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Ahmad Samed Al-Adwan, Amr Al-Madadha and Zahra Zvirzdinaite

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Article abstract

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Modeling Students' Readiness to Adopt Mobile Learning in Higher Education: An Empirical Study



Ahmad Samed Al-Adwan[1], **Amr Al-Madadha**[2], and **Zahra Zvirzdinaite**[3]
[1]Al-Ahliyya Amman University-Jordan, [2]Princess Sumaya University for Technology-Jordan, [3]University of Wales-UK

Abstract

Mobile devices are increasingly coming to penetrate people's daily lives. Mobile learning (m-learning) is viewed as key to the coming era of electronic learning (e-learning). In the meantime, the use of mobile devices for learning has made a significant contribution to delivering education among higher education students worldwide. However, while m-learning is being widely adopted in developed countries, the adoption of such an approach in developing countries is still immature and underdeveloped. Developing countries are facing several challenges and lagging behind in terms of adopting m-learning in higher education. Thus, this paper explores the factors that have an impact on students' intentions and readiness to adopt m-learning in higher education in Jordan. Based on the data collected from the field, we examine Jordanian students' requirements and preferences in terms of m-learning design, and we also investigate their concerns about adopting m-learning. This empirical study collected data from students using a paper-based questionnaire. The results reveal that students' intentions to adopt m-learning is influenced by several factors that include the relative advantage, complexity, social influence, perceived enjoyment, and the self-management of learning. By providing a picture of students' willingness to adopt m-learning, this study offers useful and beneficial implications for developers of m-learning applications and for educational providers to guide the design and implementation of comprehensive m-learning systems.

Keywords: mobile learning, m-learning adoption, e-learning, technology acceptance, technology acceptance, perceived enjoyment, self-management of learning, developed countries

Introduction

With technology becoming increasingly more powerful, it is spreading and dominating many aspects of people's lives, particularly education (Al-Adwan, Al-Adwan, & Smedley, 2013). Technology has provided the education field with significant tools to support educational processes (Seliaman & Al-Turki, 2012). In particular, the considerable advancement of mobile technology over the past decade, the increasing proliferation of mobile devices, and the availability of the Internet have made mobile learning (m-learning) the current trend in learning in higher education worldwide (Shorfuzzaman & Alhussein, 2016). The affordability, sophistication, and popularity of mobile devices among higher education students have encouraged education providers to consider using them as a new medium of learning. Mobile devices are increasingly becoming more capable of performing all the functions that are necessary in the learning process. Mobile technology consists of various applications and tools that allow learning to be more dynamic and accessible, so that students are no longer restricted to their classrooms when it comes to interacting with learning processes (Callum, Jeffrey, & Kinshuk, 2014).

M-learning is defined in a range of ways throughout the literature. According to Farley, Murphy, and Rees (2013), researchers are struggling to provide a particular definition of m-learning that is educationally relevant and sufficiently different from e-learning. Traxler (2007) points out that the characteristics of m-learning raise several difficulties in terms of developing a unified definition of m-learning. He identified three main characteristics that contribute to the difficulty of defining m-learning - contextual, personal, and situated characteristics. In the context of higher education, Osman, El-Hussein, and Cronje (2010) argue that the portability and mobility of mobile devices have a significant influence on the definitions of m-learning that have been broadly presented in the literature. Considering a mobile device as a signifier, three main categories can be interpreted based on the concepts of mobility: the mobility of learners, the mobility of technology, and the mobility of learning in the landscape of higher education. Based on the above, Wang, Wu, and Wang (2009) define m-learning in the context of higher education as the "delivery of learning to students anytime and anywhere through the use of wireless Internet and mobile devices, including mobile phones, personal digital assistants (PDAs), smart phones and digital audio players" (p. 93). They state that m-learning is viewed as the follow up of e-learning, the concepts of which are rooted in distance education. The mobility and ubiquity of mobile devices prevent learning from being restricted to a specific time and location (Osman et al., 2010). Mobile devices have the capacity to connect to the Internet and deliver instructions and materials to students at anytime and anywhere. M-learning promotes learner-centred and personalized learning approaches by enabling students to interact and engage with educational processes away from traditional learning places such as classrooms and desktop computers. In other words, mobile devices offer place independence that enables both students and tutors to manage their time effectively.

While m-learning offers significant potential capabilities (Callum & Jeffrey, 2013), the adoption of such technology faces many challenges, which suggests that the adoption of m-learning is not an easy decision to make (Wang et al., 2009). In spite of the rapid growth and capabilities of mobile technology and networks, m-learning is considered as an emerging trend and is still in its infancy in higher education (Thomas, Singh, & Gaffar, 2013). The slow adoption of m-learning rates by higher education institutions may relate to several challenges. According to Tabor (2016), these challenges include connectivity, small screen sizes, limited computation power, limited memory capacity, short battery life, reduced input capabilities, unfriendly user interfaces, and complex input methods. Small keyboard or touch screens may require learners to allocate more time searching for information than they need to read it. Therefore, the success of m-learning is fundamentally based on students' willingness to adopt a new technology that is different from previous learning styles. In order to provide suitable m-learning services, it is critical to investigate students' adoption processes (Liu, 2008; Shorfuzzaman & Alhussein, 2016). According to Sarrab, Al Shibli, and Badursha (2016), the key success factors with regard to m-learning essentially depend on students' desire and intellectual engagement in m-learning activities. Thus, examining students' perceptions and readiness to adopt m-learning is significantly important for the successful implementation of this technology in higher education.

