Behavioral Intention to Use IoT Technology in Healthcare Settings

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Abstract—**Rapid scaling of using the Internet of Things (IoT) technology has been seen recently in numerous applications in healthcare to deliver proper services. This was motivated by the declining size and cost of the employed IoT devices. Developing such technology has been well investigated in the literature; however, few studies have explored the factors influencing its adaptation in the healthcare setting. In this study, we investigate the core factors that influence the acceptance of using IoT for Healthcare Purposes in the Kingdom of Saudi Arabia (KSA). Accordingly, a theoretical framework, based on the Technology Acceptance Model (TAM), was developed and tested empirically. The modified model added variables that provide a better explanation of the acceptance of healthcare technology. To ground our conceptual idea, a survey was designed and performed on 407 patients (207 males, 200 females). The Partial Least Square Structural Equation Modeling (SEM) technique was applied to analyze the effect of eight hypothesized predicting constructs on the collected data. Results revealed that cost, privacy concerns, and perceived usefulness were the most significant predictors of behavioral intention to use. However, attitude and perceived connectedness were found to be irrelevant in predicting the intention to use IoT. Ultimately, results found that there is no correlation between gender and behavioral intention.**

Keywords-Internet of Things; healthcare; technology acceptance model (TAM); structural equation model

I. INTRODUCTION

Internet of Things (IoT) technology is a system of interrelated smart devices (computers, sensors, etc.) that are connected to the Internet to develop new capabilities and services [1]. These services aim to improve system performance and quality of life, e.g. in healthcare, communication, education, etc. [2]. IoT has many advantages to offer, for example, the Internet of Medical Things (or the internet of healthy things). Internet of Medical Things is an application of IoT for medical and health-related purposes [3], where IoT devices (devices for monitoring blood pressure, heart rate, or specialized implants, such as pacemakers, or advanced hearing aids) are used to enable remote health monitoring process [4]. This process can significantly improve the quality of life for patients, especially for chronic diseases, as they can be monitored in non-clinical environments such as

their home. While IoT delivers an impressive set of benefits, concern exists over the extent of IoT technology use by patients. In other words, as any new technology proposed, it has the potential to enhance the provided services and achieve its goals when intended users understand it. But, if the technology meets resistance to use or acceptance, it will be underutilized or completely abandoned. The lack of user acceptance has been long identified as an obstacle to the success of new technologies [5]. Therefore, it has become crucial for practitioners and decision-makers to better understand the factors that influence the adoption of IoT, since it is considered an essential step toward the development of a successful healthcare system [6].

Many models and theories have been proposed to examine and predict the acceptance of new technologies. One might consider the Technology Acceptance Model (TAM) [7], the Unified Theory of Acceptance and Use Technology [8] and the Theory of Reasoned Action [9]. The TAM model is employed in this study to understand and estimate the users' adoption behaviors toward modern technologies [7]. This is due to the fact that TAM is the most common and cited model in the IS research [10] and healthcare domain [11, 12], because of its adequate explanatory power and parsimonious structure [13]. Being said that, TAM has not been widely tested in developing countries [14]. Consequently, the author of [15] emphasizes on the importance of examining TAM in different cultures to ensure adequate reliability and validity. Moreover, TAM does not serve equally across cultures, and the inconsistency in previous studies' results highlight the importance of conducting this research in the KSA context [16, 17]. KSA remains relatively unexplored in terms of technology acceptance, while investment in healthcare system technology is promised for future projects. Hence, this study aims to examine the individual patients' perceptions towards the adoption of IoT technology in KSA by applying the TAM model.

II. RESEARCH MODEL

Our purpose is to study the acceptance of using IoT technology in the healthcare sector in KSA from a conceptual viewpoint. We propose a theoretical model that extends TAM with its original four factors, Perceived Usefulness (PU),

