



Implementing Artificial Intelligence in the United Arab Emirates Healthcare Sector: An Extended Technology Acceptance Model

Shaikha FS Alhashmi¹, Said A. Salloum^{1,2}, and Chaker Mhamdi^{3,4}
shaikha.alattar@hotmail.com; ssalloum@sharjah.ac.ae; shaker@buc.edu.om

¹ Faculty of Engineering & IT, The British University in Dubai, Dubai, UAE

² Research Institute of Sciences & Engineering, University of Sharjah, Sharjah, UAE

³ University of Manouba, Tunisia

⁴ Al Buraimi University College, Oman

Abstract. The United Arab Emirates (UAE) has recently focused on implementing Artificial Intelligence (AI) projects in the government healthcare sector to help manage chronic diseases and early detection. However, successful AI implementation depends on adoption and acceptance by decision-makers, physicians, nurses, and patients. This paper develops and tests a modified Technology Acceptance Model (TAM) to explore critical success factors (CSFs) for the adoption of AI in the healthcare sector. The most widely used CSF variables for TAM are Perceived Usefulness (PU), Perceived Ease of Use (PEU), Attitudes toward Use (ATU) and Behavioral Intention to Use (BIU). However, a review of 23 qualitative and quantitative studies of TAM literature from 2015 to 2018 suggested that five key external factors should be included in CSF studies using TAM. An extended model was developed (ETAM) and tested using a qualitative study comprising 53 employees working in the Dubai IT and healthcare sectors. The study showed that managerial, organizational, operational and IT infrastructure factors have a positive effect on PU and PEU and, hence, should be included as CSFs in determining the implementation of AI in the healthcare sector.

Keywords: *United Arab Emirates; critical success factors; extended technology acceptance model; artificial intelligence; healthcare.*

1. Introduction

Governments of the UAE are increasingly implementing technology strategies, including the adoption of AI in the public and business sectors (Government.ae). Many initiatives are underway, including the Dubai Electricity and Water Authority (DEWA). The purpose of this study is to present and test a model to assist in the successful adoption of AI in the Dubai government health sector, specifically to improve services for patient monitoring (Dubai Health Authority 2018); however, the CSFs identified in the ETAM developed and tested herein apply to AI adoption for other types of medical and healthcare services. The paper proceeds with a literature review that reveals five key external factors that should be included as CSFs in existing TAMs. It then develops an ETAM and tests its hypotheses using standard methodological measures for internal consistency and validity and a qualitative survey to assess its effectiveness in predicting the successful adoption of AI in healthcare. There are many different definitions of AI in the literature (Ghannajeh et al., 2015; Mokyry, 2018). However, the most relevant for this paper, given the scope for AI adoption across medical and healthcare practices is the broad conception provided by (Mijwel, 2015) who uses the term to refer to human intelligence processes that are simulated by computer systems including learning, reasoning, problem-solving, speech recognition and planning.

2. Literature Review

Recently, nobody can deny the role of AI and how it is incorporated in various applications, including reinforcement learning (Al-Emran, 2015a), robots (Al-Emran, 2015b), NLP (Al-Emran, Zaza, & Shaalan, 2015), data mining (Saa, Al-Emran, & Shaalan, 2019), and internet of things (IoT) (Al-Emran, Malik, & Al-Kabi, 2020), among others. TAM is a widely used method for determining CSFs for AI implementation in industries including the healthcare sector (Alharbi & Drew, 2014; Phatthana & Mat, 2011). However, a literature review of 23 TAM healthcare studies between 2015 and 2018 revealed they ignored criteria often included in other sectors such as information technology, education, business, and government. See for example, studies by (Abdullah & Ward, 2016; Al-Emran & Teo, 2019; Noor Al-Qaysi, Mohamad-Nordin, & Al-Emran, 2018; M. Alshurideh, Salloum, Al Kurdi, & Al-Emran, 2019; Mezhuyev, Al-Emran, Fatehah, & Hong, 2018; Mezhuyev, Al-Emran, Ismail, Benedicenti, & Chandran, 2019; S. A. S. Salloum & Shaalan, 2018; San & Yee, 2013; Strudwick, 2015). Some of these factors are system quality, computer playfulness, self-efficacy, content quality, subjective norm, accessibility, enjoyment, and information quality. Moreover, a review of successful AI implementation in other industry sectors suggested that an extended model (ETAM) should include five CSF categories: managerial, organizational, operational, strategic, and IT infrastructure, each of which is discussed in section 3 below. This current study is the first to use this ETAM model to assess CSF for AI implementation in the healthcare sector including outcomes based on different user types.

3. Model and Hypotheses

The five factors comprising the ETAM model and its resulting hypotheses used in the study are as follows.

3.1. Managerial Factors

According to (Costantino, Di Gravio, & Nonino, 2015), managerial factors refer to the influencers within an organization that impact efficiency and outcomes including the adoption of new technology (Mhamdi, 2017a; S. A. Salloum, Mhamdi, Al-Emran, & Shaalan, 2017; S. A. Salloum, Mhamdi, Al Kurdi, & Shaalan, 2018; Zu'bi, Al-Lozi, Dahiyat, Alshurideh, & Al Majali, 2012). Moreover, the role of management is to build trust and establish organizational norms in the work environment (Ammari, Al kurdi, Alshurideh, & Alrowwad, 2017). Trust is important for employees in the health sector because it affects individual attitudes within a particular organizational culture (Alshurideh, 2016). Establishing certainty in the validity of assertions made by an individual create shared subjective and social norms and beliefs whereby the majority of people believe that others in the group will conform to certain behaviors, and these norms are assumed by management to create social pressures that govern specific practices (S. A. Al-Mohammadi & Derbel, 2015; E Derbel, 2014; Emira Derbel, 2017a, 2019a; Mhamdi, 2017b; S. A. Salloum et al., 2017; S.A. Salloum, Al-Emran, Monem, & Shaalan, 2018). Hence, individuals act within certain guidelines when performing new practices rather than motivated by their own beliefs or emotions (S. Al-Mohammadi, 2014; Alshurideh, Alhadid, & Al kurdi, 2015). Moreover, sound management is important in the adoption of AI in healthcare settings, particularly endorsement by medical staff (Bennani & Oumlil, 2014). As (Alloghani, Hussain, Al-Jumeily, & Abuelma'atti, 2015) show, the perception of trust in the adoption of AI in medical settings has a positive influence on PU and PEU of new technology, particularly because AI may replace or augment human actions in medical procedures. PU and PEU have long been established as key CSFs in the successful adoption of AI (M. T. Alshurideh, Salloum, Al Kurdi, Monem, & Shaalan, 2019; E Derbel, 2014; Emira Derbel, 2017b, 2019b; S. A. Salloum & Al-Emran, 2018; S. A. Salloum, Al-Emran, Shaalan, & Tarhini, 2019; S. A. S. Salloum & Shaalan, 2018). Therefore, the role of management through the creation of trust in effecting the adoption of AI gives rise to the following two hypotheses in the proposed ETAM model:

H1a: Managerial factors have a positive impact on PU.

H1b: Managerial factors have a positive impact on PEU.

3.2. Organizational Factors

In addition to the managerial support for AI in the healthcare sector providers, organizations must be equipped with the appropriate skill sets and training, which may involve global partnerships with leading technology providers. A study by (Navimipour & Charband, 2016) showed that appropriate training programs assist individuals to accept advanced technologies because they enhance their skills (Alshraideh, Al-Lozi, & Alshurideh, 2017). Relevant expertise within the workplace also increases the possibility that new technology will be accepted by target users (M Alshurideh, Nicholson, & Xiao, 2012; Venkatesh, Thong, & Xu, 2016). Since organizational variables, including technological partnerships, training and local skill sets enable PU and PEU of new technologies, the following hypotheses were formulated:

H2a: Organizational factors have a positive impact on PU.

