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MOBILE LEARNING ADOPTION FRAMEWORK: AN EMPIRICAL INVESTIGATION FROM LEARNERS PERSPECTIVE

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ABSTRACT

The purpose of this research was to identify factors influencing the adoption of mobile learning from learners' perspective. Mobile learning has become an emerging educational platform which is gaining popularity in the context of developed countries. However, there is research gap that abstains from providing a complete view of mobile learning adoption in the context of developing countries. To the best of our knowledge, no notable conceptual model is proposed in order to measure students' intention towards mobile learning. In order to address the gap, Mobile Learning Adoption Model (MLAM) is proposed on the basis of Technology Acceptance Model (TAM) and Unified Theory of Technology and Use of Technology (UTAUT) model. An online survey is conducted to collect data from 158 students at undergraduate, graduate and postgraduate level in Pakistan. Structural Equation Modeling (SEM) is employed to observe the data fit for measurement model by using AMOS 20. The results of the study revealed differences in the perception of students belonging to the discipline of Information Technology (IT) and Non-IT. In addition, two constructs i.e. mobile readiness and perceived mobility are found to be strongest contributors in influencing the behavioural intention of students towards mobile learning systems. The authors assert that the key findings are useful for policy makers, decision makers and researchers. The proposed mobile learning adoption model i.e. MLAM can be used as a guideline for the implementation of mobile learning systems in Pakistan.

Keywords: *Mobile Learning, TAM, UTAUT, Technology Adoption*

1) INTRODUCTION

The use of Information Technology (IT) in education has been focused on facilitating learning in prescribed environment, such as lecture theaters/halls or computer laboratories. Nevertheless, one of the prime advantages of adopting m-Learning is its interdependence of both location and time. As a result, mobile devices usage e.g. smartphones has extended the learning process among the masses, liberating the learners from ties to a certain location. The technology proliferation has changed the dimension of the education field by adapting technical innovations (Baek et al., 2008; Özdoğan et al., 2012). The digitalised era has widened the horizon of education delivery approaches for learning community who are geographically located at a distant place (Kanwal and Rehman, 2014; Moore et al., 2011). A number of research studies have emphasized the importance of technology as a value addition medium in classroom teaching (Baek, Jung and Kim, 2008) that erupted a new learning "waveform" known as "mobile learning" (Leung and Chan, 2003). The limitation of a wired network connection to access internet is faced by the students and professionals who are frequently mobile in nature (Al-Mushasha and Hassan, 2009). In order to overcome the limitation, a system which realises the demand of the hour (mobility) is needed by learners' community (Al-Mushasha and Hassan, 2009; Motiwalla, 2007). "Mobility" enables learners to perform learning activities at their favorite place and pace (Cheon et al., 2012). Mobile learning involves intersection of mobile computing along with electronic learning to provide personalised learning anytime anywhere (Leung and Chan, 2003; Quinn, 2000; Triantafillou et al., 2008). On the other hand, (Liu et al., 2010a; Liu et al., 2010b) discusses that availability of mobile technologies do not ensure its usage awareness in the possible consumer. According to Cheon et al. (2012) usage of mobile services is not apt because the end users are still hesitant. The lack of awareness in adoption of m-Learning indicates room for investigation which is undertaken in this research work. Moreover, the researchers such as (Cheon et al., 2012; Liu et al., 2010a; Liu et al, 2010b; Lowenthal, 2010; Özdoğan et al., 2012; Park et al., 2011; Wang et al., 2009) have recommended determining the intentions of users to adopt m-Learning.

From published research studies on m-Learning, no notable integrated conceptual model is proposed for exploring intentions to adopt m-Learning. The existing studies have widely customised Technology Acceptance Model (TAM) in m-Learning context to explore the intentions

(Chang et al., 2012). TAM determines the indirect effect on the intentions through the operational factors (perceived usefulness and perceived ease of use) of the particular system. For example, perceived ease of use to perceived usefulness which indirectly affects the intentions of users for acceptance of a novel system. From the literature, the other notable model addressed is Unified Theory of Technology and Use of Technology (UTAUT) in m-Learning context. The unified theory of acceptance and use of technology determines the direct effect on intentions for adoption of novel system. In TAM, the independent factors have a direct effect on other factors relaying an indirect effect on intention, whereas in UTAUT the independent factors have a direct effect on intentions. Therefore, these adoption models are individually investigated to explore the intentions of users' to adopt m-Learning. Hence, to fill the potential gap between the existing models on m-Learning, a model is proposed in which influential factors have direct and indirect effect on intentions.

The purpose of this research is to identify the influential factors and their relationships that shape up the behavioural intention for adoption of m-Learning. There is room for research as partial issues of adoption are brought to light. The research work aims to fill this gap by investigating the existing literature on m-Learning. A conceptual integrated model is constructed for determining the intentions of users in Pakistan. The vibrant researchers are trying to reduce the gap between mobile learning theoretical world and practical implications. The researchers' attention has grown from negligible interest to dynamic level in m-Learning (Liu et al., 2010a; Liu et al., 2010b). Many research studies on mobile learning addresses different aspects such as design and development (Little, 2012), applications (Cheon et al., 2012), mobile learning challenges and capabilities (Hashemi et al., 2011), technical issues (Leung and Chan, 2003; Quinn, 2000), and learning approaches (Cheon et al., 2012; Özdoğan et al., 2012; Romano et al, 2005; Shen et al., 2008). Mobile technology especially mobile phones are gaining popularity in society (Liu et al., 2010a; Liu et al., 2010b; Motiwalla, 2007) due to its affordable cost and fast delivery mechanism (Leung and Chan, 2003; Park et al., 2011). One of the essential requirements of mobile learning is mobile technology. Thus, the availability of mobile technologies does not ensure its usage awareness in the potential consumers (Cheon et al., 2012; Liu et al., 2010a; Liu et al., 2010b). Moreover, (Liu et al., 2010a; Liu et al., 2010b) mentioned that mobile telephony along with a 3G connection is hugely dispersed among consumers but actual usage of high-tech mobile services are not apt because consumers are still hesitant. The research studies conducted on "adoption of mobile learning" are few in number that explores learners' behavioural intention either through TAM or UTAUT independently (Cheon et al., 2012; Liu et al., 2010a; Liu et al., 2010b; Lowenthal, 2010; Özdoğan et al., 2012; Park et al., 2011; Wang et al., 2009).

United Nation Educational, Scientific and Cultural Organization (UNESCO) rank Pakistan at 180th position in literacy rate worldwide. It is obvious from the statistics that deployment of mobile learning systems will help students in learning along with boosting overall literacy rate of country. In Pakistan, there are 139 millions of users who are making use of smart phones. Moreover, these users belong to the age group of 21-30. Currently, no mobile learning systems have been deployed in the country. Therefore, there is a need to deploy such systems. This research will make an attempt to identify the critical factors which influence the adoption of mobile learning.

To best of our knowledge, no notable integrated conceptual model is proposed measuring intentions of users towards m-Learning. The integrated conceptual model presents an overall picture of determinants and their relationships for adoption of mobile learning framework. Further, guidelines on behavioural intentions are formulated for better understanding of regulating authorities about promoting user's adoption of m-Learning. The main objectives of the study are as follow:

- To identify the potential influential factors and their relationships on m-Learning adoption from existing literature.
- To propose a "Mobile Learning Adoption Model (MLAM)" based on the existing fundamental models for identifying comprehensive set of potential determinants influencing m-Learning adoption.
- To validate the model through empirical evaluation of influencing determinants on behavioural intention of users to use and adopt m-Learning in higher level of education.

The conceptual model presents a complete picture of the influential factors that determines users' adoption of mobile learning. Moreover, university students are potential audience with education level of undergraduate, graduate and post graduate belonging to diverse disciplines for empirical evaluation. Section 2 describes the related work done so far on m-Learning. Section 3 summaries proposed model constructs and their relationship in m-Learning context. Section 4 research methodology, is about how and which techniques are used to validate the proposed model and formulated hypotheses. Section 5 performs data analysis and discusses results of significant relationships, differences between IT and non-IT groups in m-Learning adoption context. The last section concludes research work done so far and the results of our experimental evaluation for measuring the intentions towards m-Learning usage and adoption. In the end, future directions are described for further research.

2) A THEORETICAL PERSPECTIVE

The adoption models such as TAM and UTAUT are discussed in existing studies for exploring users' intentions to use m-Learning. Davis (1989) proposed TAM for predicting users' intentions towards a novel system. The fundamental model is used to identify the effect of external factors on the users' belief, attitude and intentions for using a novel system by researchers (Davis, 1989). TAM postulates two strong beliefs i.e. perceived usefulness and perceived ease of use that assist in acceptance of Information Systems (IS). Later, attitude is eliminated from TAM due to its weak correlation with perceived usefulness and behavioural intention [5, 6]. On the other hand, the research presented by Venkatesh and Davis (2000) focuses on the acceptance behavioural models which review similarities and dissimilarities in existing models to illustrate a new model known as UTAUT. Venkatesh and Davis (2000) demonstrated the UTAUT model by providing empirical evidence of theory for IT acceptance. The existing studies have addressed either TAM or UTAUT in m-Learning context. On the basis of these validated studies, a thorough study is performed on the constructs of base model for keeping the constructs relationships intact to measure intentions. The determinants of m-Learning are extracted from the existing studies. Table 1 summarises the source studies, influential factors, significant factors and adopted factors from the existing studies.

