Examining Factors that Impact Students and Faculty Acceptance and Adoption of M-learning at Jazan University, Saudi Arabia

Ahmad Almufarreh

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Introduction

The integration of mobile technologies into various aspects of Saudi Arabian lives has become ubiquitous. Mobile technologies provide individuals with functionalities that exceed conventional computers. Users of mobile technologies are provided with the advantages of being connected anytime and anywhere. According to Al-Hujran et al. (2014), mobile penetration in Saudi Arabia reached more than 185% in 2010, indicating that mobile technologies have become an essential component in everyday activities of Saudi society, including education. Although mobile technologies are the most noticeable technologies in Saudi higher education institutes, the paradigm of mobile learning (M-learning) is still in the development stage (Al-Hujran et al., 2014). M-learning emerged with the evolution of mobile devices and has extended the scope of learning by providing opportunities for instructors and students to teach and learn anytime, anywhere and on the move (Thomas, Singh & Gaffar, 2013). M-learning has various definitions in the literature ranging from a device description to being an extension of e-learning to more advanced definitions relating to preferences and pedagogy of mobile learners (Akour, 2009; Traxler, 2005; Watson & White, 2006). In this research paper, M-learning refers to "a learning model that provides ubiquitous, mobile, and anytime access to educational and university resources empowered by a mobile technology in its connected or disconnected state" (Akour, 2010, p. 33).

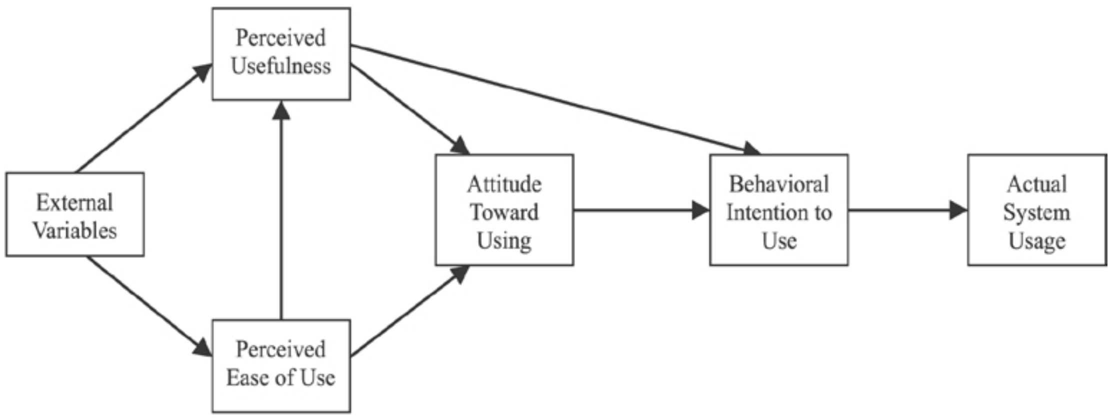
According to Akour (2010), decisions relating to the adoption of new technologies and learning models in education such as M-learning are often made at the institutional level; however, it is the user acceptance of these new technologies that leads to the successful implementation and adoption of a new technology in teaching and learning contexts. Thus, investigating the factors that impact students and faculty acceptance and adoption of M-learning has become a major research interest to many researchers. Such investigations are conducted through the use of adoption models or frameworks (Al-Hujran et al., 2014). These models help to identify factors that influence users' acceptance of any technology. Thus, in order to examine which factors lead to the successful implementation of M-learning from the perspectives of faculty and students, this paper presents a review of related literature.

Review of the Literature

The literature review presents important theories of technology acceptance, studies on mobile-technology acceptance, and M-learning studies that have been conducted in Saudi Arabia. In addition, the M-learning acceptance model (MLAM) is reviewed. Research regarding factors that influence user acceptance and adoption of technology innovations has been conducted since 1980 (Venkatesh, Morris, Davis, & Davis, 2003). Recent research of technology acceptance is related to social science, particularly innovation diffusion theory or IDT. According to Rogers (2003), diffusion is the process by which an innovation is communicated via channels over time among social system members. Although, IDT provides a useful framework that helps explain the reasons for technology use over time, the framework does not consider cognitive processes that influence a user's acceptance of technological innovation (Akour, 2009). To address the impact of cognitive processes on the acceptance of technological innovation, Dillio and Morris (as cited in Akour, 2010) stated that in order to understand behavioral intent, researchers must understand the dynamics of the decision-making process. In addition, the theory of reasoned action (TRA) addresses the impact of cognitive processes on the acceptance of technological innovation. According to Fishbein and Ajzen (1975), TRA specifies that behavior intention is a function of two factors: an attitude toward behavior and a subjective norm, which is an individual's perception of social pressure. Attitude refers to the individual's own performance of the behavior, rather than his or her performance in general. Subjective norms refer to a function of beliefs, termed normative beliefs. TRA assumes that individuals are rational and they consider the implications of their actions prior to deciding whether to perform a particular behavior (Fishbein & Ajzen, 1975). This means that users will use technologies if they recognize that there would be positive outcomes associated with using them. According to Samara and Gunawardena (2014), three derivations of TRA were developed including the theory of planned behavior (TPB), the technology acceptance model (TAM), and The universal technology adoption use theory (UTAUT).