H2b: Organizational factors have a positive impact on PEU.

3.3. Operational Factors

Operational factors comprise variables used to evaluate the requirements of a desired service (Al-dweeri, Obeidat, Al-dwiry, Alshurideh, & Alhorani, 2017; Christensen, Thomas, Calleya, & Nielsen, 2018). These factors generally refer to the human-technology interface where perceived enjoyment

of user-interaction is a key CSF in the acceptance of new technology (Alghizzawi, Ghani, et al., 2018; Alghizzawi, Salloum, & Habes, 2018; Bennani & Oumlil, 2014; M. Habes, Salloum, Alghizzawi, & Alshibly, 2018; Mohammed Habes, Salloum, Alghizzawi, & Mhamdi, 2019; S. A. Salloum, Al-Emran, & Shaalan, 2018; Who, 2011). Further, perceived levels of enjoyment are related to the amount of perceived effort required by AI users (Alshurideh, 2010; Who, 2011), particularly in the healthcare sector. Since operational factors influence PU and PEU, the following hypotheses were formulated:

H3a: Operational factors have a positive impact on PU.

H3b: Operational factors have a positive impact on PEU.

3.4. Strategic Factors

Strategic factors comprise the way an organization assists all stakeholders to achieve success (ELSamen & Alshurideh, 2012; Zare, 2017). In the healthcare sector, these factors comprise user satisfaction which is the most important CSF in AI adoption because it impacts PU and PEU. Satisfaction refers to the level in which doctors and project managers are comfortable with the adoption of new technology. Although perceived levels of enjoyment and required skill sets and expertise may overlap with user satisfaction as a variable, its CSFs across relevant stakeholders in an organization must be measured. Since user satisfaction is a key variable in measuring CSF for AI in terms of its impact on PU and PEU measured by different stakeholders, the following hypotheses were formulated:

H4a: Strategic factors have a positive impact on PU.

H4b: Strategic factors have a positive impact on PEU.

3.5. IT Infrastructure Factors

IT infrastructure variables determine the physical aspects of hardware systems within an organization (Alkalha, Al-Zu'bi, Al-Dmour, Alshurideh, & Masa'deh, 2012; Dahiya & Mathew, 2016). They comprise system, content and information quality (Al Dmour, Alshurideh, & Shishan, 2014). System quality determines the variables of availability, usability, adaptability, and reliability (Shannak et al., 2012). Several studies showed that system quality is a CSF for the adaption of AI in the healthcare sector. Further, in the case of AI adoption, the impact of the overall design appeal of the technology is important. Content quality refers to the depth of AI functionality and its ability to meet new service needs (Solano-Lorente, Martínez-Caro, & Cegarra-Navarro, 2013). There is a positive relationship between the content

quality of AI and PU in the healthcare sector (Fathema, Shannon, & Ross, 2015; Solano-Lorente et al., 2013) and PEU. Information quality refers to the way that AI projects in the healthcare domain process information for patient monitoring and management (Basak, Gumussoy, & Calisir, 2015). It must present data regarding patient treatment and management of health conditions in a timely, comprehensive and easily comprehensible manner (Alshurideh, 2014; San & Yee, 2013). Information quality can also refer to user perceptions concerning the quality of information produced by AI (Altamony, Alshurideh, & Obeidat, 2012; Solano-Lorente et al., 2013). Therefore, information quality refers to the level at which the physicians and patients receive precise and well-timed data based on AI systems, and this affects PU and PEU (Bashiri, Ghazisaeedi, Safdari, Shahmoradi, & Ehtesham, 2017). Hence, based on the literature review regarding IT infrastructure, two hypotheses can be formulated:

H5a: Infrastructure factors have a positive impact on PU.

H5b: Infrastructure factors have a positive impact on PEU.

3.6. TAM Constructs

The TAM model explains the general elements of acceptance that illustrates user behavior, including beliefs regarding PU and PEU.

3.6.1 Perceived Ease of use (PEU)

The PEU of any given system is defined as the level of technology used having the perception of proper use of the defined technology. PEU has a significant direct or indirect relationship with BIU, which is a key CSF of successful AI implementation (Alloghani et al., 2015; Phatthana & Mat, 2011). BIU is measured by various factors. In the healthcare sector, PEU is specifically related to the physician's perceptions of technology (Phatthana & Mat, 2011). Hence, the following hypotheses can be formulated:

H2a1: PEU positively affects the BIU of AI projects in the healthcare sector.

H2a2: PEU positively affects the perceived usefulness to implement AI projects in the healthcare sector.

H2a3: PEU positively affects attitudes toward the implementation of AI projects in the healthcare sector.

3.6.2 Perceived Usefulness (PU)

PU refers to the level in which users expect new technology to improve job performance (Alharbi & Drew, 2014) and, in the healthcare sector, it is the measure by which AI improves a physician's performance (Alloghani et al., 2015). Moreover, the physician's perceptions determine the extent to which it will be implemented (Emad, El-Bakry, & Asem, 2016). Hence, the following hypotheses can be formulated:

H2b1: PU positively affects attitudes toward the implementation of AI projects in the healthcare sector.

H2b2: PEU positively affects the behavioral intention to implement AI projects in the healthcare sector.

3.6.3 Attitude Toward Use (ATU)

ATU refers to the extent people have positive or negative feelings toward an object or event, and it is significantly associated with BIU (Baharom, Khorma, Mohd, & Bashayreh, 2011). The identification of these attitudes helps in understanding the technology use (Al-Emran, Alkhoudary, Mezhuyev, & Al-Emran, 2019; N. Al-Qaysi, Mohamad-Nordin, & Al-Emran, 2019b, 2019a; N. Al-Qaysi, Mohamad-Nordin, Al-Emran, & Al-Sharafi, 2019; Malik & Al-Emran, 2018). In the current study, a physician's ATU refers to the level of positive or negative feelings they have toward the implementation of AI projects in the healthcare sector, which in turn, affects adoption and use. Therefore, the following hypothesis can be formulated:

H2c: ATU positively affects the behavioral intention to implement AI projects in the healthcare sector.

3.6.4 Behavioral Intention to Use (BIU)

A physician’s intention to implement AI projects in the healthcare sector can define the proposed levels of BUI to use a particular system. Various studies have also shown that BIU has a direct and significant influence on the actual system use of AI projects in the healthcare sector (Fayad & Paper, 2015); (Helia, Indira Asri, Kusurini, & Miranda, 2018). Hence, the following hypothesis can be formulated:

H2d: BIU positively affects AI system choice for implementation in the healthcare sector.

3.6.5 Actual System Use (ASU)

ASU refers to the period that the technology system is utilized after being accepted and adopted by the respective subject (Teeroovengadam, Heeraman, & Jugurnath, 2017). In the healthcare sector, it refers to the period of use after implementation by IT and health staff. However, this construct is dependent on other TAM constructs, particularly BIU. Hence, the following hypothesis was formulated:

H2e: ASU is positively affected by BIU in the implementation of AI projects in the healthcare sector.