Table 1: Determinants of m-Learning – Theoretical Investigation of Existing Studies

Reference	Influential Factors *(Existing Studies)*	Significant Factors *(Existing Studies)*	Adopted Factors *(Existing Studies)*
(Wang et al., 2006)	Perceived Credibility Self-efficacy Perceived Financial Resources Perceived Usefulness Perceived Ease of Use	All	Perceived Usefulness Perceived Ease of Use
(Huang, Lin and Chuang, 2007)	Perceived Usefulness Perceived Ease of Use Perceived Enjoyment Perceived Mobility	All	Perceived Usefulness Perceived Ease of Use Perceived enjoyment Perceived mobility
(Wang et al., 2009)	Performance Expectancy Effort Expectancy Social Influence Perceived Playfulness Self-management of Learning	All	Performance Expectancy Effort Expectancy Social Influence Perceived Playfulness
(Lowenthal, 2010)	Performance Expectancy Effort Expectancy Self-management Behavioural intention	Performance Expectancy Effort Expectancy Behavioural Intention	Performance Expectancy Effort Expectancy Behavioural Intention
(Liu et al., 2010a; Liu et al., 2010b]	Perceived Ease of Use Perceived Near-term Usefulness Perceived Long-term Usefulness Personal Innovativeness	Perceived Long-Term Usefulness	Perceived Usefulness Perceived Ease of Use
(Teo, 2011)	Perceived Usefulness Perceived Ease of Use Subjective Norm Facilitating Conditions Attitude Towards Use Behavioural Intention to Use	Perceived Usefulness Perceived Ease of Use Facilitating Conditions Attitude Towards Use Behavioural Intention to use	Perceived Usefulness Perceived Ease of Use Subjective Norm Behavioural Intention to Use
(Cheon et al., 2012)	Attitude Subjective Norm Behavioural Control	Behavioural Control	Subjective Norm
(Mahat et al., 2012)	Self-efficacy Personal Innovativeness Mobile readiness	Personal Innovativeness Mobile Readiness	Mobile Readiness

Reference	Influential Factors *(Existing Studies)*	Significant Factors *(Existing Studies)*	Adopted Factors *(Existing Studies)*
(Park et al., 2011)	Perceived Ease of Use Perceived Usefulness Self-efficacy Relevance student major System Accessibility Subjective Norm Attitude Behavioral Intention	Attitude	Perceived Usefulness Perceived Ease of Use Subjective Norm Behavioural Intention
(Özdoğan et al., 2012)	Perceived Usefulness Perceived Ease of Use Facilitating Conditions Reward/motivation Peer Influence External Influence Computer Self-efficacy Personal Innovativeness User Interface Mobility Attitude	Perceived Usefulness Facilitating Condition	External Influence Mobility Perceived Usefulness Perceived Ease of Use
(Tan et al., 2012)	Perceived Usefulness Perceived Ease of Use Subjective Norm	All	Perceived Usefulness Perceived Ease of Use Subjective Norm
(Padilla-Meléndez et al, 2013)	Perceived Usefulness Perceived Ease of Use Perceived Playfulness Attitude Intention to Use	Perceived Usefulness Perceived Playfulness Intention to Use	Perceived Ease of Use Perceived Usefulness Perceived Playfulness
(Park et al., 2014)	Perceived Ease of Use Perceived Usefulness Perceived Enjoyment Perceived Control and Skill Perceived Mobility Perceived Connectedness Perceived Satisfaction Attitude	Perceived Usefulness Perceived Enjoyment	Perceived Ease of Use Perceived Usefulness Perceived Enjoyment Perceived Mobility

From the Park et al. (2014) study, attitude is the strongest followed by mobile readiness and subjective norm among the extrinsic and intrinsic motivational factors including TAM nomological structure. Cheon et al. (2012) addresses behavioural intention is key determinant to provoke users' perception towards m-Learning. Lowenthal (2010) deduce that performance expectancy and effort expectancy are motivational factors of behavioural intention towards m-Learning. The determinants have no mediating effect of moderating variables on the students' intention to use m-Learning. Chang et al. (2012) justified that perceived usefulness has greater impact than intrinsic motivational variables on continuance intention to use English m-Learning System (EMLS). The other motivational factors are perceived convenience and perceived playfulness along with the existing TAM nomological structure i.e. perceived usefulness and perceived ease of use are proven to be effective in predicting and explaining the continuance intention to use the EMLS. Huang et al. (2007) presented that the perceived ease of use, perceived usefulness, perceived enjoyment and perceived mobility all are significant factors in the study to predict and explain the individuals' acceptance of m-Learning. Wang et al. (2009) study results indicate that performance expectancy, effort expectancy, social influence, perceived playfulness, and self-management of learning are all significant determinants of behavioural intention to use m-Learning. The mobile learning adoption factors are affected by individual differences like age and gender. The age difference has moderating effects on the effort expectancy and social influence on m-Learning for usage intention. Similarly, the gender difference has moderating effects on the social influence and self-management of learning on m-Learning use intention.

Liu et al. (2010a) and Liu et al., (2010b) reveals that perceived near-term/long-term usefulness and personal innovativeness are significant factors in influencing m-Learning adoption in concern for continuance usage. Perceived long-term usefulness is most influential determinant of behavioural intention in adoption of mobile learning. Wang et al. (2006) found that perceived usefulness, perceived ease of use, perceived credibility, self-efficacy and perceived financial resources are influential determinants for inclining consumers intention towards usage of m-services. Teo (2011) study of technology acceptance is evaluated in the instructional settings shows that perceived usefulness, perceived ease of use, attitude towards use, and facilitating conditions have a positive direct influence on behavioural intentions of teachers. Baek et al. (2008) explored teacher's intention to use technology which is a deviated paper from the specific context of study i.e. m-Learning acceptance and adoption framework. However, from the conclusion the strongest factor is "adapting to external requests and others' expectations" in a technology oriented classroom settings. It can be considered as "social influence or subjective norm" which is derived from other individuals' belief. Moreover, adoption of the technology in classroom setting is only apt due to external pressure to meet up the policies of institutes or to keep pace with the co-fellows. Park et al. (2014) aims to determine the intention to use mobile social networking games assessing the mobility effect in games. The perceived usefulness and perceived enjoyment are key determinants of behavioural intentions and attitude to use social networking games in mobile environment including other motivational factors such as perceived ease of use, perceived control and skill, perceived mobility, perceived connectedness and perceived satisfaction in mobile social networking games.

Ye et al. [42] reflect perceived usefulness and perceived ease of use to be significant influential elements for implication of users' intention. The external variables and interest are popularised factors of m-Learning for acceptance. Mahat et al. (2012) analyse self-efficacy, personal innovativeness and students' mobile readiness from the assessment results based on mean and standard deviation show that personal innovativeness and mobile readiness are important as compared to self-efficacy from the practically experienced participants of m-Learning. Ozdogan et al. (2012) found perceived usefulness and facilitating condition as the strongest variables in the context of m-Learning. Padilla-Melendez et al. (2013) statistical analysis reflect perceived usefulness and perceived playfulness are found to be key drivers for the adoption and use of Blended Learning System (BLS) depending on users' gender. The perceived playfulness has more significant impact on female regarding playfulness. Similarly, male has more significant impact of perceived usefulness than female. Additionally, the gender difference has moderated effects on motivational factors on users. Liu et al. (2010a) and Liu et al., (2010b) contributed a literature review study that demonstrates perceived usefulness, perceived ease of use, perceived mobility and perceived quality as significant factors. Tan et al. (2012) revealed that subjective norm, perceived usefulness and perceived ease of use are more influential variable for friends, family and coworkers opinion matter in adoption and usage of m-Learning.

3) PROPOSED MODEL

In this section, the research model is proposed for adoption of m-Learning in society. The direct and indirect effects of influential factors on intention are described in the following section.

3.1) Mobile Learning Adoption Model (MLAM)

The research model proposed in this research is based on foundational models of TAM and UTAUT to determine intentions of users' to use m-Learning. UTAUT and TAM are customised for proposing an integrated conceptual model named as Mobile Learning Adoption Model (MLAM) measuring behavioural intention of students. The influential factors of the MLAM model are Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Perceived Playfulness (PP), Perceived Mobility (PM), Mobile Readiness (MR) on Behavioural Intention (BI). Figure 1 demonstrates Behavioural Intention (BI) as dependent variable and other factors as independent variables for predicting the intentions to use and adoption of m-Learning systems.

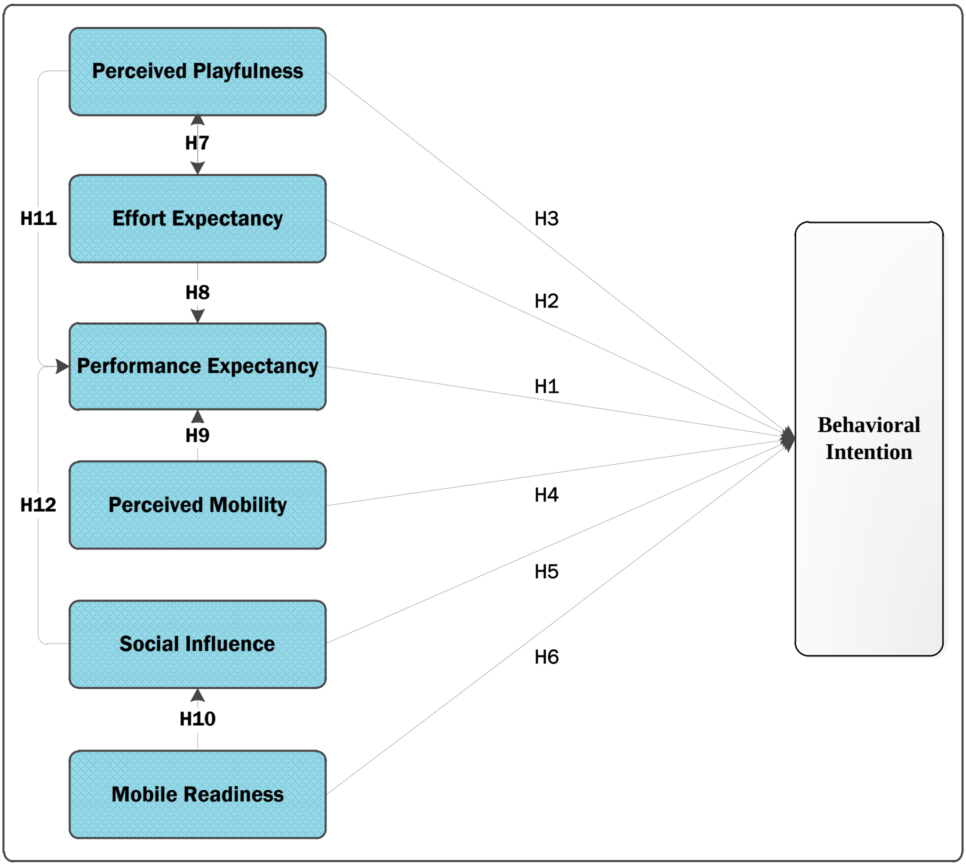

Figure 1: Proposed Mobile Learning Adoption Framework

The independent variables retain certain bound of association with other independent variables. The independent variable acts as intermediary variable to measure the effect of behavioural intention on m-Learning adoption. The direct and indirect relationships are assessed to evaluate the strength of MLAM for learners. The MLAM model adds two additional relationships having a direct effect on behavioural intention for acceptance of m-Learning. Perceived mobility and mobile readiness are explored for a direct effect on behavioural intention of learners. Each relation in Figure 1 is based on the observation of existing studies. The detailed insights of the relationships are presented in Appendix A. The extension of models can be easily seen from each entry of the table that point out the weak aspects of the existing validated studies.