Research Objectives

Developing countries generally struggle to utilise educational technology and implement effective distance learning in their education systems (Deb, 2011). Compared to developed countries, developing countries lack telecommunication infrastructure required for successful implementation of distance learning. Additionally, the lack of human and economic resources prevents developing countries to acquire and utilise distance learning.

Another conventional aspect is that the neutrality of IT among cultures is dissimilar, as each technology represents the culture of its producing country (Shaukat & Zafar, 2010). Developed countries are more sensitive to technology since the creation and design of the technology reflects the aspirations and demands of their culture and thus can be beneficially employed immediately. Consequently, developing countries, which passively adopt technology as standard products, will struggle to cope with the radical changes caused by the adoption of technology. Technology was originally designed in industrialised and developed countries, and this may lead to socio-cultural barriers that diversely affect the acceptance of technology in developing countries. Deb (2011) points out that

> Successful use of IT requires much more than mere installation and application of systematized knowledge. It also requires the application of implied knowledge regarding the organization and management of the technology and its application to the contextual environment in which it is to be used. This implied IT knowledge often represents experience with the deployment of previous technology accumulated over time, such experiences contributing towards the shaping of new technology. (p.35)

In Jordan, m-learning has not been formally adopted in the higher education institutions. On the other hand, this has not been the case for e-learning as various e-learning technologies are currently being utilized by both students and lecturers. However, the expectations with regard to adopting e-learning in Jordanian higher education institutions are still below those operating at the international level (Almarabeh & Mohammad, 2013). According to the reports of the Jordanian Telecommunication Regulatory Commission (TRC) (2016), the number of mobile users reached 14 million by the first quarter of 2016, with a penetration rate of 148%. Additionally, the total number of internet users in Jordan is around 8.1 million with a penetration rate of 84%; however, the increased number of mobile devices and wireless networks does not necessarily indicate that m-learning will be adopted without any obstacles. Therefore, in order to successfully adopt m-learning in higher education, several factors must be addressed, specifically the driving factors that influence students' acceptance (Thomas et al., 2013; Callum, 2010).

While m-learning is being widely adopted in educationally developed countries, Jordan, as a developing country, is still lagging behind and facing a variety of challenges in terms of adopting m-learning. Developed countries such as the USA, the UK, and Japan are establishing policies and plans to meet the growing demand associated with learning (Shorfuzzaman & Alhssein, 2016). They are developing learning strategies and plans that make best use of educational technologies, specifically mobile devices. Based on the above discussion, it is clear that several studies have been conducted in educationally developed countries to adopt m-learning in practice. Thus, it is important to investigate the factors that influence students' perceptions of m-learning and their readiness to adopt m-learning technology in higher education in developing countries. Therefore, the aim of this study is to help overcome the lag in m-learning adoption in the context of higher education institutions in developing countries, especially in Jordan. Therefore, this study investigates the influence of several factors on students' intention to use m-learning. These factors include: relative advantage, complexity, social influence, perceived enjoyment, facilitating conditions, and self-management of learning. Beside the importance of self-management of learning to m-learning adoption, it has not been intensively examined. Additionally, this study examines the moderating effects of three variables include: age, gender, and course type. To our knowledge, compared to age and gender, the moderating effects of course type have not been investigated in the context of m-learning.

The Research Model

Organizations invest heavily in information systems (IS) and information technology (IT) to improve performance, reduce costs, and increase service quality (Mojtahed, Nunes, & Peng, 2011). Despite the magnificent performance improvements associated with using IS, users often resist using such systems. Such resistance results in frustration for organizations due to the financial loss associated with low success rates. Therefore, the lack of user acceptance is considered as the pivotal obstacle to the success of new IS (Abbasi, Tarhini, & Hassouna, 2015). As a consequence, several models have been proposed in the IS literature attempting to clarify the socio-technical phenomenon of users' acceptance of IS. The Technology Acceptance Model (TAM) (Davis, 1989) and its extensions, and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh, Morris, & Davies, 2003) are among these noteworthy theoretical models aiming to investigate users' behavioural intentions and/or usage of IS and IT. These models have been widely used in many IS contexts such as healthcare informatics (Al-Adwan, 2015), online shopping (Celik, 2016) and banking (AlKailani, 2016). According to Mojtahed et al. (2011), the original versions of technology acceptance theories and models are rarely employed by researchers as they stand. Therefore, researchers tend to modify these models' constructs and relations by incorporating additional context-specific elements in order to address the requirements and contexts of particular studies. M-learning has its own distinctive characteristics, and it also differs from other IS/IT contexts (Almasri, 2015). Thus, since the focus of this paper is to investigate students' perceptions when it comes to adopting m-learning, it proposes a contextualized framework that is developed specifically to examine the adoption of m-learning by students in the context of higher education. As Figure 1 suggests, the proposed framework consists of seven constructs. M-learning is not officially implemented in Jordanian higher education, and thus the dependent variable of the research framework is behavioural intention (BEI) rather than usage behaviour. The independent variables include relative advantage (RAD), complexity (COM), facilitating conditions (FCO), perceived enjoyment (PEN), social influence (SIN), and the self-management of learning (SML).

