Predicting mobile learning acceptance: An integrated model and empirical study based on the perceptions of higher education students

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This research extends the unified theory of acceptance and use of technology (UTAUT) model based on the expectation-confirmation and self-determination theories. It is aimed at exploring students' perspectives regarding the acceptance of mobile learning (m-learning) in higher education. Although UTAUT receives considerable attention in technology acceptance research, the present study is unlike previous work, in that it is among the first to integrate the self-determination and expectation-confirmation theories with this model to better understand m-learning adoption, particularly in developing countries. A total of 246 undergraduate students responded voluntarily to an online questionnaire. The resulting findings suggest that integrating the UTAUT model with variables that represent learners′ basic psychological needs can highly affect their acceptance of m-learning technology. These findings are discussed further for their theoretical and practical implications.

Implications for practice or policy:

- In mobile learning, teachers need to create meaningful learning tasks to facilitate students' learning.
- Teachers should be aware of the importance of confirming learners' initial expectations of mobile learning's benefits, to ensure greater learning effectiveness.
- Students should feel no pressure in their decision to adopt mobile learning.
- Higher education institutes need to exploit the benefits of mobile learning, given that students have high willingness to accept it, but adequate training and facilities should be provided.

Keywords: UTAUT, expectation-confirmation theory, self-determination theory, mobile learning adoption, Saudi Arabia, higher education

Introduction

The integration of educational technologies into the teaching and learning process is becoming ubiquitous in contemporary education. It has been demonstrated that such technologies can help improve learning outcomes and learners′ perceptions (Al-Azawei, 2019a, 2019b; Orús et al., 2016). A variety of electronic media have been used as vehicles for learning, such as the Internet, audiotape, videotape, CD-ROMs, intranet, interactive TV and smart devices. However, the "rapid growth of mobile and wireless technologies [has] resulted in increasing use of mobile devices in education" (Nikou & Economides, 2017, p. 56). According to Al-Emran et al. (2016), mobile learning (m-learning) may be defined according to three perspectives. First, it refers to learning that takes place via small smart devices. Moreover, it is a specific form of learning, which has evolved from the broader term of *distance learning*. Finally, it represents the next generation of e-learning, which is based on mobile devices. Thus, m-learning may represent a more innovative means of communication and knowledge sharing for learners and educators, in addition to the inherent features of mobile devices such as mobility and flexibility (Kumar Basak et al., 2018).

Nevertheless, m-learning is not without its limitations. In terms of the input, output, processing and memory capabilities of mobile devices, it is often evident that they lack features such as a user-friendly keyboard and screen. Moreover, they can be slow and have low processing and storage memory (Asabere, 2012; Kumar Basak et al., 2018). Aside from this, parents may have negative attitudes to their children using this technology (Kumar Basak et al., 2018), and the users themselves may have low willingness to accept it (Abu-Al-Aish & Love, 2013). Therefore, the acceptance of m-learning receives considerable attention as it is still an evolving topic (Briz-Ponce et al., 2017; Nikou & Economides, 2017). In particular, the adoption of m-learning has been examined based on the perceptions of students and teachers (Al-Emran et al., 2016; Aliaño, et al., 2019; Althunibat, 2015; Gómez-Ramirez et al., 2019; Nikou & Economides, 2017; Thomas et al., 2013).

To elaborate on the above, there is currently a dearth of research dedicated to identifying m-learning acceptance in higher education, based on an integrated model. The key aims of this study were threefold:

- Highlight the predictability of the unified theory of acceptance and use of technology (UTAUT) model (Venkatesh et al., 2003) for m-learning.
- Shed light on the role of the expectation-confirmation theory (Oliver, 1981) and self-determination theory (Ryan & Deci, 2000) in explaining m-learning acceptance.
- Investigate the integration of the UTAUT model with the expectation-confirmation and self-determination theories.

The rationale underpinning this extension is that these theories can complement each other. To clarify, while UTAUT ignores the role of initial expectation and its confirmation when predicting technology acceptance, this role is taken into consideration in the expectation-confirmation theory, as well as the way in which initial expectation is formed by users, and confirmation after use can influence their choice of whether to enact a particular behaviour. Moreover, UTAUT fails to consider the influence of psychological needs in its investigation of technology acceptance. Conversely, the self-determination theory suggests three psychological needs that affect intrinsic motivation. In turn, these can influence users' decisions to accept a particular technology. To the best of our knowledge, this has not been investigated in the earlier literature. Accordingly, the present study attempts to bridge the identified research gap and extend previous work on m-learning acceptance, especially in developing countries.

Theoretical background

M-learning

The rapid development of mobile technology is evidence of the wireless revolution and its role in many sectors, including education (Rosman, 2008). Its adoption in education could be due to enhanced network infrastructure capacity, high bandwidth Internet and advancement in connecting such technologies wirelessly. M-learning offers the possibility of delivering learning anywhere and at any time.

Over the past century, there has been a dramatic increase in the use of mobile devices in the education sector. As a result, many international universities have applied this technology, for example, Aoyama Gakuin University in Japan, where the effectiveness of m-learning for enhancing learners' performance has been confirmed (Anzai, 2013). This approach to teaching and learning is interesting, in that it enables access to learning materials anywhere and at any time, including outside working hours, as well as in multiple formats, such as audio, visual, or textual modes, according to learnersʹ preferences. In turn, the recent adoption of m-learning in education requires further investigation to identify the factors potentially affecting its acceptance. Although there have been numerous studies examining the importance of mobile education, very few have focused on applying it to serve educational programs in developing countries (Hoi, 2020).