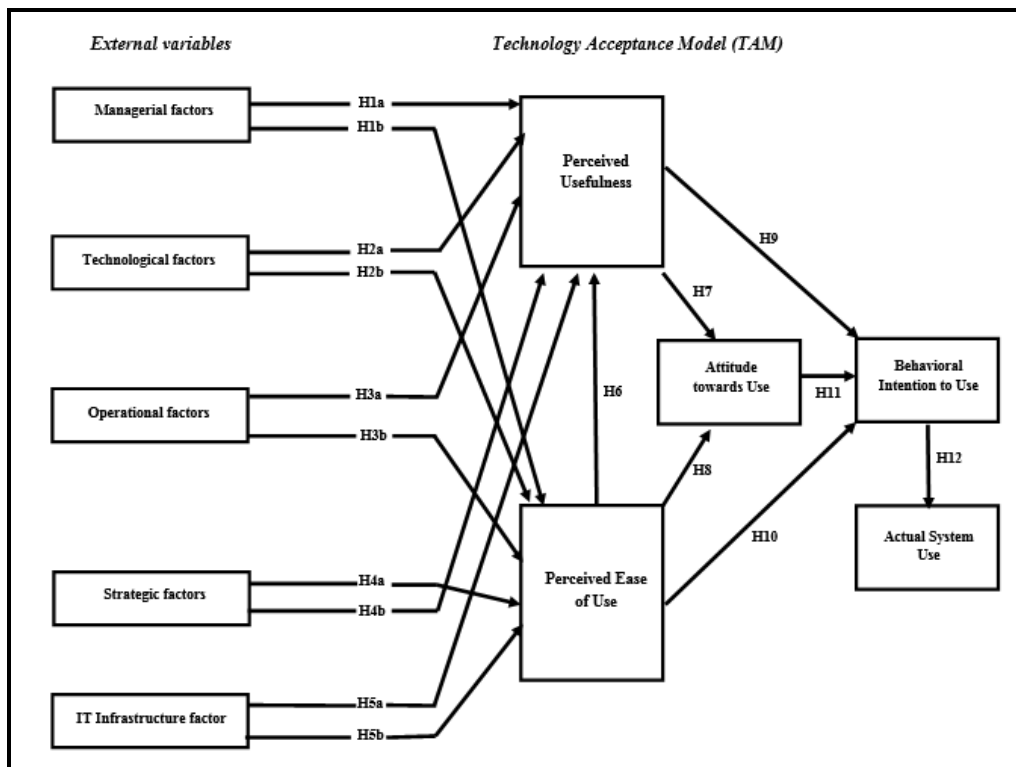


Figure 1. Extended TAM Model.

4. Research Methodology

4.1. Sample description

The population targeted by this study comprised of both IT and health staff. In total, 53 surveyors were considered to take part in this study. The 13 health centers in Dubai that physicians selected for the study were picked from include: Al Barsha Health Center, Nad Al Hamar Health Center, Al Safa Health Center, Al Badaa Health Center, Al Mankhool Health Center, Al Lusaily Health Center, Al Khawaneej Health Center, Al Towar Health Center, Nad Al Sheba Health Center, Al Mamzar Health Center, Al Mizhar Health Center,

Family Gathering, and Za'abeel Health Center. Each of the health centers in the list above was represented by ten physicians in this research. The sample population was selected based on the availability of the physicians as the tight schedules of the research participants were put into consideration. The selection of the sample population was conducted using a purposive sampling method. According to (Tongco, 2007), purposive sampling is a non-probability sampling technique that the researcher has to rely on individual's personal judgment while selecting the members of the sample population to take part in the study. This sampling technique is known for coming up with a population that aims at providing clear information to serve a given purpose. That is why only health and IT staff from registered healthcare centers in Dubai were involved in answering the survey questionnaire. Besides, the accuracy level required for this research is 90%, according to the confidence level calculator I will need 53 responses in order to get all the answers that allow this accuracy percentage.

4.2. Survey Structure

As aforementioned above, this particular research study relied on a questionnaire survey tool to collect data from the participants. After being developed, the questionnaire survey was uploaded online, and respondents were provided with the link. Generally, the questionnaire was structured in such a way that it captured all the items that could provide precise data concerning critical success factors for implementing Artificial Intelligence projects in the healthcare sector. Structurally, the survey tool was segmented into six different parts. Part A only comprised of demographic information regarding the research respondents. Part one only comprised of demographic information regarding the research respondents. Part two addressed managerial factors as Part three captured prompts on operational factors. Strategic factors, IT infrastructure factors and organizational factors were placed in parts four, five and six respectively. In all the parts, there were at least three questions that asked participants on their perceptions about the factors. In total, the questionnaire survey utilized in this research study has 26 items. Again, the survey employed used a 5-point Likert scale with multiple choices structured as follow: 1-strongly disagree, 2-disagree, 3-neutral, 4-agree, and 5-strongly agree.

5. Findings and Discussion

5.1. Measurement Model Analysis

Partial Least Squares-Structural Modelling (PLS-SEM) was used to analyze the measurement and structural models (Chin 1998) using industry-standard SmartPLS software V. 3.2.6 (Ringle, Wende & Will 2005). We followed the guiding principles provided by (Al-Emran, Mezhuyev, & Kamaludin, 2018) for employing PLS-SEM in the IS domain. The measurement model (Outer Model) describes the relationship between the indicators, while the structural model (Inner Model) describes the relationship between the latent constructs. PLS-SEM was employed with the highest probability model to measure the proposed model (Anderson & Gerbing, 1988). To measure reliability and convergent validity, various measurements were carried out including Factor Loadings, Average Variance Extracted and Composite Reliability. Factor loadings were used to determine the weight and correlation value of all questionnaire variables as perceived indicators. A larger load value can signify factor dimensionality. Reliability is measured using Composite Reliability (CR). An accurate value is provided by CR using factor loadings employed by the formula. The average extent of variance in the specified variable defining the latent construct is known as the Average Variance Extracted (AVE). A discriminate validity value of more than one factor means that the convergence of each factor can be assessed using AVE. As shown in Table 1, the experimental outcome for questionnaire reliability and convergent validity was more than the standard value for the reliability and convergent validity. Table 1 presents a summary of the reliability and validity of the questionnaire, together with the analytical outcomes for each factor by depicting the variable attained from the questionnaire.

5.2.1 Assessment of the Structural (Outer) Model

5.2.1.1 Convergent validity

Factor loadings, variance extracted and reliability (including Cronbach's Alpha and CR) were used as indicators (Hair, Black, Babin, Anderson & Tatham 1998) to determine the comparative degree of convergent validity. For every construct, the reliability coefficient and CR exceeded 0.7, which suggests

internal consistency between construct measurements (Hair et. al. 1998). Cronbach's alpha value was more than the standard value of 0.7 (Gefen et. al. 2000; Nunnally & Bernstein 1978), as shown in Table 1 while composite reliabilities of constructs ranged from 0.774 to 0.864. Regarding variance extracted, all AVE values ranged from 0.668 to 0.820, which accounted for a minimum of 50% variance (Falk & Miller 1992). Hence, convergent validity was achieved by assessing the constructs using appropriate measures.

5.2.1.2 Discriminate validity

Table 2 shows that all AVE values were more than the squared correlation between constructs in the measurement model; and hence, criteria for discriminate validity were fulfilled (Fornell & Larcker 1981; Hair et al. 1998). The constructs should normally show at least 50% measurement variance when the AVE is higher than 0.5. To assess discriminate values, SmartPLS was utilized. The loadings and cross-loadings are given in Table 3. It is evident from the detailed assessment of the loadings and cross-loadings that there is widespread loading of all the measurement items on their own latent constructs rather than dependent loading on other constructs. The AVE analysis is given in Table 2, where the bold diagonal items represent the square root of the AVE scores. Conversely, the off-load diagonal elements represent correlations among the constructs. Table 2 clearly shows that AVE values ranged between 0.824 and 0.946, which is more than the proposed value of 0.5, and suggests that for each construct, the AVE is greater than any correlations between them. This demonstrates a higher variance of all constructs within their own measures instead of variance with other constructs in the model, and this improves discriminate validity.