3.2) Determinants of Direct Effect on Intentions

TAM nomological factors perceived usefulness and perceived ease of use are mapped on performance expectancy and effort expectancy respectively (Venkatesh, 2000). In addition, performance expectancy and effort expectancy are critical factors to measure intention in various adoption studies of m-Learning (Chang et al., 2012; Huang et al., 2007; Jackson et al., 2013; Liu et al., 2010a; Liu et al., 2010b; Lowenthal, 2010; Wang et al., 2009; Tan et al., 2012). TAM2 have an additional construct "subjective norm" as compared to core TAM model which was later rooted as "social influence" determinant in UTAUT model (Venkatesh and Davis, 2000). Perceived playfulness is an influential factor having positive effect on intention to use m-Learning (Chang et al., 2012; Park et al., 2014). Perceived mobility impacts on perceived usefulness in m-Learning context (Huang et al., 2007). Prior studies pointed out that perceived mobility is an indirect influential factor in the adoption model of m-Learning. Hence, a direct influence on behavioural intention is evaluated for m-Learning perspective. Mobile readiness is evaluated indirectly for exploring intentions to use m-Learning (Cheon et al., 2012; Mahat et al., 2012). Similarly, mobile readiness direct effect is measured for m-Learning context.

3.3) Determinants of Indirect Effect on Intentions

TAM fundamental relation of perceived ease of use directly effects perceived usefulness to determine the intentions (Davis, 1989). A positive influence of perceived mobility on performance expectancy is assessed in pioneering studies (Huang et al., 2007; Park et al., 2014). Users who find the system interesting and playful tend to have a better performance expectancy which helps in shaping up the intentions (Padilla-Meléndez et al, 2013). Perceived playfulness significantly affects performance expectancy to determine the intentions (Chang et al., 2012; Padilla-Meléndez et al, 2013). Social influence impacts performance expectancy which is also an indirect effect on intention (Özdoğan et al., 2012; Park et al., 2011; Teo, 2011). Peer students and instructors readiness are antecedent of subjective norm, in simple words subjective norm is influenced by users' readiness (Cheon et al., 2012). A unidirectional relationship is formed between perceived playfulness and effort expectancy in many studies. Later studies postulated a reverse relation from perceived ease of use to perceived playfulness for exploratory technology acceptance. Ease of use stimuli happiness and pleasure emotions in users while interacting with m-Learning system which lead to acceptance (Chang et al., 2012; Park et al., 2014). However, both distinct unidirectional relations found to be significant in shaping users perception relating to adoption. Further, a bidirectional relation between effort expectancy and perceived playfulness is formulated from the facts of past adoption theories.

4) RESEARCH HYPOTHESES

The formulated hypotheses are based on the proposed constructs of conceptual model to apt mobile learning. The hypotheses are as follow:

4.1) Performance Expectancy (in relation to User Intention)

Performance Expectancy (PE) elucidates the usefulness associated with the use of technology. In the context of mobile learning, PE is the extent to which users' think that their work performance will be enhanced. Mobile learning provides multiple benefits to its users'. It provides students' greater control of their learning environment. Thus, m-Learning enables the learners to learn as per their individual needs. In addition, students have flexibility to learn at any place at any time. This tool is used for easy access of information and delivery of knowledge in a more manageable way. PE is a key determinant for determining the behavioural intention of learners. The behavioural intention is the extent to which users are willing to use a technology [5, Wang et al., 2009; Tan et al., 2012). The learners' willingness to use mobile learning system is assessed through the intention variable. The usefulness of using m-Learning system motivates the learners' to use and adopt for acquiring knowledge.

H1: *Performance Expectancy will have a positive influence over the behavioural intention to use mobile learning.*

4.2) Effort Expectancy (in relation to Behavioural Intention)

Effort Expectancy (EE) plays an important role in influencing the adoption intentions of learners. The EE is related to comfort and ease of use. The ease to operate involves the individual's perception about the usage of technology/system. In the context of mobile learning, users of mobile learning do not face any difficulty while interacting with mobile learning systems. In addition, they are able to handle their tasks more conveniently. In earlier studies, EE is a salient feature in determining the perception about adoption of emerging technology (Venkatesh and Davis, 2000; Wang et al., 2009; Tan et al., 2012). It is also highlighted in existing studies that learners' will be more willing to adopt mobile learning, if they will find that technology / system is helpful in performing their task efficiently and effectively. In TAM literature, perceived ease of use which maps to EE has been found a significant predictor in many information systems studies.

H2: *Effort Expectancy will have a positive influence over the behavioural intention to use mobile learning.*

4.3) Perceived Playfulness (in relation to Behavioural Intention)

Users are not always logical in their thinking. However, emotional aspects which are mostly overlooked should be considered in order to measure the students' intention to adopt and use mobile learning. While considering the emotional aspects, perceived playfulness is taken into the picture. Playfulness is a complex measure comprises of individual's pleasure, enjoyment, interests and involvement. Moon and Kim (2001) defines the perceived playfulness as an intrinsic factor associated to the state of mind. The users' extensive involvement in using an IT system is incubated through a sense of pleasure and enjoyment through perceived playfulness (Chang et al., 2012; Moon and Kim, 2001). If the students feel pleasure, interest and enjoyment while interacting with the mobile learning systems then it is encountered that their intention to adopt mobile learning systems will be high (Moon and Kim, 2001).

H3: *Perceive Playfulness will have a positive influence over the behavioural intention to use mobile learning.*

4.4) Perceive Mobility (in relation to Behavioural Intention)

Perceived Mobility (PM) symbolises user awareness about mobility in the context of mobile learning. Mobility is composed of different elements including convenience, expediency and immediacy (Huang et al., 2007; Park et al., 2014). Through mobility, students can access data information from anywhere and at any time which removes the restriction of being in class room settings in order to learn something. In addition, PM element involves the transmission of data irrespective of location. In other words, mobility enables the students to learn in new dynamic environments. The concept of mobile learning emerges due to the mobility aspect of mobiles. Therefore, PM is one of the critical factors influencing the students' intention to adopt mobile learning systems. If the students will be aware of mobility perspective of mobiles then their intention to adopt and use mobile learning systems will be high.

H4: *Perceived Mobility will have a positive influence over the behavioural intention to use mobile learning.*

4.5) Social Influence (in relation to Behavioural Intention)

Social Influence (SI) is a significant predictor in predicting one's intention to use m-Learning. It is also conceptualised as subjective norms, social beliefs and normative beliefs. It is perceived as a social pressure from peers or individuals' in order to get engage in a certain behaviour or not. The social factor is explored in order to determine the potential effects on the behavioural intention of learners' in adopting and using mobile learning. In addition, social influence is proven to be significant for new technology usage (Mathieson, 1991; Moore and Benbasat, 1991; Thompson et al., 1991; Venkatesh and Davis, 2000). If the students feel that their actions are influenced by their peers or individuals who are important to them then their intention to adopt and use mobile learning systems will be high. In prior studies, SI is found to be significant concern in order to influence the behavioural intention of learners to use mobile learning.

H5: *Social Influence will have positive influence over the behavioural intention to use mobile learning.*

4.6) Mobile Readiness (in relation to Behavioural Intention)

The construct of mobile readiness is included to analyse the current state of applications, data, environment and methods for mobile device management. The availability of mobile device which has enabled internet along with installed mobile application will be basic requirement for mobile readiness (Mahat et al., 2012). The availability of mobiles which provides support for internet promotes the usage of mobile learning. If the students will have internet enabled mobiles then their intention to adopt and use of mobile learning systems will be high. In addition to this, the students must have a high level of confidence in using mobile technology as a part of their learning process which is essential to ensure that mobile learning will be successful. The mobile readiness direct effect is measured on behavioural intention in order to measure the acceptance and use of mobile learning.

H6: *Mobile Readiness will have a positive influence over the behavioural intention to use mobile learning.*

4.7) Perceived Playfulness (in relation to Effort Expectancy)

Playfulness is a composite measure consisting of one's pleasure, interest, involvement and enjoyment. In this hypothesis, perceived playfulness acts as an antecedent of effort expectancy. According to the hypothesis condition, perceived playfulness will positively influence over the effort expectancy which indirectly influences users' intention to use and adopt mobile learning. The involvement in any task leads to ease and comfort in performing that task which ultimately influences the students' intention to adopt and use mobile learning. If the students are highly involved in any task then there are more chances that they will feel ease and comfort while performing that task. The relationship is encountered in many past studies (Chang et al., 2012; Huang et al., 2007; Padilla-Meléndez et al, 2013; Park et al., 2014). The bi-directional relationship is explored in the literature between effort expectancy and perceived playfulness. Therefore, the relationship is formed as:

H7: *Perceived playfulness will have a positive influence over the effort expectancy to use mobile learning and vice versa.*

4.8) Effort Expectancy (in relation to Performance Expectancy)

In TAM model, the perceived ease of use is an antecedent of perceived usefulness in modeling the users' intention to adopt m-Learning (Davis, 1989). Perceived usefulness is mapped on performance expectancy and perceived ease of use is mapped on effort expectancy respectively. In the context of mobile learning, it is regarded as the ease associated while performing any task ultimately impacts the usefulness of the system. If the students contemplate that the task of interacting with mobile learning system is easy, then their perception towards the usefulness of mobile learning systems will be positive. The said relationship will positively impact the students' intention towards the adoption and use of mobile learning systems. Hence, TAM is a foundational model. Therefore, the relationship is formulated between effort expectancy and performance expectance which determines the indirect effect on behavioural intention for using mobile learning system. Thus, the relationship is found to be consistent with existing studies (Venkatesh and Davis, 2000; Wang et al., 2009; Tan et al., 2012) and formulating the following hypotheses:

H8: *Effort Expectancy will have a positive influence over the performance expectancy to use mobile learning.*

4.9) Perceived Mobility (in relation to Performance Expectancy)

In this hypothesis, perceived mobility acts as an antecedent of performance expectancy. Mobility is considered as a core element for mobile learning systems. Due to this factor, learning may take place at any time and also at any place (Huang et al., 2007; Park et al., 2014). In this study, perceived mobility is defined as "the extent of user awareness of the mobility value of mobile services and systems". There are several studies in the literature which support the relationship between perceived mobility and performance expectancy. According to this hypothesis, perceived mobility enhances the performance expectancy of the students to adopt and use mobile learning system. The strong belief on the usage of mobility feature will positively enhances the usefulness of mobile learning systems. Therefore, the following hypothesis is formed as:

H9: *Perceived Mobility will have a positive influence over the performance expectancy to use mobile learning.*

4.10) Mobile Readiness (in relation to Social Influence)

The students must have full confidence in order to make use of mobile technology as a part of their learning process. In order to make mobile learning successful, usage of technology enabled mobiles is a pre-requisite for mobile readiness. In this study, the relationship of mobile readiness over social influence is adapted from the previous study to examine the effects of user intention to adopt and use mobile learning (Cheon et al., 2012). It is also highlighted that if the students are prepared to make use of technology enabled mobiles then there are more chances that the adoption of mobile learning systems will be high. In other words, usage of mobile learning systems will also impact peers, individuals, friends and co-workers. In order to measure the impact of mobile readiness over the social influence, the hypothesis is formed as follows:

H10: *Mobile Readiness will have a positive influence over the social influence to use mobile learning.*

4.11) Perceived Playfulness (in relation to Performance Expectancy)

The construct of perceived playfulness motivate the learners' towards the usefulness of mobile learning systems which ultimately impacts the intention to adopt and use of mobile learning systems. The excitement, involvement and interest in the usage of mobile learning systems ultimately enhance the usefulness of such systems. If the users of the system get more engaged, involve and take more interest in any particular system then there are more chances that these users will perceive such systems more useful. The said relationship is not true for all kinds of users. However, the relationship is found to be significant in existing studies of (Chang et al., 2012; Padilla-Meléndez et al, 2013). Therefore, the following relationship is formed as:

H11: *Perceived playfulness will have a positive influence over the performance expectancy to use mobile learning*

4.12) Social Influence (in relation to Performance Expectancy*)*

The social influence might positively affect the performance expectancy of mobile learning. The social pressures of peers may impact over the usefulness of mobile learning systems (Wang et al., 2009). It is hypothesized that due to the peer pressure, individuals may think that mobile learning systems are very productive in order to learn about their courses. In this way, social influence may positively impact over effort expectancy. The relationship may not turn out to be significant for all kinds of users. In addition, the relationship is found to be consistent with the existing study of mobile learning adoption (Özdoğan et al., 2012). Therefore, the hypothesis is formed as follows:

H12: *Social Influence will have a positive influence over the performance expectancy to use mobile learning.*

5) RESEARCH METHODOLOGY

5.1) Research Design

According to Babin et al. (2003), research design possesses simple set of instructions carried out for development of project. A strategic plan gives a detail insight of the processes for the investigation of problem. There are numeral ways to distinguish a research depending on the nature, purpose, data collection and data analysis of the study. The exploratory research is followed to examine the hypothesis testing and data analysis. The detailed steps of methodology taken in this research study are shown in Figure 2.

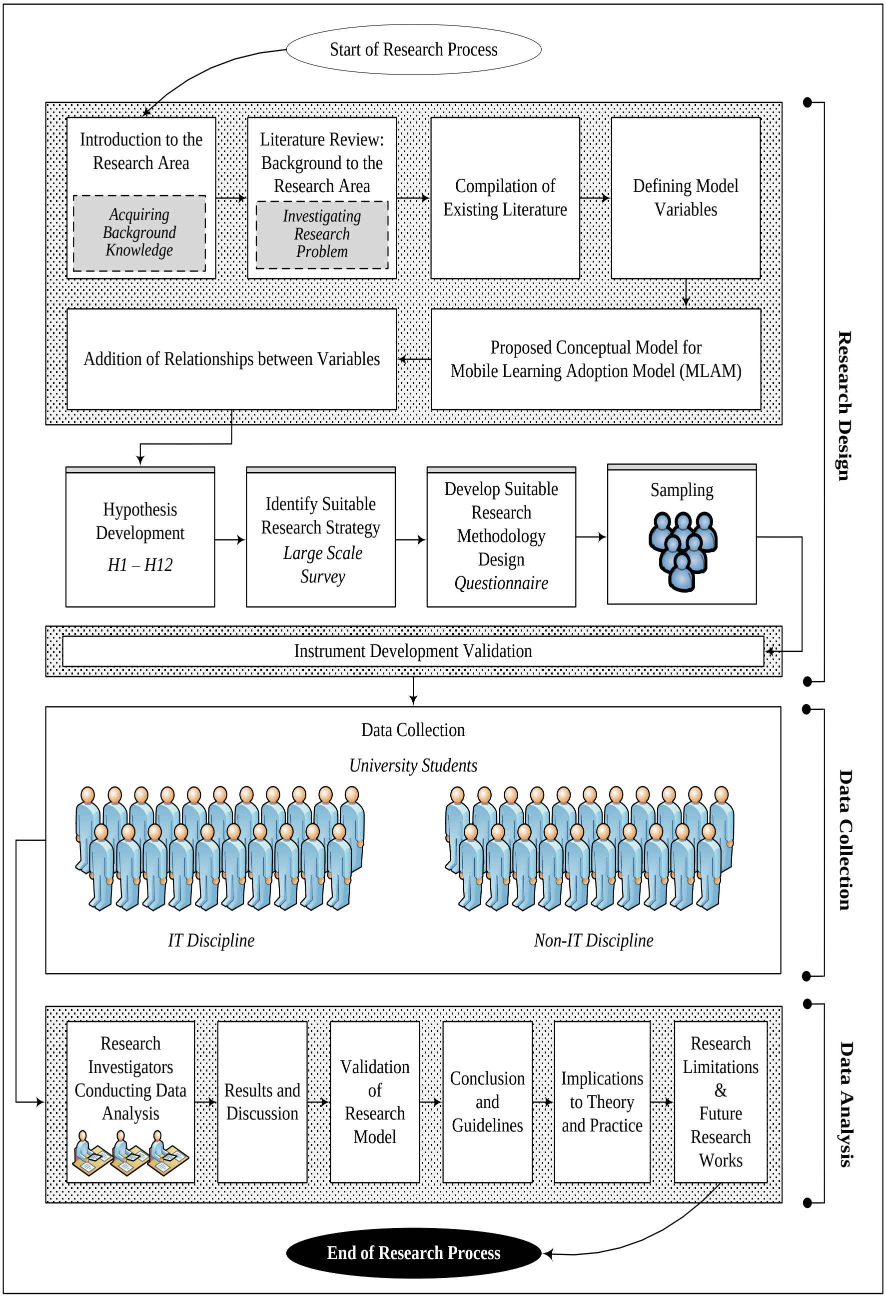

Figure 2: Research Design

The systematic process describes the performed activities in the Figure 2 presenting a complete picture of the research design. The research work is based on existing studies leading to customisation, value additions, model featuring, validity check of proposed model factors and their relations sums up with conclusion and guidelines.

5.2) Model Validation Technique

MLAM is validated through empirical evaluation for determining the influential factors effect on behavioural intention of users. Survey Research is used to assess the opinions, perceptions and thoughts of the different groups of people on the predetermined set of questions (Pfleeger, 2001). Many studies have used research instrument to validate the conceptual model for evaluating various beliefs on adoption and usage of IT system (Huang et al., 2007; Lee, 2006; Liu et al., 2010a; Liu et al., 2010b, Mahat et al., 2012; Wang et al., 2006; Tan et al., 2012).

5.3) Survey Instrument Development

The survey instrument is an integral part of a survey process with clear illustration of defined activities (Pfleeger, 2001). The survey instruments are designed on the basis of previous research studies within m-Learning domain (Liu et al., 2010a; Liu et al., 2010b; Tan et al., 2012). The survey instruments wording is modified for clear context delivery of m-Learning to respondents. Two experts performed the pretesting of the measure for developing concise survey. A five point Likert-type scale is used ranging from strongly agree to strongly disagree which is suitable for long questionnaires (Pfleeger, 2001).

5.4) Data Collection

The target respondents for validation of MLAM are university students belonging to different educational levels i.e. undergraduate, graduate and post graduate students. The participants are asked to evaluate their perception of m-Learning by completing the questionnaire. For data collection, the participants are divided into two groups: IT and non-IT disciplines. The data is collected through an online survey in the month of April, 2014. The URL of the survey is shared through emails with an enclosing cover letter. The participants self-administered the questionnaire by selecting the appropriate level of agreement with the statement. The invalid and incomplete responses are discarded from the data set and a total of 158 usable responses are selected for analysis.

5.5) Sampling and Sample Size Determination

Purposive sampling is employed because it reduces time in subject selection. The purposive sampling represents a group of sampling units who are appropriate for the study as the sample frame is based on limited number of people who have interest or experience in the relevant research area. To strengthen the survey, an appropriate sample size is required. The minimum sample size for conducting survey is carried out by two distinct formulas for determining the best model fit. The formulas are:

- 50 + 8K (1)
- 50 + 8K, here k is the number of independent variables in the model
- 50 + 8(6)
- 50 + 48 = 98

The other minimum sample size formula is:

- 104 + K (2)
- 104 + K, here k is the number of independent variables in the model
- 104 + 6 = 110

However, to strengthen the survey findings an appropriate sample size is required which is not less than 110. Green (1991) suggests to calculate both of the above formulas for sample size determination and to use the largest value sample size. In addition, for SEM analysis sample size of 150 will be sufficient for model convergence and proper solution of problem (Anderson and Gerbing, 1991).

6) ANALYSIS AND FINDINGS

This section analyses the internal consistency of research instrument, demographics of respondents, data fit of model and inclination of respondents towards m-Learning adoption (through sample independent t-test).

