Solving the mystery of mobile learning adoption in higher education

Ahmad Samed Al-Adwan*

Faculty of Business,
Department of Information Systems,
Al-Ahliyya Amman University,
P.O. Box 19328, Amman, Jordan
Email: a.adwan@ammanu.edu.jo
*Corresponding author

Amer Al-Adwan

Division of Audiovisual Translation (MAAT),
College of Humanities and Social Sciences,
Hamad Bin Khalifa University,
Doha, Qatar
Email: aadwan@qf.org.qa

Hilary Berger

Cardiff School of Management,
Cardiff Metropolitan University,
Llandaff Campus, Cardiff CF5 2YB, UK
Email: HBerger@cardiffmet.ac.uk

Abstract: The rapid expansion in users of mobile devices, particularly among university students, makes mobile learning (m-learning) the modern style of learning for the new millennium. Thus, it is important to identify and explore the factors that may influence students' intention to use m-learning. In Jordan, research on mobile learning adoption is still very narrow. For the purpose of this study, we propose a framework that is based on the unified theory of acceptance and use of technology (UTAUT) model, to explore the potential factors that may impact students' intention to acceptance and use of m-learning in developing countries such as Jordan. The proposed framework is empirically tested using a total of 444 paper-based questionnaires, collected from students at four Jordanian universities. The results reveal that effort expectancy, performance expectancy, trust expectancy, self-management of learning, system functionality and social influence are significant determinants of m-learning adoption, and explain 64.8% of the variance in the students' intentions to adopt m-learning. Gender and uncertainty avoidance are found to have moderating effects on some of the relationships of the research model. These findings offer multiple useful implications for m-learning adoption, in terms of both research and practice.

Keywords: higher education; Jordan; mobile learning; multi-group analysis; self-management of learning; structural equation modelling; technology acceptance; trust expectancy; uncertainty avoidance; UTAUT.

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Biographical notes: Dr Ahmad Samed Al-Adwan, an Assistant Professor of Information Systems/the Faculty of Business at Al-Ahliyya Amman University, Jordan. He holds a Ph.D. in Management Information Systems Studies/ e-business from University of Wales. He is particularly interested in using management information systems to inform long-lasting developments in ICTs. His research interests include user acceptance of ICT and information system, modelling ICT, E-learning, SME, management information systems, E-commerce, mobile learning, e-business and healthcare information technology. His research has appeared in several international journals.

Dr Amer Al-Adwan is currently an Assistant Professor of Audiovisual Translation in the College of Humanities and Social Sciences, Hamad Bin Khalifa University. He obtained his doctorate in Translation and Intercultural Studies from the University of Manchester in 2009. Before joining HBKU, he worked at Jordan University and the Applied Science University, Jordan, as an Assistant Professor, where he taught several courses of translation and intercultural studies. He also worked for few international institutions, including BBC Arabic and Aljazeera English, as a translator and a subtitler. His research interests focus on audiovisual translation, discourse analysis, ICT in education, intercultural studies, politeness theory and media translation.

Dr Hilary Berger is a reader in Information Systems in the Cardiff School of Management at Cardiff Metropolitan University where she currently combines teaching duties in parallel with extended research activities. She has a breadth of teaching expertise and experience across a variety of subject areas and audiences within both the private and public sectors. Her research within the information systems domain has been published widely in both European and international arenas.

1 Introduction

Today, the rapid growth of mobile technology is significantly diffusing over the globe (Shiyadeh, Rad and Jooybari, 2013). The remarkable increase in the availability of mobile devices and fast internet connections offers people the opportunity to be connected anywhere and anytime (Al-Hujran, Al-Lozi and Al-Debei, 2014). Therefore, mobile devices are increasingly becoming an important element in people's daily life activities and such devices are now utilised in various domains such as banking, commerce and education.

In the higher education field, the popularity of mobile technologies among students has increased interest in utilising mobile devices in the educational processes (Jaradat, 2010). The spread of mobile devices and the availability of wireless networks within university campuses encourage higher education to integrate mobile learning (m-learning) into their traditional education system (Abu-Al-Aish and Love, 2013).

Georgiev, Georgieva and Smrikarov (2004) describe the relationship between m-learning, e-learning and distance learning, explaining that m-learning is a subset of e-learning, and e-learning is a subset of distance learning. As the term 'mobile' indicates, m-learning in the first place is based on the use of wireless network connections. Thus, the concept of m-learning represents the learning experience of anytime and anywhere, where cables are not always necessary to establish connection. The e-learning guild (2007) defines m-learning as "any activity that allows individuals to be more productive when consuming, interacting with, or creating information, mediated through a compact digital portable device that the individual carries on a regular basis, has reliable connectivity, and fits in a pocket or purse." Furthermore, Wang, Wu and Wang (2009) refer to m-learning as the delivery of learning materials to students anywhere/anytime through the use of mobile devices (i.e. mobile/smart phones, digital audio players, tablet PCs, personal digital assistants and wireless internet connections).

Despite the fact that e-learning and distance learning enable learning away from classrooms, m-learning allows learning to take place away from a fixed location (Wang, Wu and Wang, 2009). Both e-learning and distance learning have been criticised for the lack of mobility and flexibility in terms of place and time (Shiyadeh, Rad and Jooybari, 2013). E-learning and distance learning are constrained by the availability of personal computers and connectivity, which means that learners must work in one place at a specific time, obligated by availability and connectivity (Jairak and Mekhabunchakij, 2009). By contrast, m-learning is considered to be the future of e-learning and distance learning (Abu-Al-Aish and love, 2013). It allows learning and information seeking to occur when and where it best fits learners' needs (Wang, Wu and Wang, 2009). It provides learners with information and educational contents regardless of location and time, and thus students and instructors can interact with academic resources while away from their usual place of learning, such as desktops and classrooms. Additionally, m-learning is known as a new wave of knowledge acquisition (Al-Zoubi, Jeschke and Pfeiffer, 2010). It addresses the immediate need of learners' information acquisition and learning requirements; knowledge acquisition is based on learners' request of information, which is obtained instantly. For instance, students could use mobile devices wherever they are to download course materials, engage with their studies, access library catalogues, respond to e-mails arriving immediately to their devices and effectively interact with their lecturers and colleagues off campus (Handal, MacNish and Peter, 2013).

Despite the significant growth and capabilities of mobile technology, wireless m-learning and e-learning remain in their infancy stage (Wang, Wu and Wang, 2009). The relevant literature indicates that m-learning still has numerous limitations and drawbacks. Park (2011) points out that mobile technology is associated with several usability issues. In this regard, Kukulska-Hulme (2009) classifies limitations of m-learning into four categories: physical attributes (i.e. small screen size, battery life and low memory), network connection (i.e. network reliability and speed), physical environmental issues (i.e. using mobile devices outdoors) and software design limitations (i.e. lack of built-in functions and difficulty in installing applications). These challenges indicate that transforming e-learning services to m-learning is not an easy task, and that students may resist accepting m-learning. Therefore, Woodcock, Middleton and Nortcliffe (2012) point out that successful implementation of m-learning significantly depends on students' willingness to adopt a new technology that is different from what they are used to in the past. Mobile devices are considered by students as basic communication tools, often unaware of the powerful potential of these devices in supporting and increasing the performance of their learning. Consequently, in order to successfully implement m-learning in higher education, an investigation of the factors that influence students' perception of m-learning is critically required (Cheon et al., 2012).