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Perceived Ease of Use (PEO), Attitude (ATT), and Behavioral Intention to Use (BI), including four new external factors: Connectedness (PCO), Convenience (PCV), Privacy (PPR), and Cost (PC) (Figure 1).
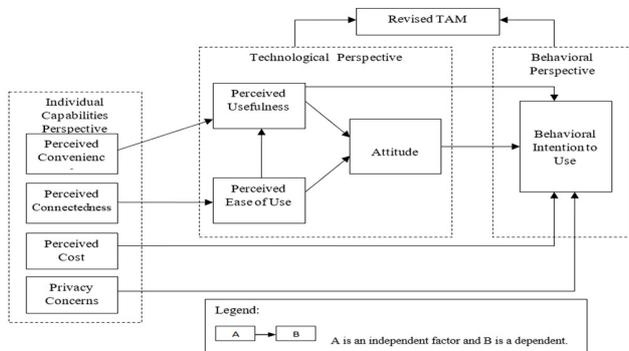
Fig. 1.   The proposed research model

A survey instrument was developed and distributed to 450 patients in order to test the research model [37]. Collected data were analyzed using the Structural Equation Model, based on the Partial Least Square approach. This method shows relationships and the quality of connections among the factors in the proposed model. In particular, we want to assess the influence of the four original factors on the intention of using IoT, by specifying the relationships between them and among the new factors that subsequently influence the usage intention. Accordingly, a set of hypotheses were set to determine if there is a correlation between these factors. Those hypotheses are listed in Table I.

TABLE I.   RESEARCH HYPOTHESES

Hypotheses	
H1	Perceived Convenience has direct effect on Perceived Usefulness
H2	Perceived Connectedness has direct effect on Perceived Ease of Use
H3	Perceived Cost has direct effect on Behavioral Intention to Use
H4	Privacy Concern has direct effect on Behavioral Intention to Use
H5	Perceived Ease of Use has direct effect on Perceived Usefulness
H6	Perceived Usefulness has direct effect on Attitude
H7	Perceived Ease of Use has direct effect on Attitude
H8	Perceived Usefulness has direct effect on Behavioral Intention to Use
H9	Attitude has direct effect on Behavioral Intention to Use

Before conducting the survey, two independent experts reviewed the instrument for ensuring its validity and relevance. The instrument was structured in two parts. The first part contained sociodemographic questions and a basic question on IoT awareness, which was "Do you have basic knowledge of IoT?", with response options ranging between "General Idea", "Good Idea," and "Already using some Services". The second part contained questions that measured the respondents' intention to use IoT for healthcare, utilizing a five-point Likert scale (from 1="strongly disagree" to 5="strongly agree"). The interval scale was used because it allows specific mathematical operations on the data collected from respondents. In order to ensure that the survey will be distributed over a sufficient number of participants so as to generalize our model, the Cochran's Sample Size Formula was utilized to calculate the minimum sample size, as it is proven reliable for use in large

populations [18]. The current study targeted adult patients and according to the KSA General Authority for Statistics data in 2016 the proportion of the adult population of Saudi Arabia is 75.2%, which equals to 23,870,215 persons. The Cochran's Sample Size Formula [18] is given as:

$$no = \frac{z^2\,(p*q)}{e^2} \quad (1)$$

where e is the desired level of perception (error margin), p is the estimated proportion of the population which has the attribute in question, $q=1-p$ and z-value is found in the Z table. In this study, we desired 95% confidence level, p=0.05 and at least 5%. A 95 % confidence level gives us z-value of 1.96, so, based on (1), the minimum sample size is 385. The instrument was distributed to 450 patients in KSA hospitals and 426 responses were obtained, out of which 19 were excluded because of missing values. Hence, data from 407 respondents were processed for the final analysis.

III.   TESTING RESULTS

A. Respondents Demographic Statistics

Descriptive statistics showing the respondents demography can be seen in Table II. There were 207 male and 200 female participants, where 27.5% of them were 55 years old or older, 21.1% were 45-54 years old, 20.1% were 35-44 years old, 16.5% were 25-34 years old, and the remainder 14.7% were 18-24 years old. 48.2% of our sample had basic knowledge of IoT, while the rest either had a good idea or already used some IoT services. Regarding the income, 23.8% registered high income with more than 190K SR, 40.3% had income 120K-190K SR, 20.4% had income 48K-120K SR, and 15.5% had less income than 48K SR.