6.1) Reliability of Research Instrument

The reliability of the research instrument is measured through internal consistency based on exiting studies (Liu et al., 2010a; Liu et al., 2010b; Özdoğan et al., 2012; Park et al., 2014; Teo, 2011; Tan et al., 2012). Cronbach alpha is used to evaluate the internal consistency of survey instrument items through the predictive analytic software SPSS 20.0. The reliability coefficient measures construct value greater than 0.7 is considered "Good" (Liu et al., 2010a; Liu et al., 2010b; Tan et al., 2012). Table 2 describes the internal reliability of each construct.

Table 2: Constructs Internal Consistency

Construct	No. of Items	Cronbach Alpha Value	Reliability Level
Performance Expectancy	6	0.813	Good
Effort Expectancy	6	0.829	Good
Social Influence	3	0.815	Good
Perceived Playfulness	5	0.843	Good
Perceived Mobility	3	0.892	Good
Mobile Readiness	5	0.857	Good
Behavioural Intention	5	0.801	Good

All the variables alpha coefficient is above 0.7 threshold value representing good internal consistency.

6.2) Descriptive Statistics

The demographic profiles of sample subjects are summarised in Table 3.

Table 3: Demographic Profiles of Participants

Socio Demographic Factors	Ranges	Frequency	Responses (%)
Age	18-25 Years	91	57%
	26-35 Years	34	22%
	36-45 Years	11	7%
	46-55years	14	9%
	56-Above	8	5%
Gender	Male	96	61%
	Female	62	39%
Computer Proficiency Level	Less Than 1 Year	5	3%
	1 To 3 Years	39	24%
	4 To 6 Years	46	29%
	7 To 9years	27	18%
	More Than 9 Years	41	25%
Education	Under Graduate Student (Hons)	31	20%
	Graduate Student (Hons)	71	45%
	Post Graduate Student	38	24%
	Doctoral Students	18	11%
Computer Assisted Software Experience	Yes	111	70%
	No	47	30%
Major Discipline	IT Students	77	49%
	Non-IT Students	81	51%

As shown in Table 3, 57% students of 18-25 years age group are more active and interested in adapting the new waveform of learning. The statistics describes that 70% of the sample population is familiar with computer aided software for educational purpose. The sample frame represents qualified people with 20% under graduate, 45% Graduate, 24% Post Graduate and 11% Doctoral Students.

6.3) Evaluation of the measurement model

The measurement model is assessed through Confirmatory Factor Analysis (CFA) in literature studies (Im et al., 2011; Liu et al., 2010a; Liu et al., 2010b; Wang et al., 2006; Wang et al., 2009). The confirmatory factor analysis tests the latent variables which cannot be measured directly. The estimation of these variables is measured through observed variables. The Maximum Likelihood Estimation (MLE) procedure is a known procedure for evaluating Structural Equation Modeling (SEM) (Teo, 2011). The AMOS 20.0 is used to conduct the CFA using the Maximum likelihood estimation (MLE). The result of CFA is estimated in Table 4 representing acceptable level of model fit.

Table 4: Model Fitness

Factors	Ideal Values	Obtained Value
X^2df (CMIN/DF)	<= 3	1.738
GFI	=>0.90	0.758
AGFI	=>0.8	0.716
NFI	=>0.9	0.765
CFI	=>0.9	0.883
RMSEA	<=0.08	0.069
TLI	=>0.90	0.871

The CMIN/DF and RMSEA is acceptable level of model fit. The measurement model values of CFI and TLI seems good as it is close to recommended values. Moreover, the other parameter estimates are also within acceptable limits.

6.4) Differences between IT and non-IT Users

The independent samples t-test is carried out to show significant differences between IT and non-IT discipline towards adoption of m-Learning. The sample size of 158 students belonging to IT and non-IT discipline is used to measure the influential factors performance expectancy, effort expectancy, perceived playfulness, perceived mobility, social influence, mobile readiness and behavioural intention of users. Table

5 illustrates influential factors with their corresponding mean, standard deviation and standard error mean for both IT and non-IT groups.

Table 5: Differences of means among two Populations

Variables	Disciplines	Means	Std. Deviation	Std. Error Mean
Performance Expectancy	1 2	4.15 3.55	0.609 0.972	0.069 0.108
Effort Expectancy	1 2	3.66 3.31	0.371 0.619	0.042 0.069
Mobile Readiness	1 2	3.92 3.35	0.603 0.782	0.069 0.087
Perceived Mobility	1 2	4.22 4.12	0.641 0.757	0.073 0.084
Social Influence	1 2	3.45 3.27	0.844 0.733	0.096 0.081
Perceived Playfulness	1 2	3.61 3.09	0.694 0.623	0.079 0.069
Behavioural Intention	1 2	4.00 3.55	0.718 0.954	0.082 0.106

There is significant difference in mean values of the each influential factor for both disciplines. The result shows noticeable high mean values of IT students than non-IT students that reflect positive influence to behavioural intention for m-Learning adoption. In Table 5, '1' represents population belonging to IT discipline and '2' represents population belonging to non-IT discipline.

Table 6 shows Levene's test and t-test for equality of means for particular influential factor assessing the impact of both disciplines i.e. IT and non-IT for the adoption of mobile learning. "Levene's test" is a part of an inferential statistics which assess the equality of variances estimated between the two groups of the sample population.

Table 6: Levene's Test for IT and non - IT Disciplines

		Levene's Test for Equality of Variance		t-test for Equality of Means				
		F	**Sig.**	**t-value**	**df**	**Sig. (2-tailed)**	**Mean Difference**	**Std. Error Mean**
PE	Equal Variances Assumed	23.121	.000	4.648	156	.000	.603	.130
	Equal Variances Not Assumed			4.700	153.366	.000	.603	.128
EE	Equal Variances Assumed	26.731	.000	4.332	156	.000	.354	.082
	Equal Variances Not Assumed			4.385	131.962	.000	.354	.081
MR	Equal Variances Assumed	8.557	.004	5.171	156	.000	.577	.111
	Equal Variances Not Assumed			5.205	149.675	.000	.577	.111
PM	Equal Variances Assumed	2.420	.122	0.944	156	.347	.106	.112
	Equal Variances Not Assumed			0.948	154.00	.345	.106	.111
SI	Equal Variances Assumed	2.737	.100	1.421	156	.157	.178	.126
	Equal Variances Not Assumed			1.416	150.536	.159	.178	.126
PP	Equal Variances Assumed	.374	.542	4.941	156	.000	.518	.105
	Equal Variances Not Assumed			4.928	152.224	.000	.518	.105
BI	Equal Variances Assumed	10.406	.002	3.332	156	.001	.449	.135
	Equal Variances Not Assumed			3.356	148.308	.001	.449	.134

The *Sig.* value is greater than .05 then group variances are equal, focusing on first row values. However, if the *Sig.* value is smaller than .05 then looking at the equal variances not assumed values from second row. By looking at the results, it is concluded that PE, EE, MR and BI group variances are not equal so focusing on "equal variances not assumed" values. Under the Sig. (2-tailed) heading values are lower than the standard level of .05. Hence, the IT discipline has a significant effect on these groups PE, EE, MR, PP and BI. Further, the means elaborate the direction of the effect between the two disciplines. The discipline that has a higher effect on computed factors is IT discipline. From the "mean value" the direction of the effect is determine as follow:

- Performance Expectancy: 1 > 2
- Effort Expectancy: 1 > 2
- Mobile Readiness: 1 > 2
- Perceived Playfulness: 1 > 2
- Behavioural Intention: 1 > 2

Two-tailed, independent sampled t-tests demonstrated that discipline significantly affected group means for PE [$t(153.37) = 4.6$, $p < .001$], EE [$t(131.96) = 4.3$, $p < .001$], MR [$t(149.68) = 5.2$, $p < .001$], PP [$t(156) = 4.9$, $p < .001$], and BI [$t(148.31) = 3.4$, $p < .01$]. For all mentioned groups, the mean was greater for discipline 1 than discipline 2. However, difference in the mean values represents less inclination of non-IT students toward m-learning. The IT users are considered as the early adopters of m-Learning as they are technology oriented students who are familiar with high technology and internet services.

6.5) Hypothesis Testing

The significance of variables is measured at $p <.001$, $p<.01$, $p<.05$ and *** represents a significant hypothesis. The H2, H3, H5, H9 and H12 are non-significant out of 12 hypotheses. Table 7 demonstrates the supported and unsupported formulated hypotheses.

Table 7: Hypotheses Testing

Hypotheses	Path	Estimates	P	Significance Level	Consistent Studies
H1	PE → BI	0.298	0.006	Moderately Significant**	(Davis, 1989; Huang et al., 2007; Teo, 2011; Wang et al., 2006; Wang et al., 2009; Tan et al., 2012)
H2	EE → BI	0.056	0.639	Non-Significant	(Liu et al., 2010a; Liu et al., 2010b; Park et al., 2011)
H3	PP → BI	0.246	0.091	Non-Significant	(Padilla-Meléndez et al, 2013)
H4	PM → BI	0.227	0.023	Significant*	**Contribution**
H5	SI → BI	0.050	0.349	Non-Significant	(Teo, 2011)
H6	MR → BI	0.309	0.046	Significant*	**Contribution**
H7	PP ↔ EE	0.454	0.000	Highly Significant***	(Chang et al., 2012; Huang et al., 2007; Padilla-Meléndez et al, 2013; Park et al., 2014)
H8	EE → PE	0.502	0.000	Highly Significant***	(Chang et al., 2012; Davis, 1989; Huang et al., 2007; Padilla-Meléndez et al, 2013; Park et al., 2011; Teo, 2011; Wang et al., 2006; Tan et al., 2012)
H9	PM →PE	0.226	0.098	Non-Significant	(Özdoğan et al., 2012)
H10	MR → SI	0.389	0.000	Highly Significant***	Nil
H11	PP → PE	0.387	0.000	Highly Significant***	(Chang et al., 2012; Padilla-Meléndez et al, 2013)
H12	SI → PE	-0.024	0.737	Non-Significant	(Özdoğan et al., 2012)

The hypotheses H1, H4, H6, H7, H8, H10 and H11 are found to be significant out of 12 hypotheses. The two additional hypotheses are incorporated formulating a direct influence on behavioural intention. The perceived mobility and mobile readiness are measured for illustrating a significant effect on behavioural intention for adoption of mobile learning. The non-significant hypotheses H2, H3, H5 do not have a direct effect on behavioural intention of learners' towards m-Learning. From hypotheses H7, H8, H10 and H11 shows performance expectancy, effort expectancy, perceived playfulness and social influence acts as intermediary factors relaying an indirect effect on behavioural intention to use m-Learning. The effort expectancy and perceived playfulness complements positively each other in inclination of learners towards m-Learning usage. The ease and fun feature involves the learners in cognitive environment that improves learning skills through m-Learning technology. The performance expectancy acts as intermediary and independent factor for m-Learning adoption and usage. From the hypotheses H8, H9, H11 and H12 the effect of effort expectancy and perceived playfulness is bridged through performance expectancy except perceived mobility and social influence in inclining the intentions of learners for m-Learning. A percentage of 70% shows familiarity with information technology for using a system is not a problem for the students. Moreover, there is a majority of 57% young participants' age ranging between 18 to 25 years old. Hence, the young intervention of participants with information technology familiarity might be the reason that learners intentions are not shaped up through effort expectancy. Similarly, social influence relationship with behavioural intention in adoption is not influenced with peers' perception. All the determinants proposed in mobile learning adoption model play an important part either directly or indirectly for motivating the learners' intention to use and adopt m-Learning.