Mobile use and acceptance in Saudi education

Over the last decade, interest in mobile education has significantly increased in Saudi universities (Abdulrahman & Benkhelifa, 2017). This trend is attributed to various factors, such as the availability of wireless networks and the rapid growth of mobile technology (Hoi, 2020). Moreover, Internet and smartphone penetration has spread throughout the Saudi population, due to its affordability, resulting in 28.8 million users in 2019 (Statista, 2020). Hence, educators and academic staff need to harness these multiple mobile applications for teaching and learning. To date, there has been an essential investment in m-learning in many of Saudi Arabia' s universities, such as Albaha University, the Saudi Electronic

University and King Abdul-Aziz University in Jeddah (Alkhaldi & Abualkishik, 2019). As a result, the Saudi government has established the requisite infrastructure for projects such as the National Center for E-learning and Distance Learning (Al-Shehri, 2010) and the Saudi Digital Library (Taala et al., 2019). Currently, the use of educational technologies such as e-learning and m-learning is on the rise in Saudi Arabia, due to the international COVID-19 crisis (Alarifi, 2020). Hence, Saudi universities have transferred their activities to the channels afforded by various educational technologies, so that learning content can be delivered to students while they self-isolate at home. These channels include learning management systems (LMSs), which can be navigated and used on different electronic devices, for example, computers, tablets, and/or smartphones.

AlEid (2019) investigated the use of mobile devices in learning at Princess Nourah University in Saudi Arabia, using a semi-experimental approach. Overall, the research findings supported the important effect of m-learning adoption on learners' perceptions. Moreover, the study demonstrated that the success of m-learning depends on Internet availability, human resources and the willingness of teachers and students to use it. Moreover, Al-Fahad (2009) conducted a research study on female undergraduate students at King Saud University, revealing their perceptions and attitudes towards the effectiveness of m-learning. The findings suggest that the availability of m-learning would improve students' retention and enrich their learning experience. More recently, Saleem (2017) investigated the use of m-learning for teaching English at Taibah University in Saudi Arabia, with results indicating that m-learning could enhance self-learning and provide practice opportunities. These studies, therefore, concluded that the use of m-learning can positively affect the teaching and learning process.

The proposed research model

Ignoring learners' perceptions can negatively influence the acceptance of educational technologies. UTAUT was used as a theoretical framework in this study to understand learners′ perceptions regarding m-learning acceptance. UTAUT has attracted significant attention in m-learning research (Aliaño et al., 2019; Gómez-Ramirez et al., 2019; Nikou & Economides, 2017). However, the ability of this model to predict technology acceptance is not high (Mtebe et al., 2016), suggesting that other factors should be integrated to improve its overall predictability power. This may indicate that the four constructs of UTAUT (effort expectancy, performance expectancy, social influence, and facilitating conditions) may be inadequate to cover all significant components in determining technology adoption. Moreover, another debate sparked by UTAUT is that it does not consider users' expectations, the confirmation of those expectations in relation to a specific technology or what affects users' psychological needs. This research, therefore, adapted UTAUT to address these limitations by proposing an integrated model based on three well-known theories.

The UTAUT model

Technology acceptance signifies the clear willingness of users to adopt technology to perform the tasks and activities for which it was intended (Walldén et al., 2015). To examine such acceptance, a large number of models have been developed to determine users' adoption of information systems. The technology acceptance model (TAM) proposed by Davis (1986) represents one of the most commonly used models for explaining technology acceptance. The updated TAM model suggests that perceived usefulness and perceived ease of use are direct predictors of behavioural intention (Venkatesh & Davis, 2000). Perceived usefulness (performance expectancy) refers to people's beliefs that a particular technology can help enhance their job performance, whereas perceived ease of use (effort expectancy) is the user's belief that implementing the technology does not require great mental effort (Davis, 1986).

However, due to the criticisms directed at TAM, other technology acceptance models have been proposed (Al-Azawei, 2017). One of the most recent of these is the UTAUT model, developed by Venkatesh et al. (2003) (see Figure 1). UTAUT also suggests two other predictors of technology acceptance, namely facilitating conditions and social influence. Moreover, Venkatesh et al. (2003) proposed gender, age, experience and voluntariness of use as moderators of the relationship between the model's variables. Facilitating conditions refer to the support that users receive from their institutes or organisations to assist their technology use, while social influence consists of social pressures on a user's decision to perform or refrain from performing certain actions, depending on the behaviour in question.

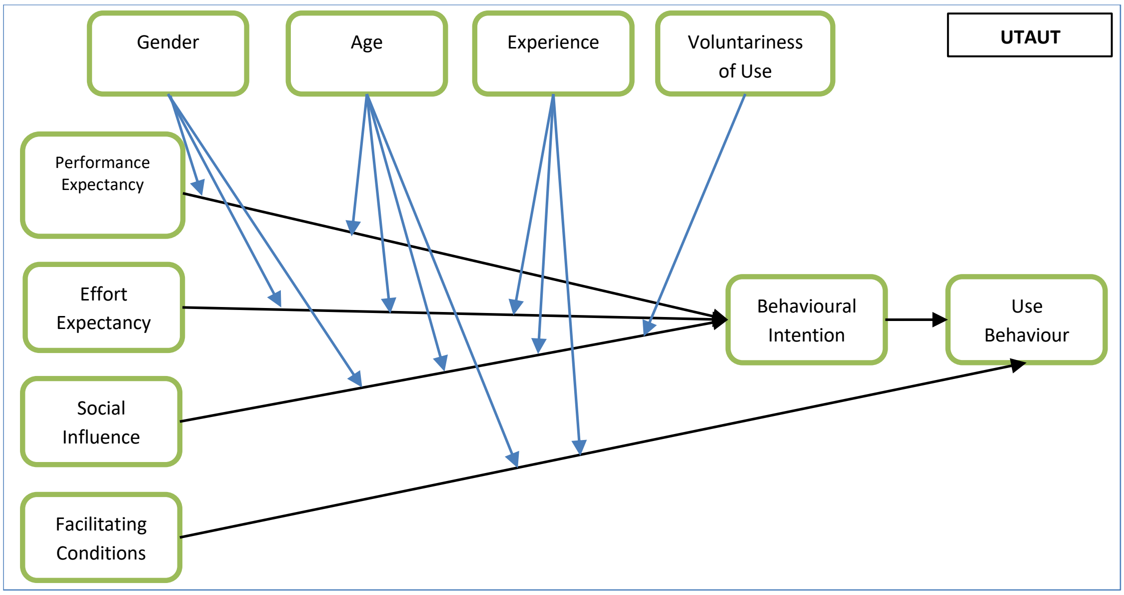

Figure 1. The UTAUT model (Venkatesh et al., 2003, p. 447)

