

Internet of things in Saudi public healthcare organizations: The moderating role of facilitating conditions**Mohammed Alarefi^{a*}**^a*Department of management information system, faculty of Business Administration, University of Tabuk, Saudi Arabia***CHRONICLE****ABSTRACT***Article history:*

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The Internet of Things (IoT) is an innovative technology that has the potential to help public hospitals better meet the demands of hospitalization. However, only a small portion of the research looked at patients' behavioural intentions (BI) to utilise IoT healthcare devices (IoTHD). This study intends to investigate the variables that influence the BI's use of IoTHD. The research suggests that the BI may be explained by factors of UTAUT. The patients of public hospitals make up the population. A questionnaire was used to obtain the data using convenience sampling. Participants in this research totalled 161. Smart Partial Least Square results demonstrated that social influence (SI) has an impact on performance expectancy (PE). Technological complexity (TC) and playfulness (PP) had an impact on effort expectancy (EE). Additionally, the BI to adopt IoTHD was impacted by PE, EE, perceived security (PS), and perceived privacy (PV). The impact of PE and EE on BI to use IoTHD was not moderated by the facilitating conditions (FC). In order to improve patients' perceptions of IoTHD usage in public health organisations, simple process and more positive word of mouth is required.

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1. Introduction

Pressure on public health institutions throughout the globe has increased as a result of population growth and rising life expectancy (Di Crosta et al., 2020; Enroth et al., 2022; Lynch et al., 2022). Hospital and healthcare organisations' global capacities are practically at their maximum. This is due to the fact that patients need hospitalisation and care in an aging population. The capabilities of public hospitals worldwide, particularly to a significant extent in underdeveloped countries, might yet be impacted by the increase in population in developing countries compared with developed countries (Gu et al., 2021). To meet the problem, technological utilisation is crucial. The Internet of Things (IoT) is a promising technology that has been used in healthcare organisations (Singh et al., 2020).

IoT is a recent breakthrough that aids in developing a system of machine-to-machine communication without human participation or interference. The system makes use of sensors and transmits user data to other devices (Datta et al., 2019). IoT applications are being used in every sphere of life, including business, healthcare, and education. According to statistics, there has been a significant growth and a strong upward trend in the number of IoT devices over the last 10 years. For instance, according to experts, there will be over 74 billion IoT devices in operation by 2025, with nearly nine gadgets for every person in the world (Habibipour et al., 2019).

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IoT is a potential technology that can address the problem of public hospital capacity. IoT wearable medical devices may track a patient's state and provide information to hospital physicians about that patient's health. This is especially true for those who have chronic illnesses and often see physicians for check-ups. The usage of various IoT wearable devices, such as a watch or smartphone, may both save lives and help relieve the congestion in public hospitals (Bhatt et al., 2017).

Despite the need for public health organisations to employ this strategy, utilisation of this method is still restricted and in its infancy (Alhasan et al., 2020). Developed nations, which have the necessary infrastructure and know-how to deploy the technology, predominate in the literature that has already been written on the use of IoTHD (Balachandar & Chinnaiyan, 2019; Menychtas et al., 2020; Shekar, 2019). Additionally, researchers focus more on the technical aspects of employing IoTHD in terms of connection, sensor, networking, and programming while the individual adoption and use of such technology is still being studied (Harwood & Garry, 2017; Lu et al., 2018; Shin & Hwang, 2017).

It has been argued in the literature so far that the majority of research on user adoption and engagement with IoT technologies is still of a technical character, and that the behavioural approach has not yet gotten sufficient attention (de Boer et al., 2018; Dong et al., 2017; Mital et al., 2018; Park et al., 2017). There is a lack of clarity and understanding among studies about the process through which the IoT might affect individual and society acceptance (Shin & Jin Park, 2017; Shin & Hwang, 2017). Research on user experiences with IoT is still in its infancy, and more work is needed to determine what elements could convince people to use IoT (Shin, 2017; Hsu & Lin, 2016).

The technology acceptance model is one of several behavioral models concerned with the spread of new technologies (TAM). Davis (Davis, 1989) is credited for creating TAM. Recent models, such as UTAUT by Venkatesh et al. (2003), are more robust than TAM and can account for a greater proportion of the variance in technology adoption. UTAUT argued that performance expectations (PE) and effort expectations (EE) influence how a new technology can be accepted by the users. Facilitating conditions (FC) and social influence (SI) are other variables that are included in UTAUT. Venkatesh and Davis (2000) created a newer version of TAM called TAM2 that places more emphasis on how well the technology suits the needs of each individual. TAM3, the most recent iteration of the original TAM, including factors like enjoyment and readjustment (Viswanath Venkatesh & Bala, 2008). Complexity is a major contributor to depression and other mental problems in the current era of sophisticated technology. Therefore, this is an extremely relevant consideration in this scenario. When it comes to the IoT, however, UTAUT and TAM have been criticised for not paying enough attention to security and privacy (Ahmadi et al., 2019; Padyab & Ståhlbröst, 2018; Shachak et al., 2019).

Few studies have looked at the question of IoTHD adoption in emerging nations like Saudi Arabia (Maswadi et al., 2022). The government is improving Saudi Arabia's infrastructure, while the elderly with chronic disease usage of technology is low. Therefore, the purpose of this research is to investigate the factors that lead patients with chronic disease in Saudi Arabia to use IoTHD. Those who need to often go to hospitals are the focus of the research. We then go on to a discussion of the study's literature evaluation, methods, results, and conclusion.

2. Literature review

This section discusses the literature related to the theoretical framework that can support the development of the conceptual framework of this paper.