The fuzzy cognitive map related to hypotheses is represented in Figure 3. The thickest line illustrates highly significant relationship (+++) among perceived playfulness and effort expectancy, effort expectancy and perceived playfulness, perceived playfulness and performance expectancy, effort expectancy and performance expectancy, mobile readiness and social influence respectively. However, moderately significant relationship (++) have been shown with moderately thick line between performance expectancy and behavioural intention. In addition to this, significant relationship (+) is shown through thinnest line between perceived mobility and behavioural intention, mobile readiness and behavioural intention respectively. However, no relationship was found between effort expectancy and behavioural intention, perceived playfulness and behavioural intention, social influence and behavioural intention, perceived mobility and performance expectancy, social influence and performance expectancy respectively. These relationships have not been represented in the following fuzzy cognitive map.

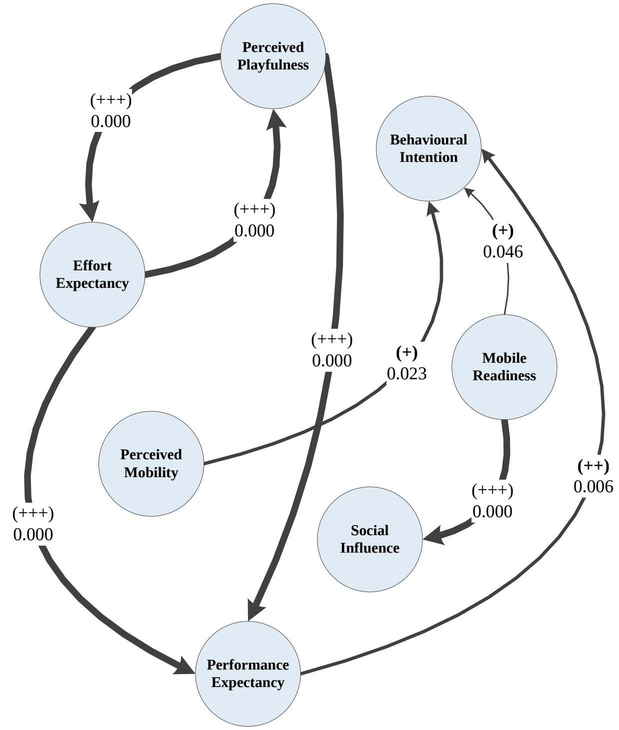

Figure 3: Fuzzy Cognitive Map

6.6) Discussion about Results

Discussion on each of the hypothesis is presented as follows:

- **H1:** *Performance expectancy will have a positive influence over the behavioural intention to use mobile learning* – During the data analysis, the relationship between performance expectancy and behavioural intention is found to be significant. The students believe that their work performance will be enhanced by the use of mobile learning systems on mobile phones. Due to the aspect of mobility, learning may take place at any time and at any place. The intention of students is positively influenced because of the usefulness of the mobile learning system. If the users think that mobile learning is useful then ultimately their intention to adopt mobile learning will be high. The finding is found to be consistent with the research studies conducted by (Huang et al., 2007; Liu et al., 2010a; Liu et al., 2010b; Lowenthal, 2010; Wang et al., 2006; Wang et al., 2009).

- **H2:** *Effort expectancy will have a positive influence over the behavioural intention to use mobile learning* – During the data analysis, it is found that effort expectancy has a non-significant effect on behavioural intention because students are more concerned in completing their tasks through technology mediated support. The result is found to be conflicting with the basic TAM model. The mobile learning task accomplishment is done irrespective of effort exerted in using a system. In order to perform learning, students train themselves accordingly to achieve high results in their learning tasks because students are more adaptive to new technology. There is also a possibility that young respondents are familiar with computer and internet services (Özdoğan et al., 2012). Hence, effort does not have a direct influence on the young students' (18-25 years) intention to use mobile learning system. The finding is consistent with the research studies of (Liu et al., 2010a; Liu et al., 2010b; Özdoğan et al., 2012) and contrary to the research findings of (Chang et al., 2012; Huang et al., 2007; Padilla-Meléndez et al, 2013; Park et al., 2011; Teo, 2011; Wang et al., 2006; Tan et al., 2012).
- **H3:** *Perceive playfulness will have a positive influence over the behavioural intention to use mobile learning* – During the analysis, it is found that perceived playfulness has a non-significant effect on behavioural intention. It may be due to the fact that the construct of perceived playfulness impact negatively over the usage of mobile learning systems which ultimately divert the students' attention from their original tasks. In addition, the high tech gadgets possess multiple features that indulge the learners with fun and enjoyment related activities without realising the time elapsed which result in wastage of time. Hence, it might be the reason of the learners' negative intention and perception about adoption and usage of mobile learning system. The finding was found to be consistent with the research work carried out by Padilla-Meléndez et al. (2013) and conflicting with the studies by (Chang et al., 2012; Park et al., 2014; Wang et al., 2006).
- **H4:** *Perceived mobility will have a positive influence over the behavioural intention to use mobile learning* – The hypothesis formulated a relationship between perceived mobility and behavioural intention which was found to be significant in determining the students' intention to use and adopt m-Learning. Due to the construct of mobility, students are able to learn in dynamic environments where learning may take place at any time and also at any place. The

mobility direct effect on behavioural intention is significant as students can access the learning contents from anywhere and also at any time. The time is properly utilised even away from their traditional learning environment. This construct was not addressed in the previous studies. Therefore, the author marks it as a contribution in the context of mobile learning. As the students understand the mobility aspect, therefore, their intention to adopt mobile learning will be high.

- **H5:** *Social influence will have a positive influence over the behavioural intention to use mobile learning* – During the data analysis, it is found that social influence has a non-significant effect on behavioural intention to use mobile learning systems. It may be due to the fact that students who have been selected for this research study believe on individualism and give preference to their own decisions. In addition, students are mostly less influenced by their peers or individuals who are important to them. Another reason of its non-significance can be the fact that students are more experienced of using internet and such learning systems. Therefore, their intention to adopt mobile learning systems is high and not influenced by their peers. The finding is consistent with the study of Teo (Park et al., 2014) as adoption intention is not influenced by others perception. With many published research work, the finding is conflicting as social influence impacts the students' perception about adopting mobile learning (Cheon et al., 2012; Park et al., 2011; Wang et al., 2009; Tan et al., 2012).
- **H6:** *Mobile readiness will have a positive influence over the behavioural intention to use mobile learning* – During the data analysis, it is found that the construct of mobile readiness is found to be significant in modeling the student's intention to use and adopt m-Learning. Mobile readiness has a direct and positive influence on the users' intention. In addition, students are eager to use innovative technology which helps in scoring better grades. It also provides a platform to the students to learn while sitting anywhere and at any time. If the students will have mobile readiness then there are more chances that they will adopt and use mobile learning systems. The construct of mobile readiness was included by the researcher. Therefore, the author marks it as a contribution in the proposed model.
- **H7:** *Perceived playfulness will have a positive influence over the effort expectancy to use mobile learning and vice versa* – During the data

analysis, it is found that perceived playfulness has significant positive effect over effort expectancy which indirectly influences students' intention to adopt and use mobile learning. The current study defines enjoyment as "the extent to which the usage of mobiles is perceived to be enjoyable aside from the instrumental value of the technology". It is revealed that fun and enjoyment aspects associated with the usage of mobile phones ultimately impact over the ease correlated with the usage of mobile learning systems on mobiles. Most of the studies consider a unidirectional relationship between perceived playfulness and effort expectancy. The relationship was found to be consistent with the existing studies of (Chang et al., 2012; Huang et al., 2007; Padilla-Meléndez et al, 2013; Park et al., 2014).

- **H8:** *Effort expectancy will have a positive influence over the performance expectancy to use mobile learning* – During the data analysis, it is found that effort expectancy has a significant positive impact over performance expectancy which indirectly influences students' intention to adopt and use mobile learning. The students' intention to adopt and use mobile learning is articulated through ease, effortless interface and navigation which encourage them to make use of mobile learning systems. The use of such ease provision interfaces and systems ultimately enhances usefulness of mobile learning systems. The relationship was found to be consistent in the past studies. In addition, the finding is consistent with TAM behavioural model having perceived ease of use (maps to effort expectancy) a significant effect over perceived usefulness (maps to performance expectancy) to determine students' perception (Chang et al., 2012; 5, Huang et al., 2007; Padilla-Meléndez et al, 2013; Park et al., 2011; Teo, 2011; Wang et al., 2006; Tan et al., 2012) about mobile learning.
- **H9**: *Perceived mobility will have a positive influence over the performance expectancy to use mobile learning* – During the data analysis, it is revealed that the indirect effect of perceived mobility on performance expectancy is found non-significant in this research study. The cause of its non-significance could be due to the fact that the extensive learning tasks may cause distractions which deviate users from their learning paths. In addition, the extensive learning is usually influenced due to the inefficient support of medium such as availability of battery charging sockets, learning environment in terms of readability and audibility, free internet services and

encouraging learning environment that positively affects performance of students during learning. The finding is indicating a consistency with existing research study of Özdoğan et al. (2012). However, results are found contradictory with (Huang et al., 2007; Park et al., 2014).