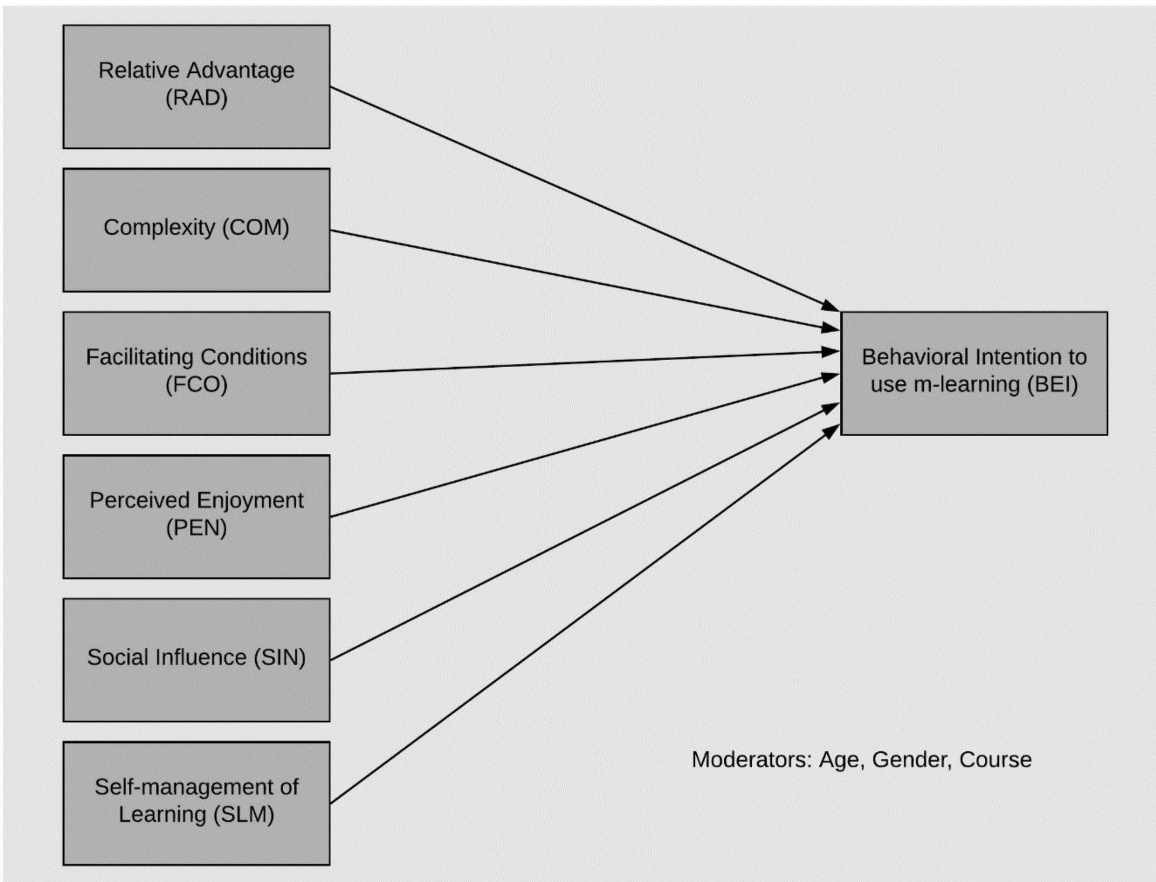

Figure 1: The research model.

Relative Advantage (RAD)

According to Rogers (2005), relative advantage refers to the extent to which an innovation or a technology is perceived as being more useful than its precursor. Relative advantage is similar to the concept of perceived usefulness from TAM, and also consistent with the performance expectancy construct from UTAUT. In the m-learning environment, this indicates that students expect to find m-learning useful, as well as to enable them to accomplish their educational tasks in an effective and timely manner (Jackman, 2014). In other words, there is a strong likelihood to adopt m-learning when students perceive it to be beneficial and useful to them. Arpaci (2014) points out that the relative advantages of m-learning over a traditional learning environment results from the distinctive characteristics of mobile devices. With features such as ubiquity, flexibility, accessibility, and connectivity, students will consider m-learning useful because it allows them to use a device of their choice, and access information conveniently without any restrictions in terms of place and time.

Complexity (COM)

Rogers (2005) refers complexity to "the degree to which an innovation is perceived a relatively difficult to understand and use" (p.15). The more an innovation or technology is easy to use, the less effort is needed to conduct a given job (Davis, Bagozzi, & Warshaw, 1992). Complexity is the opposite to the construct of effort expectancy from UTAUT and the perceived ease of use construct from TAM. Rogers (2005) points out that complexity has a negative influence on the adoption rate of an innovation. Venkatesh (1999) suggests that effort-oriented constructs are expected to have a significant effect during the initial stages of using a new innovation, and the effect of effort expectancy will be decreased as the users acquire more experience. Although it has been claimed that the effect of complexity is not as important as relative advantage, its significance has been widely recognized recently in the domain of user interaction, interface, and usability (Joo, Lim, & Lim, 2014). As a consequence, it has been argued that complexity can be a key barrier to the adoption of a new innovation. With regard to m-learning, if students perceive hardware and software for m-learning to be user-friendly, then they may be very keen to adopt it in their education (Sahin, 2006). Students will be expecting the different activities and processes of m-learning to be easy and to function simply, particularly in the light of the limited capabilities of mobile devices such as smart phones (Liaw, Hatala, & Huang, 2010). Mobile devices have less capabilities (i.e., small memories, limited screens, and slow processors) compared to PCs.

