Determinants of Medical Internet of Things Adoption in Healthcare and the Role of Demographic Factors Incorporating Modified UTAUT

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***Abstract*—Medical Internet of Things (mIoT) is the IoT sub-set with vast potential in healthcare. However, the adoption of eHealth solutions such as mIoT has been a critical challenge in the health sector of the Kingdom of Saudi Arabia. Therefore, this study was conducted to explore the mIoT adoption determinants in Saudi public hospitals. Methods: A total of 271 participants were recruited from public hospitals in Riyadh, and a modified UTAUT model named UTAUT-HS was developed in this study to test its relevance with respect to mIoT adoption. Results: Ten path relationships were tested in this study, out of which six showed significant results. Similarly, three variables (Computer and English Language Self-efficacy or CESE, Performance Expectancy or PE and Social Influence or SI) showed a significant direct relationship with the behavioural intention to adopt mIoT. Furthermore, CESE showed the strongest relationship and emerged as a major sub-set of Effort Expectancy (EE) for mIoT adoption. However, moderator analysis showed substantial variations between different study demographic groups. In particular, the current study findings unravelled a comparatively novel relevance of Perceived Threat to Autonomy (PTA) for mIoT adoption for clinical and non-clinical and for older and younger participants. Conclusion: The study concludes that UTAUT-HS is an adequate model to explain the mIoT adoption in healthcare. However, it also suggests conducting future large-scale studies in KSA and elsewhere to validate the relevance of UTAUT-HS in other contexts and with much more confidence.**

Keywords*—Medical internet of things; eHealth adoption; modified UTAUT; demographics and IT adoption

I. Introduction

The term "Internet of Things" (IoT) was coined by Kevin Ashton in 1999, who was a British technology pioneer and worked at the Massachusetts Institute of Technology [1,2]. IoT has many definitions; however, in broad terms, it can be defined as a combination of different components, such as smart devices or machines that communicate with each other over the Internet, gather information, and make decisions without human intervention [3]. Medical Internet of things or mIoT is the application of IoT in healthcare and simply can be defined as a consolidation of devices and applications that can link to information technology systems in healthcare using a range of networking technologies [4]. mIoT has tremendous capabilities in healthcare and it ranges from reducing healthcare costs, load on clinicians and medical errors [5,6, 7] to improving treatment outcomes, compliance by patients and overall quality of healthcare [8,9].

However, despite a wide range of advantages, a recent systematic review on IoT adoption suggests that the inclusion and acceptance of IoT in healthcare is still low [10]. It is important to note that successful implementation and adoption of new technologies such as mIoT is not an easy process and is affected by many main interrelated factors, namely social, personal, technical, and organisational factors [11]. However, it has been suggested by many researchers that the greatest challenge of mIoT and AI adoption in healthcare is not the efficacy of the technology but the acceptance by the clinicians [12,10]. The adoption of any new technology in any society is a complex process and the process becomes more challenging if the society is comparatively restrictive in nature, such as the Kingdom of Saudi Arabia and the technology has enormous disruptive power, such as mIoT.

Moreover, in KSA, the resistance to change and to adopt new technology, lack of compliance by the healthcare staff and inadequacies in the policies to introduce and implement new IT-based solutions have created already bad condition worse for the introduction of more complex eHealth solutions such as mIoT [13]. For instance, the past eHealth research (Electronic Health Record {EHR} systems) conducted in the Kingdom suggests that there was underutilisation of EHR functionalities across the board in the hospital [14]. Moreover, healthcare professionals have reported data entry time, lack of adequate IT training and support, the complexity of technology, lack of customizability option of the EHR systems, and disturbance in communication between doctors and patients as grave barriers linked with EHR adoption [14]. Therefore, it is likely that the introduction of mIoT in the Kingdom will experience significant resistance and interruptions. Also, no quantitative studies are available investigating the adoption determinants of mIoT in Saudi hospitals. Thus, research focused on understanding the adoption dynamics of mIoT in the Kingdom of Saudi Arabia should be conducted to support the smooth uptake of these technologies.

To achieve the aim of this study, a brief description of prevailing technology adoption theories is provided to propose the current study framework. Detailed information pertaining to each component of the proposed framework, along with the rationale for their inclusion, is provided in the following sections. Moreover, the relevance of the selected moderators in the current study framework is also established in the subsequent sections.

A. Past Theories Related to the Adoption of New Technologies

A significant body of research has been conducted to determine the factors associated with the adoption of new innovations/ technologies and aspects related to human behaviours. The most famous theories incorporated by researchers investigating the adoption of new technologies include the Theory of Reasoned Action (TRA) proposed in 1975, The Technology Acceptance Model (TAM) proposed in 1989, The Theory of Planned Behaviour (TPB) proposed in 1991, The Unified Theory of Acceptance and Use of Technology (UTAUT) proposed in 2003 and The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) proposed in 2012 [15,16,17,18,19].

The Unified Theory of Acceptance and Use of Technology or UTAUT was proposed in 2003 and was based on eight past theories, which included TRA, TAM, TPB, Innovation Diffusion Theory (IDT), Combined TAM-TPB (C-TAM-TPB), Social Cognitive Theory (SCT) and Model of PC Utilization (MPCU) [18]. UTAUT included four main constructs; Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC). Along with these four constructs, UTAUT also incorporated four moderators (age, gender, experience and voluntariness), which were assumed to influence the constructs [15]. However, it is essential to note that only PE, EE and SI were directly linked with Behavioural Intention to Adopt Technology (BI), while FC was majorly linked with the actual use of the technology.

Since the development of UTAUT, it has been used by various studies from a broad range of disciplines to explore and explain the adoption of technology majorly at an individual level [20]. Moreover, it has been suggested that the variance explaining power of UTAUT is about 70% and it has outperformed all the other past eight models (eight models explained between 17% and 53% of the variance in BI) that were used to construct UTAUT [18].