Concerning the use of UTAUT variables in m-learning acceptance research, Briz-Ponce et al. (2017) found that social influence significantly affects m-learning adoption. In line with the above research, Gómez-Ramirez et al. (2019) also showed social influence to be a significant antecedent of m-learning acceptance. Moreover, Althunibat (2015) and Nikou and Economides (2017) highlighted that both effort expectancy and performance expectancy are predictors of behavioural intention to use m-learning. In a study conducted by Aliaño et al. (2019), the findings indicated that social influence, effort expectancy, performance expectancy and facilitating conditions are significantly associated with the behavioural intention to use m-learning. Furthermore, Althunibat (2015) supported that facilitating conditions are a predictor of effort expectancy, and Davis (1986) confirmed that perceived ease of use (effort expectancy) is a determinant of perceived usefulness (performance expectancy). Based on such outcomes, the hypotheses for the current study were as follows:

H1: Social influence has a significant effect on the behavioural intention to adopt m-learning.
H2: Facilitating conditions have a significant effect on the behavioural intention to adopt m-learning.
H3: Effort expectancy has a significant effect on the behavioural intention to adopt m-learning.
H4: Performance expectancy has a significant effect on the behavioural intention to adopt m-learning.
H5: Facilitating conditions have a significant effect on effort expectancy in the adoption of m-learning.
H6: Effort expectancy has a significant effect on performance expectancy in the adoption of m-learning.

Expectation-confirmation theory

The expectation-confirmation theory was first suggested in marketing research to investigate consumers' post-purchase behaviour and satisfaction (Oliver, 1981). The theory assumes that before purchasing a product or using a service, consumers form an initial expectation. After purchasing and using the product for a period of time, they form particular perceptions of the product performance. Accordingly, consumers draw a comparison, based on their initial expectation and perceived performance of the product, thereby indicating the extent to which that expectation is confirmed. Repurchase behaviour is affected by the level of expectation and confirmation, which can be called satisfaction. This is very similar to information system use, where users also make an initial decision, which is affected by their experience of use and, finally, either sustained or changed negatively (Bhattacherjee, 2001). Although this theory is still referred to in terms of expectation, empirically, such pre-consumption is transformed by post-consumption expectation, namely performance expectancy or perceived usefulness (Dwivedi et al., 2012).

The expectation-confirmation theory is widely applied in information systems research (Dwivedi et al., 2012). For example, Venkatesh et al. (2011) integrated the variables suggested in this theory with the UTAUT model, in order to investigate the behavioural intention to accept e-government technologies, whereupon its overall effectiveness was highly supported. Moreover, Bhattacherjee (2001) proposed an information systems continuance model based on the expectation-confirmation theory. The resulting findings showed confirmation to be a predictor of satisfaction, whereas perceived usefulness (performance expectancy) was influenced by confirmation.

Although previous studies suggest confirmation as a predictor of satisfaction, whereby the latter then influences the intention to use (Lai & Zhao, 2019; Wijaya et al., 2019), the current study hypothesised a direct relationship between expectation-confirmation and behavioural intention. The philosophy behind this assumption stems from the empirical research confirming that identical constructs can be adopted to predict perceived satisfaction and technology acceptance (Al-Azawei et al., 2017; Capece & Campisi, 2013; Weng et al., 2015). According to this discussion, we assumed that:

H7: Confirmation has a significant effect on the behavioural intention to adopt m-learning.
H8: Confirmation has a significant effect on performance expectancy to adopt m-learning.

Self-determination theory

Self-determination theory consists of two key elements: intrinsic and extrinsic motivation, as well as a group of psychological needs, collectively referred to as motivation (Gagné & Deci, 2005). Motivation is defined as the reason for undertaking an activity. Extrinsic motivation is not self-determined, unlike intrinsic motivation, which is self-determined. The self-determination theory suggests that intrinsic motivation is based on three key elements of psychological need: competence, the need for relatedness, and autonomy (Roca & Gagné, 2008). According to Ryan and Deci (2000), competence refers to the user's desire to feel effective in attaining important outcomes, whereas relatedness is the user's desire to feel a sense of connection with others. Finally, autonomy is the user's desire to self-regulate and self-initiate behaviour. The theory suggests that these three items (competence, relatedness, autonomy) can be satisfied when engaging in many different behaviours, which also vary among individuals and may differ between dissimilar cultures.

Self-determination theory has been applied to determine the acceptance of information systems. Roca and Gagné (2008) extended TAM by including these three psychological items to determine e-learning adoption. In their model, Roca and Gagné proposed that autonomy and competence are predictors of perceived usefulness, perceived playfulness, and perceived ease of use, whereas perceived relatedness is purely a determinant of perceived usefulness and perceived playfulness. The empirical findings supported all suggested hypotheses, except for the influence of perceived relatedness on perceived usefulness. In a similar context, Sørebø et al. (2009) integrated the self-determination and expectation-confirmation theories into an understanding of teachers' continuance behaviour in e-learning use. Sørebø et al. suggested that these three items are predictors of perceived usefulness and intrinsic motivation. The research outcomes suggested that perceived relatedness was not a significant predictor of perceived usefulness and intrinsic motivation, while the two other variables were determinants of confirmation and performance expectancy. Hence, perceived relatedness was not included in the present study. Consequently, we proposed that:

H9: Perceived competence has a significant effect on the behavioural intention to adopt m-learning.
H10: Perceived autonomy has a significant effect on the behavioural intention to adopt m-learning.

Figure 2 presents the proposed research model.