2 Study contribution

In developing countries such as Jordan, the use of mobile technology is increasing dramatically. A significant number of learners in some developing countries are bypassing their personal computers, moving directly to mobile devices. In Jordan, for instance, the number of wireless internet connections is continuously increasing and is likely to be a key factor in promoting and implementing m-learning. According to the statistics of the Jordanian Telecommunication Regulatory Commission (2014), there are 5.6 million internet users (74% of the population), 1.3 million mobile broadband subscribers, 377,269 fixed telephone lines (5.1%) and around 11 million mobile phone users (147%). Such statistical figures show that mobility in Jordan is significantly growing. Moreover, the advanced technological developments in mobile semiconductors (i.e. flash memory) and the wide spread of sophisticated types of wireless communication (i.e. 3G/4G and WiMax) make m-learning more feasible in Jordan (Al-Zoubi, Jeschke and Pfeiffer, 2010).

Several studies investigate students' acceptance of m-learning in higher education in developing countries such as Guyana (Thomas, Singh and Gaffar, 2013), Saudi Arabia (Al-Hujran, Al-Lozi and Al-Debei, 2014) and Thailand (Jairak, Praneetpolgrang and Mekhabunchakij, 2009). In Jordan, while e-learning has attracted considerable attention (Al-Adwan, Al-Adwan and Smedley, 2013), little research (Almasri, 2015) has been conducted to investigate the factors that might influence higher education students' behavioural intention (BEI) to adopt m-learning. These studies have focused on the technological and organisational considerations and overlooked individual considerations of students. This study suggests that the overreliance on technological (i.e. usefulness and ease of use perceptions) and organisational (i.e. management support) aspects, as the main salient beliefs to predict students' BEI regarding adoption of m-learning, created a gap between the current understanding of m-learning acceptance and potential adoption strategies.

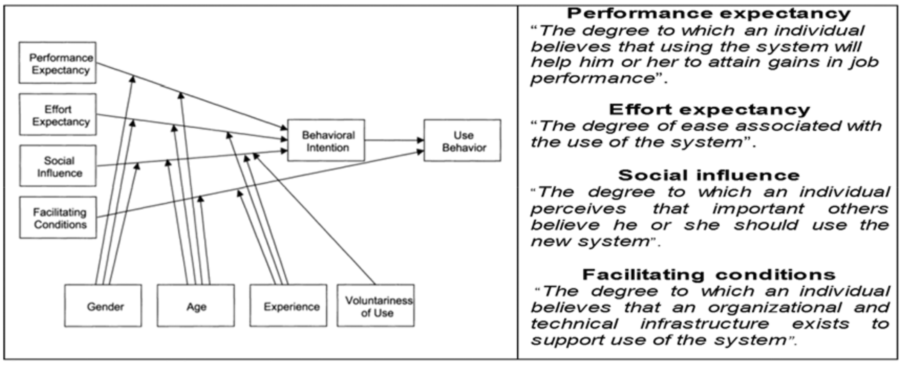
Thus, this study tackles these gaps by predicting and exploring the determinants of BEI to accept m-learning in Jordan, based on an extended version of the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003). Particularly, this study investigates the potential impact of students' perceptions of trust and self-management of learning (SEL) on their intentions to accept m-learning. Additionally, since the neutrality of technology varies from one culture to another, this study also pays special attention to the investigation of the moderating effects of uncertainty avoidance (UNA) on students' intention to use m-learning in a developing country such as Jordan. The results of this study are expected to help in assessing the readiness of higher education in Jordan to be involved in m-learning activities, and develop suitable strategies that would ensure a successful implementation of m-learning.

3 Research conceptual framework

3.1 Theoretical background

The UTAUT, as proposed by Venkatesh et al. (2003), integrates components across eight prominent models of technology acceptance in IT/IS research. Venkatesh et al. (2003) compared these eight models by an empirical study, and based on the results, they proposed the UTAUT. The results showed that the UTAUT explained 70% of the variance in IT usage behaviour providing a significant enhancement over any of the eight models and their extensions. As Figure 1 illustrates, four salient factors (constructs) are captured as salient antecedents of BEI and usage behaviour. These constructs are as follows: effort expectancy (EE), performance expectancy (PE), facilitating conditions and social influence (SI). Furthermore, the UTAUT suggests the relationships between these constructs and intention and usage behaviour are moderated by four key variables. This includes gender, experience, age and voluntariness of use.

Figure 1 The unified theory of acceptance and use of technology



Source: Adopted from Venkatesh et al. (2003)

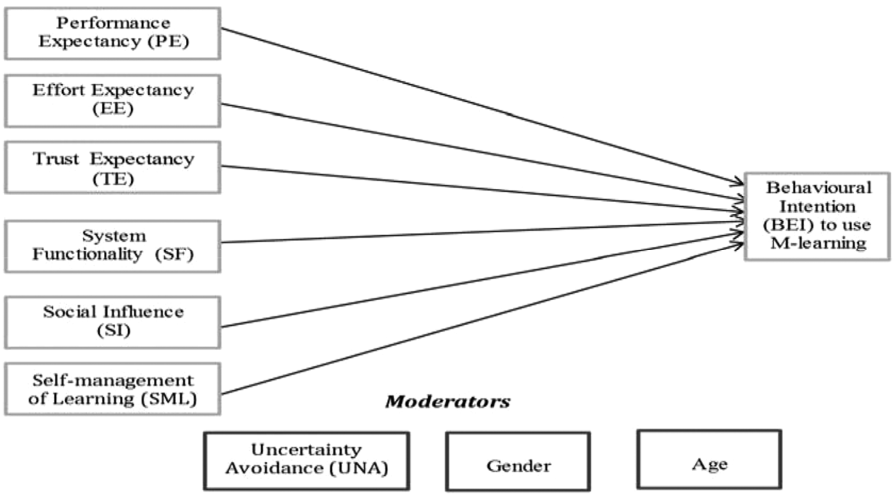
Venkatesh et al. (2003) confirmed the considerable enhancement in explaining IT usage behaviour by the UTAUT, and also encouraged other scholars to validate and test the model with different technologies, contexts, users and moderators. UTAUT is applicable in the context of m-learning. In m-learning, students are required to use m-learning systems to achieve learning activities which suggesting that the m-learning system is an information technology (Wang, Wu and Wang, 2009); thus, the UTAUT can be a useful tool to explore the implementation challenges of m-learning. Therefore, this study adopted the UTAUT as the base of the theoretical framework due to its substantial explanatory power, and its applicability to the context of the study.

3.2 Conceptual framework development

M-learning has unique characteristics and is also different from traditional IT contexts (Almasri, 2015). Therefore, the basic constructs of the traditional technology acceptance models, such as UTAUT, may fail to fully reflect the particular impacts of m-learning context factors that potentially form user acceptance (Pedersen and Ling, 2003).

Corresponding to the above suggestion, this study aims at providing a context-specific model that considers the nature of m-learning and users' factors in the context of higher education. Therefore, this study investigates the effect of three new factors on BEI to use m-learning. These new factors are as follows: trust expectancy (TE), SEL and system functionality (SF) (Figure 2). Furthermore, besides gender and age, the current study explores a new moderating effect that maybe generated by UNA on m-learning use intention. To our knowledge, this type of analysis does not exist in the literature on both developed and developing countries. In Jordan, m-learning is still in its early infancy and there are no tangible m-learning initiatives implemented in higher education. Thus, the dependant variable of the proposed model is the BEI rather than the actual use behaviour construct. This study is conducted in voluntary (non-compulsory) sittings and subsequently the influence of voluntariness as a moderator has been omitted. Additionally, both facilitating conditions and experience constructs were not measured because there have been no actual m-learning activities implemented in Jordan.