Constructs	Items	Factor Loading	Cronbach's Alpha	CR	AVE
Actual Use	AU1	0.863	0.894	0.822	0.710
	AU2	0.966			
	AU3	0.873			
	AU4	0.965			
Intention to use Social Networks	IU1	0.825	0.892	0.774	0.690
	IU 2	0.899			
	IU 3	0.789			
	IU 4	0.855			
Perceived Ease of use	PEU1	0.889	0.775	0.788	0.668
	PEU2	0.746			
	PEU3	0.919			
	PEU4	0.847			
Perceived Usefulness	PU1	0.955	0.819	0.845	0.766
	PU2	0.959			
	PU3	0.822			
	PU4	0.817			
Perceived Playfulness	PP1	0.766	0.713	0.864	0.820
	PP2	0.888			
	PP3	0.811			
	PP4	0.936			

Table 1. Convergent validity results conforming acceptable values (Factor loading, Cronbach's Alpha, CR \geq 0.70 & AVE > 0.5).

	Actual Use	Intention to use Social Networks	Perceived Ease of use	Perceived Usefulness	Perceived Playfulness
Actual Use	0.946				
Intention to use Social Networks	0.583	0.835			
Perceived Ease of use	0.357	0.651	0.847		
Perceived Usefulness	0.444	0.523	0.212	0.881	
Perceived Playfulness	0.143	0.425	0.356	0.513	0.824

Table 2. Fornell-Larcker Scale.

	Actual Use	Intention to use Social Networks	Perceived Ease of use	Perceived Usefulness	Perceived Playfulness
AU1	0.863	0.123	0.576	0.171	0.470
AU2	0.966	0.525	0.343	0.433	0.353
AU3	0.873	0.390	0.181	0.184	0.288
AU4	0.965	0.252	0.422	0.382	0.326
IU1	0.252	0.825	0.256	0.224	0.379
IU 2	0.394	0.899	0.138	0.228	0.332
IU 3	0.444	0.789	0.461	0.182	0.425
IU 4	0.346	0.855	0.178	0.533	0.524
PEU1	0.275	0.142	0.889	0.644	0.448
PEU2	0.423	0.423	0.746	0.342	0.420
PEU3	0.431	0.474	0.919	0.299	0.439
PEU4	0.527	0.346	0.847	0.422	0.483
PU1	0.546	0.334	0.117	0.955	0.432
PU2	0.314	0.257	0.322	0.959	0.396
PU3	0.389	0.245	0.212	0.822	0.426
PU4	0.377	0.286	0.272	0.817	0.428
PP1	0.356	0.454	0.353	0.222	0.766
PP2	0.245	0.376	0.273	0.372	0.888
PP3	0.322	0.413	0.216	0.463	0.811
PP4	0.334	0.146	0.525	0.545	0.936

Table 3. Cross-loading results.

5.2.2 Assessment of the Structural (Inner) Model

5.2.2.1 Coefficient of Determination

The coefficient of determination (R^2 value) measure is the standard method used to examine a structural (Inner) model. Using this coefficient, the predictive accuracy of the model is determined by a process involving the squared correlation among a given endogenous construct's actual and predicted values. The coefficient denotes an exogenous latent variable's combined impact on an endogenous latent variable. The squared correlation of the actual and predicted values of the variables is given by the coefficient. Hence, the coefficient also shows the degree of variance in the endogenous constructs explained by every exogenous construct recognized with it. Chin (1998) suggests that coefficient values exceeding 0.67 are strong, values from 0.33 to 0.67 are considered direct, those from 0.19 to 0.33 are weak, and those less than 0.19 are inadmissible. As Figure 2 shows, 63% of external factor constructs in the model have positive values, and therefore, it has moderate predictive power. Further, Table 4 and Figure 2 show that the constructs of Intention to use Social Networks and Actual Use have high predictive power since their R^2 values are approximately 61% and 63% respectively.

Constructs	R ²	Results
Intention to use Social Networks	0.613	High
Actual Use	0.627	High

Table 4. R² of the endogenous latent variables.

5.2.2.2 Structural Model Analysis

To analyze the various hypothesized associations, the structural equation modeling was used (see Table 5). (Al-Emran & Salloum, 2017; Milošević, Živković, Manasijević, & Nikolić, 2015) stated that the values of fit indices that were computed showed that there was a suitable fit for the structural model to the data for the given research model. As per the opinion of (Milošević et al., 2015), this study recommends the intended values of fit indices, there is fitting structural model fit to the data for the research model (Al-Marouf, Salloum, AlHamadand, & Shaalan, 2019; Al-Shibly, Alghizzawi, Habes, & Salloum, 2019; Alghizzawi, Habes, & Salloum, 2019; Alhashmi, Salloum, & Abdallah, 2019; Alomari, AlHamad, & Salloum, n.d.; Muhammad Alshurideh, 2018; Muhammad Alshurideh, Al Kurdi, & Salloum, 2019; Mohammed Habes et al., 2019; S. A. Salloum, Al-Emran, Khalaf, Habes, & Shaalan, 2019; S. A. Salloum, Alhamad, Al-Emran, Monem, & Shaalan, 2019; S. A. S. Salloum & Shaalan, 2018; Said A Salloum et al., 2019; Said A Salloum, Al-Emran, Shaalan, & Tarhini, 2018) (see Fig. 2). It can be seen in Table 4 that all the values were in the given range. In addition to it, few direct hypotheses also showed support (Ma & Yuen, 2011). The resulting path coefficients of the suggested research model are shown in Figure 2. Generally, the data supported sixteen out of seventeen hypotheses. All endogenous variables were verified in the model (PU, PEOU, AT, BI, and AU). Based on the data analysis hypotheses H1a, H2a, H3a, H3b, H4a, H5a, H5b, H6, H7, H8, H9, H10, H11, and H12 were supported by the empirical data, while H4b was rejected. The results showed that Perceived Usefulness significantly influenced Managerial factor ($\beta=0.312$, $P<0.05$), organizational factors ($\beta=0.189$, $P<0.05$), Operational factors supporting ($\beta=0.147$, $P<0.05$), Strategic factors ($\beta=0.206$, $P<0.05$), IT Infrastructure factor ($\beta=0.527$, $P<0.001$) and Perceived Ease of Use ($\beta=0.242$, $P<0.001$), hypothesis H1a, H2a, H3a, H4a, H5a and H6 respectively. Perceived Usefulness and Perceived Ease of Use were determined to be significant in affecting Attitude towards use ($\beta=0.116$, $P<0.001$) and ($\beta=0.256$, $P<0.001$) supporting hypotheses H7 and H8. Perceived Usefulness and Perceived Ease of Use were determined to be significant in affecting Behavioral intention to use ($\beta=0.502$, $P<0.001$) and ($\beta=0.105$, $P<0.01$) supporting hypotheses H9 and H10. Furthermore, Perceived Ease of Use was significantly influenced by four exogenous factors: Managerial factor ($\beta=0.163$, $P<0.05$), organizational factors ($\beta=0.139$, $P<0.05$), Operational factors ($\beta=0.255$, $P<0.05$), and IT Infrastructure factor ($\beta=-0.605$, $P<0.001$) which support hypotheses H1b, H2b, H3b, H4b and H5b. The relationship between Strategic factors and Perceived Ease of Use ($\beta=0.033$, $P=0.696$) is statistically not significant, and Hypotheses H4b is generally not supported. Finally, the relationship between Attitude towards use and Behavioral intention to use ($\beta=0.697$, $P<0.001$) is statistically significant, and Hypotheses H11 is generally supported, and the relationship between Behavioral intention to use and Actual System Use ($\beta=0.901$, $P<0.001$) is statistically also significant, and Hypotheses H12 supported. A summary of the hypotheses testing results is shown in Table 5.