II. Proposed Framework for the Current Study - The Unified Theory of Acceptance and Use of Technology for Hospital Staff (UTAUT-HS)

Comparing the characteristics of the past study models, the current study considered UTAUT as the most suitable model to develop the current study framework (Fig. 1). The original UTAUT model proposed four key constructs: PE, EE, SI and FC. However, FC is considered to be affecting the actual use of IT and not directly linked with the adoption or acceptance of IT in the original UTAUT model. Thus, it was excluded from the current study proposed framework. Further, based on the literature search conducted on the adoption of IT technologies in the Saudi healthcare system and elsewhere, three additional components, Computer and English language Self-Efficacy (CESE), Perceived Threat to Autonomy (PTA), Confidentiality Concerns (CC), were included in the current study proposed framework. Similarly, two moderators; gender and age, were adopted from the UTAUT model and two more; occupation and education, were included in the proposed framework.

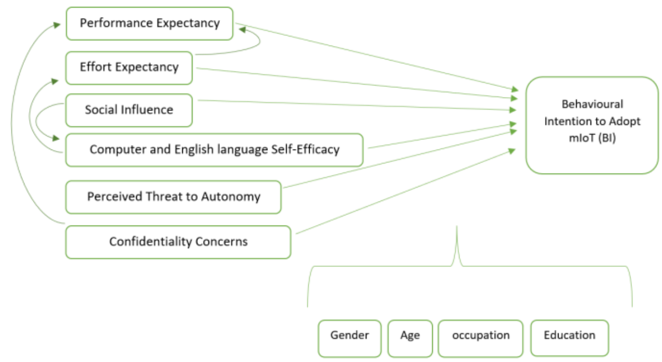

Fig. 1. Study framework - The Unified Theory of Acceptance and Use of Technology for Hospital Staff (UTAUT-HS).

A. Performance Expectancy (PE)

Performance Expectancy is defined as the extent to which a particular technology brings about effectiveness in work performance and this concept is similar to Perceived Usefulness (PU) from TAM [21,18,17]. Gao et al. [22] suggested that when healthcare consumers believe that the introduction of IoT will enable them to improve effectiveness, they are more likely to accept the technology. As far as eHealth is concerned, PE has been reported by many studies to be a significant contributing factor for technology adoption among healthcare professionals [23,24,25]. Moreover, the lack of PE of information technology was also observed to be a crucial hurdle in healthcare, and the literature concerning the adoption of EHR in KSA has suggested lack of Perceived Usefulness (PU) or PE to be contributing 15% of all barriers [26].

H1: Performance Expectancy (PE) will have a positive influence on the Behavioural Intention to Adopt mIoT (BI). Age, gender, occupation, and education will moderate the influence of PE on BI.

B. Effort Expectancy (EE)

Effort Expectancy (EE) is regarded to be clearly linked with the ease of use of Information technology and it is similar to the Perceived Ease of Use (PEOU) from TAM [27,15]. In other words, it refers to the extent to which an individual considers the use of technology free of effort. A range of past studies has endorsed the substantial influence of PEOU and it has been reported that EE plays a positive role in the adoption or acceptance of healthcare information systems, clinical decision support systems, adverse event reporting systems and many more [28,29,30,31]. The significance of PEOU is also supported by Alqahtani et al. [27], who suggested that 15% of all EHR adoption barriers in the KSA were linked to PEOU [26].

H2: Effort Expectancy (EE) will have a positive influence on the Behavioural Intention to Adopt mIoT (BI). Age, gender, occupation, and education will moderate the influence of EE on BI.

H3: Effort Expectancy (EE) will have a positive influence on Performance Expectancy (PE).

C. Social Influence (SI)

Social influence is defined as the perception of an individual about a product, technology or services, which is substantially influenced by the perception of people around him/her and it is similar to the subjective norm from TRA and TBP [32,33,19]. In the case of IoT or mIoT technology, the majority of the potential users lack adequate information about it. Thus, the impact of SI is even amplified in the decision-making process [32]. The social network has a crucial role in the adoption or acceptance of IoT technologies since it has been a general observation that IoT users seek assistance and advice from family, peer and colleagues to clear uncertainties about the product [34].

Moreover, in the healthcare context, many studies have found a substantial role of SI on technology acceptance among doctors and physicians [24,35]. Similarly, it is also hypothesised that the norms will affect the expectations linked with the Computer and English Self-efficacy of healthcare professionals. Since, KSA is conventionally considered a reserved culture and a lot of significant changes are introduced under the progressive 2030 Vision approach, thus there is more significant uncertainty about the influence of SI on the intention to adopt mIoT [36,37,38,39].

H4: Social Influence (SI) will positively influence the Behavioural Intention to Adopt mIoT (BI). Age, gender, occupation, and education will moderate the influence of SI on BI.

H5: Social Influence (SI) will have a positive influence on the Computer and English Self-efficacy (CESE).

D. Computer and English Language Self-Efficacy (CESE)

Self-efficacy is defined as the self-evaluation of an individual to conduct a particular task and in terms of mIoT adoption, CESE is associated with the self-evaluation of computer skills and English language proficiency [40]. In the healthcare context, mIoT technology adoption remains a significant issue and is substantially associated with technological skills and abilities [22]. Moreover, past literature has indicated the lack of familiarity of doctors with information technology to be a significant barrier obstructing the adoption and use of those technologies [41,42]. The Kingdom of Saudi Arabia has also witnessed this issue and has reported it in many past studies conducted in the healthcare environment [43,44,45,46].

Despite the fact that many studies in KSA have highlighted this issue, only a few studies have explored the role of this issue in the acceptance of information technologies by healthcare professionals [43,44,45,41,42]. Concerning English language proficiency, a vital link has also been found with eHealth use in the Kingdom [44,45].

H6: Computer and English language Self-Efficacy (CESE) will positively influence the Behavioural Intention to Adopt mIoT (BI). Age, gender, occupation, and education will moderate the influence of CESE on BI.

H7: Computer and English language Self-Efficacy (CESE) will have a positive influence on the Effort Expectancy (EE).