- **H10:** *Mobile readiness will have a positive influence over the social influence to use mobile learning* – During the data analysis, it is found that mobile readiness has a significant and positive effect on social influence that invokes learners' to promote the usage of mobile learning. The vivacious mobile learners who are experienced in using the mobile learning system refer their perceptions to other individuals or peers, friends and other community members who are important to them. In this way, it can be concluded that experienced users of mobile learning systems influence their peers/individuals, friends and other co-workers towards the adoption and use of mobile learning systems. The result of the hypothesis is found contradictory with the research findings of Cheon et al. (2012).
- **H11:** *Perceived playfulness will have a positive influence over the performance expectancy to use mobile learning* – During the data analysis, it is found that perceived playfulness has a significant and positive impact over the performance expectancy which ultimately impacts the adoption and usage of mobile learning systems. It is also revealed that fun, excitement and enjoyment influence the perception of users by highlighting that such mobile learning systems are very much useful for them. In this way, the perceived playfulness has substantially increased the performance of mobile learning systems with the element of enjoyment and curiosity. The findings of the current study are found to be consistent with the research work conducted by (Chang et al., 2012; Padilla-Meléndez et al, 2013).
- **H12:** *Social influence will have a positive influence over the performance expectancy to use mobile learning* – During the data analysis; it is found that the indirect effect of social influence on performance expectancy is found to be non-significant in this research study. The reason for its non-significance can be due to the lack of peer and external pressure from government and external bodies. It can also be assumed that students are more independent in making their own decisions. Therefore, their perception is not influenced by the peers / individuals, friends and co-workers. In this way, students

may decide themselves about the adoption and usage of mobile learning systems. The finding is found to be consistent with the research study of Özdoğan et al. (2012) and contradicted by (Park et al., 2011; Teo, 2011).

6.7) Revised Mobile Learning Adoption Model

Figure 4 signifies the revised mobile learning adoption model (RMLAM) after validation of the model in the context of Pakistani society. The model shows the relationship of highly significant variables with the thickest line. However, moderately significant relationships have been represented with thinner line and significant relationships have been shown with the thin line. In addition, non-significant relationships have been shown with the dotted lines. Overall, the set of indices were used to check the structural model. A comparison of all fit indices with their recommended values provides a benchmark for a good model fit. In addition, the standardized path coefficients of structural model are discussed in detail. The relationship of mobile readiness (MR) with behavioral intention (BI) has the largest beta value ($\beta = 0.309$) which shows that mobile readiness has the strongest impact over the dependent variable i.e. behavioral intention. In addition, perceived mobility with the beta value of ($\beta = 0.227$) has the second largest impact over the dependent variable i.e. behavioral intention which is followed by the performance expectancy having beta value of ($\beta = 0.298$) with moderately significant effect over the dependent variable i.e. behavioral intention. However, the variables of effort expectancy, perceived playfulness and social influence were not found to be significant in relation with the dependent variable i.e. behavioral intention. Despite of the direct relationships of independent variables with the dependent variable i.e. behavioral intention, relationships have also been encountered among independent variables. The highly significant relationships have been found among effort expectancy and performance expectancy with the beta value ($\beta = 0.502$) followed by perceived playfulness and effort expectancy with the beta value of ($\beta = 0.454$) and perceived playfulness and performance expectancy with the beta value of ($\beta = 0.387$). However, the relationships among mobile readiness and social influence, perceived mobility and performance expectancy were not found to be significant. Lastly, the relationship between social influence and performance expectancy was found to be negative and non-significant.

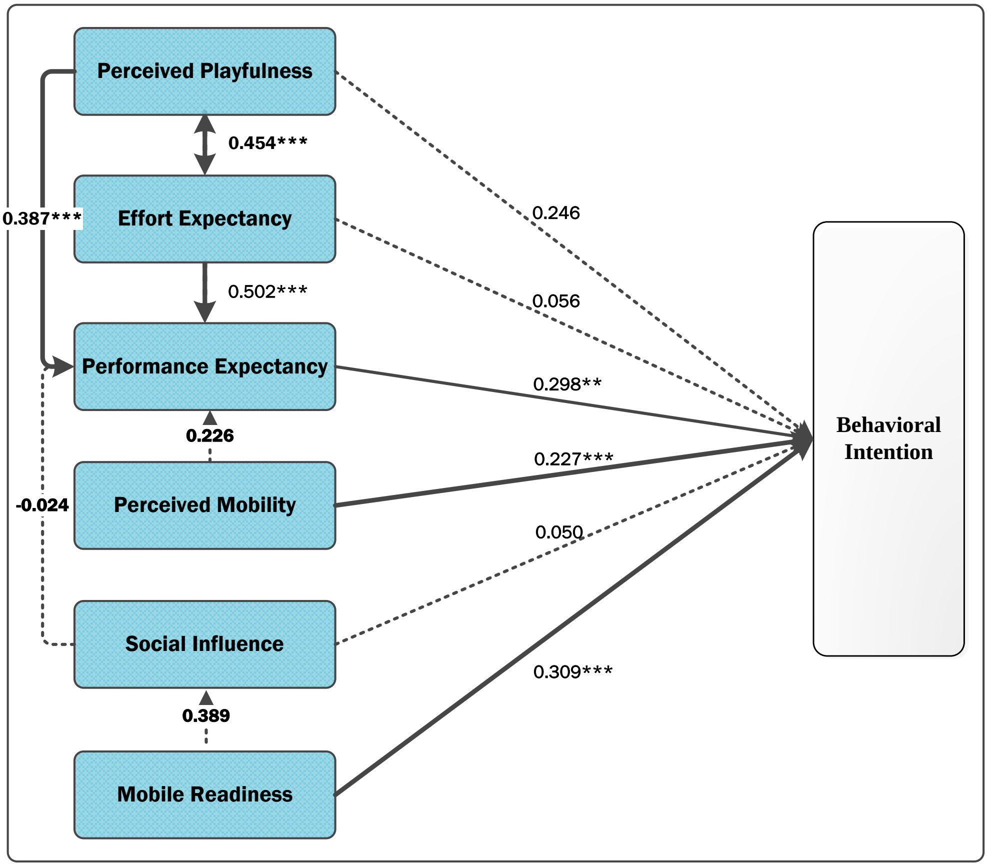

Figure 4: Revised Mobile Learning Adoption Model (RMLAM)

Note: *P < 0.05 *; P < 0.01 **; P < 0.001****

The significance of variables is measured at three probability levels as mentioned in note above. Three stars (***) have been used in order to represent highly significant relationships, two stars (**) have been used to represent moderately significant relationships and single star (*) is used to represent significant relationship. However, dotted lines have been used to represent non-significant relationship as depicted in Figure 4.

7) CONCLUSION

The research objective is to propose a MLAM that determines the behavioural intention of users. The foundation of model is built on two theoretical adoption models i.e. TAM and UTAUT. These models are customised and extended depending on the previously validated studies. The extraction of the influential factors and their anatomy on the intentions to use and adopt m-Learning is the chief objective of the research. The identification of determinants and their relationship is scrutinised from the strongly supported factors of the compiled literature. These influential factors are involved in formulating a conceptual integrated model for adoption of m-Learning. The filtration of the previous validated studies finds out some commonly hypothesized relationships among potential factors for predicting intention towards m-Learning. A research model is developed by keeping in consideration the base models of TAM and UTAUT with incorporation of two new relations in MLAM. The assumed relations involve mobile readiness and perceived mobility factors that have a direct relation with the behavioural intentions of user. The purposive sampling technique is used for data collection among various educational levels of users. An online research instrument is designed and distributed among the potential users by circulating the survey URL. All the participants are students of various disciplines categorise in two distinctive groups i.e. IT and non-IT with Pakistani nationality. The independent samples t-test is performed drilling the effects' on the two classified distinctive groups. The results of t-test revealed that IT students are more incline to use and adopt m-Learning than non-IT students.

A confirmatory factor analysis is steered using AMOS 20.0 to validate the integrated model of m-Learning. The determinants and relationship among them is analysed with the maximum likelihood method. The confirmatory factor analysis summarises how well the data fits the theoretical model of m-Learning. The hypotheses testing shows 8 out of 12 relations have proven to be significant for determining the behavioural intention towards m-Learning. The influencing factors are directly and indirectly affecting behavioural intention of m-Learning adoption and usage. The research work is an effort for promoting education through mobile learning system. The understanding of critical factors assists in the implementation of m-Learning systems in Pakistan.

7.1) Findings and Guidelines

The recommendation and findings are presented as follow for regulating authorities, policy makers, practitioners, researchers and academicians. The recommended guidelines are given below:

- The learning community is unaware about available mobile learning services. Therefore, the regulating authorities need to make an effort on promoting the potential advantages and benefits associated with the usage of mobile learning in the education sector. In this way, learners' can perceive usefulness of mobile learning as well as high performance is achieved in learning tasks.
- The policy makers of Pakistan should focus on out spread of mobile learning to increase the literacy rate of Pakistan. Wei-Han Tan et al. (2012) claims that m-Learning promotes lifelong learning anywhere at any time.
- The mobile regulating associations of Pakistan should provide updates and maintenance features to exercise m-Learning applications and systems in the country. Updates and maintenance features add value to perceived mobility that positively influences intentions of users in adoption of m-Learning.
- The practitioners should provide the inducement to users for using m-Learning instead of traditional ways of learning. The encouragement is associated with ease and fun features of m-Learning system in usage and adoption.
- From the findings, mobile readiness has a significant effect on intentions of users which reveals that users are ready to use m-Learning systems. Therefore, educational sector of Pakistan should establish a proper infrastructure supporting m-Learning contents to acquire knowledge through m-Learning devices which will develop a sense of self-study among the citizens.
- The results concluded that social influence has a non-significant effect on intentions due to lack of m-Learning familiarity in Pakistani citizens. Hence, to emphasis on the external pressure, coworkers' reviews and peer influence, trainee sessions and orientations should be held in order to avoid under usage of m-Learning resources.
- Mobility is one of the basic factors in establishment of successful m-Learning for instant access anywhere (Liu et al., 2010a; Liu et al., 2010b). Therefore, the governing bodies and strategy analysts of

Pakistan should think of providing the mobile learning devices through instalment schemes to assure learning on the go.