Perceived Enjoyment (PEN)

Making the process of learning enjoyable and less tiresome to students is constantly considered one of the main aspects of importance in educational environments (Huang, 2014). Davis et al. (1992) state that perceived enjoyment refers to the level to which the use of an innovation is enjoyable aside from any performance consequences that may be anticipated. Perceived enjoyment is considered as an intrinsic motivator in which users are involved in an activity due to their interest in the activity (Iqbal & Qureshi, 2012). Prior research suggests that the acceptance of new systems is influenced by the perception of intrinsic-related constructs such as perceived playfulness and enjoyment (Masrek, 2015). This is because individuals who experience gratification and pleasure during the use of an innovation or a system are more likely to use it subsequently. Intrinsic motivators such as perceived enjoyment, are widely used to examine individuals' perceptions of educational innovation (Wang et al., 2009). Previous studies indicate that perceived enjoyment is a substantial factor when it comes to students' intentions to use m-learning (Jung, 2014; Cheng, 2014). Liu, Han, and Li (2010) explain that while the learning process in general may generate a sense of stress and pressure for students, it is important to develop m-learning applications that are enjoyable and interesting to help smoothen the adoption decision. Additionally, it has been argued that students are intrinsically encouraged to engage with learning activities particularly when they sense that the learning style is viewed as enjoyable, novel, and exciting. Therefore, mobile technologies are expected to lead to a learning environment that allows students to access the learning process in a more enjoyable fashion (Martin & Ertzberger, 2013).

Social Influence (SIN)

Social influence is defined by Venkatesh et al. (2003) as "the degree to which an individual perceive that important others believe he or she should use the new system" (p. 451). Social influence is viewed by users as the social advantage that results from the use of a new technology. From the m-learning perspective, previous research demonstrates that students' decisions to use m-learning is significantly influenced by peer students and/or important individuals such as instructors (Mtebe & Raisamo, 2014; Abu-Al-Aish & Love, 2013). The literature suggests that the impact of social influence will be significant in the initial phases of m-learning and will gradually decrease over time as m-leaning becomes more widely used (Ugur, Koc, & Koc, 2016).

Self-Management of Learning (SML)

Self-management as a learning construct is regarded as one of the fundamental issues in the educational field due to its significant role in enabling positive learning performances and acting as a crucial determinant of learning achievement (Huang, 2014). Smith, Murphy, and Manhoney (2003) refer to SML as "the degree to which an individual perceives self-discipline and can engage in autonomous learning" (p. 60). Wang et al. (2009) point out that SML encourages independent, self-directed, and autonomous learning. Self-regulated students are the ones who are cognitively and behaviourally active participants of their own learning processes, without depending on others (e.g., instructors, parents) (Zou & Zhang, 2013). Abar and Loken (2010) explain that self-directed learning requires students to sustain cognitions and behaviours systematically in order to achieve learning goals. In the context of m-learning, the skill of self-directed learning is an essential success factor when it comes to engaging with flexible delivery, distance education, and resource-based learning such as m-learning (Prajapati & Patel, 2014). Students are away from instructors, peers, and education providers, and thus they are required to acquire skills and competences to manage their own learning effectively.

Facilitating Conditions (FCO)

The construct of facilitating conditions refers to the extent to which individuals believe that both technical and organisational infrastructures exist to support the use of a particular technology (Venkatesh et al., 2003). Facilitating conditions refer to technical and organisational facilitators that help users to overcome obstacles related to the use of a technology. They have a great impact on technology adoption and infusion, as many studies highlight the important role of facilitating conditions in influencing adoption behaviour (Lu Chun-Chun-Sheng, & Chang, 2005). The availability of proper facilitating conditions (e.g., training courses, technical support, and adequate resources) is crucial for technology adoption (Aypay, Celik, & Aypay, 2012). The absence of facilitating conditions could lead to a negative impact on IT usage and behavioural intentions as the absence of facilitating resources generates obstacles to usage, or could discourage the formation of negative behavioural intentions towards usage. According to Iqbal and Qureshi (2012), students face several technical challenges when they switch to m-learning. Technical issues such as limited processing speed, low bandwidth, unfriendly user interface, and less surf-ability may prevent users adopting m-learning. The devices used in m-learning range from mobile devices to laptop computers that acquire heterogonous capabilities such as memory capacities, computational power, and display for ubiquitous media learning access (Hossain & El Saddik, 2008). Thus, learning materials have to be transcoded to be viewed effectively by learners from any device. Consequently, guidance and technical support are essential to facilitate students' engagement with m-learning

(Concannon, Flynn, & Compbell, 2005). In particular, the functionality of personal mobile devices and support from learning providers appear to be vital factors.

Methodology

The focus of this study is to investigate students' behavioural intentions when it comes to adopting m-learning in higher education in Jordan. Consequently, the participants who took part in this research are undergraduate students from different courses at two Jordanian universities (see Table 1). Convenience sampling technique was used to identify the participants to whom 350 paper-based questionnaires were sent. Faculty staff at both universities participated in facilitating the distribution and collection of the questionnaire. While a total of 350 questionnaires were distributed to participants, 234 questionnaires were returned indicating a response rate of 66.8%. Out of the 234 returned questionnaires, six were reported as incomplete and thus were excluded from further analysis. Overall, a total of 228 (n=228) questionnaires were acceptable for analysis. As the sample's profile shows in Table 1, 60% of the participants were male and 40% were female. The largest age group was participants aged <20 years old, representing 42% of the sample, and participants aged between 20-27 formed 39% of the sample. More than half of the participants (56%) use smartphones to access the internet, while only 8% use desktop/PC. Also, 23% of the participants use laptops and users of tablets made up 12% of the sample. Such percentages reflect the popularity of mobile devices among higher education students.