2.1. Theoretical Framework

When it comes to the acceptance of new technology, there are a few different theories that may be used to analyse people's decisions and determine which technology to embrace. The UTAUT model is considered to be one of the most effective models. This research employs UTAUT, which indicates that the utilisation of technology is determined by the anticipated advantages from utilising a specific technology as well as the expected physical and mental efforts (Viswanath Venkatesh & Bala, 2008). Additional variables of UTAUT include the influence of others which is referred to in UTAUT as social influence. Facilitating conditions is also another critical variable that has been introduced by UTAUT. Complexity of technology might be a factor that hinder the usage of the technology. Additionally, the perceived playfulness (PP) since the IoT is being a wearable device might affect the perception of expected efforts. Furthermore, the effect of others might change the perception of users regarding the benefits of using a new technology such as IoTHD. Therefore, this study proposes that complexity of such technologies, have a significant role in defining the EE, whilst the social impact and importance of the technology may decide the PE. UTAUT suggested that the PE and EE would have an effect on the adoption of a new technology. The UTAUT was criticised for not making sufficient use of technology considerations. In order to take into account criticism, the level of security offered by the IoTHD is being taken into consideration as a crucial variable in this research. In addition, privacy (PV) which is part of the technological considerations is significant when discussing a technology such as IoTHD (V Venkatesh et al., 2003). Further, the FC is essential predictors in UTAUT. However, limited studies examined its moderating role.

2.2 Conceptual Framework and Hypotheses Development

This research hypothesised that PE is impacted by SI, and that EE is affected by technological complexity, as well as perceived levels of playfulness (PP). It was anticipated that both the PE and EE would have direct effects on the IoT healthcare usage, and these effects are expected to be moderated by way of the facilitating conditions (FC), which served as a moderator. It is anticipated that both privacy (PV) and perceived security (PS) would have an immediate impact on IoT healthcare usage. In the following section, the hypotheses of this study are discussed. Fig. 1 shows the conceptual framework of this study.

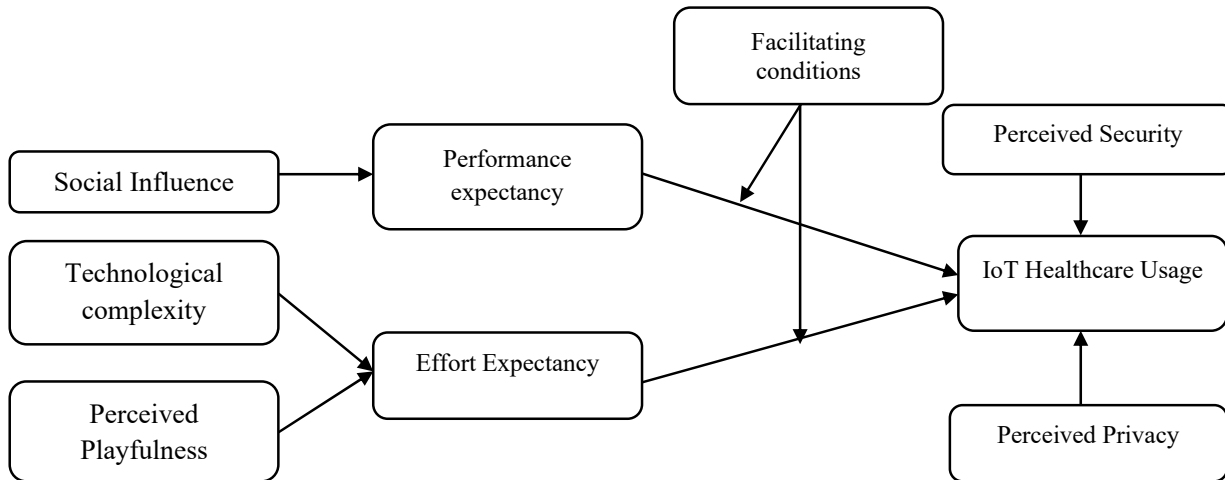


Fig. 1. Conceptual Framework

2.2.1 SI and PE

SI refers to an individual's view of significant persons who have an impact on their decision-making (Ajzen, 1991). UTAUT posited that the SI is a significant variable that has the potential to influence the BI (Ajzen, 1991; V Venkatesh et al., 2003). To be more explicit, models such as TAM3 suggested an interdependent relationship between SI and PE (Viswanath Venkatesh & Bala, 2008). Previous research has also investigated the connection between SI and PE and discovered that there is a positive relationship between the two variables (Çelik, 2011; Chang et al., 2017; Kurdi et al., 2021). As a result, it has been suggested that:

H₁: *SI has a positive impact on PE.*

2.2.2 Technological complexity and EE

Theory of diffusion of innovation (DOI) suggests that technology complexity (TC) is a factor that influences EE. When users are uninformed about a technology, they often experience feelings of apprehension whenever they consider utilising it (Pal et al., 2018). The effects of TC on EE are not entirely clear. According to the findings of research (Shen & Eder, 2009), TC does not have an impact on EE, however studies (Rahmi et al., 2018; Zheng & Li, 2020) indicated that TC is an important factor in determining EE. It is widely held that a significant factor in EE in Saudi Arabia is apprehension towards technological advances. Therefore, the following is postulated as a hypothesis:

H₂: *TC has a significant impact on EE.*

2.2.3 PP and EE

According to TAM3, perceived playfulness (PP) is one of the variables that determines EE. When it comes to accessing the internet of things on a smart phone or on a watch, this variable is more context dependent. The literature does not typically look at the variable in question. Users that are curious about the IoT and enjoy following technological developments are more likely to find that utilising the technology provides them with a positive experience (Koch et al., 2020; Siron et al., 2020). PP impacted significantly the EE in several previous studies (Koch et al., 2020; Siron et al., 2020) thus, this study proposed the following:

H₃: *PP affects the EE.*

2.2.4 PE and IoT healthcare usage

Individuals' perspectives on the benefits they get from the use of a technology are referred to as PE (Kayali & Alaaraj, 2020). The PE is connected to the BI and is considered to be one of the most important aspects of UTAUT. When consumers feel

that the Internet of Things will benefit them, they are more likely to utilise it, which has a favourable influence on their BI. This has been shown in a number of earlier studies (Dhagarra et al., 2020; Karahoca et al., 2018; Mital et al., 2018). Therefore, this study proposed that PE will have a positive impact on the BI toward IoTHD.