TPB was developed by Ajzen (1991) and it assumes that in addition to attitudinal and normative factors, perceived behavioral control also impacts an individual's behavioral intention. The TPB extended the TRA to consider cases where individuals do not have complete control over situations. The TPB assumes that actions of human are guided by three considerations. First are behavioral beliefs about the likely outcomes of the target behavior, which lead to favorable or unfavorable attitudes toward the target behavior. The second consideration is related to normative beliefs about the expectations of others, which produce subjective norms or perceived social pressure. The third consideration is related to controlling beliefs about available resources and anticipated obstacles, which give rise to perceived behavior control (Ajzen, 1991).

TAM was developed by Davis (1989), and it was used in Information Technology contexts and added the constructs of ease of use and usefulness to TRA. The perceived ease of use (PEU) means "the degree to which the user expects the target system to be free of efforts" (Davis et al., 1989; p. 985). The second construct is perceived usefulness (PU), which refers to the user's "subjective probability that using a specific application system will increase his or her job performance" (Davis et al., 1989, p. 985).



Source: Davis *et al.* (1989, p. 985)

***Figure 1*: TAM (Davis et al., 1989)**

As presented in Figure 1, the constructs of perceived usefulness and perceived ease of use determine a user's intention to use a technological innovation with the intention to use serving as a mediator of accepting the usage of actual technology. In addition, the perceived ease of use impacts perceived usefulness. The underlying links between the two main constructs of TAM and users' attitudes, intentions, and actual system use (acceptance) are specified using the TRA.

UTAUT was developed by Venkatesh, Morris, Davis, and Davis (2003) and it is an integrated model for predicting the probability of technology innovation acceptance. UTAUT has four main keys variables that determine the behavior intention of users, which include performance expectancy (usefulness), social influence, facilitating conditions (behavior control) and expectancy (ease of use). In addition, this model takes into consideration the moderating effects of age, gender, experience, and opting in to use in relation to the four main key determinants of behavior intention.

Mobile Technology Acceptance Research

Mobile technology research has developed from a research interest into a major research field (Liu, Han, & Li, 2010). Various situations and contexts with a wide range of mobile technology users have been examined using the TAM model (Akour, 2010). The following are examples of empirical research that used TAM to investigate the acceptance of mobile technology in various contexts.

Biljon and Kotze (2007) examined factors that influence the adoption of the mobile device. They analyzed and studied literature on mobile devices adoption and the mobile contexts to understand theories, concepts, and models that impact the adoption of mobile device use. In their study, they combined different technology acceptance models and proposed Mobile Phone Technology Adoption Model (MOPTAM), which is an extension of the original TAM model. In developing MOPTAM, researchers focused on determining factors that influenced mobile device usage including social influence, facilitating conditions, perceived usefulness, perceived ease of use, and behavior intention. Biljon and Kotze (2007) collected data by surveying 59 computer science students from a South African university. Facilitating conditions consisted of the mobile-device infrastructure, system quality, system service, cost of the service, and cost of the mobile device. The results indicated that social factors are correlated with perceived ease of use. Facilitating conditions are correlated with perceived ease of use, perceived usefulness, and actual use. Therefore, MOPTAM highlights the important of examining social influence factors and facilitating conditions when adopting mobile device use.

Lu, Yu, Liu, and Yoa (2003) proposed another technology acceptance model of wireless Internet via mobile devices (WIMD). Their model extended the original technology acceptance model TAM by adding factors including user differences, complexity of technology, wireless trust, social influence, and facilitating conditions. These factors determined usefulness and ease of use, which determines a user's intention to adopt the Internet via mobile devices. Researchers examined the proposed WIMD model by surveying MBA students in a southern regional university in the United States. The examination of WIMD revealed that system functions, interface design, speed of transferring data, mobile capability, and wireless security all contribute to the acceptance of mobile technology.