E. Perceived Threat to Autonomy (PTA)

Perceived Threat to Autonomy (PTA) is not a new concept as [47] Walter & Lopez (2008) described PTA as the extent to which an individual thinks that incorporating a particular technology or system will compromise his/her control over the procedures, policies and functions of their work [47]. However, this concept has become substantially relevant with respect to the adoption or acceptance of mIoT. Conventionally, it is believed that healthcare professionals and in particular, doctors hold a high level of professional autonomy and the introduction of mIoT can affect the power dynamics in the healthcare environment [48,47]. Safi et al. [49] noted that the doctors in their study highlighted the possible interference of technology with their autonomy in their diagnostic process. The doctors showed high concerns related to the use of eHealth tools by the management to control them. These perceptions ultimately led to a negative attitude toward the acceptance of change brought by the technologies [49].

Carcary et al. [50] asserted that one of the key reasons for resistance to IoT is its very different nature from other eHealth technologies. The key new component in IoT is AI or machine learning (which has not been a major part of past technologies). AI is perceived as a direct threat because of its capability to replicate the human performance. The research conducted in the Saudi healthcare environment has shown the understating of this barrier by healthcare professionals, especially doctors. The studies by Abdullah and Fakieh [51] and Qurashi et al. [52] have reported that doctors and other healthcare employees are worried about their job security due to AI. Moreover, the qualitative study by Alsulame et al. [48] concluded that healthcare professionals are resistant to the adoption of eHealth technologies due to the fear that they might lose their privileges, which suggests a loss of respect and autonomy. Therefore, the following hypothesis was developed.

H8: Perceived Threat to Autonomy (PTA) will have an influence on the Behavioural Intention to Adopt mIoT (BI). Age, gender, occupation, and education will moderate the influence of PTA on BI.

F. Confidentiality Concerns (CC)

Confidentiality Concerns (CC) can be defined as the extent to which the use of a particular technology can increase the risk of loss of personal or important information. Past research conducted in the Kingdom of Saudi Arabia has frequently reported CC causing major hurdle in the acceptance of eHealth technologies [53,54,55,44,45]. For instance, the study by Albarrak et al. [53] found that 90% of the doctors showed concerns about patient privacy (among other concerns) for the adoption of telemedicine. Similarly, Alqahtani [54] study noted privacy and security issues as major obstacles preventing Saudi healthcare from adopting IoT technology. Moreover, past research has also identified an association between CC and PE, which suggests the indirect effect of CC on the acceptance of technology [56].

Among all healthcare professionals, doctors are believed to be concerned about CC the most, even more than the patient themselves [41]. This could be because they are at the frontline and feel more responsibility for patient information protection. It is visible from the observation that doctors who use even basic eHealth technologies such as EHR have suggested an increased risk of confidentiality and security issues while comparing EHR with paper-based record systems [41]. Even though many past studies in KSA have highlighted CC to be a significant obstacle to mIoT and e-health adoption and use, the literature investigating the influence of CC on the adoption intention of mIoT is limited, highlighting the need for CC to be included in the current study framework [55,44,45].

G. Moderators in the Framework

1) Gender: Hoque [57] argues that gender as a moderator of technology adoption have received less attention compared to other demographic factors age, experience or culture. However, past studies conducted on the adoption of technology have found significant influence of gender [58,59,60]. Despite this some of the most commonly used technology acceptance models such as TAM have made no reference of the impact of gender on the IT acceptance model [57]. Overall, it has been suggested that male possess less suspicions about technology and hold more positive views them, while female lack confidence in computer usage [57,61]. However, with respect to mIoT, the study by Karahoca et al. [62] found out that male showed more privacy and healthcare vulnerability concerns than females. While other studies have suggested that male's provided higher score on PU Or PE and PEOU or EE compared to females [63].

However, again these patterns are not consistent and varies substantially from technology to technology or region to region. For instance, the Bangladeshi study on mHealth adoption showed that male provided higher scores on PEOU than females (0.6556 versus 0.1445, $t = 3.784$), while females provided higher PU scores (0.3244 versus 0.0140, $t = 2.104$) [57]. However, the key standpoint behind the role of gender on technology adoption is associated with the social roles rather than any biological mechanism and there is major discrepancy among male and female societal roles in KSA, therefore this aspect is quite important for the Kingdom [64].

H9: Confidentiality Concerns (CC) will have a negative influence on the Behavioural Intention to Adopt mIoT (BI). Age, gender, occupation, and education will moderate the influence of CC on BI.

H10: Confidentiality Concerns (CC) will have a negative influence on Performance Expectancy (PE).

2) Age: Age is another noteworthy factor that may influence the adoption of mIoT. Sivathanu [65] conducted a study to evaluate the adoption factors for IoT-based healthcare wearables. The study found that older individuals experience mainly three types of barriers (traditional, usage and risk barriers), which are related to age and can influence (reasons against) the adoption of IoT-based healthcare wearables [65]. Similarly, the study found that elderly participants were more inclined toward visiting doctors in person rather than conducting online consultations. They believe that doctors provide more personalised healthcare services in person and also believe that the use of eHealth or wearable healthcare devices is a challenging task. Given that the current study is aimed to be conducted in KSA, the aspect of age become significantly important due to the rapidly changing cultural environment in the Kingdom, which might increase the generational gap and consequently widen the perceptual gap towards mIoT technology [66,67].

These presumptions related to elderly participants are also proved by various past studies conducted in the healthcare domain. For instance, the study by Parthasarathy et al. [68], focus on the concerns associated with the adoption of EMR, showed that negative beliefs and attitudes towards the use of computers and inadequate motivation to change readiness negatively influenced IT adoption among nurses. The research concluded that these negative factors were most commonly found among older nurses. Moreover, it was asserted that a one-size-fits-all training style is inadequate in healthcare for adopting new technologies [68]. The study by Al Otaybi et al. [69] is one of those few studies which showed that age difference in healthcare is a determining factor with respect to EMR satisfaction. Hence, age is considered a predisposing factor in technology adoption, and healthcare organisations are often challenged to provide a wholistic environment that can meet the needs of all, support change readiness and enhance the digital competency of all healthcare professionals [70].