Table 1

The Sample's Profile

Measure	Item	Frequency	Percentage (%)
Gender	Male	137	60%
	Female	91	40%
Age	<20	96	42%
	20-27	89	39%
	>27	43	19%
Mobile device used to access Internet	Desktop/PC	17	8%
	Laptop	53	23%
	Smart phone	127	56%
	Tablet	28	12%
	Other	3	1%
Course	Translation and Languages	39	17%
	Educaton	21	9%
	Business Adminstration	79	35%
	Finance and Accounting	57	25%
	IT related	32	14%

Data was collected from participants through a survey questionnaire comprising of 27 items in order to evaluate the seven constructs (see Table 2). A 4-point Likert rating scale was used to measure all the items, ranging from (1) strongly agree to (4) strongly disagree. All items were adopted from previous and well-established mobile technology research (Shorfuzzaman & Alhussein, 2016; Celik, Sahin, & Aydin, 2014; Wang et al., 2009). In order to evaluate the content validity, the questionnaire form has been approved by at least five experts in the domain of IS and educational technology. Finally, the questionnaire form was translated into Arabic by a professional translator. In order to evaluate the accuracy of the translation process, another professional translator was employed to translate the questionnaire form back into English.

Table 2

The Questionnaire Form

Construct	Item
Self-management of learning (SML)	SML1: "I am self-directed when it comes to study".
	SML2:"In my studies, I set goals and have a high degree of initiative".
	SML3: "I am able to manage my study time effectively and easily complete assignments on time".
	SML4: "In my studies, I am self-disciplined and find it easy to set aside reading and homework time".
Perceived Enjoyment (PEN)	PEN1: "Using m-learning will give enjoyment to me for my learning".
	PEN2: "Using m-learning will lead to my exploration".
	PEN3: "When using m-learning, I will not realise the time elapsed".
	PEN4: "Using m-learning will give enjoyment to me for my learning".
Relative Advantage (RAD)	RAD1: "I would find m-learning useful in my learning".
	RAD2: "Using m-learning enables me to accomplish learning activities more quickly".
	RAD3: "Using m-learning increases my learning productivity".
	RAD4: "If I use m-learning, I will increase my chances of getting a promotion".
Social Influence (SIN)	SIN1: "People who influence my behaviour will think that I should use m-learning".
	SIN2: "People who are important to me will think that I should use m-learning".
	SIN3: "The seniors in my organisation have been helpful in the use of m-learning".
	SIN4: "In general, my organisation has supported the use of m-learning".
Facilitating Conditions (FCO)	FCO1: "I have the resource necessary to use mobile learning".
	FCO2: "I have the knowledge necessary to use mobile learning".
	FCO3: "A specific person or group should be available for assistance with mobile learning difficulties".
	FCO4: "Internet speed would be appropriate for m-learning".
Complexity (COM)	COM1: "My interaction with m-learning would be clear and understandable".
	COM2: "It would be easy for me to become skilful at using m-learning".
	COM3: "I would find m-learning easy to use".
	COM4: "Learning to operate m-learning is easy for me".
Behavioural Intention (BEI)	BI1: "I intend to use m-learning in the future".
	BI2: "I predict I would use m-learning in the future".
	BI3: "I plan to use m-learning in the future".

Data Analysis

Structural equation modeling (SEM) was utilized to examine the relationships among the constructs of the prosed framework. SmartPLS 3 software was used to conduct the statistical analysis. The first phase of the analysis was to assess the measurements' validity and reliability. The second stage was the structural model analysis to examine the suggested relationships (paths) of the research's framework.

Measurement Model

In the measurement model analysis, the reliability procedures are conducted by evaluating the individual item reliability and the constructs' composite reliability (Wong, 2013). The individual item reliability is evaluated by the significance of individual items' loadings. The loading of each individual item on its underlying construct should be ≥ 0.707, whereas the composite reliability (CR) and Cronbach Alpha (α) of each construct should be ≥ 0.7 (Koufteros, 1999). As is demonstrated in Table 3, the loadings of all items on their theoretical constructs were ≥ 0.707. In addition, the values of CR and α for each construct were all ≥ 0.7.

Table 3

The Measurement Model Analysis (n=228)

Construct	Item	Loading	CR	α
Self-management of learning (SML)	SML1	0.84	0.92	0.89
	SML2	0.88		
	SML3	0.87		
	SML4	0.86		
Perceived Enjoyment (PEN)	PEN1	0.90	0.92	0.88
	PEN2	0.88		
	PEN3	0.86		
	PEN4	0.79		
Relative Advantage (RAD)	RAD1	0.88	0.94	0.92
	RAD2	0.90		
	RAD3	0.91		
	RAD4	0.89		
Social Influence (SIN)	SIN1	0.93	0.95	0.93
	SIN2	0.92		
	SIN3	0.91		
	SIN4	0.89		
Facilitating Conditions (FCO)	FCO1	0.81	0.87	0.80
	FCO2	0.80		
	FCO3	0.82		
	FCO4	0.75		
Complexity (COM)	COM1	0.76	0.89	0.84
	COM2	0.89		
	COM3	0.83		
	COM4	0.79		
Behavioural Intention (BEI)	BI1	0.95	0.96	0.94
	BI2	0.94		
	BI3	0.93		

The validity procedures are included in terms of convergent and discriminant validity. Based on Hair, Sarstedt, and Ringle (2012), convergent validity was evaluated by assessing the values of the average variance extracted (AVE) for each construct. In order to claim the questionnaire has convergent validity, the AVE values of each construct should be ≥ 0.5. Table 4 demonstrates that all AVE values for each construct was ≥ 0.5. Discriminant validity was evaluated by comparing the average variance extracted (AVE) with the squared correlation between constructs. Hair, Hult, and Ringle (2013) explain that the values of AVE should be higher than the squared correlation of a construct and that of other constructs in the model. Table 4 indicates that the previous condition has been met by all constructs.