H₄: *PE affects IoT healthcare usage.*

2.3.5 EE and IoT healthcare usage

One of the key UTAUT variables, EE, is thought to have an impact on BI. In earlier research, several contexts were used to study the relationship between EE and BI. For example, the research of (Solangi et al., 2018) examined the relationship between EE and BI in medical equipment and discovered a favourable connection. The research (Choi & Kim, 2016) discovered a beneficial relationship between EE and BI's utilisation of IoT. According to (Mital et al., 2018) in the context of IoTHD, EE positively affects BI. Similar results were obtained in Turkey by (Karahoca et al., 2018). There are studies that, however, discovered no connection between the two factors (El-Masri & Tarhini, 2017). As a result, it is assumed:

H₅: *EE affects IoT healthcare usage.*

2.3.6 Perceived security and IoT healthcare usage

The term "perceived security" (PS) refers to how people feel about the IoT's security and reliability (Zhang et al., 2014). Several researches highlighted the significance of PS in relation to IoT applications. Examples of references discussing the significance of PS for IoT adoption and repurchase intent may be found in , (Pinochet et al., 2018). Similarly, (Chouk & Mani, 2019) discovered a favourable correlation between PE and the use of smart services. According to the results of this research, increased PS will lead to wider IoTHD adoption. Therefore, it is speculated:

H₆: *PS affects IoT healthcare usage.*

2.3.7 PV and IoT healthcare usage

PV refers to the confidentiality of using the IoT and the concern of users regarding their personal information (Kayali & Alaaraj, 2020). Privacy has been found to affect the usage of electronic medical records (Rawwash et al., 2020; Saleh et al., 2020). High level of perceived privacy was found to significantly affect the usage of IoT (Enaizan et al., 2020). This study proposes that a high level of perceived privacy will positively affect the IoT healthcare usage.

H₇: *PV affects IoT healthcare usage.*

2.3.8 FC as a Moderator

FC is proposed by UTAUT to have a direct effect on the BI. FC is essential for deploying the technology since it provides the support in terms of infrastructure and essential requirement to use the technology (Kayali et al., 2019). Tarhini, Hone, et al. (Tarhini et al., 2015) found that FC has a positive impact on behaviour to use technology. Solangi et al. (Solangi et al., 2018) indicated that there is a positive link between FC and use of IoT. Few studies examined the moderating role of FC. For instance, FC was tested as a moderator in the adoption of safe motherhood (Rai & Biswas, 2022). In Saudi Arabia, FC can facilitate the usage of technology and an encouraging factor for such usage. High level of FC will enhance the perception of benefits and needed effort. Thus, the following is proposed.

H₈: *FC moderates the effect of PE on IoT healthcare usage.*

H₉: *FC moderates the effect of EE on IoT healthcare usage.*

3. Research methodology

The positivist paradigm and the deductive method are the two approaches that underpin the research philosophy. The survey is the foundation of the research approach, and cross-sectional are used in the data collection process. Patients who attend medical facilities in the Kingdom of Saudi Arabia made up the study's population. In order to acquire the data, we are using convenience sampling. This method of sampling was chosen since it is difficult to have a database that has information on the people who are afflicted with chronic diseases. A questionnaire is used as the tool for this research. The questionnaire is an amalgamation of questions taken from a number of different earlier research. The measurements for PE (four items), FC (five items), and EE (five items) were taken from (Karahoca et al., 2018), while PS (five items) was taken from (Park & Kim, 2014), and PV (five items) and IoT healthcare usage (five items) were taken from (Lian, 2015). Measurement of SI (four items), TC (four items), and PP (4 items) were adopted from several researchers (Viswanath Venkatesh & Bala, 2008) (Kayali & Alaaraj, 2020; Venkatesh & Davis, 2000).

The questionnaire was translated into Arabic and then evaluated by language specialists who are fluent in both English and Arabic. It was determined via the administration of a pilot research to assess the Cronbach's Alpha (CA) of the measurement, and it was discovered that all of the measures are reliable with CA values that are more than 0.70, as is indicated by Sekaran and Bougie (2019). In order to gather field data, it was requested that the administration of five different public hospitals assist in the distribution of the questionnaire. In all, 391 surveys were mailed out, and reminder emails were sent in an effort to elicit further replies. As a direct consequence of this, a total of 183 responses to the questionnaire were gathered. According to the findings of a certain group of researchers (Hair, Hult, Ringle, Sarstedt, et al., 2017), employing Smart Partial Least Square (Smart PLS) may be successful with replies ranging from 100 to 150.