Liao, Tsou, and Huang (2007) analyzed factors impacting subscribers' usage of mobile services in Taiwan. Their research model was based on TAM; however, they extended the original model by adding perceived enjoyment as a key factor influences users' adoption of mobile services. The data for their study was collected from participants (N=532) via a web survey. The results of the study indicated that perceived enjoyment positively influences usefulness. In addition, enjoyment had higher significant effect on attitude than usefulness. This indicates that enjoyment is a key factor impacting users' adoption of mobile services and it should receive closer attention and given more considerations by designers to drive more enjoyment from the process of using mobile services. Moreover, ease of use, perceived enjoyment, and usefulness were found to be positively correlated to attitude, which in turn mediates behavior intention towards using mobile services. Therefore, the results suggest that usage of mobile services is determined by users' perceptions of their usefulness and how convenient it is to use mobile services, by ease of use or effortless it is to communicate with each other, and by perceived enjoyment of how many attractive services are provided by mobile services providers.

Further research on TAM was conducted by Bled (2003) to examine the adoption of a mobile parking service. The TAM model used in this study was an extended model that included motivational factors of usefulness and self-expressiveness. To evaluate the extended model, researchers set up a study of a mobile parking services trial for users, which was announced using large posters in a major parking area. A total of 465 participants were surveyed via an online questionnaire. The researcher found that intention to use mobile parking is determined by the direct extrinsic motivational influence of usefulness, the derived motivational influence of self-expressiveness, and the attitudinal influence represented by attitudes towards use. Moreover, the researcher found that attitudes towards use are determined by ease of use and usefulness. Self-expressiveness has no significant impact on attitudes towards use. However, usefulness is significantly influenced by both ease of use and self-expressiveness, so that mobile parking services are perceived as more useful if being more self-expressive. Thus, self-expressiveness has an indirect and a direct influence on intention to use mobile parking services.

Based on previous studies, TAM was extended by many different researchers to investigate the acceptance and adoption of mobile technologies in several contexts. Studies pointed out that external factors of TAM differ based on contexts, types of users, and technologies. However, there are some external factors that play an important role in accepting various mobile technologies. A high quality infrastructure and efficient system functions highly contribute to the acceptance of various mobile technologies (Biljon & Kotze, 2007; Liao, Tsou, & Huang, 2007). In addition, personal and social factors paly a critical role for adopting and accepting mobile technologies (Biljon & Kotze, 2007; Lu, Yu, Liu, and Yoa, 2003; Liao, Tsou, & Huang; 2007; Bled, 2003). Personal and social factors are the extent to which a user perceives that important others believe she or he should use a mobile technology (Venkatesh et al., 2003). The main purpose of all external factors is to increase fit and explanatory power of TAM. Thus, to understand factors that provide further insight into users' adoption and acceptance in learning contexts, studies of M-learning that employed TAM are examined in detail.

M-learning Acceptance Research

Despite the increase of M-learning research, factors that influence the acceptance and adoption of M-learning have not been comprehensively examined (Liu et al., 2010). According to Liu et al. (2010), adapting TAM for investigating the acceptance of technology that is designed for personalized usage can be a challenge because TAM was originally designed for examining technology acceptance in organizational contexts. As a result, Liu et al. proposed an extended TAM by adapting the concepts of perceived near-term usefulness (PNTU), perceived long-term usefulness (PLTU), and personal innovativeness (PI) to examine the acceptance of M-learning. Their model was assessed based on data collected from 230 undergraduate students in Zhejiang Normal University in China via a survey. The results reveal that perceived ease of use (EOU) did not significantly influence a user's behavior intention to adopt M-learning. In addition, researchers found that PI and PLTU/PNTU have positive impacts on the intention of M-learning adoption, while PLTU has a significant impact on PNTU. In addition, personal innovation was revealed to be a predictor of both PLTU and ease of use. However, PLTU was found to be the strongest determinant of adopting M-learning. Thus, offering high-quality content that complies with future goals of learners is critical for accepting M-learning.

Moreover, Munguatosha et al. (2011) proposed an extended model of TAM for adopting social learning software that is mobile enabled with the traditional learning systems in higher education in the developing countries of Africa. Their model added various factors to the original TAM model, including proper budgeting, organizational culture, time and external resources.

Data for assessing their model was collected from various institutes across Tanzania via 70 interviews and 1,230 responses to an online survey. Munguatosha et al. found that adoption of mobile enabled social learning in developing countries requires self-efficacy (SE), technical support (TS), administrative support (AS), infrastructure (I), system interactivity (SI), and a flexible organizational culture. In addition, budgeting and accountability are important factors for adopting social learning software. Moreover, the significant of system interactivities agree with the study findings of Liao, Tsou, and Huang (2007) in which attractive and interactive services of mobile services were found to be significant factors. Furthermore, other research confirmed that a high quality infrastructure contributes to the acceptance and adoption of mobile technology projects (Biljon & Kotze, 2007; Liao, Tsou, & Huang, 2007).

