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Implementing Artificial Intelligence in the United Arab Emirates Healthcare Sector

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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.

I.BACKGROUND

Governments of the UAE are increasingly implementing technology strategies, including the adoption of AI in the public and business sectors (Government.au). 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; Mokyr, 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.

II.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, & AlKabi, 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.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 were formulated: H3a: Operational factors have a positive impact on PU. H3b: Operational factors have a positive impact on PEU

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.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 (SolanoLorente, 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. 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.

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.

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, & AlEmran, 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 sectorA 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, Kusrini, & Miranda, 2018). Hence, the following hypothesis can be formulated: H2d: BIU positively affects AI system choice for implementation in the healthcare sector.ASU refers to the period that the technology system is utilized after being accepted and adopted by the respective subject (Teeroovengadum, 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.

III.METHOD

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.

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.

IV.FINDINGS AND DISCUSSION

Measurement Model Analysis

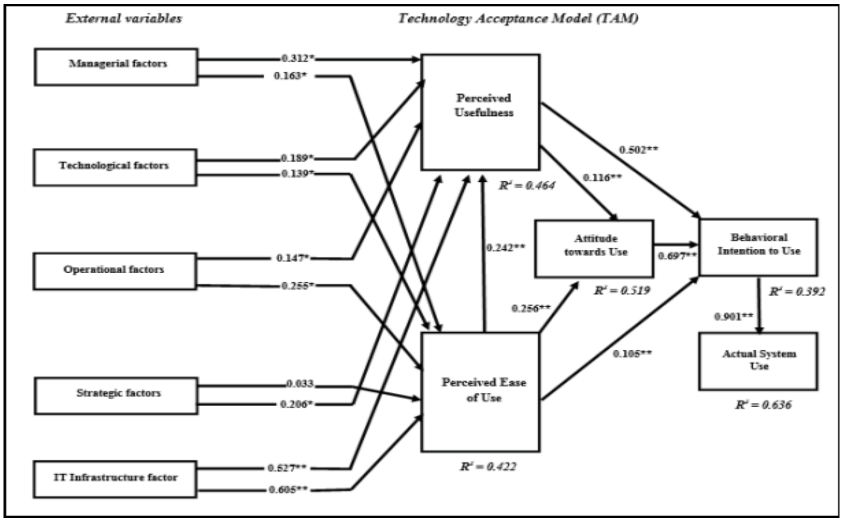
Partial Least Squares-Structural Modelling (PLS-SEM) was used to analyze the measurement and structural models (Chin 1998) using industry-standard SmartPLS software V. 3.2.6 (Ringle, Wende & Will 2005). We followed the guiding principles provided by (Al-Emran, Mezhuyev, & Kamaludin, 2018) for employing 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. Table1 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

Assessment of the Structural (Inner) Model

The coefficient of determination (R2 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 R2 values are approximately 61% and 63% respectively.

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-Maroof, 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 (β= 0.312, p<0.05. organizational factors (β= 0.189, P< 0.05. Operational factors supporting (β= 0.147, Strategic factors (β= 0.206, P<0.05), IT Infrastructure factor (β= 0.527, P<0.001) and Perceived Ease of Use (β= 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 (β= 0.116, P<0.001) and (β= 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 (β= 0.502, P<0.001) and (β= 0.105, P<0.01) supporting hypotheses H9 and H10. Furthermore, Perceived Ease of Use was significantly influenced by four exogenous factors: Managerial factor (β= 0.163, P < P<0.05), organizational factors (β= 0.139, P<0.05), Operational factors (β= 0.255, P<0.05), and IT Infrastructure factor (β= -0.605, P<0.001) which support hypotheses H1b, H2b, H3b, H4b and H5b. The relationship between Strategic factors and Perceived Ease of Use (β= 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 (β= 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 (β= 0.901, P<0.001) is statistically also significant, and Hypotheses H12 supported.

V.CONCLUSION

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 R2, 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 R2 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' R2 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

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