3) Occupation: Hospitals include a range of staff members, which includes but not limited to doctors, nurses, pharmacists, IT staff and management employees. Further, among doctors, there are various categorizations based on their skills and qualifications. Therefore, the difference in the field of practice may produce a difference in attitude towards the adoption of the same technology. This inference is supported by the systematic review conducted by Boonstra et al. [71] on the adoption of EHR in hospitals. The review suggested that the leadership has to focus on the work conducted by different healthcare professionals and the impact of health information technology on the flow of those works to ensure a smooth technology transition [71].

It is essential to consider that a particular occupation in the hospital encompasses specific roles, responsibilities and duties, determines the level of interaction with other colleagues and patients and requires certain level of education [72,73,74]. All these factors can influence the knowledge and perception towards e-health technologies or more precisely, towards mIoT. For instance, the study by Afolaranmi et al. [75] found a significant correlation between good EHR knowledge and different hospital professions. Among clinical professions, pharmacists showed the highest positive knowledge of EHR, followed by resident doctors and nurses/midwives. Thus, these aspects are essential and occupation should be included as a moderator for the adoption of mIoT.

4) Education: Similar to gender, age and occupation, education is another significant determinant that can act as a substantial moderator in the current study. Past studies have indicated a significant role of the level of education on technology awareness and perception in the healthcare sector [76,45,77]. Healthcare professionals holding a master's or above education have been identified to be significantly more eHealth aware than their counterparts with a bachelor's or below education [76,45,77]. Similarly, Saudi research by Hasanain et al. [45] indicated a statistically significant association between EMR literacy, computer literacy, English language proficiency level and healthcare professionals' education level. Thus, the inclusion of education as a moderator was important for the current study.

III. Methodology

The current study aimed to evaluate the determinants that were associated with the adoption of mIoT among hospital care staff in Saudi Arabia. To achieve this aim, Ministry of Health (MOH) hospitals in Riyadh were selected for the recruitment of the participants. MOH hospitals are public entities, providing 60% of the total healthcare services in the Kingdom [78]. The selection of Riyadh was made because it is the biggest city in the Kingdom and is at the forefront to receive technological innovation in the country [44]. Thus, 271 participants, including doctors, nurses, pharmacists, and non-clinical personals i.e., IT individuals, technicians and managerial personnel working in the MOH hospitals in Riyadh, were recruited. Before the recruitment, relevant ethics approvals were sought from the Latrobe University, Melbourne, Australia (ethics no HEC19482) and from the MOH of Kingdom of Saudi Arabia (ethics no: 21-79 E).

A. *Data Analysis*

Model testing is an integral part of research as it allows the researcher to identify the relationship between different variables included in the study model. Therefore, structural equation modeling (SEM) using SmartPLS version 3 was incorporated in this research for model testing. SEM is a complex multivariate statistical analysis technique that permits researchers to examine the nature and significance of relationships among various exogenous and endogenous variables [79]. Also, conducting SEM using SmartPLS is particularly beneficial as it requires no assumptions related to the distribution of the study data and is suitable for a comparatively small sample size [80,81].

IV. Study Model Validation – Main Results

To check the indicator reliability, SmartPLS version 3 was used to calculate the Factor loadings (Table X in Appendix) of the indicators included in each variable. Henseler et al. [82] suggested that a factor loading of 0.7 or higher is considered highly satisfactory, whereas the value of 0.5 or above is considered acceptable [83]. Table I demonstrates that all outer loadings were above 0.7; hence the acceptance criterion was fulfilled. The second parameter for model evaluation was the assessment of construct reliability which was carried out by measuring Cronbach's Alpha and Composite Reliability (CR) (Table I). The value of Cronbach's Alpha and CR above 0.7 is considered adequate to establish internal consistency reliability [83]. Table I shows that all values for Cronbach's Alpha, CR and rho_A (similar to CR calculated by SmartPLS) were higher than 0.7; hence this criterion was also fulfilled.

For the assessment of validity, the variables were evaluated for convergent and discriminant validity. Convergent validity measurement was carried out by calculating the Average Variance Extracted (AVE) through SmartPLS [83]. [83] Hair et al. (2011) suggested that an AVE value of greater than 0.5 is considered acceptable to determine the convergent validity of the variables. Table I illustrates that all variables had an AVE value of greater than 0.5; hence no adjustment was required.

Discriminant validity is another significant factor that is required to be evaluated to assess the quality of the measurement model. Discriminant validity measures the extent to which the indicators are different from each other empirically [84,85]. The discriminant validity can be measured by using the Fornell & Larcker criterion method, the Heterotrait-monotrait (HTMT) ratio of correlation, and by evaluating the cross-loadings of the indicators. The latent variable should explain better variance of its own indicator compared to the variance of other latent variables. Thus, the values in the Fornell-Lacker method for each latent variable should be higher than the correlation with other latent variables. Table II illustrates that the AVE square root values for each latent variable were greater than all the other correlations; hence this criterion was satisfied [84,85].

TABLE I. Internal Consistency, Reliability and Validity Results for the PLS-SEM Measurement Model

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
BI	0.927	0.928	0.965	0.932
CC	0.933	0.933	0.957	0.882
CESE	0.949	0.949	0.963	0.868
EE	0.943	0.944	0.959	0.855
PE	0.904	0.912	0.933	0.777
PTA	0.913	0.922	0.938	0.792
SI	0.959	0.960	0.971	0.892

TABLE II. Fornell-Lacker Results for Discriminant Validity Testing

	BI	CC	CESE	EE	PE	PTA	SI
BI	0.966						
CC	0.631	0.939					
CESE	0.810	0.690	0.932				
EE	0.762	0.648	0.833	0.924			
PE	0.699	0.538	0.715	0.837	0.882		
PTA	0.761	0.873	0.813	0.749	0.630	0.890	
SI	0.768	0.728	0.797	0.810	0.742	0.851	0.944

The other method to assess the discriminant validity includes the evaluation of HTMT ratios of correlation [84,85]. [82] Henseler et al. [82] suggested that this method is superior to the Fornell-Lacker method as it can achieve higher rates of specificity and sensitivity. The acceptable threshold of the HTMT ratio ranged between 0.85 and 0.90, and anything above these values can indicate issues of discriminant validity [86,87]. Table III demonstrates a PTA-CC HTMT ratio of 0.957, which required treatment. To identify the point of concern, cross-loadings were checked [84,85].

