International Journal of Intellectual Human Resource Management (IJIHRM)

2021; 2(2): 08-14
https://journals.gulfuniversity.org/index.php/ijhrm
DOI: 10.46988/IJIHRM.02.02.2021.002
ISSN: 2535-9800 (Print); ISSN: 2536-0043 (Online)

Impact of Individual Belief, Facilitating Condition, and Habits on the Acceptance and Support to Use Mobile Training

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Article Info

Article history:
Received 20 May 2021
Received in revised form 20 June 2021
Accepted 29 August 2021
Published 01 October 2021

Abstract

Implementation and adoption of mobile training are still nascent in the public sector in the UAE. A successful migration model for a mobile training system relies on user support and acceptance as well as the decision to migrate to mobile training. The study aims to investigate a comprehensive range of the factors that influence the intention to use and support to change to mobile training in the Sharjah police general command – UAE. The proposed conceptual framework includes Individual Beliefs (attitude) (IB), Facilities Condition (FC), Habits (HA), Intention to Use Mobile Training (IUMT), and support to change to mobile training (SCMT). The study's target population is all the staff members of the General Department of Sharjah Police in the Emirate of Sharjah, which has a total of 7,715 employees and a sample size of 367. The final dataset includes 373 respondents collected from 19 different departments by using the quota sampling technique. Results of intention to use mobile training (IUMT), illustrate a satisfactory predictive power; the three variables; IB, FC, and HA can explain 44.6% of the variance. The precedence of the impacts based on the path coefficient is individual belief, facilitating conditions, then habit. Results of support to change to mobile training (SCMT), illustrate a moderate predictive power; the four variables; IUMT, IB, FC, and HA can explain 63.6% of the variance. The precedence of the impacts based on the path coefficient is the intention to use mobile training, then individual belief. The three main predictors have impacts on the support to change to mobile training (SCMT) either directly or indirectly. Based on the total effect, the precedence of the three main variables is individual belief, facilitating conditions, then habit.

Keywords: Individual Belief, Facilities Condition, Habit, Intention to Use, Support to Change, Mobile Training

1. Introduction

Mobile learning is a critical component of higher education, and thus its acceptance and adoption receive growing interest, however, recent studies have indicated that although many universities have extended their online learning platforms to mobile services, students' interest and usage of m-learning is not as high as expected (Alexander et al., 2019). For instance; Chao (2019) examined a proposed UTAUT model in the context of m-learning by surveying recruiting university students in central Taiwan. The proposed conceptual framework has four external variables, mobile self-efficacy, perceived enjoyment, satisfaction, and trust and the results shows that the four variables have influence on students 'effort expectancy, performance expectancy, and satisfaction toward m-learning (Chao, 2019). Besides, policymakers and educators promoting the usage of m-learning can program and deliver some education and training courses in various mobile computing technologies to build old people's (Montrieux et al., 2015). Even if these courses are not directly related to m-learning, they can still help older people develop positive ease-of-use beliefs, which can, in turn, influence their behavioral intention to use m-learning (Al-Emran et al., 2020).

What is of interest is what the conceptual and the abstract units of the infrastructure mobile learning, as well as training, entail informal beyond the conceptual level, as well as the development of the units of the infrastructure and their relational properties artifacts in practice (Manley & Chen, 2017). Users are the main stakeholder in making the effective use of new mobile training systems. Therefore, the perceptions of employees as the main stakeholder of the system acceptance are important in the process for mobile training system adoption. Mobile technology is thought to have the ability to build interesting learning environments that engage learners (Harley et al., 2019). When exploring the recent and most related theories of technology acceptance, the UTAUT 3 model is an excellent base because it includes three essential antecedent variables, which is attitude, facilitating conditions, and habit. Venkatesh make it flexible to add precedence factors and antecedents variables according to the different systems and applications (Venkatesh et al., 2016).

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Therefore, this article is proposing a conceptual framework that include three dimensions of technology acceptance including employees' attitude, facilitating conditions, and habit of using the system, which can contribute to the proper decision and adoption of the mobile training system in UAE.

2. Literature Review

2.1. Individual Belief

Individual Belief (Attitude) developments have also led to the use of mobile technologies for educational purposes, the successful integration of mobile learning (m-learning) (Al-Emran et al., 2016). Earlier studies have confirmed that learning anywhere and anytime is only possible with mobile devices. The development in technology has shifted the attitude of individuals which also varies from society to society (Moote et al., 2020). In the mobile learning context, many studies use the technology acceptance (TAM) model and unified theory of acceptance and use of technology (UTAUT) as a base for the inclusion of individual belief. Many studies examined the influence of individual belief (attitude) on behavioral intention and found significant effect (Dwivedi et al., 2019). It is a cutting-edge platform mostly driven by smartphones and its usage is increasing in educational society day by day, it is the widely used technology of the modern world and due to the proliferation of technology, the education sector is getting benefits (Collins & Halverson, 2018).