Figure 2 The research model



3.2.1 Effort expectancy

Effort expectancy refers to the level of ease an individual perceives with the use of a technology. Venkatesh et al. (2003) employ three main constructs from various models to capture the concept of EE. These constructs include perceived ease of use (the Technology Acceptance Model-TAM, TAM2), ease of use (the Innovation Diffusion Theory-IDT) and complexity (the Model of PC Utilisation-MPCU). Davis (1989) points out that the perception of ease of use has been recognised as a salient belief when it comes to the acceptance of new technologies. Perceived ease of use has been regarded as a significant factor, particularly during the early stage of adoption. In the context of technology-mediated education, m-learning should be simple and easy to operate, especially since handheld mobile devices have a relatively slower central processing unit and smaller memory than desktop/notebook computers (Liaw, Hatala and Huang, 2010). According to Venkatesh et al. (2003), the existing literature of information technology adoption suggests that the impact of EE on BEI will be stronger for female users who have had little experience with systems. Additionally, it has been noted that males have lower computer anxiety and higher computer self-efficacy than women and there is a similar trend with effort perception, while a low computer self-efficacy leads to a reduction in ease of use perception (Venkatesh and Morris, 2000).

3.2.2 Performance expectancy

Performance expectancy represents the extent to which an individual believes that the use of a technology results in benefits and enhances his/her job performance. Five constructs from existing models have been used to form the construct of performance expectance: perceived usefulness (TAM/TAM2 and C-TAM-TPB (combined TAM and the Theory of Planned Behaviour-TPB)) job-fit (MPCU), extrinsic motivation (the Motivational Model-MM), outcome expectation (the Social Cognitive Theory-SCT) and relative advantage (IDT) (Venkatesh et al., 2003). In terms of PE, it is suggested that students will perceive m-learning as helpful since it allows them to access information quickly, at a place and time of their convenience, and using a device of their choice (Hadi and Kishik, 2014). According to the definition of m-learning in this study, educational materials are received through wireless internet and mobile devices, and therefore m-learning can be viewed as an extension of computer use. Prior studies suggest that there are significant gender differences towards computer use (Venkatesh et al., 2003). Sun and Zhang (2006) posit that males are more pragmatic, task-oriented and encouraged by achievements than women. This is directly associated with performance outcome perceptions and indicates that the influence of PE will be higher for males than females (Yang, 2013).

3.2.3 Social influence

Social influence is referred to as the degree to which an individual perceives that others think she/he should use the new system/technology. Venkatesh et al. (2003) derive the construct of SI from three major constructs: image (IDT), subjective norms (TRA, TPB, TAM2 and C-TAM-TPB) and social factors (MPCU). In the context of m-learning, SI (i.e. lecturers, peers) is expected to have an important influence on students' BEI to use m-learning. Yang (2013) points out that the SIs of educators, providers and colleagues play a key role in increasing students' perceptions of the great value of adopting m-learning. Wang, Wu and Wang (2009) and Venkatesh et al. (2003) indicate that the effect of SI on BEI is moderated by gender, such that the impact will be stronger for females than males. Females have more awareness of others' feelings when compared to men and, as a consequence, women are more likely to be influenced by others (Venkatesh and Morris, 2000).

3.2.4 Self-management of learning

Self-management of learning is defined as the level to which an individual believes she/he is self-disciplined and involves in a highly autonomous learning environment (Smith, Murphy and Mahoney, 2003). In m-learning environments, learners are physically separated from their instructors and colleagues, which in turn require learners themselves to self-manage their personal learning (Yang, 2013). This triggers a fundamental need for learners to control their own learning. Therefore, m-learning is solely based on self-direction and SEL. Such principles have been intensively highlighted as a 'resource based' or 'flexible learning', which require students to engage with a variety of materials and sources, independently of teachers, offering the freedom to seek information that best suits their learning style (Liu, Han and Li, 2010). It has been suggested that learners with high self-management capabilities are most likely to be involved with m-learning activities (Wang, Wu and Wang, 2009). Therefore, students' SEL is expected to have a positive influence on BEI. Furthermore, it has been noted that males are more likely to show autonomous traits than females.

3.2.5 Trust expectancy

The nature of wireless mobile technology makes it vulnerable to several forms of interferences (Lu et al., 2008). Thus, in the mobile services context, trust is considered a vital factor towards the acceptance of such services, and has a positive effect on usage BEI. According to Alzaza and Yaakub (2012), trust is defined as the extent to which an individual feels secure and confident about relying on service or technology. The concept of trust in mobile technology context can be captured by three key elements: security, reliability and privacy (Lu et al., 2008). Reliability is concerned with the probability that the system continues in achieving its intended tasks within a specific period of time and under a given set of conditions (Saha et al., 2001). Therefore, TE plays a key role in influencing the perception of the mobile technologies. The primary justification is that trust decreases the need for control, understanding and monitoring of the situation and, in turn, makes adoption easier. In the m-learning environment, it is important for students that information exchange should take place within a trustful environment (Alzaza and Yaakub, 2012). Personal information privacy and data protection concerns are considered key factors in influencing m-learning acceptance, such that the lack of privacy and security standards will negatively affect students' BEI to use m-learning. Additionally, wireless connection is another concern for students, where the reduction of associated risk to an acceptable level would positively influence students' BEI to use m-learning.

3.2.6 System functionality

System functionality refers to the characteristics and features of the technology itself. From the perspective of m-learning, learners' satisfaction is significantly related to the quality of the system's functions (Liaw, Hatala and Huang, 2010). Valk, Rashid and Elder (2010, p.120) suggest that mobile devices ideally make student-centred learning possible by allowing students to "customise the transfer of and access to information in order to build on their skills and knowledge and to meet their own educational goals." Consequently, the main objective of m-learning systems is to assist learners with viewing, browsing, collecting, retrieving, sharing and managing knowledge (Liaw, Hatala and Huang, 2010). Such activities require the functions of m-learning systems to be simple, communicative and adaptive. Although handheld devices used in m-learning have limited capabilities (i.e. memory, small screen, processors), the functions of these devices should be customised for learners in order to be seamless to operate, reduce time-consuming tasks and provide meaningful interaction by supplying various communication platforms (Liaw, Hatala and Huang, 2010). For instance, m-learning devices should offer learners with applications that allow them to display educational materials in a friendly manner, conducive to browsing and reading.

3.2.7 Uncertainty avoidance

The present study additionally investigates the moderating effects of UNA in the context of m-learning. Among Hofstede's four cultural dimensions (1993), power distance and UNA are the most influential cultural factors that can explain technology adoption rates among countries. However, the principles of the power distance dimension are indirectly covered by the SI construct. Consequently, this research focuses on UNA as the key cultural factor that impacts technology adoption.

According to Hofstede (1993), UNA is defined as the extent to which individuals in a culture desire structured situations over unstructured ones. Structured situations are mainly characterised by clear rules and how one should behave. Furthermore, Rogers (2003, p.6) refers to uncertainty as the degree "to which a number of alternatives are perceived with respect to the occurrence of an event and relative probabilities of these alternatives." Uncertainty indicates a lack of information, structure and predictability. Consequently, individuals are encouraged to seek information and thus reduce the level of uncertainty. However, such information seeking is considered as an uncomfortable state of mind. Additionally, newness perception is a kind of uncertainty that may be generated by an innovation. Perceived newness of a technology and the uncertainty related to such newness is a fundamental aspect when it comes to either adopting or rejecting the technology. Consequently, perceived trust, risk and reliability are recognised to be key attributes of uncertainty (Rogers, 2003). From mobile technology perspective, perceived risk is referred to users' perception of the potential uncertainty resulting from subsequent unpredictability when engaging with mobile transactions and activities (Cao et al., 2015).