TABLE III. HTMT RATIO FOR DISCRIMINANT VALIDITY TESTING

	BI	CC	CESE	EE	PE	PTA	SI
BI							
CC	0.678						
CESE	0.863	0.732					
EE	0.815	0.691	0.880				
PE	0.760	0.581	0.770	0.902			
PTA	0.811	**0.957**	0.856	0.791	0.669		
SI	0.813	0.769	0.835	0.851	0.792	0.900	

Three issues were identified in the indicator 36, 39 and 42, because their cross-loadings were higher in other latent variables compared to theirs, thus these were dropped. HTMT ratios were checked again, and it showed that the issue was resolved (Table IV).

TABLE IV. RE-CHECKING HTMT RATIO FOR DISCRIMINANT VALIDITY TESTING

	BI	CC	CESE	EE	PE	PTA	SI
BI							
CC	0.683						
CESE	0.863	0.744					
EE	0.815	0.691	0.880				
PE	0.760	0.564	0.770	0.902			
PTA	0.733	**0.895**	0.760	0.714	0.583		
SI	0.813	0.734	0.835	0.851	0.792	0.835	

Note: Indicators 36, 39 and 42 were dropped because their cross loadings were higher in other latent variables compared to theirs.

A. *Structural Model Results*

The structural model evaluates the strength and significance of the relationship between independent and dependent variables by assessing the R square, path coefficient (β) and its significance level, which is assessed through the t-test and p-value [88]. R square provides the extent of variance explained by the independent variable, while β explains the strength of an effect from the independent variable to the dependent variable. Similarly, a t-value of above 1.96 and a p-value of below 0.05 suggests the significance of the relationship [88].

Fig. 2 and Table V demonstrate the path coefficients (β) and the corresponding significance levels. It can be observed that out of six independent variables for the Behavioural Intention to Adopt mIoT (BI), only three variables showed a significant relationship. Three variables - CESE, PE and SI positively influenced the BI. Also, out of these three, CESE had the strongest effect ($\beta = 0.437$, $p < 0.001$), followed by SI ($\beta = 0.175$, $p = 0.024$) and PE ($\beta = 0.148$, $p = 0.032$). Further, CESE -> EE, EE -> PE and SI -> CESE showed a significant strong positive relationship. Of these three, EE -> PE showed the strongest relationship ($\beta = 0.858$, $p < 0.001$). Further, 71.2% variance in BI was explained by the independent variables, which suggests a good fit. Similarly, 70.1% variance in PE was explained by EE, 69.4% variance in EE was explained by CESE and 63.6% variance in CESE was explained by SI.

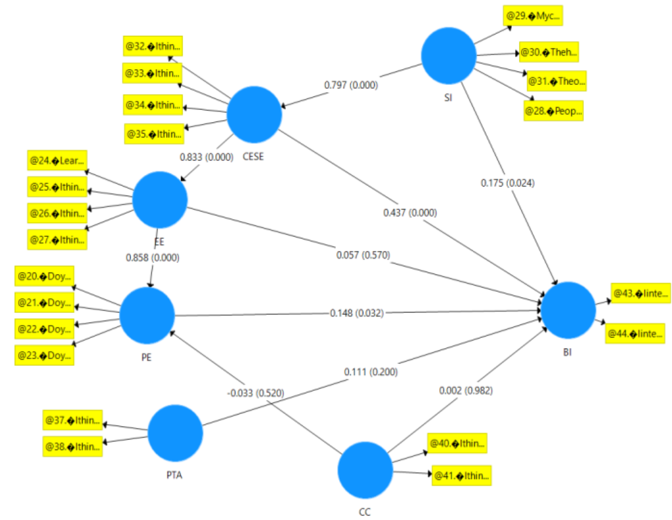

Fig. 2. Overall structural model results including path coefficients and (p values).

TABLE V. OVERALL, PATH COEFFICIENTS, T STATISTICS AND P VALUES OF THE MODEL

	Path coefficients	T Statistics	p values
CC -> BI	0.002	0.023	0.982
CC -> PE	-0.033	0.644	0.520
CESE -> BI	0.437	5.798	0.000
CESE -> EE	0.833	19.175	0.000
EE -> BI	0.057	0.568	0.570
EE -> PE	0.858	17.713	0.000
PE -> BI	0.148	2.139	0.032
PTA -> BI	0.111	1.281	0.200
SI -> BI	0.175	2.255	0.024
SI -> CESE	0.797	20.413	0.000

B. *Moderator Analysis*

1) Gender: Sub-group analysis was conducted for gender, which included separate analyses for male and female participants. Table VI illustrates that out of six independent variables for the BI, two variables showed a significant relationship for male (CESE and PE) and only one showed a significant relationship for female (CESE) participants. Also, the strength of relationships between CESE and BI and PE and BI were stronger for male participants compared to female and overall results (Table VI). Moreover, SI -> CESE, CESE -> EE and EE -> PE showed significant positive relationships for both male and female participants, however, male participants showed comparatively stronger relationships. With respect to R square values, 81.2% variance in BI was explained by the model for male participants, while this percentage was only 51.9% for female participants.

TABLE VI. PATH COEFFICIENTS AND P VALUES OF MALE AND FEMALE PARTICIPANTS

Gender	Male		Female	
	Path coefficients	p Values	Path coefficients	p values
CC -> BI	-0.021	0.844	0.003	0.974
CC -> PE	-0.064	0.306	0.000	0.997
CESE -> BI	0.537	0.000	0.379	0.002
CESE -> EE	0.877	0.000	0.739	0.000
EE -> BI	0.072	0.544	-0.019	0.917
EE -> PE	0.867	0.000	0.816	0.000
PE -> BI	0.178	0.045	0.110	0.353
PTA -> BI	0.115	0.364	0.080	0.407
SI -> BI	0.103	0.362	0.252	0.079
SI -> CESE	0.825	0.000	0.718	0.000

2) Age: Sub-group analysis was conducted for age and separate analysis for participants aged 18 to 35 years and 36 to 70 years was conducted. Table VII shows that out of six independent variables, three variables (CESE, PE and PTA) showed a significant positive relationship for the 18 to 35 years group and two variables (CESE and SI) showed a significant positive relationship for the 36 to 70 years group with BI. Similarly, the 18 to 35 years group showed a significant positive relationship between PTA and BI (β = 0.258, p = 0.031), which is not shown by the overall results. On the other hand, the 36 to 70 years showed a non-significant negative relationship between PTA and BI. Moreover, the strength of CESE with BI was much stronger for the 36 to 70 years group compared to the 18 to 35 years group (β = 0.536 vs 0.353, respectively) (Table VII).