The evolution of digital networks and electronic communication reshaped individuals and groups communication and entertainment, and this transformation has a tremendous effect on education platforms and learning approaches include the commence of mobile learning (Anbalagan, 2020). The mobile learning increases the ability of students to learn and memorize things for long, by associating feeling with it as well as providing entertainment for learners (Metom et al., 2020). Mobile entertainment is also one of the important determinants in measuring the attitude and behavioral intention of students (Molina et al., 2020). In digital communications, informativeness is measured as a vital construct that has a significant effect on the attitude of individuals, due to the rapid development of mobile devices and mobile internet usage, users can access wireless networks to browse information anytime, anywhere (Alameddine et al., 2020).

2.2. Facilitation Conditions

The construct of facilitating conditions was originally suggested to be a primary predictor of actual usage and not behavioral intention. The idea is that facilitating conditions in terms of access, infrastructure, training, technical support, and other related issues would mainly affect the nature, type, and frequency of use and not the behavioral intentions of users (Alharbi et al., 2020). Previous studies indicated that in the context of developing countries, the influence of facilitating conditions on technology adoption is not direct (Kamal et al., 2020). These are perceptions of individuals that technical and organizational infrastructure required to use and support an intended system are available and thus intention to adopt new technologies should not be an issue (Dwivedi et al., 2019). The experience shows that the slow access and continuous downtimes of e-learning sites is the major cause of the lack of motivation in adopting and use of e-learning (Arnaert et al., 2020). Therefore, need to ensure and sustain the availability of e-learning sites 24/7 by reducing the down times to less than 1%, and improving access to a reasonable speed to encourage users and build their confidence that the system is available when needed Institutions should as well consider alternative sources of electricity like solar, use of inverters and power generators as means to sustain the availability of e-learning systems (Kuppusamy, 2019).

2.3. Habits

Habits are routine behaviors done on a regular basis. They are recurrent and often unconscious patterns of behavior and are acquired through frequent repetition. A habit can also be thought of as a link between a stimulus and a response. It serves as a mental connection between a trigger thought or event (stimulus) and our response to that trigger (the response). This indication will drive people to use smartphones in public places and it can be recognized as a habit disorder, the use of a mobile phone could be categorized as a habitual behavior (De-Sola et al., 2019). The new trend of studies is emphasizing exploring how technology usage habits, mobile payment usage habit, mobile service usage habit (other than mobile payments), cell phone usage habit, learning, and online shopping habit, affect consumers' intention to continue using mobile payments (Alalwan, 2020). The effect of mobile payment usage habit on their future usage of mobile payments pertains to the first three levels while the effect of their online shopping habit, mobile service usage habit, learning, and cell phone usage habit (Moorthy et al., 2019). With advanced technology nowadays, has made the citizen become more dependent on a smartphone, the excessive use of smartphones is considered to be a problematic mobile phone use as behavioral addiction such as loss of control, tolerance, and withdrawal (Mitchell & Hussain, 2018).

2.4. Intention to Use Mobile Training

These challenges mean that adaptation to mobile learning is not an easy job, and users may be inclined to not accept mobile learning, thus, the success of mobile learning may depend on cost-effectiveness, wireless infrastructure reliability, and comfort level learners with mobile learning (Edwards, 2017). A number of studies investigated the intention of using mobile learning by adopting the Technology Acceptance Model as a foundation for research design (Chau & Hu, 2002). A major deficiency of TAM is lacking outer variables that have effects on the intention of users for using technology (Elshafey et al., 2020). The results of the study indicated that performance expectancy, effort expectancy, social influence, perceived playfulness, and self-management of learning were important moderators of behavioral intention to use mobile learning (Al-Emran et al., 2020). Moreover, researchers investigated the effect of gender and age differences on moderators of mobile learning acceptance in the study, according to the researchers, there were three main results about the effects of gender and age differences on mobile learning acceptance of pre-service teachers (Alasmari & Zhang, 2019). This research extends the TAM by adding three new variables digital literacy, information, and communications technology (ICT) anxiety, and ICT teaching self-efficacy to determine a more complete picture of lecturers' behavioral intention to use mobile learning (Chang et al., 2017). According to the TAM, the intention to use new technology is determined by two factors, perceived usefulness and perceived ease of use (Imawati et al., 2018).