Hofstede (2009) states that the Arabic society (Jordan is an Arabic country) is high in UNA. In societies with high UNA, activities are highly structured, and these societies tend to feel threatened by ambiguity. Therefore, high UNA cultures try to reduce unstructured situations by establishing more formal and clear rules in order to minimise such ambiguity. According to Veiga, Floyd and Dechant (2001), if a technology reduces ambiguity and uncertainty then high UNA cultures would perceive it as valuable and adopt it faster than expected. For high UNA cultures, trust is one of the most important concerns when making use of new technology (Alshare and Al-Garni, 2014). If the use of a technology reduces the uncertainty, individuals' trust perception would be increased and also their fear from information security would be reduced. Furthermore, because individuals with high UNA seek predictability and clarity, they will place significant importance on a system's functionality and information quality to help them eliminate ambiguity. Additionally, they are expected to seek others' opinions in order to reduce the uncertainty (Sun and Zhang, 2006).

In terms of m-learning, it might be expected that individuals in these societies would feel better about their learning under conditions where they are better able to learn anywhere/anytime which, in turn, provides reassurance and reduces uncertainty and anxiety about their learning affairs. These practices would promote behaviour and outcome controls and thus would offer a high degree of clarity in terms of PE. Furthermore, m-learning systems' functions and features are preferred to be specific, well-defined and easy to learn, and hence will be considered favourably by individuals in high UNA cultures.

4 Research methodology

4.1 Sample and data collection

This study began by collecting data from undergraduate students at four of the largest Jordanian universities. The data collection process started in May 2015. Questionnaire survey (paper-based) was used as the primary method of collecting data. A convenience sampling technique was employed to distribute the questionnaire to students of different courses at the four universities, with assistance from academic staff. A total of 600 questionnaires were distributed to students, of which 458 questionnaires were returned. Of the returned questionnaires, 14 were reported as incomplete and therefore were eliminated. As a result, 444 questionnaires were usable and valid for analysis, giving a response rate of 74%. Table 1 presents the respondents' characteristics.

Table 1 The respondent's profile ($N = 444$)

		Frequency	*Per cent*
Gender	Male	226	50.9
	Female	218	49.1
	Total	444	100
Age	<20	305	83.56
	>20	139	16.44
	Total	444	100
Mobile device	Smart phone	180	40.5
	PAD/palmtop	139	31.3
	Both smart phone and PAD/palmtop	125	28.2
	Total	444	100
Course	IT related	151	34.01
	Tourism	41	9.23
	Banking and finance	56	12.61
	Translation and languages	17	3.83
	Telecommunication	29	6.53
	Education	23	5.18
	Business administration	114	25.68
	Other	13	2.93
	Total	444	100

4.2 Measurement

The questionnaire form consists of 32 items whereby the independent variables include six constructs with 24 items, one moderator with four items, and the dependent variable comprises of four items. All items were measured by a 4-point Likert scale, ranging from (1) strongly agree to (4) strongly disagree. In order to ascertain content validity, it has been suggested to adopt measurement items that were previously validated and tested within well-established research. Accordingly, the items used to measure EE, SI, PE and BEI were adopted from Abu-Al-Aish and Love (2013), Thomas, Singh and Gaffar (2013) and Venkatesh et al. (2003). The items measured for TE was adopted from Saleh and Mashhour (2014) while those for SEL were adopted from Wang, Wu and Wang (2009), Yang (2013) and Smith, Murphy and Mahoney (2003). The four UNA items were adopted from Sanchez-Franco et al. (2009). Finally, four items were selected from Liaw, Hatala and Huang (2010) to measure SF.

The measurement items were modified based on m-learning context, and also translated from English to Arabic. A reverse translation was then conducted to ensure consistency. The first draft questionnaire was examined by experts from the m-learning/e-learning field and was also piloted by a small group of the study sample, before the distribution process. The aim of this step was to identify any issues that may affect the questionnaire validity and reliability. As a result, minor amendments and modifications were made based on the comments and feedback of the experts.

5 Results and data analysis

The structural equation modelling approach, particularly the partial least square (PLS), was used to examine the proposed relations (paths) in the research model. SmartPLS software version 2.0 was used to analyse the collected data. As recommended by Henseler, Ringle and Sinkovics (2009), a sequential two-step process was carried out to test the proposed paths in the research model. The two steps include are as follows:

1 the measurement model

2 the structural model.

The measurement model aimed to assess both the reliability and validity of the model's constructs (latent variables). On the other hand, the structural model aimed to test the structural equation paths between latent variables. Multi-group analysis was utilised to examine the moderating effects of gender on the proposed relationships (Chin, 2000). The moderating effect of UNA was measured by the product-indicator technique suggested by Chin, Marcolin and Newsted (2003).

5.1 The measurement model (constructs reliability and validity)

The reliability and validity of the measurement model were assessed before proceeding to assess the structural model. Therefore, it was important to evaluate how well the constructs were measured by their indicator variables, individually and jointly. To achieve this, individual item reliabilities, constructs' reliabilities and convergent and discriminant validities were examined. Individual item reliabilities were examined by the square of the standardised loading of each item (an item's commonality) on to its underlying construct (Kwong and Wong, 2013). The loading value of each item that relates to a construct should be at least equal to or higher than 0.707, and the square item's loading should be ≥0.5 (Hair, Hult and Ringle, 2013). As Table 2 shows, the loadings of all items satisfied the recommended threshold and exceeded the value of 0.70, and all items achieved a squared loading greater than 0.5. Such results indicate that all items were individually reliable.

Table 2 Individual items' and constructs' reliability and validity ($N = 444$)

Construct	*Item code*	*Item loading*	*Item's commonality (square item's loading)*	α^a	CR^b	AVE^c
Social influence (SI)	SI1	0.85	0.72			
	SI2	0.83	0.68	0.87	0.91	0.71
	SI3	0.84	0.7			
	SI4	0.85	0.72			
Behavioural intention (BEI)	BEI1	0.95	0.90			
	BEI2	0.98	0.96	0.95	0.97	0.92
	BEI3	0.97	0.94			
	BEI4	0.94	0.88			
Performance expectancy (PE)	PE1	0.89	0.79			
	PE2	0.93	0.86	0.93	0.94	0.82
	PE3	0.92	0.84			
	PE4	0.88	0.77			
Effort expectancy (EE)	EE1	0.95	0.90			
	EE2	0.98	0.96	0.96	0.98	0.93
	EE3	0.96	0.92			
	EE4	0.97	0.94			
System functionality (SF)	SF1	0.82	0.67			
	SF2	0.89	0.79	0.88	0.92	0.72
	SF3	0.86	0.73			
	SF4	0.84	0.68			
Uncertainty avoidance (UNA)	UNA1	0.97	0.94			
	UNA2	0.98	0.96	0.97	0.98	0.93
	UNA3	0.95	0.90			
	UNA4	0.96	0.92			
Trust expectancy (EE)	TE1	0.89	0.79			
	TE2	0.90	0.81	0.92	0.95	0.80
	TE3[d]	0.91	0.82			
	TE4	0.89	0.79			

Table 2 Individual items' and constructs' reliability and validity ($N = 444$) (continued)

Construct	*Item code*	*Item loading*	*Item's commonality (square item's loading)*	α^a	CR^b	AVE^c
Self-learning and management (SEL)	SEL1	0.86	0.73			
	SEL2	0.88	0.77	0.91	0.93	0.78
	SEL3	0.91	0.82			
	SEL4	0.89	0.79			

[a]α: Cronbach's alpha.

