. |  |
| BI1: I intend to use mobile learning in the future. | Behavioral intention (Venkatesh et al. 2003) |
| BI2: I predict I would use mobile learning in the future. |  |
| BI3: I plan to use mobile learning in the future. |  |
| BI4: I aim to use mobile learning instead of the traditional ones. | (Carlsson et al. 2006) |