2.5. Support to Change to Mobile Training

The delivery and support of learning using mobile 'phones and in the last five years have steadily assumed a place in further and higher education, supporting distance learners and part-time students (Traxler, 2005). Support to change to mobile training can be defined as any educational provision where the sole or dominant technologies are handheld or palmtop devices (Traxler, 2020). Support to change to mobile training could include mobile 'phones, smartphones, personal digital assistants (PDAs) and their peripherals, perhaps tablet PCs and perhaps laptop PCs, but not desktops in carts and other similar solutions (Ennouamani et al., 2020). This will emerge as educationalists become more confident in exploiting and integrating the diversity of ways that mobile devices can interact with the outside world, including cameras and speech technologies (Banini, 2019). If it is to emerge, it will need to refer back to theories and accounts of for example informal learning, situated learning, and bite-sized learning that have little connection with e-learning or other forms of technology-supported learning (Traxler, 2020). M-learning supports performance with easy access to information, which can at once impact students' performance in a learning environment, facilitating their education (Al-Emran et al., 2020). Mobile learning also helps students facing financial, family, or health problems in migrating out to university classes, finally, M-learning is self-motivated, self-disciplined that supports studying with time waste, studying anywhere and at any time (Al Murshidi, 2017).

3. Conceptual Framework of the Study

The research framework of this particular study has individual belief, facilitation conditions, habits as independent variables, which have a direct impact to support to change to mobile training. Besides, to the mediating impact of intention to use mobile training in the relationship between determinates individual belief, facilitation conditions, habits, and support to change to mobile training (As seen in Figure 1).

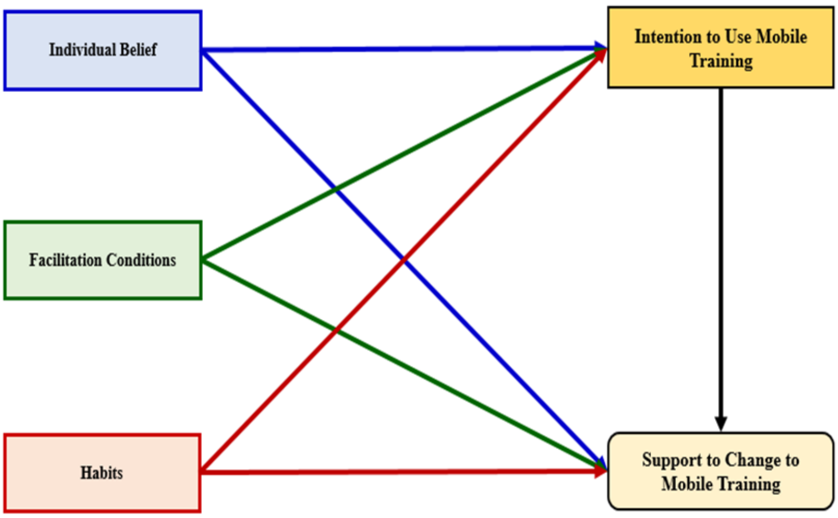

Fig. 1. Conceptual Framework of the Study

4. Research Methods

Research design is a structure and strategy to investigate the research question. The nature of this study is a quantitative approach. Sekaran and Bougie (2016) have identified business research has three types 1) exploratory, 2) descriptive, and 3) causal. This research is exploratory in nature because it explores new areas of the public sector in the UAE. Previous knowledge includes a sufficient amount of knowledge that can be built upon to discover new information that is more profound and relevant to the subject of study. The measurement used on each variable is cited through previous studies where the items will be applied in order to answer the research questions. The design is one-shot or cross-sectional as the data will be gathered just once, perhaps over a period of days or weeks, or months, in order to answer research questions. A questionnaire will be distributed to all respondents and collected after they complete answer the measurement. The validity of the survey instrument is observed in its content and one of the methods of checking validity is by using the face validity method, in which a test is subjectively viewed as covering the concept it purports to measure.

The questions that ask for variables' perceptions are designed to be answered on an ordinal scale of five-point, in which 1 is the high level of disagreement (extremely disagree) and 5 is the high level of agreement (extremely agree). This scale is known as the Likert-5 scale which is mostly used by scholars in social-based studies. A Five-point Likert-type scale was used to increase response rate and response quality along with reducing respondents' "frustration level" (Babakus and Mangold 1992). The structural equation modeling (SEM) is among the very most proper process for the number of causes including it is greatest among existing procedures which are actually very leading and deliver the additional durable option of analyst issues which just van certainly not be attained from numerous regressions. According to Hair et al. (2016), the (partial least squares) PLS strategy serves specifically when the exclusive objective of making use of structural modeling is actually to obtain explanation and forecast regarding the constructs. SmartPLS software is used as the main tool for analysis to perform two sets of examinations: measurement model tests and structural model tests. Measurement model tests include tests for validity and reliability for the model and the dataset. However, the main results for relations and predictions are coming from structural model tests, in which regression-based analysis is applied by using the PLS algorithm, bootstrapping, and blindfolding.