[b]CR: composite reliability.

[c]AVE: average variance extracted.

[d]Reversed item.

Construct reliability refers to the internal consistency of constructs, and is assessed by evaluating the composite reliability and Cronbach's α of each construct (Kwong and Wong, 2013). The cut-off value for both composite reliability and Cronbach's α is 0.7. All constructs in this study demonstrated high internal consistency, as the constructs' composite reliability and Cronbach's α values are above the preferred level of 0.7 (Table 2). Convergent validity was assessed by the average variance extracted (AVE) and by examining items' cross-loadings (Hair, Hult and Ringle, 2013). In this study, all items were found to satisfy this condition. An AVE value of ≥ 0.5 indicates that the construct explains at least 50% of the variance of its items. Table 2 illustrates that the AVE values are higher than 0.5 and therefore it can be concluded that the constructs of the research model have adequate convergent validity.

Discriminant validity indicates that constructs are measuring distinctly different dimensions and concepts. In this study, discriminant validity was assessed by Fornell-Larcker's (1981) criterion. To claim that a construct is discriminately valid, the construct's AVE value must be substantially higher than its squared correlation with any other construct. In other words, a construct needs to be more internally correlated than it is correlated with any other construct(s). As Table 3 indicates, this condition has been satisfied by all constructs and thus, adequate discriminant validity is demonstrated. Finally, tolerance and variance inflation factor (VIF) values were examined in order to check multicollinearity. In this study, the values of VIF for all constructs were <5, and also tolerance coefficients were substantially higher than 0.2. Such results confirm the absence of multicollinearity in the study's data set (Field, 2000).

Table 3 Discriminant validity results

			Latent variable correlations							
Construct	*AVE*		*BEI*	*EE*	*UNA*	*PE*	*SEL*	*SF*	*SI*	*TE*
BEI	0.92	BEI	1							
EE	0.93	EE	0.6324[a] (0.399)	1						

Table 3 Discriminant validity results (continued)

		Latent variable correlations								
Construct	*AVE*		*BEI*	*EE*	*UNA*	*PE*	*SEL*	*SF*	*SI*	*TE*
UNA	0.93	UNA	0.7061 (0.498)	0.5873 (0.344)	1					
PE	0.82	PE	0.614 (0.376)	0.5443 (0.296)	0.6582 (0.433)	1				
SEL	0.78	SEL	–0.5904 (0.348)	–0.4818 (0.232)	–0.6575 (0.432)	–0.5746 (0.330)	1			
SF	0.72	SF	0.6327 (0.4003)	0.5344 (0.285)	0.6538 (0.427)	0.5968 (0.355)	–0.5051 (0.255)	1		
SI	0.71	SI	0.4818 (0.232)	0.2853 (0.081)	0.399 (0.159)	0.2969 (0.088)	–0.3186 (0.101)	0.3286 (0.107)	1	
TE	0.80	TE	–0.6158 (0.378)	–0.4722 (0.222)	–0.5619 (0.315)	–0.5583 (0.311)	0.5451 (0.297)	–0.5144 (0.264)	–0.3547 (0.125)	1

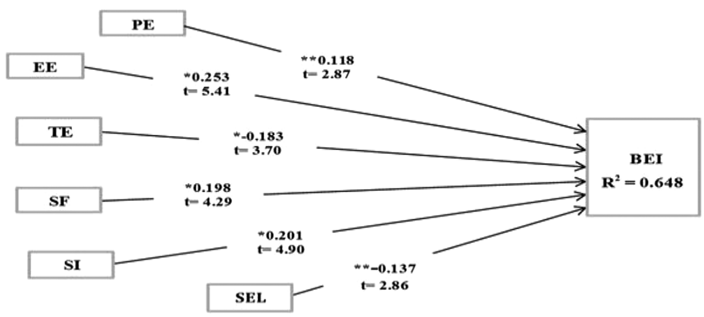
[a]Correlation.

[b]( ) = the squared correlation.

5.2 *The structural model (path analysis)*

Having established a reliable and validated measurement model, the next stage was to examine the proposed structural equation paths. In this stage, the explanatory power (R^2) of the model and the path coefficients (β) values for the suggested paths were determined. As Figure 3 shows, R^2 was 0.648 which indicates that the six independent variables explained 64.8% of the variance in the dependant variable BEI. Such a result indicates that the research model achieved a moderate explanatory power ($0.75 > R^2 > 0.50$) (Kwong and Wong, 2013). With regard to path analysis, the significant regression coefficients (β) were based on *t* values obtained by the PLS Bootstrap procedure. Figure 3 shows that the main six path coefficients were significant. According to the path analysis, EE ($\beta = 0.253$), SI ($\beta = 0.201$), SI ($\beta = 0.198$) and PE ($\beta = 0.118$), acted as facilitators to use m-learning, as all had positive effects on BEI. On the other hand, the path analysis suggests that SEL ($\beta = –0.137$) and TE ($\beta = –0.183$) had negative effects on BEI and, accordingly, both acted as inhibitors to use m-learning.

Figure 3 The path analysis



*$p < 0.001$, **$p < 0.01$, significant level 1-tail, observed *t* value

5.3 Moderating effects

As described earlier, the moderating effects of UNA on EE → BEI, SF → BEI, TE → BEI and PE → BEI were examined by product-indicator technique. In order to assess the strength of the moderating effect, the effect size (f^2) was also reported in the work of Cohen (1988). The value of f^2 evaluates the increase in R^2, relative to the proportion of the variance of the dependant variable that remains unexplained. Cohen (1988) suggests that f^2 values of 0.02, 0.15 and 0.35 imply weak, moderate and substantial effect, respectively. As Table 4 indicates, UNA moderates several relationships in the research model.

Table 4 Moderating effect of UNA, f^2 = effect size = $(R^2_{\text{incl}} - R^2_{\text{excl}}) / (1 - R^2_{\text{incl}})$

	Model 1 (main effects)	*Model 2 (interaction model)*			
Structural relation	β	R^2	β	R^2	f^2
PE → BEI	0.118	0.648	0.109*	0.669	
EE → BEI	0.253	0.648	0.199*	0.665	–
TE → BEI	–0.183	0.648	–0.122**	0.671	–
SF → BEI	0.198	0.648	0.144**	0.671	–
SI → BEI	0.201	0.648	0.192	0.668	
PE × UNA → BEI	–	–	–0.095***	0.669	0.06
EE × UNA → BEI	–	–	0.035$^{\text{n.s}}$	0.665	0.02
TE × UNA → BEI	–	–	–0.194***	0.671	0.07
SF × UNA → BEI	–	–	–0.107***	0.671	0.07
SI × UNA – BEI	–	–	0.074$^{\text{n.s}}$	0.668	0.06
SEL × UNA → BEI	–	–	–0.088$^{\text{n.s}}$	0.668	0.06

*p<0.001; **p<0.01; ***p<0.05; n.s= not significant

The analysis of interaction effects indicates that the increase in UNA among students leads to a negative impact on their BEI towards m-learning use, by lessening their perceptions of PE (PE × UNA → BEI, β = –0.095) and SF (SF × UNA → BEI, β = –0.107). Particularly, the results suggest that the increase in UNA by one standard deviation would decrease the impact of PE and SF on BEI directly by –0.014 and –0.037, respectively. Furthermore, UNA also was found to positively moderate the relationship of TE → BEI. The interaction term between TE and UNA (TE × UNA → BEI, β = –0.194) suggests that one standard deviation increase in UNA would increase the negative impact of TE on BEI directly by –0.027. Finally, the UNA had no significant moderating effects on EE → BEI (EE × UNA → BEI, β = 0.035) and SI→ BEI (SI × UNA → BEI, β = 0.074).