TABLE II.   DEMOGRAPHIC INFORMATION OF THE RESPONDENTS

Characteristics		Frequency	Percent %
Age	18-24	60	14.7
	25-34	67	16.5
	35-44	82	20.1
	45-54	86	21.1
	55 or older	112	27.5
	Total	**407**	**100.0**
Gender	Male	207	50.9
	Female	200	49.1
	Total	**407**	**100.0**
Income (SR)	<48K	63	15.5
	48K-120K	83	20.4
	120K-190K	164	40.3
	190K or more	97	23.8
	Total	**407**	**100.0**
Basic knowledge of IoT	General idea	196	48.2
	Good idea	144	35.4
	Already using IoT	67	16.5
	Total	**407**	**100.0**

B. Normality Testing

Skewness and kurtosis have been calculated using the SPSS platform to test the normality of the used data set. Normality tests are used to determine whether a dataset has normal distribution. In this study, skewness was used to measure the asymmetry of the probability distribution of a random variable about its mean, while Kurtosis was utilized to tell the height

and sharpness of the central peak, relative to the standard bell curve. Skewness and kurtosis values can be positive or negative or even undefined. If skewness value is between -0.5 and 0.5, and if kurtosis value is between -2 and +2, they are acceptable and prove normal univariate distribution [19]. As shown in Table III, all factors have obtained values in the acceptable range, which reflects a high degree of normality.

TABLE III.   NORMALITY OF THE DATASET

Factor		Skewness	Kurtosis
Behavioural Intention to Use (BI)	**BI1**	0.453	-0.802
	BI2	0.387	-1.128
	BI3	0.197	-1.133
Perceived Usefulness (PU)	**PU1**	-0.092	-0.084
	PU2	0.136	-0.037
	PU3	0.089	-0.133
	PU4	0.042	-0.348
	PU5	0.075	-0.058
	PU6	-0.030	-0.201
Perceived Ease of Use (PEO)	**PEO1**	0.017	-0.705
	PEO2	0.099	-0.592
	PEO3	0.141	-0.581
	PEO4	0.244	-0.824
	PEO5	0.140	-0.442
	PEO6	0.087	-0.605
Attitude (ATT)	**ATT1**	-0.062	-0.535
	ATT2	-0.132	-0.440
	ATT3	0.030	-0.864
Perceived Connectedness (PCO)	**PCO1**	0.328	-0.114
	PCO2	0.237	0.044
	PCO3	0.240	-0.268
Perceived Cost (PC)	**PC1**	-0.262	-1.083
	PC2	-1.035	-0.272
	PC3	-0.533	-1.092
Privacy Concerns (PPR)	**PPR1**	0.462	-0.842
	PPR2	0.578	-0.825
	PPR3	0.349	-1.174
Perceived Convenience (PCV)	**PCV1**	0.474	-0.417
	PCV2	0.500	-0.482
	PCV3	0.477	-0.288

C. Validity Testing

Cronbach's alpha is calculated to measure the internal consistency for the reliability of the used questionnaire, measuring how a set of items is closely related as a group. Table IV presents all the factors that are used, where the value of Cronbach's alpha obtained is greater than 0.7, which reflects a high degree of internal reliability [20].

TABLE IV.   INSTRUMENT'S INTERNAL CONSISTENCY

Factor	No. of Questions	Cronbach's Alpha
BI	3	0.894
PU	6	0.929
PEO	6	0.874
ATT	3	0.939
PCO	3	0.863
PC	3	0.883
PPR	3	0.783
PCV	3	0.875

D. Convergent Validity

In order to measure the convergent validity, the average variance extracted (AVE) and the composite reliability have

been calculated for every factor, as shown in Tables V and VI. The corresponding factor loading for every construct exceeds the threshold value of 0.60, which is a minimum requirement criterion for the convergent validity test to pass [21]. Also, for every construct, the value obtained for AVE is higher than the recommended level of 0.5 [22].

TABLE V.   FACTOR LOADING

	PU	PEO	ATT	PCV	PCO	PC	PPR	BI
PU	0.793							
	0.761							
	0.820							
	0.829							
	0.898							
	0.863							
PEO		0.701						
		0.745						
		0.729						
		0.722						
		0.738						
		0.761						
ATT			0.912					
			0.984					
			0.859					
PCV				0.816				
				0.829				
				0.866				
PCO					0.806			
					0.955			
					0.718			
PC						0.802		
						0.867		
						0.869		
PPR							0.771	
							0.816	
							0.650	
BI								0.822
								0.861
								0.887