The variables CESE -> EE, EE -> PE and SI -> CESE showed a significant positive relationship for both groups (Table VII). Also, the 36 to 70 years group showed a significant negative relationship between CC -> PE (Table VII). With respect to the R square, 78.6% variance in BI was explained by the model for the 36 to 70 years group, while this percentage was 64.6% for the 18 to 35 years group.

TABLE VII. PATH COEFFICIENTS AND P VALUES OF 18 TO 35 AND 36 TO 70 YEARS OLD PARTICIPANTS

Age	18 to 35		36 to 70	
	Path coefficients nts	P Values	Path coefficient s	values
CC -> BI	-0.020	0.856	0.049	0.584
CC -> PE	0.076	0.423	-0.112	0.043
CESE -> BI	0.353	0.000	0. 536	0.000
CESE-> EE	0.826	0.000	0.821	0.000
EE -> BI	0.048	0. 708	0.012	0.944
EE -> PE	0. 760	0.000	0. 904	0.000
PE ->BI	0.162	0.043	0.151	0.192
PTA ->BI	0.258	0.031	-0.053	0.653
SI -> BI	0.106	0.338	0.269	0.036
SI -> CESE	0.751	0.000	0.821	0.000

3) Education: Sub-group analysis was conducted for education and bachelor and above (high education) and diploma and below (low education) groups were analysed. Table VIII shows that out of six independent variables, two variables showed a significant relationship with BI for both groups. However, the nature of variables varied between groups – CESE and PE showed a significant positive relationship with BI for the high education group. In contrast, CESE and SI showed a significant positive relationship with BI for the low education group. Moreover, the strength of CESE with BI was much stronger for the low education group compared to the high education group (β = 0.442 vs 0.366, respectively). The variables CESE -> EE, EE -> PE and SI -> CESE showed a ssignificant positive relationship for both groups. With respect to the R square, 82.2% variance in BI was explained by the model for the low education group, while this percentage was 60.5% for the high education group.

TABLE VIII. PATH COEFFICIENTS AND P VALUES OF HIGH AND LOW EDUCATION GROUPS

Education groups	Bachelor's and above		Diploma and below	
	Path coefficients	p Values	Path coefficients	p values
CC -> BI	-0.010	0.933	0.003	0.971
CC -> PE	-0.026	0.775	-0.040	0.423
CESE -> BI	0.366	0.001	0.442	0.000
CESE -> EE	0.851	0.000	0.808	0.000
EE -> BI	0.050	0.720	0.161	0.257
EE -> PE	0.773	0.000	0.925	0.000
PE -> BI	0.236	0.007	-0.063	0.603
PTA -> BI	0.110	0.372	0.134	0.247
SI -> BI	0.139	0.231	0.279	0.017
SI -> CESE	0.728	0.000	0.884	0.000

4) Occupation: Sub-group analysis was conducted for occupation and clinical and non-clinical groups were analysed. Table IX shows that the variables CESE and SI showed a significant positive relationship with BI for the clinical group, while CESE, PE and PTA showed a significant positive relationship with BI for the non-clinical group. Moreover, the strength of CESE with BI was stronger for the non-clinical group compared to the clinical group (β = 0.525 vs 0.424, respectively). Also, the non-clinical group a significant positive relationship between PTA and BI (β = 0.340, p = 0.017), while the clinical group showed a non-significant negative relationship (β = - 0.100, p = 0.368).

The variables CESE -> EE, EE -> PE and SI -> CESE showed a significant positive relationship for both groups. With respect to the R square, 84.5% variance in BI was explained by the model for the non-clinical group, while this percentage was 60.7% for the clinical group.

TABLE IX. PATH COEFFICIENTS AND P VALUES OF CLINICAL AND NON-CLINICAL GROUPS

Occupation	Clinical		Non-clinical	
	Path coefficients	p Values	Path coefficients	p values
CC -> BI	0.077	0.356	-0.078	0.491
CC -> PE	-0.013	0.848	-0.060	0.387
CESE -> BI	0.424	0.000	0.525	0.000
CESE -> EE	0.779	0.000	0.887	0.000
EE -> BI	0.006	0.973	-0.021	0.831
EE -> PE	0.839	0.000	0.877	0.000
PE -> BI	0.131	0.235	0.242	0.003
PTA -> BI	-0.100	0.368	0.340	0.017
SI -> BI	0.314	0.019	-0.002	0.989
SI -> CESE	0.764	0.000	0.823	0.000

V. MODEL DISCUSSION

This study model explained 71.2% variance in BI, which demonstrates a good fit and shows that the majority of the factors predicting mIoT adoption were included in the model. Also, the variance explained by the current study model is very similar to the potential of the original UTAUT model [89]. In total, ten path relationships were tested in this study and results concluded six significant relationships (hypothesis supported), out of which three variables showed a significant direct relationship with the behavioural intention to adopt mIoT.

Three variables - CESE, PE and SI positively influenced the BI. Also, out of these three, CESE had the most potent effect ($\beta = 0.437$, $p < 0.001$), followed by SI ($\beta = 0.175$, $p = 0.024$) and PE ($\beta = 0.148$, $p = 0.032$). The current study did not show the significant effect of EE on BI. However, a very strong effect of CESE on EE ($\beta = 0.833$, $p < 0.001$) was observed in this research. This concludes that computer and English language competence is a major sub-determinant of the overall Effort Expectancy of mIoT use. There is very limited research available regarding IoT adoption among healthcare professionals; thus, the current study's findings were compared with IT adoption by healthcare professionals. The strong influence of CESE or self-efficacy is supported by [90,91,92]. These studies concluded that self-efficacy, including but not limited to computer skills, had a strong impact on the Perceived Ease of Use and subsequent indirect effect on the adoption of technologies.