As mentioned previously, multi-group analysis was used to examine the moderating effects of gender groups. The nature of the moderating gender variables was categorical in the questionnaire; therefore, further refinements were not required to divide the sample into groups. To examine the moderating effect, the sample was split into desired groups (sub-groups) and the main model's parameters (i.e. path coefficients) were re-estimated for each sub-group. Corresponding to Carte and Russell (2003), sub-models were acceptable in terms of sample size for each group, constructs' reliability, validity and explanatory power. Because the standard errors (SE) of the proposed path-relations in the sub-models were not significantly different from one another, a *t*-test approach was used to examine the significant differences between the path coefficients (Chin, 2000). *T*-static was computed by Chin's equation (2000) as follows:

$$t = \frac{\text{path}_{\text{sample\_1}} - \text{path}_{\text{sample\_2}}}{\left[\sqrt{\frac{(m-1)^2}{(m+n-2)} * \text{SE}^2_{\text{sample1}} + \frac{(n-1)^2}{(m+n-2)} * \text{SE}^2_{\text{sample2}}}\right] * \left[\sqrt{\frac{1}{m} + \frac{1}{n}}\right]}$$

Path sample-1 and path sample-2 represent the corresponding path coefficients in the two sub-models, and *m* and *n* are the respective sub-sample sizes. SE2 sample-1 and SE2 sample-2 are the standard errors for the respective sub-model path coefficients. Additionally, the *t*-statistics were assessed with (m + n – 2) degrees of freedom. As Table 5 indicates, the only significant difference between the two gender groups was in terms of the relationship between EE and BEI. Particularly, EE → BEI was positively significant for the overall sample (β = 0.253), but was significantly stronger for females (β = 0.43) than males (β = 0.18). In terms of the age moderator, there were no significant differences between the two age groups.

Table 5 Moderating effects of gender

		All sample (N = 444)	*Male (N = 226)*	*Female (N = 218)*	
	Structural relation	*Model 1 (main effects)*	*Model 2*	*Model 3*	*t-Test*
Gender	PE → BEI	$p = 0.118$	$p = 0.14$	$p = 0.08^{\text{n.s}}$	$t = 0.77^{\text{n.s}}$
	EE → BEI	$p = 0.253$	$p = 0.18$	$p = 0.43$	$t = 3.11$**
	SEL → BEI	$p = -0.137$	$p = -0.12$	$p = -0.14$	$t = 0.23^{\text{n.s}}$
	SI → BEI	$p = 0.201$	$p = 0.18$	$p = 0.21$	$t = 0.43^{\text{n.s}}$
		$R^2 = 0.648$	$R^2 = 0.663$	$R^2 = 0.579$	
		All sample (N = 444)	<20 (N = 305)	>20 (N = 139)	*t*-Test
Age	PE → BEI	$p = 0.118$	$p = 0.21$	$p = 0.14$	$t = 0.63^{\text{n.s}}$
	EE → BEI	$p = 0.253$	$p = 0.26$	$p = 0.29$	$t = 0.25^{\text{n.s}}$
	SEL → BEI	$p = -0.137$	$p = -0.23$	$p = -0.18$	$t = 0.56^{\text{n.s}}$
	SI → BEI	$p = 0.201$	$p = 0.21$	$p = 0.19$	$t = 0.84^{\text{n.s}}$
		$R^2 = 0.648$	$R^2 = 0.674$	$R^2 = 0.628$	

n.s, not significant.

6 Discussion

The results illustrate that PE, EE, SI, TE, SEL and SF were all significant determinants of m-learning use intentions. The current study found EE to be a major facilitator of m-learning use intentions. EE was the strongest predictor of BEI to use m-learning. Research across various countries indicates varied results on the influence of EE on students' intention to adopt m-learning. Although Jambulingam (2013) and Yang (2013) did not find any support for this, other studies (Jairak, Praneetpolgrang and Mekhabunchakij, 2009; Al-Hujran, Al-Lozi and Al-Debei, 2014) found a positive relationship between students' EE and their intentions to adopt m-learning. The current study suggests that the more students perceive m-learning as easy to use for learning activities, the more they engage in m-learning. Today, the use of mobile devices among students of Jordanian universities, particularly smart phones, is very popular. Maybe using mobile devices seems to be routine for most of these students. Consequently, they may consider the use of such devices does not result in extra efforts, as it appears similar to using it for other tasks.

As for EE, PE was found to be a significant predictor of m-learning adoption as it had a positive impact on students' intention to adopt m-learning. The result is consistent with earlier studies (Joo et al., 2014; Kang, Liew and Lim, 2015) and contradicts findings of Park, Nam and Cha (2012). The result suggests that the more students consider m-learning as a useful tool for learning and increasing their productivity, the more they are willing to engage in m-learning.

Social influence was found to have a positive effect on students' intention to adopt m-learning. This result is in line with previous research (Abu-Al-Aish and Love, 2013), but it is inconsistent with others (Jambulingam, 2013). This result indicates that students do not develop their decisions in isolation from their social environment. Particularly, the more students recognise that peers, faculty and individuals important to them believe that they should use m-learning, the more likely they are to be motivated to adopt m-learning.

In agreement with Liaw, Hatala and Huang (2010), SF had a positive effect on students' BEI. This result suggests that if students perceive the m-learning characteristics and functionalities as valuable, they will be more likely to make use of m-learning. According to the SF scale used in this study, mobile devices are assumed to be used by students as a means for reading, retrieving, gathering and sharing educational materials in usable manners.

Surprisingly, the findings of this study suggest that SEL was a key barrier towards m-learning adoption as it had a negative effect on students' BEI to use m-learning. This result is in line with the findings of Yang (2013), but contrary to the findings of Wang, Wu and Wang (2009). This result implies that students with low autonomous learning capabilities will be more likely to avoid m-learning than students with higher autonomous learning capabilities. Furthermore, an interesting finding was also found that SEL is negatively interacted with both PE (PE × SEL → BEI = –0.112) and SF (SF × SEL → BEI = –0.098). These findings were not proposed in the research model, but are worthy of mention. This implies that the lower students' SEL, the less they will perceive the value of the functionality and usefulness of m-learning. A plausible justification may be that Jordanian students still consider lecturers as the centre of their education and thus, students prefer formal and well-structured education channels (i.e. classrooms). Al-Adwan and Smedley (2012) examined the factors influencing e-learning acceptance in two Jordanian universities. Their findings indicate that self-motivation to learn impedes e-learning adoption. They state that lecturers are considered the main source of motivation and information, and students strictly follow tutors' directions. Additionally, they point out that students in Jordan are very keen to accomplish their tasks because they are (and are expected to be) pushed by their lecturers. Successful m-learning adoption requires students to be self-disciplined and able to control their learning activities, and to involve an autonomous learning environment.