Furthermore, Chen and Huang (2010) developed and tested a novel mobile knowledge management learning software. The software is based on knowledge management theory, which consists of five steps for learning processes, including acquire, store, share, apply, and create knowledge. These researchers examined learner acceptance of the software based on their learning processes and the degree of satisfaction in the quality of a system using the original TAM. The research variables included learners' perceived ease of use (PEOU), perceived usefulness (PU) and behavioral intention (PI) of acceptance of mobile knowledge management learning software. Data for this study was collected from 132 undergraduate students with elementary education majors. In addition, researchers observed participants interacting with the software. Chen and Huang observed that system quality and successful completion of tasks were better with devices that had more capabilities. They also found an increase in users' performance of knowledge application when the system was perceived to be a beneficial learning tool. In addition, the study shows that PEOU can predict U. This means that the ease of use of a mobile knowledge management software can enhance learning and improve computer interaction usefulness for individuals. As a result, perceived ease of use and perceived usefulness are predictors of users' behavioral intention to adopt a mobile knowledge management software.

Mathur (2011) used TAM to investigate the linear relationship between students' perceptions of usefulness and ease of use with the students' intent to use Blackboard Mobile Learn (BML). Data for this study was collected from 98 community college students in two different community colleges in the U.S. via a survey. Findings of the study indicated that students' perceptions of both usefulness and ease of use were significantly related to their intent to use BML. Thus, if students perceive applications of M-learning to be useful and easy to use, they will intend to use these applications. According to Mathur, there were few functions of BML that were perceived to be useful, including announcements, information about college services, contacts, and the My Grade interface of BML. Findings were inconclusive for assignments, course documents, and discussions because users could have alternative access to those functions through personal computers.

Furthermore, Sek et al. (2010) examined how TAM can be used as a practical tool for predicting early user acceptance of smart phones for learning. Researchers evaluated the relationships among perceived usefulness, perceived ease of use, attitude towards using, and users' intent to use smartphones for learning. In this study, an introductory demonstration of a smartphone for a digital system course was presented to users who had no prior experience using a smartphone. The analysis of TAM results showed that both users' attitude and perceptions positively influence behavior intention and actual use of smartphones. Sek et al. pointed out two important implications of the study's findings. First, TAM is a useful model for identifying potential risks of rejection of M-learning. Second, the capabilities of M-learning systems must be communicated early to users to develop informed opinions regarding ease of use and usefulness of the system.

In addition, Akour (2010) developed the Mobile Learning Acceptance Model (MLAM) to examine factors that impact students' acceptance of M-learning. MLAM incorporates user readiness, extrinsic influence, university commitment, and quality of service as independent factors that impact the main constants of TAM. Data for evaluating MLAM was collected from 251 undergraduate students. The findings of investigating MLAM show that the most significant predictor of usefulness is user readiness. Thus, it is important to improve users' positive attitudes by educating them about M-learning in the early stages of implementation. In addition, it was found that usefulness is the most significant predictor of behavior intention. This means that M-learning services must provide students (users) with their preferred functionality. Moreover, it was found that extrinsic influence was the most significant predictor of ease of use. Akour (2010) also recommends that examining perceptions of faculty towards M-learning is necessary to evaluate the extent to which these findings can be generalized. He also recommends examining potential differences in users' perceptions between age groups and between users with various technological skills.

Moreover, Marss (2013) examined perceptions of students and faculty towards acceptance of M-learning in online higher education using MLAM. The population for this study was online undergraduate and graduate level students and faculty in an American university. Data for this study was collected from 294 faculty and 123 students via an online survey. Study results indicated that faculty perceptions of usefulness were strongly influenced by ease of use followed by user readiness, extrinsic influence, and finally quality of services. In addition, faculty perceptions of ease of use were strongly influenced by user readiness followed by extrinsic influence and quality of services. Moreover, faculty attitudes were influenced by perception of usefulness followed by ease of use. Faculty behavioral intentions were most strongly influenced by ease of use followed by attitudes and perceived usefulness.

Students' perceptions of usefulness were most strongly influenced by ease of use followed by extrinsic influence, user readiness, and last by quality of services. Student perceptions of ease of use were most strongly influenced by extrinsic influence followed by quality of services and user readiness. Students' attitudes were influenced in the same way as faculty, mostly by perceptions of usability followed by ease of use. Overall, the study results showed that the younger the user and greater the level of experience the user had using M-devices, the more positive they were about M-learning. Furthermore, Marrs (2013) stresses that M-learning acceptance is still quite new and much research remains to be conducted to further the knowledge base in this field. Therefore, she recommended that researchers investigate M-learning acceptance in government, businesses, and higher educational institutions in other countries using MLAM.