7.2) Implications to Theory and Practice

The implications to theory and practice are presented as follows:

- *Academic Implications:* The research work proposed mobile learning adoption model (MLAM) on the basis of existing adoption models i.e. TAM and UTAUT. The proposed model i.e. MLAM overcomes the shortfalls of the preceding models by integrating the influential factors of mobile learning from the existing studies (Huang et al., 2007; Özdoğan et al., 2012; Padilla-Meléndez et al, 2013; Teo, 2011; Wang et al., 2009; Tan et al., 2012). Besides the influential factors found in the base model, two new relationships have been incorporated in the proposed model and evaluated in the context of mobile learning. In addition to this, the research study adds value to reveal the immense effects of students' behavior belonging to IT and non-IT disciplines.
- *Practical Implications:* The study introduces a research instrument for assessing the adoption and usage of mobile learning. With the help of the research instrument, policy makers, practitioners and regulating authorities are able to understand a complete picture of the influential factors that determine users' adoption of mobile learning in the context of Pakistan. The guidelines are proposed which will aid in producing fruitful mobile learning systems in order to promote education in the remote areas of Pakistan.

7.3) Research Limitations

This study has some limitations which have been addressed here. Firstly, the sample was collected from online users. Thus, the opportunity to generalise results to whole population is not possible. The results are confined to the people who are internet users. Secondly, two variables i.e. perceived mobility and mobile readiness are found to be significant in the context of internet users. However, there is a possibility that these variables may not turned out to be significant while keeping in consideration whole population. In addition, research study is required to consider both populations i.e., online and offline user groups in order to provide full geographical coverage and also to generalise results over the whole population. Finally, user perceptions regarding the adoption of mobile learning can be measured by giving trainings about the specific mobile learning systems to the target group. In this way, change in perception regarding adoption of mobile learning can also be analysed.

7.4) Future Research Recommendations

For future research work, experts' feedback would strengthen the proposed adoption model. The face-to-face interviews would maintain the decorum of the extended model factors with critical review of the perception of students on m-Learning in Pakistan. At present, no research work has been presented on the adoption of mobile learning in Pakistan. A limited research studies are presented on mobile learning usually belonging to non-Asian region. The technology is not a hurdle in acceptance and use of m-Learning emphasized by researchers (Liu et al., 2010a; Liu et al., 2010b). The pressure is on the perceptions of the users that shape up the decision to adopt a novel system. Hence, a need is there to test the influential factors from time to time as the perceptions change with the passage of time. For the success of the mobile learning adoption, the regulating authorities and policy makers perception should be measured in future studies. The effects of the user intentions can be observed over long periods of time. Hence, longitudinal study can assist in viewing a better picture of m-Learning in Pakistan.

REFERENCES

Al-Mushasha, N. and Hassan, S. (2009). A Model for Mobile Learning Service Quality in University Environment. International Journal of Mobile Computing and Multimedia Communications, 1(1), pp.70-91.

Anderson, J. and Gerbing, D. (1991). Predicting the performance of measures in a confirmatory
factor analysis with a pretest assessment of their substantive validities. Journal of Applied Psychology, 76(5), pp.732-740.

Babin, B., Money, A., Samouel, P. and Hair, J. (2003). Essentials of business research methods. Hoboken, New Jersey: John Wiley & Sons.

Baek, Y., Jung, J. and Kim, B. (2008). What makes teachers use technology in the classroom? Exploring the factors affecting facilitation of technology with a Korean sample. *Computers & Education*, 50(1), pp. 224-234.

Chang, C., Liang, C., Yan, C. and Tseng, J. (2012). The Impact of College Students' Intrinsic and Extrinsic Motivation on Continuance Intention to Use English Mobile Learning Systems. *The Asia-Pacific Education Researcher*, 22(2), pp.181-192.

Cheon, J., Lee, S., Crooks, S. and Song, J. (2012). An investigation of mobile learning readiness in higher education based on the theory of planned behavior. *Computers & Education*, 59(3), pp.1054-1064.

Davis, F. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, 13(3), p.319.

Green, S. (1991). How Many Subjects Does it Take To Do A Regression Analysis. *Multivariate Behavioral Research*, 26(3), pp.499-510.

Hashemi, M., Azizinezhad, M., Najafi, V. and Nesari, A. (2011). What is Mobile Learning? Challenges and Capabilities. *Procedia - Social and Behavioral Sciences*, 30, pp.2477-2481.

Huang, J., Lin, Y. and Chuang, S. (2007). Elucidating user behavior of mobile learning. *The Electronic Library*, 25(5), pp.585-598.

Im, I., Hong, S. and Kang, M. (2011). An international comparison of technology adoption. *Information & Management*, 48(1), pp.1-8.

Jackson, J., Yi, M. and Park, J. (2013). An empirical test of three mediation models for the relationship between personal innovativeness and user acceptance of technology. Information & Management, 50(4), pp.154-161.

Kanwal, F. and Rehman, M. (2014). E-Learning Adoption Model: A case study of Pakistan. *Life Science Journal*, 11, pp.78 - 86.

Lee, Y. (2006). An empirical investigation into factors influencing the adoption of an e-learning system. Online Information Review, 30(5), pp.517-541.

Leung, C. and Chan, Y. (2003). Mobile learning: a new paradigm in electronic learning. In: *The 3rd IEEE International Conference on Advanced Learning Technologies, 2003. Proceedings.*. IEEE.

Little, B. (2012). Effective and efficient mobile learning: issues and tips for developers. Industrial and Commercial Training, 44(7), pp.402-407.

Liu, Y., Han, S. and Li, H. (2010a). Understanding the factors driving m-learning adoption: a literature review. Campus-Wide Info Systems, 27(4), pp.210-226.

Liu, Y., Li, H. and Carlsson, C. (2010b). Factors driving the adoption of m-learning: An empirical study. *Computers & Education*, 55(3), pp.1211-1219.

Lowenthal, J. (2010). Using Mobile Learning: Determinates Impacting Behavioral Intention. *American Journal of Distance Education*, 24(4), pp.195-206.

Mahat, J., Ayub, A., Luan, S. and Wong, (2012). An Assessment of Students' Mobile Self-Efficacy, Readiness and Personal Innovativeness towards Mobile Learning in Higher Education in Malaysia. *Procedia - Social and Behavioral Sciences*, 64, pp.284-290.

Mathieson, K. (1991). Predicting User Intentions: Comparing the Technology Acceptance Model with the Theory of Planned Behavior. *Information Systems Research*, 2(3), pp.173-191.

Moon, J. and Kim, Y. (2001). Extending the TAM for a World-Wide-Web context. *Information & Management*, 38(4), pp.217-230.

Moore, G. and Benbasat, I. (1991). Development of an Instrument to Measure the Perceptions of Adopting an Information Technology Innovation. *Information Systems Research*, 2(3), pp.192-222..

Moore, J., Dickson-Deane, C. and Galyen, K. (2011). e-Learning, online learning, and distance learning environments: Are they the same?. *The Internet and Higher Education*, 14(2), pp.129-135.

Motiwalla, L. (2007). Mobile learning: A framework and evaluation. *Computers & Education*, 49(3), pp.581-596.

Özdoğan, K., Başoğlu, N. and Erçetin, G. (2012). In: *Exploring Major Determinants of Mobile Learning Adoption*. IEEE, pp.pp. 1415-1423.

Padilla-Meléndez, A., del Aguila-Obra, A. and Garrido-Moreno, A. (2013). Perceived playfulness, gender differences and technology acceptance model in a blended learning scenario. Computers & Education, 63, pp.306-317.

Park, E., Baek, S., Ohm, J. and Chang, H. (2014). Determinants of player acceptance of mobile social network games: An application of extended technology acceptance model. *Telematics and Informatics*, 31(1), pp.3-15.

Park, S., Nam, M. and Cha, S. (2011). University students' behavioral intention to use mobile learning: Evaluating the technology acceptance model. *Br J Educ Technol*, 43(4), pp.592-605.

Pfleeger, S. (2001). Principles of Survey Research: Part 1: Turning Lemons into Lemonade. SIGSOFT Software Engineering Notes.

Quinn, C. (2000). *LiNE Zine - mLearning: Mobile, Wireless, In-Your-Pocket Learning*. [online] Linezine.com. Available at: http://www.linezine.com/2.1/features/cqmmwiyp.htm [Accessed 21 Feb. 2014].

Romano, N., Sharda, R. and Lucca, J. (2005). Computer-Supported Collaborative Learning Requiring Immersive Presence (CSCLIP): An Introduction. Information Systems Frontiers, 7(1), pp.5-12.

Shen, L., Callaghan, V. and Shen, R. (2008). Affective e-Learning in residential and pervasive computing environments. Information Systems Frontiers, 10(4), pp.461-472.

Tan, G., Ooi, K., Sim, J. and Phusavat, K. (2012). Determinants Of Mobile Learning Adoption: An Empirical Analysis. Journal of Computer Information Systems, (52).

Teo, T. (2011). Factors influencing teachers' intention to use technology: Model development and test. Computers & Education, 57(4), pp.2432-2440.

Thompson, R., Higgins, C. and Howell, J. (1991). Personal Computing: Toward a Conceptual Model of Utilization. MIS Quarterly, 15(1), p.125.

Triantafillou, E., Georgiadou, E. and Economides, A. (2008). The design and evaluation of a computerized adaptive test on mobile devices. Computers & Education, 50(4), pp.1319-1330.

Venkatesh, V. (2000). Determinants of Perceived Ease of Use: Integrating Control, Intrinsic Motivation, and Emotion into the Technology Acceptance Model. Information Systems Research, 11(4), pp.342-365.

Venkatesh, V. and Davis, F. (2000). A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. Management Science, 46(2), pp.186-204.

Wang, Y., Lin, H. and Luarn, P. (2006). Predicting consumer intention to use mobile service. Information Systems Journal, 16(2), pp.157-179.

Wang, Y., Wu, M. and Wang, H. (2009). Investigating the determinants and age and gender differences in the acceptance of mobile learning. British Journal of Educational Technology, 40(1), pp.92-118.