Hyp.	Relationship	Path	t-value	p-value	Direction	Decision
H1a	Managerial factor -> Perceived Usefulness	0.312	3.235	0.015	Positive	Supported
H1b	Managerial factor -> Perceived Ease of Use	0.163	2.163	0.031	Positive	Supported
H2a	Organizational factors -> Perceived Usefulness	0.189	2.499	0.013	Positive	Supported
H2b	Organizational factors -> Perceived Ease of Use	0.139	4.405	0.035	Positive	Supported
H3a	Operational factors -> Perceived Usefulness	0.147	1.873	0.042	Positive	Supported
H3b	Operational factors -> Perceived Ease of Use	0.255	1.604	0.046	Positive	Supported
H4a	Strategic factors -> Perceived Usefulness	0.206	3.129	0.002	Positive	Supported
H4b	Strategic factors -> Perceived Ease of Use	0.033	0.391	0.696	Positive	Not supported
H5a	IT Infrastructure factor -> Perceived Usefulness	0.527	7.428	0.000	Positive	Supported

H5b	IT Infrastructure factor -> Perceived Ease of Use	0.605	7.197	0.000	Positive	Supported
H6	Perceived Ease of Use -> Perceived Usefulness	0.242	3.268	0.001	Positive	Supported
H7	Perceived Usefulness -> Attitude towards use	0.116	4.737	0.004	Positive	Supported
H8	Perceived Ease of Use -> Attitude towards use	0.256	6.883	0.008	Positive	Supported
H9	Perceived Usefulness -> Behavioral intention to use	0.502	7.036	0.005	Positive	Supported
H10	Perceived Ease of Use -> Behavioral intention to use	0.105	7.379	0.006	Positive	Supported
H11	Attitude towards use -> Behavioral intention to use	0.697	17.897	0.000	Positive	Supported
H12	Behavioral intention to use -> Actual System Use	0.901	77.891	0.000	Positive	Supported

Table 5. Results of structural Model.

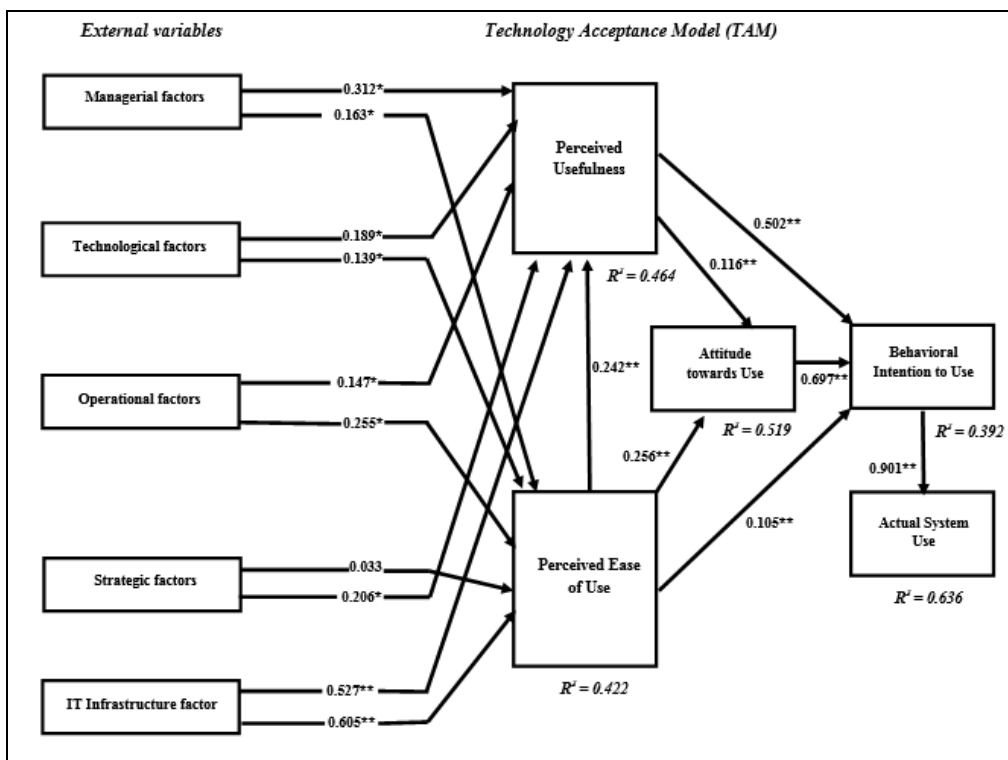


Figure 2. Path coefficient results.

6. Conclusion and Future Studies

6.1. Study Contributions and Discussion

This study proposed that the external CSFs used for the successful adaption of AI projects within the healthcare sector were managerial, operational, organizational, strategic and IT infrastructure factors, which have not previously been included in the literature concerning TAMs in the health care sector. As shown in Table 5, seventeen sub-hypotheses were derived from the literature and the questionnaire, which were tested by a PLS-SEM methodology to link indicators to the latent constructs. It was found that PU significantly influenced Managerial and Organizational, Operational, Strategic, and IT Infrastructure factors and the PEU hypothesis H1a, H2a, H3a, H4a, H5a and H6 respectively. Perceived U and PEU were determined to be significant in affecting ATU supporting hypotheses H7 and H8. PU and PEU were

determined to be significant in affecting BIU (supporting hypotheses H9 and H10). Further, PEU was significantly influenced by four exogenous factors: managerial, organizational, operational and IT Infrastructure factors, which support hypotheses H1b, H2b, H3b, and H5b. However, the relation between PEU and strategic factors, and hence, H4b was not supported at ($\beta = 0.033$, $P = 0.696$). Hence, except for one external factor, all proposed hypotheses sharing positive relations.

The total number of cases dedicated to bootstrapping in the current study involves 300 cases that are suitable for the sample size. The total outcome of the analyzed 17 hypotheses was provided in Table 5. The coefficient of determination R^2 , refers to the values that are part of the variance in the actual variable and the predictable variables of the endogenous constructs. (Chin, 1998) proposed that an R^2 value of more than 0.67 is high, between 0.33 and 0.67 to be moderate and between 0.19 and 0.33 is a weak area. According to Table 4 the Endogenous variables' R^2 for actual system use, attitude toward use, Behavioral intention to use, perceived ease of use and perceived usefulness have resulted between 0.636 and 0.464 and the results are moderate power for all of it. Also, the CR of variables showed the various hypothesized associations, the model of structural equation was utilized, and the results illustrated that out of the seventeenth hypothesis all of it were supported except one hypothesis.

The ETAM model, therefore, suggests that project managers and key influencers in the health domain must consider external factors outlined in the extended model because, apart from strategic factors, these impact key CSFs including PU, PEU, BIU, ATU, and ASU.

6.2. Limitations and Future Directions

This first, an analyzes used for (TAM) external factors by reviewing 23 literature studies in different segments such as health care, education and government within the year range of 2015 and 2018. Second, after discovering most of the factors with the use of (TAM) extension, a new model was initiated to support this dissertation paper. Third, a proper suitable assessment for the new model was through the use of a fit approach called PLS-SEM. Moreover, a survey questionnaire employed to gather the required data and the target audience for this survey were health and IT staff working in different entities and the total number of participants was 53 employees. A total of 17 hypotheses 16 out of it was supported by this research, and the findings illustrate a positive relationship between the factors and the variables of the model. Managerial factors, organizational factors, operational factors and IT infrastructure factors demonstrated a positive relationship with the Perceived Ease of Use and Perceived Usefulness. However, the strategic factors illustrated a negative relationship with the Perceived Ease of Use.

Various adaptations have been left for future research to be examined due to time shortage (interview physicians, doctors, and health staff is usually time and effort consuming, requiring long process and procedures. It could be significant if future studies consider only government hospitals across the UAE and propose a unique modified model concerning the physicians' practice process with patients. The modified (TAM) model in his dissertation can be constructed by focusing on one critical success factor and study it deeply from different angles.

Acknowledgment

This work is a part of a dissertation submitted in fulfilment of MSc Informatics (Knowledge & Data Management), Faculty of Engineering & IT, The British University in Dubai.