Most studies that employed TAM in learning contexts confirmed that perceived usefulness and perceived ease of use determine an individual's intention to accept and adopt M-learning. However, Liu et al. (2010) found that perceived ease of use did not significantly influence user's behavior intention to accept and adopt M-learning. In addition, data provided by the main constructs of TAM did not supply more meaningful information on users' opinions about a specific system (Zabukovsek & Bobek, 2013). Therefore, researchers of M-learning acceptance and adoption incorporated and tested additional factors with TAM to improve its explanatory utility. These improvements of TAM open opportunities to researchers to find evidence to enhance the certainty and robustness of the extended TAMs or to refute them.

M-learning in Saudi Arabia

In order to facilitate education in Saudi Arabian universities, the education system has moved slowly from traditional learning approaches to distance and digital learning. According to Al-Shehri (2012), the Saudi government has established multiple projects to encourage the implementation of digital and distance learning, such as the Saudi Electronic University, the Saudi Digital Library, and the National Center of E-learning and Distance Education. In addition, the mobile infrastructure in Saudi Arabia is well established, with the result that mobile penetration in Saudi Arabia reached more than 185% in 2010 and most citizens acquire new mobile devices with improved features every year (Al-Hujran et al., 2014; Narayanasamy & Mohamed, 2013). For instance, at Jazan University, which is not located in main cities, everyone own at least one smartphone (Narayanasamy & Mohamed, 2013). However, M-learning as a new pedagogical approach is still in the development stages in Saudi Arabia (Chanchary & Islam, 2012; Alwraikat & Al-Tokhaim, 2014). Several funded studies were conducted to capture and examine the current practices of M-learning in Saudi Arabia.

Al-Fahad (2009) examined the attitudes and perceptions of 186 undergraduate students at King Saud University towards the effectiveness of M-learning. The study indicated that the future of M-learning in Saudi Arabia is promising, since almost every student owns a smartphone with cutting-edge technologies. It also showed that the majority of students supported the flexibility feature of M-learning to access learning resources independent of time or location. Al-Fahad highlighted that participants' perspectives changed from passive learners to truly engaged learners who intellectually and emotionally engaged in their learning activities. However, some participants expressed concerns about M-learning due to the expensive cost of data plans required to implement it.

In addition, Chanchary and Islam (2011) conducted a study at Najran University to explore the perceptions of students towards M-learning as well as prospects and technological challenges. Data for this study was collected from 131 undergraduate students via an online survey. Study results showed that students' attitude towards M-learning is positive. They liked the flexibility of this learning environment, the increased capability of accessing learning resources immediately, and its improved methods of communication between peers and instructors. However, a large number of participants had no idea what M-learning was or how it could facilitate their learning. They would like their instructors to implement a blended learning approach in which M-learning is combined with face-to-face instruction.

Furthermore, Nassuora (2012) studied the factors affecting the use of M-learning at Al-Faisal University by adopting a Unified Theory of Acceptance and Use of Technology (UTAUT) model. Data for this study was collected from 80 undergraduate students via a survey. The study indicates that the majority of students were unfamiliar with the concept of M-learning; however, students' perceptions towards M-learning and acceptance of M-learning were positive. The results showed that a positive attitude led to the behavioral intention to accept and adopt M-learning. In addition, the researcher suggests that university administration should provide an M-learning system that is aligned with users' perception.

Al-Hujran, Al-Lozi, and Al-Debie (2014) examined factors affecting college students' behavioral intentions to use M-learning using the UTAUT model. Data for this study was collected from 215 undergraduate students via an online survey. Their study shows that performance expectancy is a main factor that influences users' intention of using M-learning. This means that the more M-learning is perceived as a way that can improve students' academic performance, the more likely they are willing to adopt this technology. Effort expectancy was also found as an influential factor in their study, meaning if users perceived M-learning solutions as user friendly, easy to use, and free of effort, then their intention to use it would be greater. However, Al-Hujran, Al-Lozi, and Al-Debie found that facilitating conditions have no impact on the adoption of M-learning. Therefore, users believe that organizational and technical infrastructures are not necessary to support the use of M-learning. This finding contradicts with the study of Munguatosha et al. (2011), where administrative support and technical infrastructure significantly impacted acceptance and adoption of M-learning in their model.

Alwraikat and Al-Tokhaim (2014) investigated differences in faculty members' attitudes toward M-learning concept at King Saud University with regard to their gender, academic rank, and academic experience. The data for their study was collected from participants (N=326) via a web survey that was developed by researchers. The results of the study indicated that the attitude of faculty members towards M-learning were high. Researchers attributed this finding because they believe that M-learning can benefits the educational environment with all its components. In addition, the results indicated that there were statistically significant differences in faculty attitudes toward M-learning with regard to gender and in favor of female. Females seem to use mobile technology more competently than the males, thus that affects their perceptions. However, in this study female faculty were (N=310) while male faculty were (N=52), thus might impacted this finding. In addition, the results showed that there were differences in attitudes between faculty members who hold the rank of Professor and faculty members who hold the rank of instructor only, these differences were in favor of instructors. In addition, there were differences in attitudes between faculty members, who have an experience of 21 years and more, and faculty members who are less than 21 years of experience, these differences were in favor of faculty members who have a 21 years of experience and more.