The gathered information underwent filtering so that its missing value, outliers, normality, and multicollinearity could be evaluated. It was determined that nine replies were missing more than 15% of the total responses, thus those responses were removed. In addition to that, 13 of the replies were determined to be anomalous. This has led to a total of 161 answers from respondents. In addition, the normality and multicollinearity of the data were analysed, and the results revealed that the data are normal and that there is no evidence of multicollinearity. All of these analyses were carried out in accordance with the recommendations found in (Hair, Hult, Ringle, & Sarstedt, 2017). The results of the analysis of the data are shown in Table 1, which demonstrates both the normality and the multicollinearity of the data.

Table 1
Data Examination

Variable	Normality		Multicollinearity	
	Skewness	Kurtosis	Tolerance	VIF
FC	-.41	-.40	.51	1.12
TC	-.31	-.43	.53	1.33
PV	-.45	-.52	.61	1.43
EE	-.81	-.34	.71	1.51
PS	-.51	-.64	.73	1.21
PE	-.81	-.54	.53	1.34
SI	-.72	-.43	.54	1.43
IoT healthcare usage	-.62	-.45	-	-

4. Findings

Descriptive information of respondents as well as the analysis of Smart PLS version 4.0 are discussed in this section.

4.1 Profile of Respondents

In all, there were 161 individuals who agreed to take part in this research. Most of the responders were men (73%), while just 27% were females. Among those who participated in the survey, the majority (71%) are between the ages of 50 and 60 years old, while 21% are 60 or older, and just 8% are younger than 50 years old. The respondents' levels of education range from high school (31%), through bachelor's degrees (44%) to less than high school (25%) degrees. 52% of those who participated in the survey are self-employed, 29% are employed by the public sector, and 19% are employed by the private sector.

4.2. Measurement Model

The factor loading (FL), composite reliability (CR), convergent validity utilising average variance extracted (AVE), and discriminant validity were evaluated in order to evaluate the measurement model (MM). With the exception of SI2, PE1, and PS2, the FL for all components is more than 0.70. As can be seen in Table 2, both the CA and CR values for each of the variables are higher than 0.70. In addition, the convergent validity is acceptable since the AVE of the variables is better than 0.50, which indicates that they are highly related to one another. The root square of the AVE is higher than the cross loading, which is significant for the discriminant validity. These analyses of assessing the MM were based on the suggestions of (Hair, Hult, Ringle, & Sarstedt, 2017).

Table 2
Result of the MM

	CA	CR	AVE	FC	IoTu	PV	EE	PS	PE	PE	SI	TC
Facilitating condition (FC)	0.89	0.93	0.82	0.91								
IoT healthcare usage (IoTu)	0.89	0.93	0.81	0.51	0.90							
Privacy (PV)	0.93	0.95	0.78	0.03	0.06	0.88						
Effort expectancy (EE)	0.94	0.96	0.84	0.42	0.48	0.02	0.92					
Perceived Security (PS)	0.89	0.90	0.70	0.27	0.51	0.03	0.32	0.84				
Performance expectancy (PE)	0.92	0.95	0.81	0.44	0.50	0.04	0.62	0.32	0.90			
Perceived playfulness (PE)	0.93	0.95	0.79	0.24	0.26	0.10	0.20	0.13	0.07	0.89		
Social influence (SI)	0.84	0.90	0.76	0.45	0.48	0.06	0.57	0.35	0.58	0.27	0.87	
Technology Complexity (TC)	0.85	0.80	0.52	0.02	0.10	0.24	0.06	0.05	0.04	0.10	0.02	0.72

4.3 Structural Model

There are several criteria to be assessed in structural models (Hair, Hult, Ringle, & Sarstedt, 2017). The R-square was assessed, and it is found that 52.1% of IoT healthcare usage can be explained by the variables. The Q-square is greater than zero indicating that the independent variable can predict the dependent variable. For the f-square, it is larger than 0.02 for all paths except for the moderators' paths which are less than 0.02. The structural model of this study is given in Fig. 2.

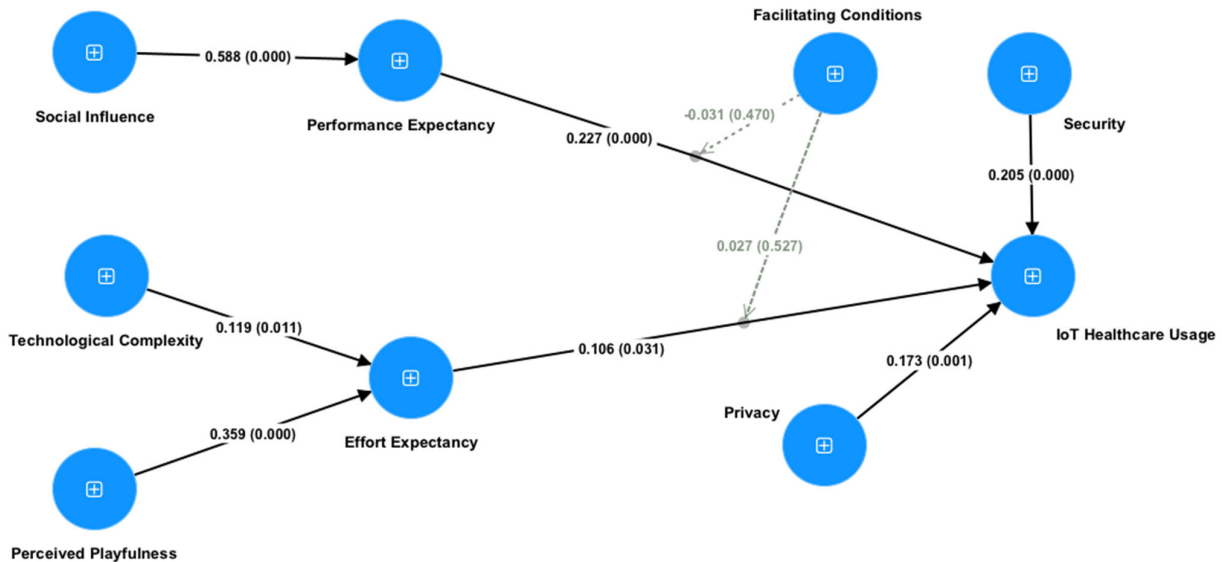


Fig. 2. Structural Model

For the path coefficient, it is given in Table 3 which shows the result of hypotheses testing of the direct and moderating effect where H refers to hypothesis, B, path coefficient, STD refers to standard deviation, T to t-statistics, and P for p-value.