References

- Abdullah, F., & Ward, R. (2016). Developing a General Extended Technology Acceptance Model for E-Learning (GETAMEL) by analysing commonly used external factors. *Computers in Human Behavior*, 56, 238–256. <https://doi.org/10.1016/j.chb.2015.11.036>
- Al-dweeri, R. M., Obeidat, Z. M., Al-dwiry, M. A., Alshurideh, M. T., & Alhorani, A. M. (2017). The impact of e-service quality and e-loyalty on online shopping: moderating effect of e-satisfaction and e-trust. *International Journal of Marketing Studies*, 9(2), 92.
- Al-Emran, M. (2015a). Hierarchical Reinforcement Learning: A Survey. *International Journal of Computing*

- and *Digital Systems*, 4(2), 137–143.
- Al-Emran, M. (2015b). Speeding Up the Learning in A Robot Simulator. *International Journal of Computing and Network Technology*, 3(3).
- Al-Emran, M., Alkhoudary, Y. A., Mezhuyev, V., & Al-Emran, M. (2019). Students and Educators Attitudes towards the use of M-Learning: Gender and Smartphone ownership Differences. *International Journal of Interactive Mobile Technologies (IJIM)*, 13(1), 127–135.
- Al-Emran, M., Malik, S. I., & Al-Kabi, M. N. (2020). A Survey of Internet of Things (IoT) in Education: Opportunities and Challenges. In *Toward Social Internet of Things (SIoT): Enabling Technologies, Architectures and Applications* (pp. 197–209). Springer.
- Al-Emran, M., Mezhuyev, V., & Kamaludin, A. (2018). PLS-SEM in Information Systems Research: A Comprehensive Methodological Reference. In *4th International Conference on Advanced Intelligent Systems and Informatics (AIS I 2018)* (pp. 644–653). Springer.
- Al-Emran, M., & Salloum, S. A. (2017). Students' Attitudes Towards the Use of Mobile Technologies in e-Evaluation. *International Journal of Interactive Mobile Technologies (IJIM)*, 11(5), 195–202. <https://doi.org/10.3991/ijim.v11i5.6879>
- Al-Emran, M., & Teo, T. (2019). Do knowledge acquisition and knowledge sharing really affect e-learning adoption? An empirical study. *Education and Information Technologies*. <https://doi.org/10.1007/s10639-019-10062-w>
- Al-Emran, M., Zaza, S., & Shaalan, K. (2015). Parsing modern standard Arabic using Treebank resources. In *2015 International Conference on Information and Communication Technology Research, ICTRC 2015*. <https://doi.org/10.1109/ICTRC.2015.7156426>
- Al-Marroof, R. S., Salloum, S. A., AlHamadand, A. Q. M., & Shaalan, K. (2019). A Unified Model for the Use and Acceptance of Stickers in Social Media Messaging. In *International Conference on Advanced Intelligent Systems and Informatics* (pp. 370–381). Springer.
- Al-Mohammadi, S. (2014). Integrating Reading and Writing in ELT. In *Focusing on EFL Reading: Theory and Practice* (pp. 260–274). Cambridge Scholars Publishing.
- Al-Mohammadi, S. A., & Derbel, E. (2015). To Whom Do We Write?: Audience in EFL Composition Classes. In *Methodologies for effective writing instruction in EFL and ESL classrooms* (pp. 197–208). IGI Global.
- Al-Qaysi, N., Mohamad-Nordin, N., & Al-Emran, M. (2019a). An Empirical Investigation of Students' Attitudes Towards the Use of Social Media in Omani Higher Education. In *International Conference on Advanced Intelligent Systems and Informatics* (pp. 350–359). Springer.
- Al-Qaysi, N., Mohamad-Nordin, N., & Al-Emran, M. (2019b). What leads to social learning? Students' attitudes towards using social media applications in Omani higher education. *Education and Information Technologies*.
- Al-Qaysi, N., Mohamad-Nordin, N., Al-Emran, M., & Al-Sharafi, M. A. (2019). Understanding the differences in students' attitudes towards social media use: A case study from Oman. In *2019 IEEE Student Conference on Research and Development (SCoReD)* (pp. 176–179). IEEE.
- Al-Qaysi, Noor, Mohamad-Nordin, N., & Al-Emran, M. (2018). A Systematic Review of Social Media Acceptance from the Perspective of Educational and Information Systems Theories and Models. *Journal of Educational Computing Research*. <https://doi.org/10.1177/0735633118817879>
- Al-Shibly, M. S., Alghizzawi, M., Habes, M., & Salloum, S. A. (2019). The Impact of De-marketing in Reducing Jordanian Youth Consumption of Energy Drinks. In *International Conference on Advanced Intelligent Systems and Informatics* (pp. 427–437). Springer.
- Al Dmour, H., Alshurideh, M., & Shishan, F. (2014). The influence of mobile application quality and attributes on the continuance intention of mobile shopping. *Life Science Journal*, 11(10), 172–181.
- Alghizzawi, M., Ghani, M. A., Som, A. P. M., Ahmad, M. F., Amin, A., Bakar, N. A., ... Habes, M. (2018). The Impact of Smartphone Adoption on Marketing Therapeutic Tourist Sites in Jordan. *International Journal of Engineering & Technology*, 7(4.34), 91–96.
- Alghizzawi, M., Habes, M., & Salloum, S. A. (2019). The Relationship Between Digital Media and Marketing Medical Tourism Destinations in Jordan: Facebook Perspective. In *International Conference on Advanced Intelligent Systems and Informatics* (pp. 438–448). Springer.
- Alghizzawi, M., Salloum, S. A., & Habes, M. (2018). The role of social media in tourism marketing in Jordan. *International Journal of Information Technology and Language Studies*, 2(3).
- Alharbi, S., & Drew, S. (2014). Using the technology acceptance model in understanding academics' behavioural intention to use learning management systems. *International Journal of Advanced*