Table 4

Discriminant Validity Analysis

	AVE	BEI	COM	FCO	PEN	RAD	SLM	SIN
BEI	0.88	1						
COM	0.70	**0.6** (0.36)	1					
FCO	0.63	0.54 (0.29)	0.27 (0.07)	1				
PEN	0.75	0.44 (0.19)	0.20 (0.04)	0.54 (0.29)	1			
RAV	0.81	0.67 (0.44)	0.66 (0.43)	0.36 (0.12)	0.21 (0.04)	1		
SLM	0.75	0.65 (0.42)	-0.44 (0.19)	-0.31 (0.09)	-0.28 (0.07)	-0.63 (0.39)	1	
SIN	0.83	0.51 (0.26)	0.64 (0.40)	0.24 (0.05)	0.08 (0.01)	0.62 (0.38)	-0.40 (0.16)	1

**Note*. Correlation in bold, ( ) =squared correlation

Structural Model

Once the validity and reliability of the measurement model was determined, the next stage was to evaluate the suggested structural paths. In particular, in this step, the values of explanatory power (R^2) and path (regression) coefficients (β) of the proposed framework were identified. As illustrated in Figure 2, the six independent variables explained 68% (R^2=0.68) of the variance in the dependent variable BEI. According to the path analysis, RAD (β=0.17), COM (β=0.2), FCO (β=0.23), PEN (β=0.15) and SIN (β=0.1) had significant positive effects on BEI, and thus they acted as factors that facilitate the use of m-learning. On the other hand, SML (β= - 0.3) had a significant negative effect on BEI, and therefore it was considered as the only obstacle towards the use of m-learning.

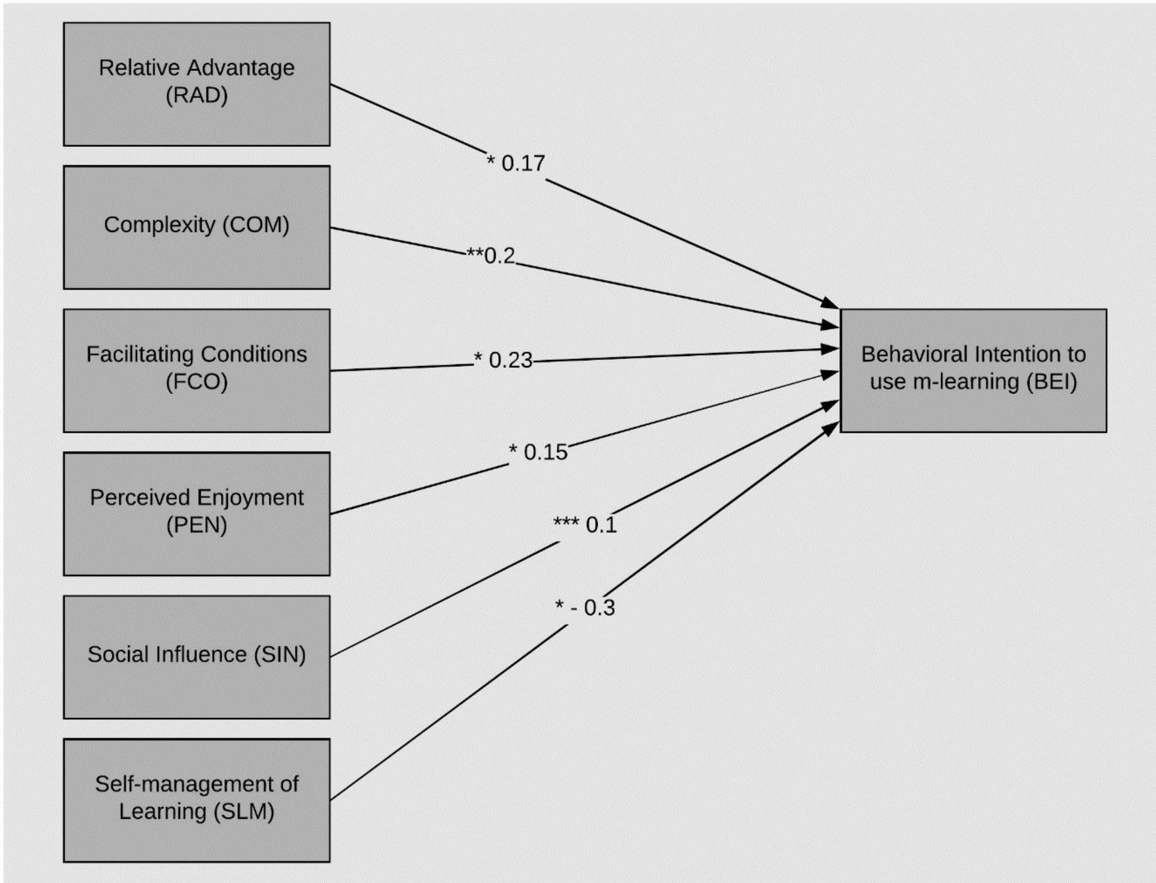

Figure 2. Structural equation modeling results.
**Note*. *p value <0.0001, ** p value < 0.001, *** p value <0.01