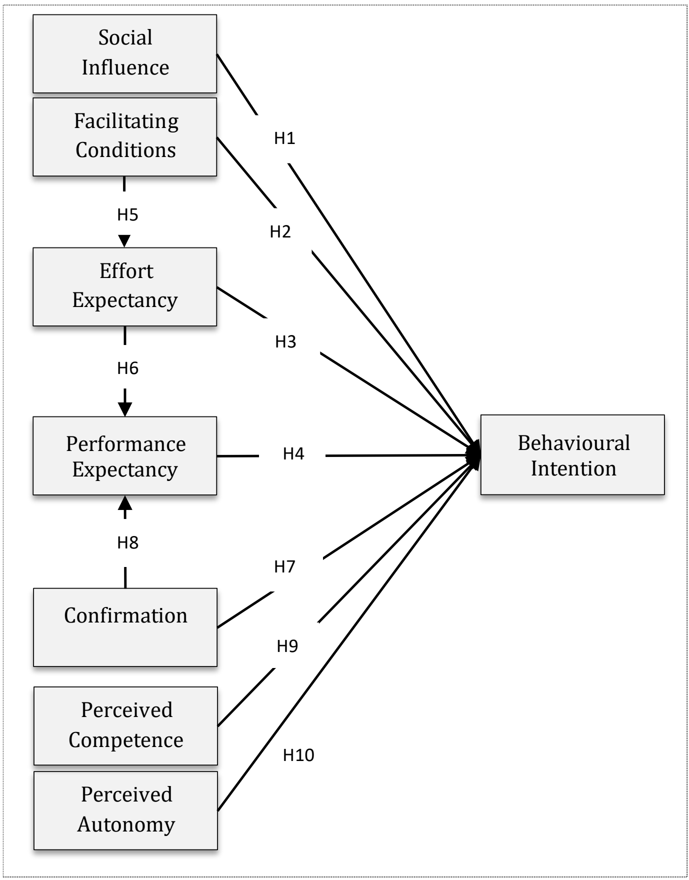

Figure 2. The proposed research model

Research methods

This research adopted a methodology based on a quantitative approach, which can be used to generate statistical findings within the scope of the study, using a systematic and empirical examination. An online questionnaire was distributed to around 300 students in a public university in the Kingdom of Saudi Arabia, during the first semester of the academic year 2019–2020. As the key focus of this study was on extending UTAUT to understand m-learning adoption, the questionnaire targeted computer science students, because they had more opportunities to take advantage of m-learning.

The research participants used a mobile device in several different ways, such as to access and read course materials, take notes, search for information relating to their discipline on the Internet, survey new studies in the Saudi Digital Library, share ideas, carry out assignments and sit online exams hosted in their university's LMS. Overall, a total of 246 valid responses were received. Thus, the response rate was 82%, as students were highly engaged by their lecturers to take part in the research. The data collection period was about 2 weeks. The participants' demographic information is presented in Table 1.

Table 1
Participants' demographic information (N = 246)

Factor	Number	%
Gender:		
- Male	96	39
- Female	150	61
Age group:		
- 18 to 22 years	192	78
- 23 years and over	54	22
Study year:		
- First	45	18.3
- Second	1	0.4
- Third	72	29.3
- Fourth	99	40.2
- Postgraduate		
Experience of mobile use:		
- Low	2	0.8
- Moderate	91	37
- High	153	62.2
In possession of a smartphone:		
- No	7	2.8
- Yes	239	97.2
Years of smartphone use:		
- Have not used it	3	1.2
- One year	1	0.4
- Two to three years	12	4.9
- Four years or more	230	93.5

The research measurement was in two parts. The first encompassed six questions about the participants' demographic features, whereas the second was intended to measure the proposed model constructs. The items used to operationalise the factors in the proposed research model were adapted from previous studies (Al-Azawei, 2018; Sørebø et al., 2009). Some changes were made to the wording of certain items to correspond to the technology targeted in this study. All items relating to the research model variables were measured based on a 5-point Likert scale, ranging from 1 for strongly disagree to 5 for strongly agree. The research factors were first measured using 29 items. However, four items were excluded from the analysis phase due to their low factor loadings. It is worth mentioning that all items were translated into Arabic, because the use of English could lead to arbitrary answers, as most undergraduate students in Arabic countries have either weak or moderate English ability. Table 2 shows the research survey items and some statistical analysis.

Table 2
Research item means, standard deviations (SD) and internal consistencies

Code	**Item**	***Mean***	***SD***	**Loadings**	**Outer weights**	***t* stat**
Performance Expectancy (PE)						
PE1	I find mobile-learning technology useful for my daily studies.	0.346	0.023	0.807	0.346	15.371
PE2	Using mobile-learning technology increases my chances of achieving tasks that are important to me in my studies.	0.294	0.021	0.789	0.294	14.140
PE3	Using mobile-learning technology helps me accomplish tasks more quickly.	0.285	0.020	0.785	0.286	14.467

PE4	Using mobile-learning technology increases my productivity during my studies.	0.326	0.022	0.816	0.324	14.601
Effort Expectancy (EE)						
EE1	It is easy for me to learn how to use mobile-learning technology.	0.277	0.016	0.871	0.278	17.954
EE2	My interaction with mobile-learning technology is clear and easy to understand.	0.356	0.026	0.849	0.354	13.514
EE3	I find mobile-learning technology easy to use.	0.299	0.020	0.838	0.298	15.069
EE4	It is easy for me to become skilled in using mobile-learning technology.	0.261	0.017	0.794	0.261	15.701
Social Influence (SI)						
SI1	People who are important to me think I should use mobile-learning technology	0.380	0.019	0.915	0.379	19.631
SI2	People who influence my behaviour think I should use mobile-learning technology.	0.355	0.017	0.916	0.355	20.932
SI3	People whose opinions I value prefer me to use mobile-learning technology.	0.377	0.024	0.871	0.377	15.755
Facilitating Conditions (FC)						
FC1	I have the necessary resources to use mobile-learning technology.	0.391	0.034	0.841	0.391	11.654
FC2	I have the necessary knowledge to use mobile-learning technology.	0.412	0.031	0.868	0.411	13.233
FC3	Mobile-learning technology is compatible with other technologies that I use.	0.383	0.030	0.818	0.383	12.934
Confirmation (Con)						
Con1	My experience of using mobile-learning technology was better than I expected.	0.430	0.018	0.917	0.429	23.955
Con2	The service level provided by mobile-learning technology was better than I expected.	0.359	0.014	0.899	0.360	25.580
Con3	Overall, most of my expectations of using mobile-learning technology were confirmed.	0.335	0.017	0.846	0.335	19.750
Perceived Competence (PC)						
PC1	I have been able to learn useful new skills in mobile-learning technology through my studies.	0.467	0.033	0.844	0.468	13.984
PC2	Most days, I feel a sense of accomplishment from studying with mobile-learning technology.	0.656	0.036	0.924	0.654	18.115
Perceived Autonomy (PA)						
PA1	I feel that I can form many opinions in deciding how to use mobile-learning technology during my studies.	0.557	0.038	0.854	0.557	14.845
PA4	I feel that I can pretty much use mobile-learning technology as I want in my studies.	0.598	0.042	0.875	0.599	14.197