The findings regarding the strongest influence of CESE (considering CESE as a major sub-part of EE) on BI are also well aligned with the previous research. Gagnon et al. [24] conducted a study with physicians and concluded that EE or Perceived Ease of Use had the strongest impact on EHR acceptance. Similarly, Chen & Hsiao [90], conducted a study with hospital staff and concluded similar results with respect to health information systems adoption. However, the Saudi studies conducted on nurses and physicians suggested that PU or PE was more important than PEOU or EE in determining professionals' acceptance of EHR [93,54]. The reason for this discrepancy could be due to the nature of the technology. EHR systems are mainly operated by humans and require effort to enter data. However, mIoT majorly relies on wearable devices to upload and AI to analyse data without human involvement, which suggests the transformation of EE from the user point of view.

Similarly, another reason could be due to the unfamiliarity of the participants with the technology, as the hospitals are not using it on a full scale. Thus, they perceived computer and English skills as the most crucial component (as these are the most integral component of all previous technologies). This inference is supported by the previous research by Alsahafi et al. [94], where EE was the most significant predictor of behavioural intention to use National Electronic Health Records by the respondents who were actually non-users of the technology in KSA. This proposes a key finding of this study as the previous dominance (major predictor) of PE or even overall EE on IT adoption is not supported in this one of the early mIoT acceptance research in KSA. Hence, other reported factors of EE, such as time required for data entry, interruption in workflow, the influence of technology on the communication between professionals and patients and many others (El Mahalli [14]), are not important for the adoption of mIoT for this study cohort. This is an essential consideration for policymakers as understanding key adoption determinants can tailor the efforts in the right direction and even assist product developers about the consumers' expectations.

The second significant determinant for the adoption of mIoT reported in this study was SI ($\beta = 0.175$, $p = 0.024$). However, SI also showed a strong effect ($\beta = 0.797$, $p < 0.001$) on the CESE (which showed the strongest effect); thus, it is just to conclude that the total effect of SI on the adoption would be more. This inference is supported by Tsourela & Nerantzaki [95], where SI was found to influence PEOU or EE and PU or PE, which influence attitude, and behavioural intention to adopt IoT technologies. SI is very important for the adoption of mIoT, especially in KSA [96]. The reasons for this are the nature of the technology (wearable devices, apps providing live data feed to the patients, improving control of patients over their health data, etc.) and Saudi society's nature. IoT products can be considered health and fashion products with aesthetic qualities, which could allow customers to articulate their characters and values [95]. This is supported by Yang et al. [97], where social image (SI) showed the strongest ($b = 0.303$, t-value = 4.66, $p < 0.001$) influence on the customers' intention to use of wearable devices.

With respect to society, Saudi Arabia is considered a conservative and enclosed community and the citizens are substantially influenced by their native culture and therefore prefer face-to-face interaction to virtual one [98]. However, this has changed due to the ruler's (Prince Muhammad bin Salman) progressive approach and the COVID-19 epidemic. There is a difference in the findings of the research conducted before and after COVID-19 in KSA and post-COVID-19 research shows that Saudi health consumers are happy with the transition toward e-health during the epidemic [99,100,101]. Thus, it is reasonable to conclude that the influence of Saudi society has inclined more towards e-health or IoT. Hence, SI is a significant predictor of mIoT adoption. This conclusion has substantial value for the IT managers and individuals responsible for the introduction of new technology in Saudi hospitals. Considering the role and value of SI, they can develop strategic plans highlighting the links between the role of mIoT and SI in the hospital to support the smooth transition towards mIoT.

Performance expectancy showed the lowest influence on BI ($\beta = 0.148$, $p = 0.032$), however, a very strong effect of EE on PE ($\beta = 0.858$, $p < 0.001$) was reported in this study, which the CESE also influenced (CESE -> EE, $\beta = 0.833$, $p < 0.001$). This relationship supports the TAM factors developed by Davis as it shows the strong impact of EE or PEOU on PE or PU. This is also supported by the previous Saudi research on EMR and EHR adoption with healthcare professionals [93,92]. However, the strength of the relationship between PE and BI in the current study is comparatively weaker than the previous studies conducted in Saudi Arabia [54,93]. The reason for this discrepancy could be due to the composition of this study cohort (comparatively fewer doctors and more non-clinical participants) or could be the nature of the technology. As mIoT is different from EMR or EHR, it is quite probable that participants cared more about the computer and English skills directly influencing EE rather than the performance concerning adoption. This is supported by Chen & Hsiao [90], where PU has substantially less impact than the PEOU on health information system acceptance by healthcare professionals.

A. *Gender and Study Model*

Sub-group analysis of the model showed differences in the relationships due to gender, which is supported by the original UTAUT model [18]. Out of six independent variables for the BI, two variables showed a significant relationship for male (CESE and PE) and only one showed a significant relationship for female (CESE) participants. Past research on gender and technology suggests that males incline more toward task accomplishment than females; therefore, as an illustration, PE tends to be more significant for males, whereas females are more concerned with effort in adopting new technology [18]. Also, the strength of the relationship between CESE and BI and PE and BI were stronger among male participants compared to female and overall results. The study by Hoque [57] found similar results where male participants showed stronger relationships than females (0.6556 versus 0.1445, $t = 3.784$) between PEOU and m-Health adoption.

This indicates that EE, as suggested by other researchers, is a substantial factor for the adoption of mIoT among women. However, for men, both EE and PE were important. This is also supported by Tubaishat [92], where male Jordanian nurses were found to have a 0.19 higher PU of EHR than females, controlling for other variables in the model. Similar findings regarding the stronger link between PU and intention to use mHealth among men compared to women were also shown by a Western study suggesting a universal moderating trend of gender on technology adoption [102].