TABLE VI.   CONVERGENT VALIDITY

Factor	No. of questions	Average variance extracted (> 0.50)	Composite reliability (> 0.70)
BI	3	0.734591	0.892418
PU	6	0.686464	0.929071
PEO	6	0.537153	0.874351
ATT	3	0.84596	0.942609
PCO	3	0.692395	0.869442
PC	3	0.716685	0.883432
PPR	3	0.560932	0.791627
PCV	3	0.701018	0.87546

E. Discriminant/Divergent Validity

The discriminant/divergent validity was also tested. Discriminant validity refers to the extent to which factors are distinct and uncorrelated. The rule is that variables should relate more strongly to their factor than to any other factor. The test was calculated using SPSS, and the result is shown in Table VII. When examining discriminant validity, the square root of the AVE for each construct should be greater than the correlational values between any two constructs. This is precisely our case: all diagonal elements have a higher correlation level between any two specific factors. Thus, the discriminant validity test is sufficed for our model.

IV. HYPOTHESES RESULTS

AMOS 23.0 has been used to test the proposed model and the corresponding hypotheses. Figure 2 and Table VII present the results of the research model. As shown, p-value is used to determine the significance of the results. In other words, our hypothesizes were tested by using the p-value to weigh the strength of the evidence. The p-value is a number between 0 and 1 and interpreted in the following way: a small p-value (≤ 0.05) indicates strong evidence against the null hypothesis, so the null hypothesis is rejected. A large p-value (>0.05) indicates weak evidence against the null hypothesis, the null hypothesis in not rejected. If p-values are very close to the cutoff (0.05), they are considered to be marginal [23]. Accordingly, results in Table VIII show that hypotheses H1, H3, H4, H5, and H8 are supported and have a high level of statistical significance ($p<0.05$), while H2, H6, H7, and H9 are not supported ($p>0.05$). For additional analysis, we found that

there is no significant correlation between Age and Behavioral Intention (r=-0.043, p=0.560, p>0.05).
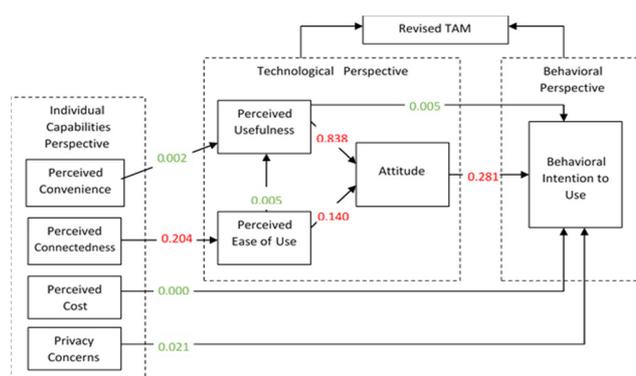
Fig. 2.   Summary of our proposed model

TABLE VII.   DISCRIMINANT VALIDITY

	PCV	PCO	PC	PCO	ATT	BI	PEO	PU
Perceived Convenience (PCV)	0.837268							
Percieved Connectedness (PCO)	0.01145	0.832103						
Percieved Cost (PC)	0.03312	0.04796	0.74895					
Privacy Concerns (PPR)	0.03168	0.03764	0.70560	0.846573				
Attitude (ATT)	0.00208	0.00043	0.00488	0.01000	0.919761			
Behavioral Intention to Use (BI)	0.00725	0.02103	0.01061	0.01416	0.00090	0.85708		
Perceived Ease of Use (PEO)	0.00001	0.00299	0.01277	0.00800	0.01877	0.00811	0.73291	
Percieved Usefulness (PU)	0.01369	0.00531	0.00341	0.00152	0.01416	0.00543	0.01020	0.82853

TABLE VIII.   HYPOTHESIS TESTING

	Hypothesis			p	Status
H1	Perceived Convenience	→	Perceived Usefulness	0.002	Supported
H2	Perceived Connectedness	→	Perceived Ease of Use	0.204	Not supported
H3	Perceived Cost	→	Behavioral Intention to Use	0.000	Supported
H4	Privacy Concerns	→	Behavioral Intention to Use	0.021	Supported
H5	Perceived Ease of Use	→	Perceived Usefulness	0.005	Supported
H6	Perceived Usefulness	→	Attitude	0.838	Not supported
H7	Perceived Ease of Use	→	Attitude	0.140	Not supported
H8	Perceived Usefulness	→	Behavioral Intention to Use	0.005	Supported
H9	Attitude	→	Behavioral Intention to Use	0.281	Not supported