Although, Saudi Arabia is reported as a country with a high percentage of mobile phone users around the world (Seliaman & Al-Turki, 2012), literature reveals that the number of published research tackling M-learning acceptance and adoption is relatively small in developing countries such as Saudi Arabia. M-learning is not a new word in universities of Saudi Arabia; however, previous studies did not examine accepting and adoption factors that impacted both students and faculty in higher education institutes at the same time. According to Altameem (2011) a successful M-learning system is utilized by considering perspectives and functions of students, and faculty members. Other research indicates that there are multidimensional differences between students and faculty members (Akour, 2010; Marss, 2013; Hoskyns-Long, 2009; Lawrence, et al., 2008; Williams, 2009). Therefore, research that helps decision makers and instructional technology practitioners understanding how both groups influence m-learning adoption and acceptance is lacking. This indicating that there is a need to fill this gap in the literature by investigating the factors that impact M-learning acceptance and adoption of both groups using a theoretical model that has an excellent reputation of robustness and explanatory power.

Comparison of Theoretical models of Technology Acceptance

Research on acceptance and adoption of M-learning is based on various theoretical models. Table 1 shows a comparison of technology acceptance models/theories in terms of their ability to explain users' intentions to accept technology (the explained variance R^2) (Samara and Gunawardena, 2014).

Theory/Model	Explained variance (R^2)
Theory of Reasoned Action (TRA)	36%
Theory of Planned Behavior (TPB)	36% - 47 %
Innovation Diffusion Theory (IDT)	40%
Technology Acceptance Model (TAM1, TAM2)	52% - 53%
Unified Theory of Acceptance and Use of Technology (UTAUT)	69%
Mobile Learning Acceptance Model (MLAM)	75.8% - 79.8%

Table 1. **Technology acceptance models comparison (Venkatesh et al. 2003; Kripanont 2007, Dulle, Minishi-Majanja & Coloete2010; Akour, 2010; Marrs, 2013)**

As presented in Table 1, the explanatory power of the Mobile Learning Acceptance Model (MLAM) is higher than other models of technology acceptance. MLAM was validated and explained a significant portion of the variance in users' intentions to accept and adopt M-learning in two different empirical studies of higher education institutes (R^2 = 77.7%, Akour, 2010; R^2= 79.8%, Marss, 2013). MLAM improves the explanatory power of TAM investigated by Venkatesh and Davis (2000) and is considered to be an extension of TAM. Literature reveals that TAM has become one of the most powerful and robust models for examining technology acceptance and usage (Davis, 1989, Davis et al., 1989; Legris et al., 2003; Mathieson, 1991;

Igbaria et al., 1995).

Thus, considering the above facts and the needed research to understand how to effectively integrate M-learning in Saudi Arabian university contexts, it is likely that MLAM will provide a solid base to investigate factors impacting students' and faculty's acceptance and adoption of M-learning in a higher education setting.

M-learning Acceptance Model (MLAM)

MLAM was adapted by Akour (2010) to examine factors that impact students' acceptance of M-learning in higher education. MLAM incorporates user readiness (UR), extrinsic influence (EI), university commitment (UC), and quality of service (QoS) as the independent factors that directly impact the user perceptions of ease of use (EoU), usefulness (U), and attitude (A). In addition, behavior intention (BI) is indirectly impacted by external factors and directly impacted by U and A. Moreover, BI is the dependent factor that predicts the acceptance of M-learning. Figure 2 below shows the relationship between the independent and dependent factors of MLAM.