Table 3
Result of Hypotheses

H	Path	B	STD	T	P	Label
H1	SI → PE	0.588	0.031	18.867	0.000	Significant
H2	TC → EE	0.119	0.047	2.548	0.011	Significant
H3	PP → EE	0.359	0.054	6.645	0.000	Significant
H4	PE → IoT Healthcare Usage	0.227	0.053	4.280	0.000	Significant
H5	EE → IoT Healthcare Usage	0.106	0.049	2.152	0.031	Significant
H6	PS → IoT Healthcare Usage	0.205	0.049	4.177	0.000	Significant
H7	PV → IoT Healthcare Usage	0.173	0.052	3.322	0.001	Significant
H8	FC × PE → IoT Healthcare Usage	-0.031	0.043	0.722	0.470	Not significant
H9	FC × EE → IoT Healthcare Usage	0.027	0.042	0.633	0.527	Not significant
	FC → IoT Healthcare Usage	0.155	0.046	3.378	0.001	

The result of the hypotheses is given in Table 3. It can be seen that the effect of SI on PE is positive at B=0.588 and P<0.001 which provides support for H1. For H2, TC affected positively on EE because and this impact is significant since P<0.05. Therefore, H2 is accepted. H3 is supported and the impact of PP on EE is significant at B=0.359 and P<0.001. For H4, the effect of PE on IoT healthcare usage is supported. Thus, H4 is supported. Similarly, the H5 is supported because the impact of EE on IoT healthcare usage is positive and significant. For H6, it is also supported because the effect of PS on IoT healthcare usage is positive. For H7, the effect of PV on IoT healthcare usage is significant. Thus, H7 is accepted. H8 is rejected because FC is not a moderating variable in the effect of PE on IoT healthcare usage because the effect (FCxPE→ IoT healthcare usage) is not significant. Thus, H8 is rejected. For H9, it is also rejected because the effect is not significant. Thus, FC did not moderate the effect of EE on IoT healthcare usage.

5. Discussion and Implications

In this study, the IoTHD was investigated in Saudi Arabia patients who were treated in public hospitals. IoT is a relatively new technology that has the potential to assist in alleviating stress and improving the care that patients get. The research investigated the impact that SI has on PE and discovered that there is a correlation between the two. This suggests that the PE will rise if a favourable word of mouth spreads among users. SI is derived from the people who surround a person, and if those individuals are positive, then the individual will have a favourable impression towards PE. It was anticipated that TC would have a detrimental impact on EE. According to the findings, there is a correlation between TC and EE. This

demonstrates that the TC of IoTHD has an influence on EE. Further, the PP has a positive effect on EE indicating that increasing the level of enjoyment while using IoT healthcare devices will lead to positive perception about EE. Previous research revealed that SI had an effect on PE (Çelik, 2011; Chang et al., 2017; Kurdi et al., 2021) and our results are consistent with previous research. It is also in keeping with the results of the literature in terms of the influence of TC and PP on EE (Shen & Eder, 2009) (Koch et al., 2020; Siron et al., 2020).

Because of the influence that PP has on EE, we may deduce that experiencing pleasure and playfulness when interacting with the IoTHD will contribute to a more favourable opinion of the ease with which the technology can be used. PE and EE have a favourable influence on BI, which indicates that the simplicity of use and the utility of the IoTHD are crucial for patients and may boost the patients' BI toward adopting the IoTHD. The favourable impact that PE and EE have on BI is consistent with the findings of previous research (Dhagarra et al., 2020; Karahoca et al., 2018; Mital et al., 2018). The fact that PS had a favourable influence on BI suggests that when the level of security provided by the IoT is high, patients would acquire a favourable attitude toward the technology. PV has an effect on IoT healthcare usage. This suggests that having a high level of privacy is an encouraging factor for the usage of IoT healthcare devices among patients in Saudi Arabia. The results in terms of PS on BI are in accordance with (Pinochet et al., 2018) whereas the findings regarding the influence of PV on BI are in agreement with (Kayali et al., 2019). The findings regarding the moderating function of FC between PE, EE, and BI were examined. FC did not moderate the effect of EE and PE, and this could be due to the fact that in Saudi Arabia, the infrastructure and the FC are high which has not produced any differences in terms of the perception of users regarding the FC.

This work has made numerous contributions to the body of literature about the IoT among public health organisations in emerging economies. The research made a contribution to the body of knowledge by focusing on the behavioural approach rather than the technological one, and it was successful in determining the element that prompted patients to make use of the IoTHD. The combination of TAM3 and UTAUT has led to the result of roughly half of the variance in BI being explained. In addition to that, the research used a moderating variable such as FC in order to provide a further explanation of the BI.