V. DISCUSSION

This study applied an extension to TAM to determine the factors that influence the acceptance of IoT technology for healthcare in KSA. Empirical research was performed to test the study's hypotheses. Most of our findings are in line with findings from previous studies that applied TAM in healthcare systems and e-health. The results offer various useful insights into the acceptance behavior on the IoT technology for healthcare. We found that cost and privacy concerns are the most significant predictors of behavioral intention to use. Moreover, results reveal that perceived usefulness is another important construct that affects the system usage, which in turn is strongly influenced by both perceived convenience and perceived ease of use. On the other hand, results show that

perceived connectedness does not affect behavioral intention, neither directly nor indirectly. However, perceived ease of use affects it indirectly through perceived usefulness. Authors in [24-27] found that perceived usefulness and perceived ease of use significantly influence behavioral intention, which is consistent with our results. This is due to the level of effort that goes into learning a new technology or service, which may far outweigh the perceived benefit of the proposed system for many people. Authors in [28-29] found that perceived usefulness was a significant indicator, however, they contradict our findings in which perceived ease of use was an insignificant predictor. This is because their study targeted patients with chronic conditions who tend to rely a lot on the diagnosis and advice (e.g. remote patient monitoring devices) from experts to facilitate disease management and reduce

medical costs. Authors [30-32] revealed that perceived cost and privacy concerns have a significant impact on forming users' intention. These findings are consistent with ours that show perceived cost as the most significant predictor affecting the behavioral intention. This implies that high cost of implementing this technology can impact the use of IoT services. Thus, inventors must consider cost when implementing this technology for healthcare purposes. Moreover, privacy concerns is another important construct that affects the entire system usage, as patients are extremely concerned and sensitive about the privacy and security of the collected data. This important factor must be kept in mind by healthcare providers as they must be able to provide a technique to support customized data accessing. The results obtained in [26] are quite different from our findings. Specifically, the authors in [26] found that perceived cost was not significantly associated with intention to use mHealth. This variation can be attributed to the availability of mobile services to the population studied in that research. Authors in [33-34] found that perceived convenience has significant impact on forming behavioral intention, which is compatible with our findings. We attribute this to the fact that IoT and the context of providing health support is a relatively new idea, while the underlying technologies are still evolving. Consequently, patients are willing to proceed with this technology and services with little effort or difficulty.

Perceived connectedness has not been extensively considered in the literature. The effect of this construct was found to be non-significant in our study. This observation is in contrast with the findings of other researchers, where connectedness plays a significant role in determining the intention to use a system [35]. This means that patients do not bother about the devices' connectedness. Consequently, patients perceive this technology to be immature and in an early developmental state. Ultimately, although many researchers have considered healthcare services [37, 38] and the use of TAM in their studies [39], we believe that our study added more variables to the original TAM model that could provide a better explanation of patients' acceptance of IoT technology.

VI.   CONCLUSION AND FUTURE WORK

This study assesses empirically the intention of Saudi patients to use IoT technology from a healthcare perspective. To this end, an extended model based upon the TAM was built with eight factors. The proposed model was validated using a instrument designed specifically for this research. In order to ensure that our model can be generalized, the survey was distributed to more than 450 participants, and the responses of 407 of them were considered valid and were further analyzed. SPSS v25.0 and AMOS v23.0 have been utilized to process the results, test the proposed model and the corresponding hypotheses. All test results met normality and validity requirements. The discriminant validity was also tested between factors, showing the sufficiency of our model. The p-value was used to determine the significance during the hypotheses testing. Results showed that perceived usefulness, cost, and privacy concerns were the leading predictors of behavioral intention to use. Moreover, the perceived usefulness

was strongly affected by both perceived convenience and perceived ease of use. However, attitude and perceived connectedness did not have any effect on behavioral intention, directly or indirectly. This research provides the groundwork to explore the process of the actual adoption of IoT services for healthcare. However, as future work, more factors should be identified and added to the model, in order to gain more insights and ensure greater success of such service. Moreover, the model could be extended to include a larger number of patients. In addition, we can extend our current findings by investigating the moderating effects of age, cultural background, and other factors.

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