Moderating Effects

Multi-group analysis was employed to examine the moderating effects of age, gender, and course groups. All moderators were categorical in the questionnaire form. The total sample was split into desired sub-groups and then the path coefficients of the main model were re-calculated for each sub-group. Based on Carte and Russell (2003) criteria of multi-group analysis, the sub-groups of age and course had to be refined because of the sample size of sub-groups of these moderators were too small to conduct multi-group analysis. Therefore, in the case of age, to the age sub-groups of 20-27 (n=89) and >27 (n=43) has been merged to form one group labeled as >20 (n=132), while the age sub-group of <20 (n=96) remained without any refinement. In the case of course, the course sub-groups of education (n=14), business administration (n=32), translation and languages (n=34), and finance and accounting (n=39) were emerged into one group labelled as other courses (n=123), the course sub-group of "IT related" (n=105) remained without any refinement. The t-test approach of Sarstedt, Henseler, and Ringle (2011) was used to determine the significant differences between path coefficients. As Table 5 demonstrates, gender and age had no significant moderating effects on the model's relationships. On the other hand, there were two significant differences between course groups specifically in terms of the relationship between COM → BEI and FCO→BEI. It was found that perceived complexity (COM) of m-learning was more salient (β = 0.23) for students who study courses (education, business administration, finance and accounting, translation, and languages) other than student who study IT related courses (β = 0.14). Similarly, it was found that perceived facilitating conditions (FCO) was more important (β = 0.27) for students who study courses other than IT related courses (β = 0.16).

Table 5

Moderating Effects

	Structural relation	Model 1 (main effect n=228)	Model 2 (Male, n=137)	Model 3 (Female, n=91)	t-test
Gender	RAD→BEI	β = 0.17	β = 0.20	β = 0.16	1.14 n.s
	COM→BEI	β = 0.2	β = 0.18	β = 0.21	1.02 n.s
	FCO→BEI	β = 0.23	β = 0.21	β = 0.22	0.11 n.s
	PEN→BEI	β = 0.15	β = 0.17	β = 0.18	0.09 n.s
	SIN→BEI	β = 0.1	β = 0.13	β = 0.15	0.94 n.s
	SLM→BEI	β = -0.3	β = -0.31	β = -0.28	1.22 n.s
	Structural relation	**Model 1 (main effect n=228)**	**Model 2 (<20, n=96)**	**Model 3 (>20, n=132)**	**t-test**
Age	RAD→BEI	β = 0.17	β = 0.21	β = 0.16	1.33 n.s
	COM→BEI	β = 0.2	β = 0.19	β =0.22	1.27 n.s
	FCO→BEI	β = 0.23	β = 0.25	β = 0.22	0.83 n.s
	PEN→BEI	β = 0.15	β = 0.18	β = 0.11	0.08 n.s
	SIN→BEI	β = 0.1	β = 0.09	β = 0.11	0.91 n.s
	SLM→BEI	β = -0.3	β = -0.32	β = - 0.29	1.31 n.s
	Structural relation	**Model 1 (main effect n=228)**	**Model 2 (IT related, n=105)**	**Model 3 (other courses, n=123)**	**t-test**
Course	RAD→BEI	β = 0.17	β = 0.19	β = 0.22	1.27n.s
	COM→BEI	β = 0.2	β = 0.14	β = 0.23	2.62 S
	FCO→BEI	β = 0.23	β = 0.16	β = 0.27	3.32 S
	PEN→BEI	β = 0.15	β = 0.11	β = 0.13	0.06 n.s
	SIN→BEI	β = 0.1	β = 0.15	β = 0.12	0.73 n.s
	SLM→BEI	β = -0.3	β = -0.33	β = -0.31	0.89 n.s

**Note*. n.s = not significant, s= significant

Discussion and Implications

The main purpose of this study was mainly to explore the factors that may influence students' intentions to use m-learning in the context of higher education. In agreement with Mtebe and Raisamo (2014) and Masrek (2015), relative advantage (RAD) is recognized as a key facilitator of m-learning adoption. When the usefulness of m-learning is increased as a tool to enhance performance, students will be more inclined to use m-learning. This result highlights students' high expectations with regard to enhancing their performance when they use m-learning. It is vital that m-learning providers and lecturers educate students about the significant benefits of m-learning. Moreover, m-learning developers are advised to focus their efforts on designing meaningful and customized applications that directly meet students' needs and increase their performance.

Similarly, in line with Wang et al. (2009) and Abu-Al-Aish and Love (2013), the results demonstrate that complexity (COM) (similar to effort expectancy) has a significant positive influence on m-learning adoption. The items used to measure the complexity construct focused on the level of difficulty when it comes to using m-learning. The more students perceive m-learning as being easy to use, the more likely they are to utilize it in their learning. The use of mobile devices, especially smart phones, among students of Jordanian universities is very popular. Due to the fact that the use of mobile devices seems to be a routine for most of students, they may perceive that using such devices for learning will not require much effort. However, m-leaning developers should take into account the need to design applications with intuitive and user-friendly interfaces.