- Computer Science and Applications*, 5(1), 143–155.
- Alhashmi, S. F. S., Salloum, S. A., & Abdallah, S. (2019). Critical Success Factors for Implementing Artificial Intelligence (AI) Projects in Dubai Government United Arab Emirates (UAE) Health Sector: Applying the Extended Technology Acceptance Model (TAM). In *International Conference on Advanced Intelligent Systems and Informatics* (pp. 393–405). Springer.
- Alkalha, Z., Al-Zu'bi, Z., Al-Dmour, H., Alshurideh, M., & Masa'deh, R. (2012). Investigating the effects of human resource policies on organizational performance: An empirical study on commercial banks operating in Jordan. *European Journal of Economics, Finance and Administrative Sciences*, 51(1), 44–64.
- Alloghani, M., Hussain, A., Al-Jumeily, D., & Abuelma'atti, O. (2015). Technology Acceptance Model for the Use of M-Health Services among health related users in UAE. In *2015 International Conference on Developments of E-Systems Engineering (DeSE)* (pp. 213–217). IEEE.
- Alomari, K. M., AlHamad, A. Q., & Salloum, S. (n.d.). Prediction of the Digital Game Rating Systems based on the ESRB.
- Alshraideh, A., Al-Lozi, M., & Alshurideh, M. (2017). The Impact of Training Strategy on Organizational Loyalty via the Mediating Variables of Organizational Satisfaction and Organizational Performance: An Empirical Study on Jordanian Agricultural Credit Corporation Staff. *Journal of Social Sciences (COES&RJ-JSS)*, 6, 383–394.
- ALSHURIDEH, M. (2010). Customer Service Retention–A Behavioural Perspective of the UK Mobile Market. Durham University.
- Alshurideh, M., Salloum, S. A., Al Kurdi, B., & Al-Emran, M. (2019). Factors affecting the Social Networks Acceptance: An Empirical Study using PLS-SEM Approach. In *8th International Conference on Software and Computer Applications* (pp. 414–418). Penang, Malaysia: ACM. <https://doi.org/10.1145/3316615.3316720>
- Alshurideh, M. T., Salloum, S. A., Al Kurdi, B., Monem, A. A., & Shaalan, K. (2019). Understanding the Quality Determinants that Influence the Intention to Use the Mobile Learning Platforms: A Practical Study. *International Journal of Interactive Mobile Technologies (IJIM)*, 13(11), 157–183.
- Alshurideh, M., Alhadid, A., & Al kurdi, B. (2015). The effect of internal marketing on organizational citizenship behavior an applicable study on the University of Jordan employees. *International Journal of Marketing Studies*, 7(1), 138.
- Alshurideh, M., Nicholson, M., & Xiao, S. (2012). The Effect of Previous Experience on Mobile Subscribers' Repeat Purchase Behaviour. *European Journal of Social Sciences*, 30(3), 366–376.
- Alshurideh, Muhammad. (2014). The Factors Predicting Students' Satisfaction with Universities' Healthcare Clinics' Services: A Case-Study from the Jordanian Higher Education Sector. *Dirasat: Administrative Sciences*, 41(2), 451–464.
- Alshurideh, Muhammad. (2016). Scope of Customer Retention Problem in the Mobile Phone Sector: A Theoretical Perspective. *Journal of Marketing and Consumer Research*, 20, 64–69.
- Alshurideh, Muhammad. (2018). Pharmaceutical Promotion Tools Effect on Physician's Adoption of Medicine Prescribing: Evidence from Jordan. *Modern Applied Science*, 12(11).
- Alshurideh, Muhammad, Al Kurdi, B., & Salloum, S. A. (2019). Examining the Main Mobile Learning System Drivers' Effects: A Mix Empirical Examination of Both the Expectation-Confirmation Model (ECM) and the Technology Acceptance Model (TAM). In *International Conference on Advanced Intelligent Systems and Informatics* (pp. 406–417). Springer.
- Altamony, H., Alshurideh, M., & Obeidat, B. (2012). Information systems for competitive advantage: Implementation of an organisational strategic management process. In *Proceedings of the 18th IBIMA conference on innovation and sustainable economic competitive advantage: From regional development to world economic, Istanbul, Turkey, 9th-10th May*.
- Ammari, G., Al kurdi, B., Alshurideh, M., & Alrowwad, A. (2017). Investigating the impact of communication satisfaction on organizational commitment: a practical approach to increase employees' loyalty. *International Journal of Marketing Studies*, 9(2), 113–133.
- Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological Bulletin*, 103(3), 411.
- Baharom, F., Khorma, O. T., Mohd, H., & Bashayreh, M. G. (2011). Developing an extended technology acceptance model: doctors' acceptance of electronic medical records in Jordan. ICOCI.
- Basak, E., Gumussoy, C. A., & Calisir, F. (2015). Examining the factors affecting PDA acceptance among physicians: an extended technology acceptance model. *Journal of Healthcare Engineering*, 6(3), 399–

- 418.
- Bashiri, A., Ghazisaeedi, M., Safdari, R., Shahmoradi, L., & Ehtesham, H. (2017). Improving the prediction of survival in cancer patients by using machine learning techniques: experience of gene expression data: a narrative review. *Iranian Journal of Public Health, 46*(2), 165.
- Bennani, A.-E., & Oumlil, R. (2014). The Acceptance of ICT by Geriatricians reinforces the value of care for seniors in Morocco. *IBIMA Publ. J. African Res. Bus. Technol. J. African Res. Bus. Technol, 2014*(2014).
- Chin, W. W. (1998). The partial least squares approach to structural equation modeling. *Modern Methods for Business Research, 295*(2), 295–336.
- Christensen, L. B. R., Thomas, G., Calleya, J., & Nielsen, U. D. (2018). The Effect of Operational Factors on Container Ship Fuel Performance. In *Proceedings of Full Scale Ship Performance*. The Royal Institution of Naval Architects.
- Costantino, F., Di Gravio, G., & Nonino, F. (2015). Project selection in project portfolio management: An artificial neural network model based on critical success factors. *International Journal of Project Management, 33*(8), 1744–1754.
- Dahiya, D., & Mathew, S. K. (2016). IT assets, IT infrastructure performance and IT capability: a framework for e-government. *Transforming Government: People, Process and Policy, 10*(3), 411–433.
- Derbel, E. (2014). Constructing Afro-Caribbean Identity through Memory and Language in Grace Nichols's *I Is Along Memored Woman*. In *Selim. Y.F and Mohamed,E (Eds). Who Defines Me: Negotiating Identity in Language and Literature, Pp 63-76*. UK: Cambridge Scholars Publishing.
- Derbel, Emira. (2017a). *Iranian Women in the Memoir: Comparing Reading Lolita in Tehran and Persepolis (1) and (2)*. Cambridge Scholars Publishing.
- Derbel, Emira. (2017b). The African Novel: The Ongoing Battle against Literary and National Neo-Colonialism. *International Journal of Information Technology and Language Studies, 1*(1).
- Derbel, Emira. (2019a). Feminist Graphic Narratives: The Ongoing Game of Eluding Censorship. *Mediterranean Journal of Social Sciences, 10*(1), 49.
- Derbel, Emira. (2019b). Teaching Literature through Comics: An Innovative Pedagogical Tool. *International Journal of Applied Linguistics and English Literature, 8*(1), 54–61.
- ELSamen, A., & Alshurideh, M. (2012). The impact of internal marketing on internal service quality: A case study in a Jordanian pharmaceutical company. *International Journal of Business and Management, 7*(19), 84.
- Emad, H., El-Bakry, H. M., & Asem, A. (2016). A Modified Technology Acceptance Model for Health Informatics.
- Falk, R. F., & Miller, N. B. (1992). *A primer for soft modeling*. University of Akron Press.
- Fathema, N., Shannon, D., & Ross, M. (2015). Expanding The Technology Acceptance Model (TAM) to Examine Faculty Use of Learning Management Systems (LMSs) In Higher Education Institutions. *MERLOT Journal of Online Learning and Teaching, 11*(2), 210–232. <https://doi.org/10.12720/joams.4.2.92-97>
- Fayad, R., & Paper, D. (2015). The technology acceptance model e-commerce extension: a conceptual framework. *Procedia Economics and Finance, 26*, 1000–1006.
- Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models With Unobservable Variables and Measurement Error. *Journal of Marketing Research, 18*(1), 39–50. <https://doi.org/10.2307/3151312>
- Gefen, D., Straub, D., & Boudreau, M.-C. (2000). Structural equation modeling and regression: Guidelines for research practice. *Communications of the Association for Information Systems, 4*(1), 1–77. <https://doi.org/10.1.1.25.781>
- Ghannajeh, A., AlShurideh, M., Zu'bi, M., Abuhamad, A., Rumman, G., Suifan, T., & Akhorshaidh, A. (2015). A Qualitative Analysis of Product Innovation in Jordan's Pharmaceutical Sector. *European Scientific Journal, 11*(4), 474–503.
- Habes, M., Salloum, S. A., Alghizzawi, M., & Alshibly, M. S. (2018). The role of modern media technology in improving collaborative learning of students in Jordanian universities. *International Journal of Information Technology and Language Studies, 2*(3), 71–82.
- Habes, Mohammed, Salloum, S. A., Alghizzawi, M., & Mhamdi, C. (2019). The Relation Between Social Media and Students' Academic Performance in Jordan: YouTube Perspective. In *International Conference on Advanced Intelligent Systems and Informatics* (pp. 382–392). Springer.
- Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (1998). *Multivariate data analysis* (Vol.