Trust expectancy was found to be another obstacle towards m-learning adoption as it had a negative effect on students' BEI. This finding contradicts with Alzaza (2012) who found trust to have positive effect on students' intentions. This result implies that students who lack trust in m-learning will be more likely to avoid the use of such systems. Based on TE scale used in this study, lack of trust related to m-learning in this study is as a result of students' low perceptions of data security and protection. Furthermore, a set of non-proposed findings emerged; the relationship between students' perceived PE and their BEI to use m-learning is negatively moderated by TE (PE × TE → BEI = –0.165). Moreover, the relationship between students' SEL and their BEI to use m-learning is positively moderated by TE (SEL × TE → BEI = 0.102). This indicates that the lower students' TE, the less they will perceive the usefulness of m-learning, and also the less they will perceive themselves as self-disciplined learners.

In terms of moderating effects, gender only moderated the relation between EE and BEI. We found that EE beliefs are more salient for females than male students when it comes to m-learning adoption. This result supports the findings of Venkatesh et al. (2003), whereas it is contrary to those of Jambulingam (2013) and Wang, Wu and Wang (2009). This may be due to the fact that female students' self-efficacy is lower than male students, in terms of using technology such as m-learning in education.

With regard to the moderating effects of UNA, we found UNA to have negative moderating effects on the relations of PE, SF and TE. To our knowledge, the moderating effect of UNA is not clearly evident in the context of m-learning adoption. Although Jordanian students showed a high level of UNA, UNA had a significantly negative effect on their BEI to use m-learning ($\beta = -0.217$). High UNA cultures value avoiding risk and seek to add structure to their environment (Perez-Alvarez, 2014). IT adoption is viewed as risky in these cultures because it involves change and uncertainty and thus, these societies consider such changes negatively. This justifies the negative interaction effects of UNA on SF and PE. This implies that high quality and useful functions are very important for high UNA students in order to reduce the risk and uncertainty involved in m-learning adoption. On the other hand, the interaction effect between UNA and TE was negative. This implies that an increase in students' UNA would lower their trust in m-learning. Individuals with high UNA exhibit low interpersonal trust and resist change.

7 Conclusion

Students' acceptance of the use of m-learning is considered a key challenge in the higher education environment, in terms of gaining strategic advantages associated with new technology. The framework of this study notably proves its capabilities with regard to predicting students' BEIs to use m-learning in Jordan. Based on the UTAUT model, this study has proposed an extended framework to investigate and predict the factors affecting university students' intentions to use m-learning in the developing country context of Jordan. The proposed framework suggests several modifications, as it adds three new constructs to the model: TE, SEL and SF. Furthermore, the proposed framework examined the potential moderating effect of UNA on m-learning use intention. The results demonstrate that PE, EE, SF and SI were found as key facilitators of m-learning adoption. Among these facilitators, EE exerted the strongest influence on students' BEI to use m-learning. On the other hand, TE and SEL were major barriers towards the use of m-learning. TE had the strongest negative impact on students' BEI to use m-learning.

The influence of EE on BEI was moderated by gender; it was stronger for females than males. Finally, the influences of both PE and SF on intention were negatively moderated by UNA, whereas the influence of TE was positively moderated by UNA.

At the broader level, the research framework offers a means of understanding of which factors determine the BEIs of students when it comes to using m-learning and how this may affect its future use. Furthermore, understanding how these factors contribute to BEIs may be used to predict m-learning acceptance as part of system development. This study conceptualises the constructs of m-learning acceptance and defines their underlying dimensionalities to develop a standardised tool with desirable properties in terms of measuring the acceptance of m-learning. The findings of this study are expected to help m-learning developers and providers to design better m-learning systems that attract and promote this new wave of education technology to a larger number of students. The following sections present both theoretical and practical implications of this study.

7.1 Theoretical contributions

Investigating students' adoption of m-learning can help to enrich the knowledge and understanding of educational information technology adoption, in light of the rapid shift in new technologies in higher education. Therefore, this study attempts to explore and predict m-learning acceptance through proposing a framework that is theoretically grounded in the UTAUT. This study extends UTAUT by building on the existing literature of technology adoption and diffusion which argues that the decision to adopt m-learning is a function of several interrelated factors. The research framework has been validated which, in turn, adds new insights for future research with different populations and settings. This study contributes to the theory of technology adoption and practice in several ways. First, it fills the theoretical gap that exists with regard to technology adoption research, which focuses on the technological and organisational factors as the main salient determinants of m-learning.

Previous studies on m-learning adoption focus on the organisational changes associated with the use of m-learning, such as organisational policies and strategies regarding resistance to change. Additionally, the m-learning acceptance literature pays particular attention to students' resistance by looking at the barriers to m-learning usage, such as whether or not m-learning is beneficial or problematic. Specifically, the overreliance on perceived ease of use and perceived usefulness as the main salient beliefs when it comes to predicting students' adoption of m-learning has weakened the current understanding of m-learning acceptance and potential adoption strategies.

Therefore, this study incorporates the notion of inhibitors and facilitators within a unified framework of m-learning acceptance, by the inclusion of the construct of TE and SEL. This modification brings an additional dimension to predict and explore the factors influencing students' acceptance of m-learning. Particularly, it aims at generating a better understanding of students' acceptance and resistance to m-learning adoption that serves to address the levels of trust and self-learning involved. The contribution of the current research attends to the often neglected rationale that lies behind the use of trust and self-learning perceptions, in predicting students' BEIs to use m-learning. Such a contribution broadens the reach of this research in terms of understanding the basis and motivations of students' resistance to the use of m-learning. According to the results, the students' TE and SEL are found to be major barriers in terms of m-learning adoption. Finally, this study introduced another modification to the understanding of m-learning by examining the moderating impact of an important cultural factor, UNA. Previous research has focused on SIs and neglected the cultural aspects and their potential impact on m-leaning adoption, especially in a country such as Jordan that is driven by a set of cultural disciplines. Overall, UNA had a negative impact on m-learning adoption as it negatively moderated the influences of TE, SEL and PE on students' BEI, which implies several required actions, as the following sections explain.

7.2 Practical contributions

7.2.1 Implications for top management and policy-makers

The findings provide useful recommendations for managers desiring to enhance students' BEIs regarding the use of m-learning. The study highlights the importance of the need for effective leadership and management support in the processes associated with m-learning selection and implementation. The students in this study have shown positive intentions to use and adopt m-learning. Since high levels of ease of use and usefulness encourage students to have more positive BEIs, management should select a system that is user-friendly and offers students significant benefits. This study asserts that SI has a direct positive impact on students' BEIs to use m-learning. Such influence is granted formally (i.e. teachers and lecturers) and informally (i.e. peers and colleagues). This finding points towards the fact that the influence of both colleagues and teachers place a positive role in the process of m-learning adoption. Consequently, m-learning providers should take into account the critical importance of SI. They can encourage m-learning by taking advantage of the SI of the potential students' close friends and lecturers. Specifically, m-learning educators and providers should first promote the usefulness of m-learning to potential early adopters, who possess a higher level of personal IT innovation than other students (Wang, Wu and Wang, 2009). Once those early adopters become familiar with and begin using m-learning, they may start convincing their colleagues to use it. Additionally, m-learning educators should leverage the value-added features of m-learning in promoting learning performance (i.e. timely knowledge, quicker response).