5. Findings

5.1. Validity and Reliability of Constructs

Internal consistency can be estimated by Cronbach's Alpha or composite reliability measures. Any measure above the threshold of 0.7 is successful. In addition, 0.6 is considered successful in exploratory research (Bagozzi & Yi, 1988; Hair et al., 2014). Table 1 shows the results of all the study variables, which show an acceptable level of reliability. For composite reliability, all the values are within the range between 0.897 and 0.954, which shows an adequate internal consistency. For Cronbach's Alpha reliability, the values are ranged from 0.845 to 0.936, which shows an adequate level of internal consistency. As all results are in the range between 0.7 and 0.95, the dataset is internally reliable and consistence.

The matrix is a refined matrix of the latent variable's correlations. The test is successful if the value in the diagonal is higher than any other value within the crossed column and raw. For instance, FC has the value of 0.930, which is higher than all the other scores within the shared column and raw. The rest of the study's variables have a good adequate level of discriminant validity. In order to assure the discriminant validity, a cross-loading test is also used, in which the items must have a proper and higher loading in their associated variables than any other loading in any foreign variable. Table 2 shows the results of cross-loading of all items in the rows and all variables in the columns. Based on the Fornell & Larcker criterion matrix and the cross-loading table, the dataset of this particular study is free of any discriminant validity problems and can proceed to the next statistical examinations.

Table 1. Constructs Reliability and Validity

	Composite Reliability	Cronbach's Alpha
Individual Belief (IB)	0.918	0.865
Facilitation Conditions (FC)	0.950	0.921
Habits (HA)	0.897	0.845
Intention to Use Mobile Training (IUMT)	0.954	0.936
Support to Change to Mobile Training (SCMT)	0.913	0.872

Table 2. Discriminant validity – Fornell-Larcker Criterion

	FC	HA	IB	IUMT	SCMT
Facilitation Conditions (FC)	0.930				
Habits (HA)	0.160	0.828			
Individual Belief (IB)	0.111	0.239	0.888		
Intention to Use Mobile Training (IUMT)	0.352	0.405	0.553	0.916	
Support to Change to Mobile Training (SCMT)	0.309	0.352	0.505	0.795	0.851

5.2. Relationships Examinations and Discussions

The predictive power and predictive relevance of the endogenous latent variables; individuals' attitude (IB), facilitating conditions (FC), habits (HA), Intention to Use Mobile Training (IUMT), and support to change to mobile training (SCMT). Results of individual belief (IB), illustrate a low predictive power and a small predictive relevance. The related R square value is 0.178 (explanation power of 17.8%) and the related Q square is 0.140 (explanation relevance of 14.0%). Results of facilitating conditions (FC) illustrate a satisfactory predictive power and a large predictive relevance. The related R square value is 0.480 (explanation power of 48.0%) and the related Q square is 0.414 (explanation relevance of 41.4%). Habits (HA), illustrate a low predictive power and a small predictive relevance. The related R square value is 0.105 (explanation power of 10.5%) and the related Q square is 0.073 (explanation relevance of 7.3%). The intention to use mobile training (IUMT), illustrates a satisfactory predictive power and a medium predictive relevance. The related R square value is 0.446 (explanation power of 44.6%) and the related Q square is 0.372 (explanation relevance of 37.2%). The three variables; IB, FC, and HA can explain 44.6% of the intention to use mobile training (IUMT) variance. Results of support to change to mobile training (SCMT), illustrate a moderate predictive power and a large predictive relevance. The related R square value is 0.636 (explanation power of 63.6%) and the related Q square is 0.452 (explanation relevance of 45.2%). The four variables; IUMT, IB, FC, and HA can explain 63.6% of the support to change to mobile training (SCMT) variance (As per table 3).