- 5). Prentice hall Upper Saddle River, NJ.
- Helia, V. N., Indira Asri, V., Kusriani, E., & Miranda, S. (2018). Modified technology acceptance model for hospital information system evaluation—a case study.
- Ma, W., & Yuen, A. (2011). 11. E-LEARNING SYSTEM ACCEPTANCE AND USAGE PATTERN. *Technology Acceptance in Education: Research and Issues*, 201.
- Malik, S. I., & Al-Emran, M. (2018). Social Factors Influence on Career Choices for Female Computer Science Students. *International Journal of Emerging Technologies in Learning (IJET)*, 13(5), 56–70.
- Mezhuyev, V., Al-Emran, M., Fatehah, M., & Hong, N. C. (2018). Factors affecting the Metamodelling Acceptance: A Case Study from Software Development Companies in Malaysia. *IEEE Access*, 6, 49476–49485.
- Mezhuyev, V., Al-Emran, M., Ismail, M. A., Benedicenti, L., & Chandran, D. A. (2019). The acceptance of search-based software engineering techniques: An empirical evaluation using the technology acceptance model. *IEEE Access*. <https://doi.org/10.1109/access.2019.2917913>
- Mhamdi, C. (2017a). Interpreting Games: Meaning Creation in the Context of Temporality and Interactivity. *Mediterranean Journal of Social Sciences*, 8(4).
- Mhamdi, C. (2017b). What Can Video Add to the Learning Experience? Challenges and Opportunities. *International Journal of Information Technology and Language Studies*, 1(1), 17–24.
- Mijwel, M. M. (2015). History of Artificial Intelligence. *Computer Science, College of Science*, Pp.1-6.
- Milošević, I., Živković, D., Manasijević, D., & Nikolić, D. (2015). The effects of the intended behavior of students in the use of M-learning. *Computers in Human Behavior*, 51, 207–215.
- Mokyr, J. (2018). *The British industrial revolution: an economic perspective*. Routledge.
- Navimipour, N. J., & Charband, Y. (2016). Knowledge sharing mechanisms and techniques in project teams: Literature review, classification, and current trends. *Computers in Human Behavior*, 62, 730–742.
- Nunnally, J. C., & Bernstein, I. H. (1978). Psychometric theory.
- Phatthana, W., & Mat, N. K. N. (2011). The Application of Technology Acceptance Model (TAM) on health tourism e-purchase intention predictors in Thailand. In *2010 International Conference on Business and Economics Research* (Vol. 1, pp. 196–199).
- Ringle, C. M., Wende, S., & Will, A. (2005). SmartPLS 2.0 (Beta). Hamburg. Available in <Http://Www.Smartpls.De>.
- Saa, A. A., Al-Emran, M., & Shaalan, K. (2019). Factors Affecting Students' Performance in Higher Education: A Systematic Review of Predictive Data Mining Techniques. *Technology, Knowledge and Learning*. <https://doi.org/10.1007/s10758-019-09408-7>
- Salloum, S. A., & Al-Emran, M. (2018). Factors affecting the adoption of E-payment systems by university students: Extending the TAM with trust. *International Journal of Electronic Business*, 14(4), 371–390.
- Salloum, S. A., Al-Emran, M., Khalaf, R., Habes, M., & Shaalan, K. (2019). An Innovative Study of E-Payment Systems Adoption in Higher Education: Theoretical Constructs and Empirical Analysis. *International Journal of Interactive Mobile Technologies*, 13(6). <https://doi.org/10.3991/ijim.v13i06.9875>
- Salloum, S. A., Al-Emran, M., & Shaalan, K. (2018). The Impact of Knowledge Sharing on Information Systems: A Review. In *International Conference on Knowledge Management in Organizations* (pp. 94–106). Slovakia: Springer.
- Salloum, S. A., Al-Emran, M., Shaalan, K., & Tarhini, A. (2019). Factors affecting the E-learning acceptance: A case study from UAE. *Education and Information Technologies*, 24(1), 509–530. <https://doi.org/https://doi.org/10.1007/s10639-018-9786-3>
- Salloum, S. A., Alhamad, A. Q. M., Al-Emran, M., Monem, A. A., & Shaalan, K. (2019). Exploring Students' Acceptance of E-Learning Through the Development of a Comprehensive Technology Acceptance Model. *IEEE Access*, 7, 128445–128462. <https://doi.org/10.1109/access.2019.2939467>
- Salloum, S. A., Mhamdi, C., Al-Emran, M., & Shaalan, K. (2017). Analysis and Classification of Arabic Newspapers' Facebook Pages using Text Mining Techniques. *International Journal of Information Technology and Language Studies*, 1(2), 8–17.
- Salloum, S. A., Mhamdi, C., Al Kurdi, B., & Shaalan, K. (2018). Factors affecting the Adoption and Meaningful Use of Social Media: A Structural Equation Modeling Approach. *International Journal of Information Technology and Language Studies*, 2(3), 96–109.
- Salloum, S. A. S., & Shaalan, K. (2018). Investigating students' acceptance of E-learning system in Higher Educational Environments in the UAE: Applying the Extended Technology Acceptance Model (TAM).

The British University in Dubai.

- Salloum, S.A., Al-Emran, M., Monem, A. A., & Shaalan, K. (2018). Using text mining techniques for extracting information from research articles. In *Studies in Computational Intelligence* (Vol. 740). Springer. https://doi.org/10.1007/978-3-319-67056-0_18
- Salloum, Said A, Al-Emran, M., Habes, M., Alghizzawi, M., Ghani, M. A., & Shaalan, K. (2019). Understanding the Impact of Social Media Practices on E-Learning Systems Acceptance. In *International Conference on Advanced Intelligent Systems and Informatics* (pp. 360–369). Springer.
- Salloum, Said A, Al-Emran, M., Shaalan, K., & Tarhini, A. (2018). Factors affecting the E-learning acceptance: A case study from UAE. *Education and Information Technologies*, 1–22.
- San, A. N. C., & Yee, C. J. (2013). The modified technology acceptance model for private clinical physicians: A case study in Malaysia, Penang. *International Journal of Academic Research in Business and Social Sciences*, 3(2), 380.
- Shannak, R., Masa'deh, R., Al-Zu'bi, Z., Obeidat, B., Alshurideh, M., & Altamony, H. (2012). A theoretical perspective on the relationship between knowledge management systems, customer knowledge management, and firm competitive advantage. *European Journal of Social Sciences*, 32(4), 520–532.
- Solano-Lorente, M., Martínez-Caro, E., & Cegarra-Navarro, J. G. (2013). Designing a Framework to Develop eLoyalty for Online Healthcare Services. *Electronic Journal of Knowledge Management*, 11(1).
- Strudwick, G. (2015). Predicting nurses' use of healthcare technology using the technology acceptance model: an integrative review. *CIN: Computers, Informatics, Nursing*, 33(5), 189–198.
- Teeroovengadam, V., Heeraman, N., & Jugurnath, B. (2017). Examining the antecedents of ICT adoption in education using an extended technology acceptance model (TAM). *International Journal of Education and Development Using ICT*, 13(3).
- Tongco, M. D. C. (2007). Purposive sampling as a tool for informant selection. *Ethnobotany Research and Applications*, 5, 147–158.
- Venkatesh, V., Thong, J. Y. L., & Xu, X. (2016). Unified theory of acceptance and use of technology: A synthesis and the road ahead. *Journal of the Association for Information Systems*, 17(5), 328–376.
- Who, X. (2011). Extending TAM: success factors of mobile marketing'. *American Academic & Scholarly Research Journal*, 1(1), 1–5.
- Zare, S. (2017). Identifying and Prioritizing Supply Chain Management Strategic Factors Based on Integrated BSC-AHP Approach.
- Zu'bi, Z., Al-Lozi, M., Dahiyat, S., Alshurideh, M., & Al Majali, A. (2012). Examining the effects of quality management practices on product variety. *European Journal of Economics, Finance and Administrative Sciences*, 51(1), 123–139.