Behavioural Intention (BI)						
BI1	I intend to use mobile-learning technology in the future.	0.272	0.009	0.884	0.271	30.769
BI2	I will always try to use mobile-learning technology in my daily studies.	0.298	0.014	0.860	0.299	21.725
BI3	I plan to use mobile-learning technology in future.	0.285	0.010	0.911	0.284	29.788
BI4	I will recommend other students to use mobile-learning technology.	0.287	0.011	0.848	0.288	27.094

Data analysis and results

As an analysis technique, this study used partial least squares (PLS) with Smart PLS 3.2.8 (Ringle et al., 2015) to identify determinants of m-learning in higher education. The data analysis encompassed two key steps: the first examining the measurement model to ensure that the gathered data achieved a good fit, and the second proceeding to the structural model as a measurement of hypotheses.

Measurement analysis

Before analysing the structural equation modelling, a pivotal step is to investigate the unidimensionality of the research model variables. The unidimensionality of each factor is confirmed if its Cronbach's alpha (internal consistency) and composite reliability (CR) values are equal to or greater than 0.7 (Garver & Mentzer, 1999). However, for exploratory studies such as this research, an internal consistency of 0.6 is also acceptable (Hair et al., 2006).

The average variance extracted (AVE) refers to the convergent validity of reflective factors that should not be less than 0.5 (Fornell & Larcker, 1981). The outer loadings of all items used to measure the research variables were greater than 0.7 as a threshold (Hulland, 1999). The data analysis also indicates that the multicollinearity assumption was not violated, as confirmed by the variance inflation factor (VIF) values. The discriminant validity of a research measurement is confirmed where the square root of the AVE for each factor in the research model is greater than the associations between the variable itself and other variables in the model (Fornell & Larcker, 1981). Based on the findings reported in Tables 2, 3 and 4, it is clear that the research measurement has met all recommended thresholds to support its validity and reliability.

To examine the relationship between the research model variables and their association with behavioural intention for m-learning, Pearson's correlation coefficient matrix was generated first. As proposed, Table 5 presents all variables that were significantly associated with the behavioural intention to use m-learning, in order to provide preliminary support for the research assumptions.

Table 3
Descriptive statistics, AVE, CR, VIF, Cronbach's alpha, outer weight and loadings of estimates made using the measurement model

	Mean	***SD***	**VIF**	**Cronbach's alpha**	**CR**	**AVE**
Behavioural Intention	4.1220	.87065	-	0.899	0.930	0.768
Confirmation	3.9513	.82245	3.179	0.866	0.918	0.788
Effort Expectancy	4.2734	.70870	2.741	0.860	0.904	0.703
Facilitating Conditions	4.0840	.75631	2.825	0.796	0.880	0.710
Perceived Autonomy	3.8374	.84514	2.174	0.663	0.856	0.748
Perceived Competence	3.9776	.89472	2.135	0.730	0.878	0.783
Performance Expectancy	4.2449	.71730	2.465	0.812	0.876	0.639
Social Influence	3.4648	.86483	1.574	0.884	0.928	0.811

Table 4
Discriminant validity of the research variables

	BI	Con	EE	FC	PA	PC	PE	SI
BI	0.876							
Con	0.680	0.888						
EE	0.599	0.666	0.839					
FC	0.480	0.644	0.737	0.843				
PA	0.607	0.633	0.569	0.673	0.865			
PC	0.575	0.698	0.530	0.532	0.575	0.885		
PE	0.663	0.702	0.635	0.560	0.508	0.588	0.799	
SI	0.505	0.514	0.487	0.421	0.394	0.402	0.573	0.901

Note. BI (Behavioural Intention), Con (Confirmation), EE (Effort Expectancy), FC (Facilitating Conditions), PA (Perceived Autonomy), PC (Perceived Competence), PE (Performance Expectancy), SI (Social Influence).

Table 5
Pearson's correlation analysis

	Con	EE	FC	PA	PC	PE	SI
BI	0.680**	0.599**	0.480**	0.607**	0.575**	0.663**	0.505**
Con		0.666**	0.644**	0.633**	0.698**	0.702**	0.514**
EE			0.737**	0.569**	0.530**	0.635**	0.487**
FC				0.673**	0.532**	0.560**	0.421**
PA					0.575**	0.508**	0.394**
PC						0.588**	0.402**
PE							0.573**

Note. BI (Behavioural Intention), Con (Confirmation), EE (Effort Expectancy), FC (Facilitating Conditions), PA (Perceived Autonomy), PC (Perceived Competence), PE (Performance Expectancy), SI (Social Influence).
**. Correlation is significant at the 0.01 level (2-tailed).

PLS analysis

In the first phase, the original constructs of UTAUT in predicting m-learning acceptance were investigated. As shown in Table 6 and Figure 3, UTAUT presents a good explanation of the variance of behavioural intention (R^2 = 0.509). Three out of four of the UTAUT constructs were significant determinants of m-learning, namely effort expectancy, performance expectancy, and social influence. This result provides good support for the original UTAUT in a non-Western context.