The results may be of significant assistance to those who make decisions in public healthcare organisations in Saudi Arabia and other nations that have characteristics that are comparable to those of Saudi Arabia. The SI is very important and has to be enhanced in order to boost the BI in the direction of using IoTHD. People will be encouraged, decision makers will be able to inform them of the benefits of utilising IoTHD, if a positive word of mouth is spread via colleges and schools, as well as through television programs and advertisements on social media. PP is another significant issue to consider. It is essential for users to enjoy while making use of the IoTHD. Therefore, a component of gamification needs to be included in the apps and programmes of IoTHD. It has been determined that the PE and EE are important for the BI. Consequently, using the IoTHD needs to be a simple and uncomplicated process. In addition to this, the utilisation needs to be advantageous for the users. It is essential that the application's security be assured. It is important to place more emphasis on the benefits of the application and to disseminate information on it in order to create a favourable environment that is conducive to its use.

6. Conclusion

This research was conducted with the intention of determining the factors that may contribute to an improvement in the BI toward IoTHD. The data gathered from patients who were treated at Saudi Arabia's public hospitals. The data demonstrated that SI had an effect on PE, while TC and PP had an effect on EE. PE and EE, as well as PS and PV, have an essential influence on BI in relation to IoTHD. The influence that PE and EE had on BI was not moderated by FC. The research accounts for roughly half of the BI's variation. These results are only applicable to the Saudi Arabia public hospitals where the study was conducted and to the patients who took part in the research. The scope of the research is restricted to the application of IoTHD. The results of this study should be replicated in future research utilising the random sample method so that the implications of the findings may be further explored. The results may also be expanded upon by evaluating patients in private hospitals, which, in comparison to public hospitals, may or may not have access to a greater variety of medical equipment. In addition, it has been proposed that future research should include other factors, such as the reliability of IoTHD and the accessibility of these applications.

References

- Ahmadi, H., Arji, G., Shahmoradi, L., Safdari, R., Nilashi, M., & Alizadeh, M. (2019). The application of internet of things in healthcare: a systematic literature review and classification. In *Universal Access in the Information Society*, 18(4). Springer Berlin Heidelberg. <https://doi.org/10.1007/s10209-018-0618-4>
- Ajzen, I. (1991). The theory of planned behavior. *Organizational behavior and human decision processes*, 50(2), 179-211. [https://doi.org/10.1016/0749-5978\(91\)90020-T](https://doi.org/10.1016/0749-5978(91)90020-T)
- Alhasan, A., Audah, L., Ibrahim, I., Al-Sharaa, A., Al-Ogaili, A. S., & Mohammed, J. M. (2020). A case-study to examine doctors' intentions to use IoT healthcare devices in Iraq during COVID-19 pandemic. *International Journal of Pervasive Computing and Communications*.
- Balachandar, S., & Chinnaiyan, R. (2019). Centralized reliability and security management of data in internet of things (IoT) with rule builder. *International Conference on Computer Networks and Communication Technologies*, 193-201.