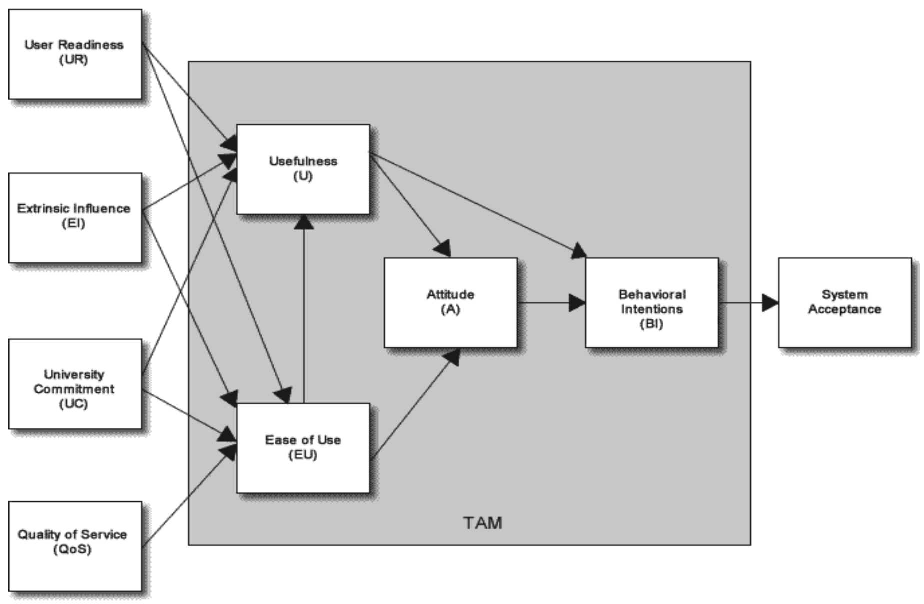


***Figure 2*: Mobile Learning Acceptance Model (Akour, 2010)**

According to Akuor (2010), user readiness (UR) is a self-perception of the user of being able to accomplish a learning task. UR consists of two concepts: mobile self-efficacy and intrinsic commitment. Mobile self-efficacy is defined as a user's perception of her/his ability to use a mobile device to accomplish learning tasks in a mobile learning environment (Chen, 2007; Akour, 2010). Intrinsic commitment is conceptualized as the measure of perceived congruency between values of users and use of M-learning (Marrs, 2013; Akour, 2010; Malhortra & Halleta, 2005). Thus, a user who perceives a congruency between value and use is committed to and enthusiastic about M-learning. Extrinsic influence (EI) refers to the combined influence that administrators and peers have on the perceptions of users (Akour, 2010; Wang, et al., 2009). In addition, EI is described as "the perceived pressure from important others to perform or not perform an action" (Moss et al., 2010, p. 303). In the context of Akour's study, university commitment (UC) refers to perceptions of users regarding the importance of university support. UC consists of various concepts, including management support, user training, technical support, and use involvement (Park & Chen, 2007). Moreover, quality of service (QoS) refers to reliability and response time, content quality, personalization, and privacy (Kuan et al., 2003; Marrs, 2013).

Research Goals

This study has three main goals, as follows:

1- To determine the factors that impact faculty and student acceptance and adoption of M-learning at Jazan University.
2- To understand the relationships between factors impacting the acceptance and adoption of M-learning.
3- To identify the extent of use of M-learning by faculty and students at Jazan University.

Research Questions

To achieve the study goals, there is a need to examine factors that determine the acceptance of M-learning from the users' perspectives. Thus, the following questions will be investigated:

1. What are the factors of MLAM that impact students' acceptance of M-learning at Jazan University?
2. What are the factors of MLAM that impact faculty members' acceptance of M-learning at Jazan University?

When the factors of accepting M-learning are examined, there is a need to determine the most important influential factors (Akour, 2010), which will help administrators to manage resources and efforts effectively. Thus, the following questions will also be investigated:

3. Which factors of MLAM are the most important and influential for students' acceptance of M-learning at Jazan University?

4. Which factors of MLAM are the most important and influential for faculty members' acceptance of M-learning at Jazan University?

To fully understand the factors that influence the acceptance and adoption of M-learning, there is a need to investigate the current practices of M-learning. Thus, the following questions will be investigated:

5. To what extent are students at Jazan University currently using mobile technologies for learning purposes?
6. To what extent are faculty members at Jazan University currently using mobile technologies for learning purposes?

Method

This section describes the research methodology that will be used in this quantitative study. The instrument of this research is adopted from Akour (2010) for investigating M-learning acceptance. In this study, the researcher uses MLAM to determine factors that influence faculty members' and students' acceptance of M-learning in a Saudi university. The research will analyze the influences that user readiness (UR), extrinsic influence (EI), university commitment (UC), and quality of service (QoS) have on usefulness (U), ease of use (EoU), attitude (A), and behavior intention (BI) to use M-learning technologies and services.

Research Setting

The selected location for conducting this study is Jazan University in Saudi Arabia where the researcher works as a lecturer in the Educational Technology department. Jazan University is a public university that was established in 2006 offering various undergraduate programs at different campuses across the Jazan area. According to Moukali (2012), the number of colleges at Jazan University has increased to the following:

- College of Islamic Law
- College of Medicine
- College of Dentistry
- College of Pharmacy
- College of Applied Medical Sciences
- College of Science
- College of Engineering
- College of Computer and Information Systems
- College of Health Sciences
- College of Arts and Humanities
- College of Architecture and Design
- Community College
- College of Business Administration
- College of Education
- College of Public Health and Tropical Medicine.