Table 6
Predictability of the UTAUT model

Relation	β	*t* value	*p* value	Findings
EE→BI	0.285	3.077	0.002	Supported
FC→BI	-0.019	0.218	0.827	Rejected
PE→BI	0.416	6.126	0.000	Supported
SI→BI	0.137	2.479	0.015	Supported

Note. BI (Behavioural Intention), EE (Effort Expectancy), FC (Facilitating Conditions), PE (Performance Expectancy), SI (Social Influence).

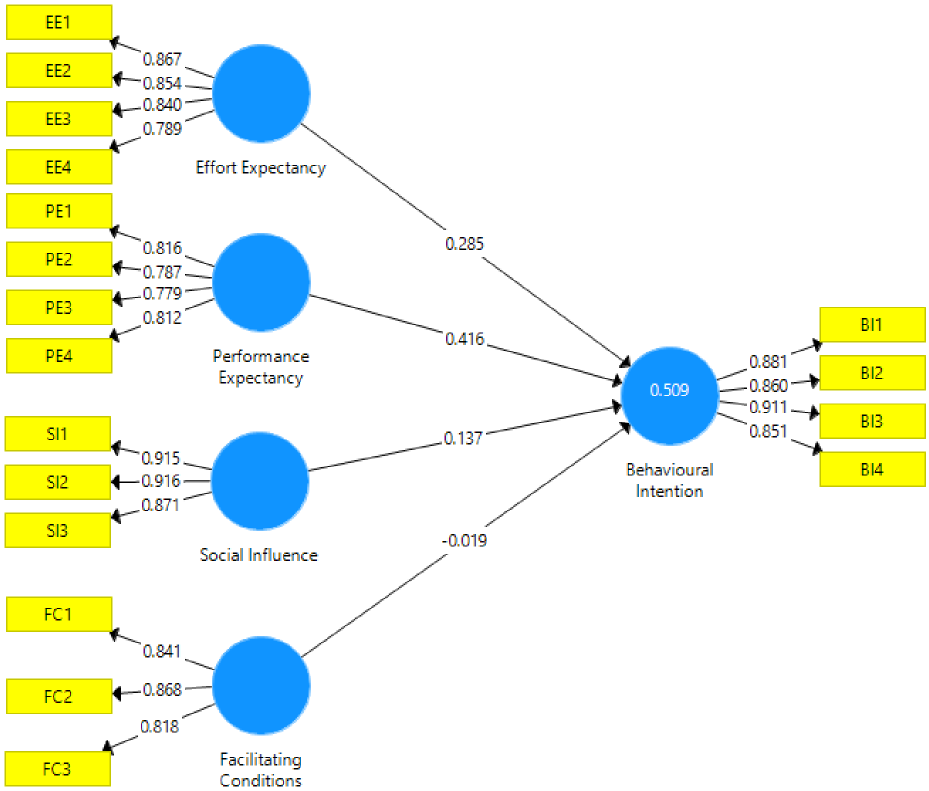

Figure 3. Predictability of the UTAUT model

In the second phase, the integrated model was examined. Table 7 and Figure 4 illustrate the findings from the PLS structural model findings. Standardised path coefficients are presented, and R^2 is depicted in combination with each endogenous construct. Overall, eight out of 10 hypotheses were confirmed (H2 to H9), where the effect of the integrated variables on m-learning acceptance was established. The p value is set as significant at 0.05.

Concerning the UTAUT constructs after extension, social influence displayed an insignificant effect on behavioural intention, thereby rejecting H1. Moreover, facilitating conditions had a significant impact on behavioural intention, consequently supporting H2. Moreover, as assumed in H3 and H4, effort expectancy and performance expectancy were significantly related to m-learning adoption. The analysis also confirmed that facilitating conditions predicted effort expectancy (H5), while effort expectancy had a significant effect on performance expectancy, thereby supporting H6.

Regarding the extended variables, confirmation was found to be a significant determinant of m-learning use and performance expectancy, confirming H7 and H8. Furthermore, perceived competence was a predictor of behavioural intention, supporting H9. Conversely, perceived autonomy was an insignificant predictor of m-learning adoption, thereby rejecting H10. Significant predictors accounted for 54.3%, 54.3% and 60.5% of the variance of effort expectancy, performance expectancy and behavioural intention respectively (R^2 = 0.543, R^2 = 0.543 and R^2 = 0.605).

Table 7
Analysis of the research model hypotheses

Hypothesis	β	*t* value	*p* value	Findings
H1: Social Influence → Behavioural Intention	0.094	1.823	0.068	Unsupported
H2: Facilitating Conditions → Behavioural Intention	-0.245	2.811	0.005	Supported
H3: Effort Expectancy → Behavioural Intention	0.206	2.245	0.025	Supported
H4: Performance Expectancy → Behavioural Intention	0.259	3.463	0.001	Supported
H5: Facilitating Conditions → Effort Expectancy	0.737	20.45	0.000	Supported
H6: Effort Expectancy → Performance Expectancy	0.298	4.201	0.000	Supported
H7: Confirmation → Behavioural Intention	0.230	2.665	0.008	Supported
H8: Confirmation → Performance Expectancy	0.504	7.770	0.000	Supported
H9: Perceived Autonomy → Behavioural Intention	0.299	4.149	0.000	Supported
H10: Perceived Competence → Behavioural Intention	0.074	1.097	0.272	Unsupported