Although the construct of the self-management of learning (SML) is not extensively examined in the context of m-learning, the results show that this construct is applicable in shaping students' intentions to adopt m-learning. The results indicate that the self-management of learning is a significant obstacle as it has a negative effect on m-learning adoption. Such a finding is in line with those of Al-Adwan, Al-Adwan, and Berger (2018), Yang (2013), and Masrek (2015), but opposed to that of Liew, Kang, Yoo, and You (2013) and Wang et al. (2009). In fact, in this study, SML is found to be the strongest predictor compared to other constructs. Such a finding implies that students who possess highly autonomous learning abilities will be more keen to use m-learning than those with low autonomous learning abilities. This may refer to the educational culture in Jordan where educators are still viewed by students the major source of their learning and subsequently well-structured learning environments (i.e., classrooms) are still favorable for students. A study conducted by Al-Adwan and Smedley (2012) concludes that Jordanian students' lack self-motivation to learn is considered one of the main obstacles toward e-learning adoption. The study found that the lack of self-motivation to learn is linked to students' beliefs that educators are the key source of learning and information and thus students prefer physical communication with their educators. Given this result, the developers of m-learning applications should design applications that are equipped with features that take into account the needs and requirements of students who are highly independent in their learning. On the other hand, educators and administrators should respond by training and encouraging students to be more independent in their learning processes.

Supported by Iqbal and Qureshi (2012), and Hadi and Kishik (2014), the results also suggest that the construct of facilitating conditions (FCO) is a significant enabler of m-learning adoption. This finding hints that the absence of facilitating conditions will affect students' intentions to use m-learning. Accordingly, m-learning providers should provide students with technical support and training courses to facilitate their interaction with m-learning applications. Additionally, m-learning providers are required to ensure the availability of free and adequate wireless networks in universities. Offering discount vouchers on different types of mobile devices would also encourage and facilitate students' engagement with m-learning. Likewise, the government could play an important role in m-learning by providing public places such as restaurants and public libraries with convenient and suitable internet access for students. This finding also alerts authorities by highlighting the importance of the continuity of updating the infrastructure required for the implementation of m-learning.

The results reveal that social influence (SIN) is found as another facilitator of m-learning adoption. In this study SIN found to be the weakest predictor compared to other constructs. This finding is consistent with those of Nassuora (2013) and Abu-Al-Aish and Love (2013), but contrary to the findings of Jambulingam (2013). According to this finding it can be concluded that students' desire to engage with m-learning is markedly increased when they are encouraged and advised by individuals who are important to them such as faculty and peers. Based on this finding, faculty members should encourage and help students to realize the benefits of m-learning. Furthermore, peers can have a significant role in promoting m-learning to other students. In particular, early adopters of m-learning can be employed as an effective tool to convince other students to use m-learning.

In agreement with Ali and Arshad (2016) and Poong Yamaguchi, and Takada (2016), perceived enjoyment is found to have a positive influence on m-learning adoption. This finding demonstrates that the more students enjoy m-learning, the more they will be encouraged to become involved in m-learning activities. Wang et al. (2009) point out that developing enjoyable and playful m-learning is crucial for attracting large numbers of users with diversified backgrounds. Consequently, such a result should alert m-learning developers' attention to the significance of enriching their applications with entertaining and pleasurable features.

In contrary with Hassan, Nawaz, Syed, Arfeen, Naseem, and Noor (2015) and Wang et al. (2009), this concludes that age and gender has no moderating effects on the structural relationships. On the other hand, two moderating effects of course type have been identified. Specifically, course type moderated the relationship between complexity, facilitating conditions, and behavioral intention to adopt m-learning (COM → BEI and FCO→BEI). Course type had two sub-groups: IT related and other courses. The results suggest that the perceived complexity and facilitating conditions are more important for students who do not study IT related courses. This may be justified by the fact that the students of IT related courses possess higher computer literacy and IT skills due to the nature of IT courses they study (i.e., computer science and programming). Such result suggest that m-learning providers should offer constant technical support and training courses for students who study courses other than IT related courses in order to increase m-learning literacy and knowledge. Furthermore, m-learning developers should clarify how students from different courses use and interact with m-learning systems. Identifying the frequency of use and the degree of complexity of tasks performed with m-learning systems may help developers customizing m-learning systems to efficiently meet students' needs from different courses.

Conclusion and Future Work

The main goal of this study has been to explore factors that influence students' behavioural intentions to adopt m-learning. To address this goal, an empirical framework drawn from several technology acceptance models has been proposed. The results of analyzing the collected data indicate that the proposed model explained 68% of the variance in students' behavioural intentions to adopt m-learning. The findings demonstrate that relative advantage, complexity, social influence, facilitating conditions, and perceived enjoyment represent key facilitators to m-learning. On the other hand, self-management of learning is considered as a key inhibitor in terms of the adoption of m-learning. This study has useful implications for m-learning providers and developers. M-learning developers should design effortless applications that are compatible with students' needs. Additionally, they should offer applications that make a difference when they are compared with previous learning styles and tools. Students are expected to recognize the benefits of m-learning on their overall learning performance. M-learning providers and educators should encourage and promote the use of m-learning. Additionally, senior management should make sure that resources and technical support for m-learning are in place whenever needed by students.

M-learning providers should pay special attention to the negative impact of self-management of learning on m-learning adoption. Addressing the causes of the low level of self-management of learning among students allows senior management to reveal the actual problems associated with the adoption of m-learning. In particular, senior management can utilize the measurement scale which has been used to measure the construct of self-management of learning to uncover the reasons behind students' resistance.

Similar to other studies, this study has several limitations. The sample of this study included students from two universities. Future studies may extend the sample population by including students of other universities. This study aimed at investigating students' behavioural intentions with regard to adopting m-learning. Further studies are needed to examine the actual use of m-learning among higher education students. In social science research, while quantitative research has several strengths, various criticisms are associated to quantitative methods (Al Adwan, 2017). Thus, since this study is based on questionnaire survey-based method, additional studies with mixed method approach (qualitative and quantitative) are required to provide a holistic understanding of m-learning adoption.

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