According to the statistics provided by Jazan University on its website, the total number of faculty members is 2,927 and the total number of students is 59,899. Although educational systems are segregated by gender, participants of this study are both male and female

Survey Instrument

The researcher will use a survey that was developed by Akour (2010) to collect data and will modify the survey to include the following:

- Cover letter
- Information about the study
- Demographics of participants, which include age, gender, college, device ownership, experience using a mobile, general mobile usage, and academic mobile usage
- Original survey items
- Comments

The researcher has reproduced two versions of the instruments to ensure that the wording is relevant to both students and faculty. Both versions are translated into Arabic and measured on a seven-point Likert-type scale. Three graduate students who speak both English and Arabic participated in the translation process to ensure that the Arabic version is accurate. In addition, cognitive online interviews will be conducted with some participants to validate the quality of the translated version (Wallen, Feldman, & Anliker, 2002). In this process, the researcher will ask participants to think aloud so that he can understand if there are problems with the questions. By thinking aloud, participants will read all questions aloud and tell the researcher what they are thinking as they read and as they choose their answers. Participants' comments from the cognitive interviews will be analyzed and any relevant changes will be made. After making all changes, the Arabic versions of surveys will be sent to a Language Translation Service to translate them back to English. This process will validate the quality of the Arabic survey and will ensure that both Arabic and English versions are similar.

The following links are the Arabic version of Akour's (2010) instrument, which were created by using Qultrics.com:

- Faculty Survey link
- Student Survey link

According to Marrs (2013), the demographic section of the survey should allow for a large range of ages, which will help in cross-sectional analysis. Age groups will be 18-24, 25-31, 32-38, 39-45, 46-52, 53-59, 60-66 and 67 years and over. In addition, the academic uses of mobile devices by Dahstrom et al. (2011) are more specific than those identified in the original survey. Thus, the following items are added to the survey:

- Communicating with professors and students by sending and receiving e-mail and texts.
- Accessing resources and applications, which include:
    - Grades
    - Review syllabus
    - Library resources
    - Course registration
    - Financial aid
    - Purchase textbooks
    - Tutoring resources
    - Order transcripts
    - Class information
    - Social network sites
    - Conduct research

    - Learn about visited locations
    - Post on the Internet
- Creating multimedia by taking pictures and making other visual aids.
- Doing class work, which includes writing papers and collecting data for class work.

Appendices B and C present the modified version of both instruments in English.

Sampling Procedures

The target population for this study is undergraduate and graduate level faculty and students at Jazan University in Saudi Arabia. As presented on the university website, the population is estimated at 59,899 students with 2,927 faculty members. The initial challenge is determining the optimal sample size that is needed to answer the research questions. However, using a sampling formula will allow the researcher to estimate the sample size (Israel, 2010). The following formula provided by Israel is used, assuming a 95% confidence level and .05 precision (α), where *N* = the total estimated population.

$$n = \frac{N}{1 + N\ (\alpha)^2}$$

$$n_{faculty} = \frac{2{,}927}{1 + 2{,}927\ (.05)^2} = 352$$

$$n_{student} = \frac{59{,}899}{1 + 59{,}899(.05)^2} = 398$$

According to Creswell (2009), selecting a random sample from the population is desirable because it will lead to a greater probability that the sample will represent the entire population. Thus, a random selection will be used in this study.

Data Collection Procedure

The researcher will obtain approval from the Institutional Review Board (IRB) of George Mason University. After that, the researcher will email deans of schools at Jazan University to request permission to recruit the required number of students and faculty members during the spring semester of 2017.

Instrument Validity

A valid instrument leads to an appropriate interpretation of data (Pallant, 2010). There are three main types of validity: content, construct, and criterion validity (Akour, 2010). The validity of content means the degree to which an instrument measures the content it was designed to measure. To establish validity of content, Akuor (2010) consulted experts in questionnaire development, sample design, and conducted a pilot study. In addition, to construct validity, Akour (2010) performed convergent validity and found that all scale correlations are significant at a p <.01 level with a two-tailed t-test. He also found that discriminant validity was achieved.

Instrument Reliability

The most used statistical test for assessing internal consistency is Cronbach's coefficient alpha (α), where the value of α should be greater than .70 (Pallant, 2010). In this study, the researcher will measure the internal consistency of each variable's survey item through correlations by using Cronbach's (α) coefficient and will also compare the results with Akour's (2010) results.

Conclusion

This paper provides an overview of the M-learning literature and models for determining the factors that influence the acceptance of new technologies. In addition, it presents the research design and a description of the survey instruments that will be used in this investigation. The surveys were adopted and translated to aid the researcher to determine the factors influencing faculty members' and students' acceptance of M-learning. These two versions of surveys were created to test the predictive power of the constructs of MLAM developed by Akuor (2010).

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