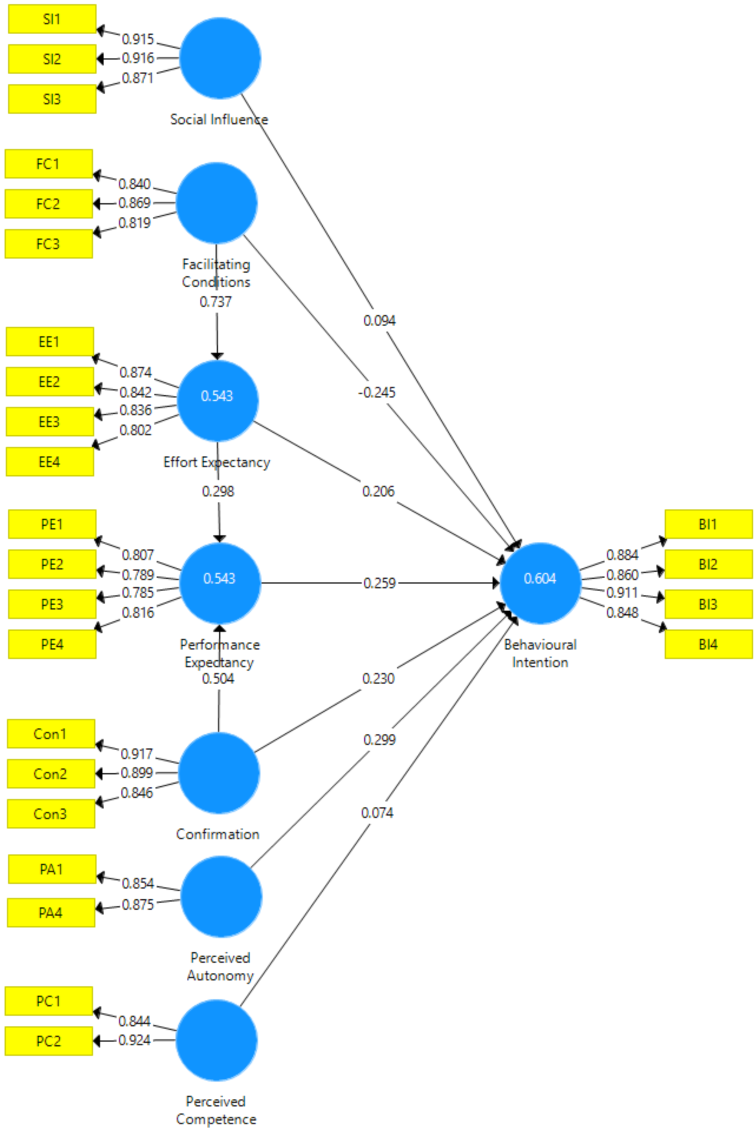

Figure 4. Structural model results

Discussion and contributions

This research aimed to investigate m-learning acceptance by integrating three theories into a single model. The proposed research framework included different variables, perfectly applied from the adopted theories to identify the antecedents of m-learning acceptance. The results suggested that the original UTAUT had good explanatory power for behavioural intention variance (50.9%). However, this was significantly improved after introducing other constructs from the integrated theories to explain 60.4% of behavioural intention variance. It was found that most of the factors included in the proposed model had a significant effect on m-learning adoption. Moreover, only facilitating conditions explained 54.3% of the variance of effort expectancy, whereas effort expectancy and confirmation accounted for 54.3% of the variance of performance expectancy.

The first aim of this research was to investigate the predictive ability of the original UTAUT model. This was achieved through a PLS approach to examining the cause and effect associations between the model's constructs. The findings indicated that UTAUT explained 50.9% of the variance of behavioural intention. Effort expectancy, performance expectancy and social influence were predictors of m-learning, whereas facilitating conditions had no significant effect on behavioural intention. Overall, such outcomes may provide empirical evidence of this model's potential to be used in different cultural contexts with different technologies. Although the model demonstrated good predictability power, we suggest that its extension could lead to better results.

Regarding the UTAUT variables after integrating the expectation-confirmation and self-determination theories, the findings support the overall effect of its factors on learners' behaviour to accept m-learning. However, social influence was found to be a weak predictor of behavioural intention. Thus, hypothesis H1 was rejected. Although this result is inconsistent with the findings of Briz-Ponce et al. (2017) and Aliaño et al. (2019) that social influence significantly affected m-learning acceptance, the result supported Nassuora (2013), whose study showed that social influence had an insignificant association with learners' m-learning behaviour in Saudi Arabia. A possible explanation is that the influence of the integrated variables was higher than the effect of social influence in the proposed model. In turn, this led to a reduction in its overall effect. The above explanation can be supported if the findings for the original UTAUT are noted (see Table 6 & Figure 3), since they clearly indicate social influence as a predictor of behavioural intention in m-learning. Iqbal and Qureshi (2012) argued that the insignificant effect of social influence on m-learning adoption in developing countries could be due to the absence of supporting technology as well as to the high cost of smartphones. Moreover, Venkatesh et al. (2003) indicated that social influence has the biggest impact at an early stage of technology adoption but may decrease over time. Conversely, Al Adwan et al. (2018) declared that students do not make technology adoption decisions outside their social environment, where peers, faculties and individuals influence their m-learning adoption. Such inconsistent findings may be attributed to several factors, including overall living costs, the specific culture of the sample under investigation or the type of antecedents included in the particular theoretical model, as some variables have more impact than others.

This research also shows that both performance expectancy and effort expectancy significantly affected the prediction of m-learning use, thereby supporting hypotheses H3 and H4. In fact, these results agree with the original assumption of the UTAUT model (Venkatesh et al., 2003). However, as found in the previous literature, performance expectancy had more influence than effort expectancy on technology adoption (Aliaño et al., 2019; Briz-Ponce et al., 2017). This may indicate that when users perceive the usefulness of a particular technology, they are willing to use it, regardless of their individual skill in its use. Accordingly, educational institutions should pay further attention to integrating valuable functions and a variety of services that could help fulfil the learners'anticipated needs.

The findings of hypothesis H5 revealed that the facilitating conditions variable predicts effort expectancy. Moreover, effort expectancy was found to be a determinant of performance expectancy, confirming hypothesis H6. Overall, these findings support recent studies (Aliaño et al., 2019; Althunibat, 2015; Nikou & Economides, 2017), which indicate that if learners feel that an educational institution is offering them the required technological support, the effort they expend in performing a particular behaviour will increase. Moreover, when users believe that they will not need much effort to enact a particular behaviour, their perception of a technology's usefulness (perceived usefulness) may be positively affected. Hence, universities and other educational institutions need to offer their students the required technical support to ensure that they use technology successfully. Training courses or workshops are also important for enhancing learners'self-confidence and reducing the effort required in their technology use.