- Bhatt, S., Patwa, F., & Sandhu, R. (2017). An Access Control Framework for Cloud-Enabled Wearable Internet of Things. *Proceedings - 2017 IEEE 3rd International Conference on Collaboration and Internet Computing, CIC 2017, 2017-Janua*, 328–338. <https://doi.org/10.1109/CIC.2017.00050>
- Çelik, H. (2011). Influence of social norms, perceived playfulness and online shopping anxiety on customers' adoption of online retail shopping: An empirical study in the Turkish context. *International Journal of Retail & Distribution Management*.
- Chang, C.-T., Hajiyev, J., & Su, C.-R. (2017). Examining the students' behavioral intention to use e-learning in Azerbaijan? The general extended technology acceptance model for e-learning approach. *Computers & Education*, 111, 128–143.
- Choi, J., & Kim, S. (2016). Is the smartwatch an IT product or a fashion product? A study on factors affecting the intention to use smartwatches. *Computers in Human Behavior*, 63, 777–786. <https://doi.org/10.1016/j.chb.2016.06.007>
- Chouk, I., & Mani, Z. (2019). Factors for and against resistance to smart services: role of consumer lifestyle and ecosystem related variables. *Journal of Services Marketing*, 33(4), 449–462. <https://doi.org/10.1108/JSM-01-2018-0046>
- Datta, P., Namin, A. S., & Chatterjee, M. (2019). A Survey of Privacy Concerns in Wearable Devices. *Proceedings - 2018 IEEE International Conference on Big Data, Big Data 2018*, 4549–4553. <https://doi.org/10.1109/BigData.2018.8622110>
- Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *Source: MIS Quarterly*, 13(3), 319–340.
- de Boer, P. S., van Deursen, A. J. A. M., & van Rompay, T. J. L. (2018). Accepting the Internet-of-Things in our homes: The role of user skills. *Telematics and Informatics*. <https://doi.org/10.1016/j.tele.2018.12.004>
- Dhagarra, D., Goswami, M., & Kumar, G. (2020). Impact of Trust and Privacy Concerns on Technology Acceptance in Healthcare: An Indian Perspective. *International Journal of Medical Informatics*, 141(February), 104164. <https://doi.org/10.1016/j.ijmedinf.2020.104164>
- Di Crosta, A., Palumbo, R., Marchetti, D., Ceccato, I., La Malva, P., Maiella, R., Cipi, M., Roma, P., Mammarella, N., & Verrocchio, M. C. (2020). Individual differences, economic stability, and fear of contagion as risk factors for PTSD symptoms in the COVID-19 emergency. *Frontiers in Psychology*, 11, 2329.
- Dong, X., Chang, Y., Wang, Y., & Yan, J. (2017). Understanding usage of Internet of Things (IOT) systems in China: Cognitive experience and affect experience as moderator. *Information Technology & People*, 30(1), 117–138. https://doi.org/http://dx.doi.org/10.1207/S15327825MCS0301_03
- El-Masri, M., & Tarhini, A. (2017). Factors affecting the adoption of e-learning systems in Qatar and USA: Extending the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). *Educational Technology Research and Development*, 1–21. <https://doi.org/10.1007/s11423-016-9508-8>
- Enaizan, O., Eneizan, B., Almaaitah, M., Al-Radaideh, A. T., & Saleh, A. M. (2020). Effects of privacy and security on the acceptance and usage of EMR: the mediating role of trust on the basis of multiple perspectives. *Informatics in Medicine Unlocked*, 100450.
- Enroth, L., Jasilionis, D., Németh, L., Strand, B. H., Tanjung, I., Sundberg, L., Fors, S., Jylhä, M., & Brønnum-Hansen, H. (2022). Changes in socioeconomic differentials in old age life expectancy in four Nordic countries: the impact of educational expansion and education-specific mortality. *European Journal of Ageing*, 1–12.
- Gu, H., Krishnan, P., Ng, D. Y. M., Chang, L. D. J., Liu, G. Y. Z., Cheng, S. S. M., Hui, M. M. Y., Fan, M. C. Y., Wan, J. H. L., & Lau, L. H. K. (2021). Probable Transmission of SARS-CoV-2 Omicron Variant in Quarantine Hotel, Hong Kong, China, November 2021. *Emerging Infectious Diseases*, 28(2).
- Habibipour, A., Padyab, A., & Ståhlbröst, A. (2019). Social, ethical and ecological issues in wearable technologies. *25th Americas Conference on Information Systems, AMCIS 2019*, 1–10.
- Hair, Hult, T. M., Ringle, C. M., & Sarstedt, M. (2017). *A primer on partial least squares structural equation modeling*. 2nd ed. Thousand Oakes.
- Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., & Thiele, K. O. (2017). Mirror, mirror on the wall: a comparative evaluation of composite-based structural equation modeling methods. *Journal of the Academy of Marketing Science*, 45(5), 616–632.
- Harwood, T., & Garry, T. (2017). Internet of Things: understanding trust in techno-service systems. *Journal of Service Management*, 28(3), 442–475. <https://doi.org/10.1108/JOSM-11-2016-0299>
- Hsu, C. L., & Lin, J. C. C. (2016). An empirical examination of consumer adoption of Internet of Things services: Network externalities and concern for information privacy perspectives. *Computers in Human Behavior*, 62, 516–527. <https://doi.org/10.1016/j.chb.2016.04.023>
- Karahoca, A., Karahoca, D., & Aksöz, M. (2018). Examining intention to adopt to internet of things in healthcare technology products. *Kybernetes*, 47(4), 742–770. <https://doi.org/10.1108/K-02-2017-0045>
- Kayali, M., & Alaaraj, S. (2020). Adoption of Cloud Based E-learning in Developing Countries : A Combination A of DOI , TAM and UTAUT. *International Journal of Contemporary Management and Information Technology*, 1(1), 1–7.
- Kayali, M., Safie, N., & Mukhtar, M. (2019). The Effect of Individual Factors Mediated by Trust and Moderated by IT Knowledge on Students' Adoption of Cloud Based E-learning. *International Journal of Innovative Technology and Exploring Engineering*, 9(2). <https://doi.org/10.35940/ijitee.J1137.129219>
- Koch, J., Frommeyer, B., & Schewe, G. (2020). Online shopping motives during the COVID-19 pandemic—lessons from the crisis. *Sustainability*, 12(24), 10247.
- Kurdi, B. Al, Alshurideh, M., Nuseir, M., Aburayya, A., & Salloum, S. A. (2021). The effects of subjective norm on the intention to use social media networks: an exploratory study using PLS-SEM and machine learning approach.