Top management should be aware of the potential inhibitors of m-learning adoption caused by TE and SEL. Both TE and SEL have negative effects on students' BEIs to adopt m-learning. Paying attention to the causes of TE and SEL enables managers to uncover the actual problems and students' reactions to m-learning. The measurement scales which have been used in this study to measure students' TE and SEL are a useful tool to evaluate and determine students' behaviour and to specify potential reasons of resistance. Consequently, the barriers to students' acceptance can be addressed prior to the rejection of m-learning.

This study has revealed that self-management and learning has negative effects on students' BEI to use m-learning. As a consequence, based on the recommendations of Wang, Wu and Wang (2009), both m-learning providers and policy-makers should reconsider the current educational activities, and target new pedagogical curriculums to stimulate and inspire their students' abilities of SEL. In addition, educators should effectively deliver these curriculums and find creative methods to normalise the habit of SEL. According to our findings, EE proves to be more salient for females than males. M-learning designers should focus on ease of use features such as friendly interfaces. M-learning educators and developers should develop attractive and suitable educational content. Since SI is a significant factor in this study, we recommend that both educators and male students cooperate to promote the m-learning features of ease of use to female students.

7.2.2 Implications for m-learning vendors and developers

The results of this study emphasise that the technological characteristics of m-learning can act as a significant facilitator to using m-learning. M-learning developers should consider students' perception of usefulness and ease of use during the design and the implementation of m-learning in order to enhance their acceptance. This study calls for an overwhelming need for easy, useful and functional m-learning. SF, EE and PE were found to have a positive influence on students' BEIs to use m-learning. Therefore, m-learning systems should be simple and easy to operate. M-learning providers should pay special attention to the ease of use and user friendliness of m-learning systems, particularly in light of the inherent features and limitations of mobile devices (i.e. small screens, multifunction keypads, storage capacities) that may potentially complicate user input and interaction. According to Wang, Wu and Wang (2009), developing intuitive data entry (i.e. touch screen menus, one touch keys, automatic writing processing) and dynamic interface features can make the interaction with m-learning easier to use and learn.

Furthermore, the results suggest that the design of m-learning should be centred on developing valuable, customised and meaningful functions and content that would meet learners' needs. According to Liaw, Hatala and Huang (2010), in order to promote the usefulness of m-learning, m-learning systems should be viable. Moreover, knowledge management tools should provide communicative and collaborative functions so that students can effectively acquire new knowledge and thus improve learning performance.

In terms of SF, m-learning designers should bear in mind the significance of communication standards and the presentation standards of educational material (i.e. navigation, interfaces compatibility, response time). Additionally, as Wang, Wu and Wang (2009) recommend, in order to provide students with a pleasant experience of m-learning, m-learning designers should realise the importance of making educational contents portable to various types of mobile devices so that students could use a device of their choice that suits a particular circumstance. A non-proposed finding has also been identified; SF positively moderated the relationship between PE and BEI ($PE \times SF \rightarrow BEI = 0.101$). This suggests that SF plays a vital role in students' perception of m-learning usefulness; the more they perceive m-learning functionalities as valuable, the more they will perceive m-learning system as useful.

This study found both SEL and TE as major inhibitors towards the adoption of m-learning. M-learning developers can enhance the level of students' SEL by providing user-friendly learning management systems with learning progress and time management control functions. These are fundamental motivators for students to be involved in autonomous and self-learning. With regard to the negative impact of TE on students' BEI to use m-learning, m-learning should possess a dependable information exchange environment, as students are required to send, communicate, view, retrieve and share their educational tasks and information via the internet (Alzaza, 2012). However, performing such activities over the internet is subject to several risks such as interception and misuse. As a result, students' trust can be solely gained by reducing risks associated with the data transaction environment to a tolerable level. As recommended by Park (2011), m-learning providers should endeavour to provide a trustful environment of information exchange and generate a positive feeling to using m-learning by employing high-quality wireless connections and utilising good security technologies to protect sensitive information.

Finally, m-learning developers have a role to play in terms of the negative impact of UNA on TE, SF and PE. Developers and designers should recognise the importance of PE, SF and TE and their roles in eliminating ambiguity in high UNA cultures. However, high UNA societies' enhanced perceptions of usefulness and performance make them more willing to use a technology (Perez-Alvarez, 2008). This is precisely the case in this study; Jordanian students may offset the risks involved for the sake of the potential enhancements the m-learning brings to both the educational process and outcomes. Therefore, m-learning should provide highly structured and specific functions and features. M-learning services and activities should be well-defined and structured into pre-defined menus and interfaces, and therefore will be considered favourably by those students with high UNA traits.

7.3 Limitations and future work

Like most empirical research, this investigation is subject to some limitations that can be tackled in the future. Firstly, this study employed a self-report questionnaire (quantitative method) to measure the various variables in the research model. Such a method of data collection is linked to common forms of bias (i.e. desirability and faking). Future studies may use a mixed-method approach (both quantitative and qualitative methods) to generate more reliable and valid results. Mixed method research design can significantly help in offering a holistic understanding of m-learning practices among university students (Wong, 2014). Secondly, although this study was homogeneous in terms of participants (university students), the study did not differentiate between students' faculties. The complexity of m-learning may vary among the different faculties and thus, a follow-up study could investigate such aspects. Finally, further studies are required to investigate educators' perceptions of m-learning, and determine whether there are potential differences compared to students' perceptions.

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Appendix: the questionnaire items used in this study

	Effort expectance (EE)
EE1:	My interaction with m-learning would be clear and understandable
EE2:	It would be easy for me to become skilful at using m-learning
EE3:	I would find m-learning easy to use
EE4:	Learning to operate mobile learning applications is going to be easy for me
	Performance expectancy (PE)
PE1:	I would find m-learning useful in my learning
PE2:	Using mobile learning will enable me to accomplish learning activities more quickly
PE3:	Using m-learning will increase my learning productivity
PE4:	The use of mobile learning will allow me to have access to more information about my courses

Appendix (continued)

	Self-learning and management (SEL)
SEL1:	When it comes to learning and studying, I am a self-directed person
SEL2:	In my studies, I am self-disciplined and find it easy to set aside reading and homework time
SEL3:	In my studies, I set goals and have a high degree of initiative
SEL4:	I am able to manage my study time effectively and easily complete assignments on time
	Social influence (SI)
SI1:	People who influence my behaviour will think that I should use m-learning
SI2:	People who are important to me will think that I should use m-learning
SI3:	The lecturers and other staff at my institution will be helpful in the use of mobile learning
SI4:	In general, my institution will support the use of mobile learning
	System functionality
SF1:	The m-learning should be a convenience tool for reading online content
SF2:	The m-learning should be a convenience tool for retrieving online content
SF3:	The m-learning should be a convenience tool for human-computer interaction
SF4:	The m-learning should be a convenience tool for gathering online resources
	Trust expectancy (TE)
TE1:	M-learning will be reliable
TE2:	M-learning will protect the data I provide very well
TE3:	Wireless communications cannot be trusted; there are just too many uncertainties
TE4:	M-learning will offer secure personal privacy
	Uncertainty avoidance (UA)
UNA1:	It is important to have learning requirements and instructions spelled out in detail so that students always know what they are expected to do
UNA2:	Rules and regularities are important because they inform students what the organisation expects of them
UNA3:	Lecturers expect students to closely follow instructions and procedures
UNA4:	Standard learning procedures are helpful to employees on the job
	Behavioural intention (BEI)
BEI1:	I intend to use mobile learning in the future
BEI2:	I plan to use mobile learning in the future
BEI3:	I predict I would use m-learning in the future
BEI4:	I aim to use mobile learning instead of the traditional ones