Table 3. Predictive Power and Predictive Relevance of Proposed Model

	Predictive Power		Predictive Relevance	
	R Square	Status	Q Square	Status
Individuals' Belief (IB)	0.178	low	0.140	small
Facilitating conditions (FC)	0.480	satisfactory	0.414	large
Habits (HA)	0.105	low	0.073	small
Intention to Use Mobile Training (IUMT)	0.446	satisfactory	0.372	medium
Support to Change to Mobile Training (SCMT)	0.636	moderate	0.452	large

Table 4 shows the findings of the relationships between the variables. The rule of thumb to accept or reject the relationship is either the p-value less than 0,05 or the t statistics is more than 1.98 (Hair Jr, Wolfinbarger, Money, Samouel, & Page, 2015). The T statistics estimates of the research designed model and the path coefficient assessment with the values of T Statistics and Beta values for the outcome variable support to change to mobile training SCMT. For the predictors of the individual's belief (IB), the path coefficient is (0.464), the facilitating conditions (FC) the path coefficient is (0.260). The predictors of the habit (HA) are the path coefficient (0.252). For the predictors of the intention to use mobile training (IUMT), the path coefficient is (0.711). The two variable facilitating conditions and habit have no significant direct effect.

Table 4. Path Coefficient Assessment of the Direct Relationships

	Path Coefficient	Standard Deviation	T Statistics	P Value (one tailed)	Status

IB → IUMT	0.464	0.035	13.280	0.000	Significant
FC→ IUMT	0.260	0.040	6.552	0.000	Significant
HA → IUMT	0.252	0.036	7.055	0.000	Significant
IB → SCMT	0.099	0.044	2.256	0.024	Significant
FC → SCMT	0.043	0.033	1.277	0.202	Non-Significant
HA→ SCMT	0.033	0.030	1.088	0.277	Non-Significant
IUMT → SCMT	0.711	0.058	12.282	0.000	Significant

Table 5 shows the mediating role of the variable intention to use mobile training (IUMT) in the relationships between the independent variables (Individuals' belief, facilitation conditions, and habits) and the dependent variable, support to change to mobile training (SCMT). The indirect relationship (IB -> IUMT -> SCMT) is significant with a P-value of 0.000 (less than 0.05) and path coefficient of 0.330, and the total effect is significant with a P-value of 0.000 (less than 0.05) and a path coefficient of 0.425 both the direct and indirect effects are significant. The indirect relationship (FC -> IUMT -> SCMT) is significant with a P-value of 0.000 (less than 0.05) and path coefficient of 0.184, and the total effect is significant with a P-value of 0.000 (less than 0.05) and a path coefficient of 0.227 the indirect effect is significant. The indirect relationship (HA -> IUMT -> SCMT) is significant with a P-value of 0.000 (less than 0.05) and path coefficient of 0.179; the total effect is significant with a P-value of 0.000 (less than 0.05) and path coefficient of 0.212 the indirect effect is significant.

Table 5. Path Coefficient Assessment of the Mediating Effects

	Direct Effect			Indirect Effect			Total Effect		Status (Mediation)
	Path Coeff	P-Value	Status	Path Coeff	P-Value	Status	Path Coeff	P-Value	
IB -> IUMT -> SCMT	0.099	0.024	Sig	0.330	0.000	Sig	0.429	0.000	Partial mediation
FC -> IUMT -> SCMT	0.043	0.202	Non-Sig	0.184	0.000	Sig	0.227	0.000	Full mediation
HA -> IUMT -> SCMT	0.033	0.277	Non-Sig	0.179	0.000	Sig	0.212	0.000	Full mediation

6. Contributions and Recommendations

This research is limited to the is the relationship between individual belief, habits, and facilitating conditions; and support to change to mobile training among employees in the Sharjah police general command of the ministry of interior – UAE. That means, the results are limited and only represent a specific group of the specific area employees. In addition, similar industries in other countries could have different contextual conditions, which may output different results. The public sector is one of the significant sectors in the UAE, but there are many other essential sectors such as SMEs, education, and many other sectors that have a major interest in the acceptance of mobile training. This study's results are limited, and the perceptions are associated with the public sector only. Data collection of closed questions can limit the perceptions of the respondents to the pre-defined questions. This study used closed-end questions and there are no open-end questions. While this approach is common in the deductive approach but adding open-end questions can provide insight for further inductive results, which may be useful for extra investigation.

This study proposed a developed model with new constructs and relations. While the model was assessed successfully, further research is needed to assess the model in different environments. One of the constraints is the limited approach of implementation, which reduces the generalization; therefore, replicating the same study in another context such as education or SMEs in the UAE and in other countries is recommended to get a better understanding and generalization. Another constraint is the participant's types and selection, employees in the Sharjah police general command of the ministry of interior – UAE, which reduce the generalization, therefore replicating the same assessment in other industries such as energy or other sector is recommended to get a better understanding and generalization. Recommendations are extended, to test the model and the instrument in other ministries or even to test whether this model can be suitable for other sectors.

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