- International Conference on Advanced Machine Learning Technologies and Applications*, 581–592.
- Lian, J. W. (2015). Critical factors for cloud based e-invoice service adoption in Taiwan: An empirical study. *International Journal of Information Management*, 35(1), 98–109. <https://doi.org/10.1016/j.ijinfomgt.2014.10.005>
- Lu, Y., Papagiannidis, S., & Alamanos, E. (2018). Internet of things: A systematic review of the business literature from the user and organisational perspectives. *Technological Forecasting and Social Change*, 136(April 2017), 285–297. <https://doi.org/10.1016/j.techfore.2018.01.022>
- Lynch, M., Bucknall, M., Jagger, C., & Wilkie, R. (2022). Projections of healthy working life expectancy in England to the year 2035. *Nature Aging*, 2(1), 13–18.
- Maswadi, K., Ghani, N. A., & Hamid, S. (2022). Factors influencing the elderly's behavioural intention to use smart home technologies in Saudi Arabia. *Plos One*, 17(8), e0272525.
- Menychtas, A., Tsanakas, P., & Maglogiannis, I. (2020). Knowledge Discovery on IoT-Enabled mHealth Applications. In *GeNeDis 2018* (pp. 181–191). Springer.
- Mital, M., Chang, V., Choudhary, P., Papa, A., & Pani, A. K. (2018). Adoption of Internet of Things in India: A test of competing models using a structured equation modeling approach. *Technological Forecasting and Social Change*, 136, 339–346. <https://doi.org/10.1016/j.techfore.2017.03.001>
- Padyab, A., & Ståhlbröst, A. (2018). Exploring the dimensions of individual privacy concerns in relation to the Internet of Things use situations. *Digital Policy, Regulation and Governance*, 20(6), 528–544. <https://doi.org/10.1108/DPRG-05-2018-0023>
- Pal, D., Funilkul, S., Charoenkitkarn, N., & Kanthamanon, P. (2018). Internet-of-Things and Smart Homes for Elderly Healthcare: An End User Perspective. In *IEEE Access*. <https://doi.org/10.1109/ACCESS.2018.2808472>
- Park, E., Cho, Y., Han, J., & Kwon, S. J. (2017). Comprehensive Approaches to User Acceptance of Internet of Things in a Smart Home Environment. *IEEE Internet of Things Journal*, 4(6), 2342–2350. <https://doi.org/10.1109/JIOT.2017.2750765>
- Park, E., & Kim, K. J. (2014). An integrated adoption model of mobile cloud services: Exploration of key determinants and extension of technology acceptance model. *Telematics and Informatics*, 31(3), 376–385. <https://doi.org/10.1016/j.tele.2013.11.008>
- Pinochet, L. H. C., Lopes, E. L., Srulzon, C. H. F., & Onusic, L. M. (2018). The influence of the attributes of “Internet of Things” products on functional and emotional experiences of purchase intention. *Innovation & Management Review*, 15(3), 303–320. <https://doi.org/10.1108/inmr-05-2018-0028>
- Rahmi, B., Birgoren, B., & Aktepe, A. (2018). A meta analysis of factors affecting perceived usefulness and perceived ease of use in the adoption of e-learning systems. *Turkish Online Journal of Distance Education*, 19(4), 4–42.
- Rai, S., & Biswas, S. N. (2022). Adoption of safe motherhood practices and the moderating role of facilitating conditions. *Journal of Social Marketing*, 12(4), 436–455.
- Rawwash, H., Masad, F., Enaizan, O., Eneizan, B., Adaileh, M., Saleh, A., & Almestarihi, R. (2020). Factors affecting Jordanian electronic banking services. *Management Science Letters*, 10(4), 915–922.
- Saleh, A. M., Al-Badareen, A. B., & Enaizan, O. (2020). *Automated user experience tool development for mobile application*. Sekaran, U., & Bougie, R. (2019). *Research methods for business: A skill building approach*. John Wiley & Sons.
- Shachak, A., Kuziemyky, C., & Petersen, C. (2019). Beyond TAM and UTAUT: Future directions for HIT implementation research. *Journal of Biomedical Informatics*, 100, 103315. <https://doi.org/10.1016/j.jbi.2019.103315>
- Shekar, A. R. (2019). Preventing Data Manipulation and Enhancing the Security of data in Fitness Mobile Application. *2019 International Conference on Smart Systems and Inventive Technology (ICSSIT)*, 740–745.
- Shen, J., & Eder, L. B. (2009). Exploring intentions to use virtual worlds for business. *Journal of Electronic Commerce Research*, 10(2), 94.
- Shin, D. H. (2017). A User-based Model for the Quality of Experience of the Internet of Things. *Information and Management*, 54(8), 998–1011. <https://doi.org/10.1016/j.im.2017.02.006>
- Shin, D. H., & Jin Park, Y. (2017). Understanding the Internet of Things ecosystem: multi-level analysis of users, society, and ecology. *Digital Policy, Regulation and Governance*, 19(1), 77–100. <https://doi.org/10.1108/DPRG-07-2016-0035>
- Shin, D., & Hwang, Y. (2017). Integrated acceptance and sustainability evaluation of Internet of Medical Things: A dual-level analysis. *Internet Research*, 27(25), 1227–1254.
- Singh, R. P., Javaid, M., Haleem, A., & Suman, R. (2020). Internet of things (IoT) applications to fight against COVID-19 pandemic. *Diabetes & Metabolic Syndrome: Clinical Research & Reviews*, 14(4), 521–524.
- Siron, Y., Wibowo, A., & Narmaditya, B. S. (2020). Factors affecting the adoption of e-learning in Indonesia: Lesson from Covid-19. *JOTSE: Journal of Technology and Science Education*, 10(2), 282–295.
- Solangi, Z. A., Solangi, Y. A., Aziz, M. S. A., & Asadullah. (2018). An empirical study of Internet of Things (IoT) - Based healthcare acceptance in Pakistan: PILOT study. *2017 IEEE 3rd International Conference on Engineering Technologies and Social Sciences, ICETSS 2017, 2018-Janua*, 1–7. <https://doi.org/10.1109/ICETSS.2017.8324135>
- Tarhini, A., Hone, K., & Liu, X. (2015). A cross-cultural examination of the impact of social, organisational and individual factors on educational technology acceptance between British and Lebanese university students. *British Journal of Educational Technology*, 46(4), 739–755. <https://doi.org/10.1111/bjet.12169>
- Venkatesh, N., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: four longitudinal field studies. *Management Science*, 46(2), 186–204.
- Venkatesh, V., Morris, M., Davis, G., & Davis, F. (2003). User Acceptance of Information Technology: Toward a Unified

View. *MIS Quarterly*, 27(3), 425–478. <https://doi.org/10.2307/30036540>

Venkatesh, Viswanath, & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision Sciences*, 39(2), 273–315.

Zhang, Z. K., Cho, M. C. Y., Wang, C. W., Hsu, C. W., Chen, C. K., & Shieh, S. (2014). IoT security: Ongoing challenges and research opportunities. *Proceedings - IEEE 7th International Conference on Service-Oriented Computing and Applications, SOCA 2014*, 230–234. <https://doi.org/10.1109/SOCA.2014.58>

Zheng, J., & Li, S. (2020). What drives students' intention to use tablet computers: An extended technology acceptance model. *International Journal of Educational Research*, 102, 101612.



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