Concerning the expectation-confirmation theory, we propose that confirmation is a predictor of behavioural intention and performance expectancy. This is a new assumption, although it has been suggested that the relationship between confirmation and behavioural intention is mediated by satisfaction (Lai & Zhao, 2019). The rationale for this assumption is that identical constructs can be used to predict satisfaction and behavioural intention. The empirical analysis in this study supports hypothesis H7, which means that when learners' initial expectations are confirmed, their willingness to adopt technology is increased accordingly. This is a key finding in the present work, as pre-acceptance perceptions are based on cognitive beliefs – for example, effort expectancy and performance expectancy – which are perhaps based on other sources, popular media or referent others (Bhattacherjee, 2001). In light of such beliefs, users' attitudes may be unrealistic or uncertain. On the contrary, confirmation reflects users' satisfaction with a technology, which may be unbiased, but more realistic in influencing their final decision. In agreement with previous research (Bhattacherjee, 2001), this study also confirms the significant influence of confirmation on performance expectancy, supporting hypothesis H8. A possible explanation of this significant association is that learners may initially have a low performance expectancy of a learning technology due to their uncertainty over its use. However, confirmation will elevate learners' performance expectancy, adjusted as a consequence of confirmation experience.

Meanwhile, concerning the self-determination theory, two of its main items were used as direct predictors of the behavioural intention to adopt m-learning: perceived autonomy and perceived competence. The first assumption was confirmed (H9), whereas hypothesis H10 was rejected. These results are consistent with a recent study conducted by Lu et al. (2019), which also confirmed that while perceived competence did not predict behavioural intention, perceived autonomy was a significant determinant of this factor. It may indicate that when learners feel they can make their own choices and initiate their activities without pressure, their willingness to adopt technology is correspondingly affected. Hence, this present research proved the self-determination theory assumption (Ryan & Deci, 2000) regarding the effect of perceived autonomy. As perceived competence refers to users' desire to feel effective in achieving important outcomes, it was expected that this factor would significantly influence behavioural intention (H10). Interestingly, the analysis rejects this assumption, suggesting instead that Saudi students care more about self-regulation than about their ability to make a pre-acceptance decision.

This study contributes to different streams of information systems, and m-learning in particular. Its key contribution is the integration of three well-known and widely accepted theories, integrating UTAUT, the expectation-confirmation theory, and the self-determination theory to investigate m-learning acceptance in higher education. Thus, it extends research that has focused exclusively on UTAUT and/or the two other theories in explaining users' behaviour towards a particular technology. Accordingly, this study establishes a broad understanding by developing a more comprehensive mode, integrating theories that originate from a quite different perspective.

Based on these theories, this research has highlighted many important findings. First, social influence revealed a weak effect on behavioural intention towards m-learning, after integrating the two other theories with UTAUT. This suggests that when learners' perceptions of confirmation and self-determination are considered, their concern for other people's opinions will be low, because other perceptions have a stronger influence on behavioural intention. Second, confirmation was found to be a strong predictor of both behavioural intention and performance expectancy. Previous literature has proposed that satisfaction is a mediator between confirmation and behavioural intention (Lai & Zhao, 2019; Wijaya et al., 2019). The current study, however, confirms a direct association between confirmation and behavioural intention, without the mediation of satisfaction. This is an interesting outcome, which suggests that learners' behavioural intention and perceptions of usefulness are significantly improved if their initial expectation is confirmed. However, the findings suggest that confirmation has a stronger effect on performance expectancy than on behavioural intention to support the original assumption of this theory (Bhattacherjee, 2001). Finally, an investigation of the two parameters of self-determination theory revealed that perceived autonomy was a significant factor in explaining behavioural intention for m-learning, whereas perceived competence had a low effect on this variable. Thus, when users felt no pressure to adopt technology, their individual willingness was significantly increased. These findings open up the possibility of using more factors to explain m-learning adoption. Therefore, the study complements earlier literature by providing a possible explanation of the role of different theories in shedding light on technology acceptance.

Conclusion

This research integrated three well-known theories to predict m-learning acceptance in higher education. The PLS technique was applied to analyse the research data. The findings support the extension of the UTAUT model through the theories of self-determination and expectation-confirmation. The original UTAUT model explained 50.9% of the variance of behavioural intention, whereas the proposed model explained 60.4% of the variance of behavioural intention to accept m-learning. Thus, the present study confirms the effect of users' basic psychological needs on their final decision to adopt a technology. Based on these outcomes, several conclusions may be drawn:

1. Although UTAUT is an effective framework for understanding technology acceptance, regardless of cultural differences or the type of technology, its overall predictability power can be improved by integrating constructs from other theories, which may have quite dissimilar assumptions.
2. Unlike other studies, this research supports a direct relationship between confirmation and the behavioural intention to adopt m-learning in the context of Saudi higher education.
3. Perceived autonomy was found to be a direct and significant predictor of the behavioural intention to use m-learning.
4. Even though social influence has a significant effect on technology adoption, its role may be reduced when considering other users' perceptions.
5. As the learners showed high perceptions of the use of m-learning for different educational activities, universities and schools could exploit the advantages of this technology to deliver learning content and enhance the learning process. More specifically, m-learning could provide an excellent opportunity for students to learn continuously in specific times of crisis, such as the current global COVID-19 pandemic.

Although this research generated significant findings, it is not without limitations. First, the data were collected from students in one discipline (computer science). Further research could focus on other specific disciplines such as medicine, engineering and the humanities to compare students' perceptions of m-learning according to discipline. However, as discussed previously, most of the current findings are aligned with literature examining m-learning adoption among students from different disciplines and cultures. This could provide some support for the generalisability of the findings. Moreover, this study examined m-learning acceptance based on students' perspectives, whereas identifying teachers' adoption and use of such technologies is another research direction that should be pursued. Finally, a quantitative research design was applied in this study. Future research could, therefore, adopt a mixed methods design, integrating both quantitative and qualitative approaches to obtain findings that are more reliable and valid for a holistic understanding of m-learning acceptance.

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