B. *Age and Study Model*

Sub-group analysis of the model was conducted for age and a separate analysis for participants aged 18 to 35 years (younger) and 36 to 70 years (senior) was conducted. The study findings showed that out of six independent variables, three (CESE, PE and PTA) showed a significant positive relationship for the younger group, and two (CESE and SI) showed a significant positive relationship for the senior group with BI. Moreover, the strength of CESE with BI was much stronger for the senior group compared to the younger ($\beta = 0.536$ vs 0.353, respectively). This stronger relationship for the older group is well supported by Venkatesh and Morris [103], who suggested that EE or CESE is more salient for older participants for IT adoption. The weaker computer skills of the middle-aged and older participants expressed through computer anxiety and less computer self-efficacy [104,105] could be the main reason for this stronger relationship. It is to assume that the participants will put more emphasis (hence a stronger relationship) on the determinants that retain the most significance for them.

PE did not show a significant relationship with BI for the senior participants, and it could be due to low mIoT knowledge among them or due to lower expectations from mIoT performance. As Al Otaybi et al. [69] showed, healthcare participants above 50 were more satisfied with EMR performance in KSA than their blow 35 years counterparts. SI only showed a significant relationship with BI for the senior participants. The reason for this could be the rapid cultural transformation occurring in KSA, which has influenced the youth, but the elderly are still intact with their culture and rely on each other, and value the opinion of the people when it comes to technology adoption [94]. The influence of aging and the role of social influence on the adoption of new technologies is also evident in the Western culture, where elderly participants expressed feelings of inadequacy in comparison to younger generations and lack of social interaction as a major barrier to the use new IT technologies [106].

Apart from these, PTA was another major factor that showed a moderate positive relationship with BI ($\beta = 0.258$, $p = 0.031$) for the younger group. In contrast, the other group showed a non-significant negative relationship between PTA and BI. This is a significant finding of our study. In contrast to past research [48, 51] PTA is not a barrier to mIoT adoption for younger participants, but it might still be for the middle-aged and elderly. This discrepancy could be explained by the power difference dynamics in the hospital environment. Younger staff in KSA, especially nurses, usually hold working or sub-managerial positions in the hospitals and they are often mismanaged or scolded by senior staff or their managers [107]. Increasing control of the top management and reducing the privacy of the behaviour conducted by the senior staff through mIoT might give a sense of transparency and reassurance to the junior employees. Hence, they perceived PTA as a significant positive determinant for adoption, which can assist them in reporting unseen misbehaviour to the top management [108].

On the other hand, senior staff might believe that mIoT can expose their professional misconduct and or can reveal their professional in-competencies and hence perceive PTA as a barrier. Also, the senior group showed a significant negative relationship between CC -> PE, which aligns with the previous research related to security concerns [13,10]. Moreover, the lack of significant effect of PE on BI for the senior group might also be explained by this finding as CC did not show any significant relationship for the overall or any other sub-group analysis.

C. Education and Study Model

The sub-group analysis of education showed that out of six independent variables, two variables showed a significant relationship with BI for both groups. However, the nature of variables varied between groups – CESE and PE showed a significant positive relationship with BI for the high education group (bachelor and above). In contrast, CESE and SI showed a significant positive relationship with BI for the low education group (diploma and below). This discrepancy could be due to the difference in the role of professionals in Saudi hospitals based on their education. It is most likely that participants with higher education were working in managerial or assistant managerial positions; as noted by Aboshaiqah & Alharbi [109] 72% of nursing managers had master's qualifications. Managers have a specific focus on performance and that is why the high-education group showed a significant effect of PE for BI [110]. Moreover, the strength of CESE with BI was much stronger for the low-education group than the high-education group ($\beta = 0.442$ vs 0.366, respectively). Again, it could be due to the varied computer skills among our study participants (high education better skills and vice versa), which is also supported by past research [111,45].

D. Occupation and Study Model

Sub-group analysis for occupation showed that out of six independent variables, two variables (CESE and SI) showed a significant relationship with BI for the clinical group, and three (CESE, PE and PTA) showed for the non-clinical group. This difference is well explained by the nature of the job of the clinical professionals [112]. Compared to other professionals in the hospitals doctors, nurses and other clinical staff are directly connected with the patients and have more potential for interaction with their colleagues; thus, SI holds substantial significance for them. In contrast, the non-clinical staff, which includes the administrators and IT personnel, have the duty of care for performance [74,110] and hence, they prioritised PE.

Moreover, the strength of CESE with BI was stronger for the non-clinical group than the clinical group ($\beta = 0.525$ vs 0.424, respectively). This could be due to the better understanding of the non-clinical participants about the computer skills required for mIoT use. Also, the non-clinical group showed a significant positive relationship between PTA and BI ($\beta = 0.340$, $p = 0.017$), while the clinical group showed a non-significant negative relationship ($\beta = -0.100$, $p = 0.368$). Again, this is a noteworthy finding of our study as it shows that the non-clinical group, which included administrators and IT personnel perceived PTA as a significant facilitator for BI as it can increase their control and support transparency in work done mainly by clinical professionals [112,108]. While as previously supported and hypothesised by the current study, PTA is a negative determinant of BI for the clinical participants, which can compromise their professional freedom and autonomy in the hospital [48].

VI. Study Contributions

This study makes a substantial contribution to the subject of mIoT adoption by hospital care staff in KSA. The findings and inference concluded in this research hold critical importance for the Saudi Ministry of Health as it is the first-ever quantitative study conducted on mIoT in Saudi hospitals and it aligns with the inclusion of the latest technology in healthcare, which is an integral part of the Saudi 2030 vision. Apart from that, the study findings are important for hospital administrators, IT managers, mIoT developers, vendors, and researchers. The following sub-sections elaborate the significance for each stakeholder.

It is strongly advised to the mIoT developers and vendors to incorporate an option of multiple languages in the mIoT systems. The current study participants showed a very strong relationship between CESE and mIoT adoption. Thus, this factor should be addressed and be prioritised.

It is recommended that the hospital administrators tailor the mIoT training program according to the demographic needs of the staff. The current study showed a disparity between the hospital staff regarding mIoT adoption as different demographic groups have shown different priorities and interests towards mIoT adoption determinants. To support equality and equity and to avoid conflict of interest among hospital staff, this study suggests the following.

It is advised to give special focus to the female, middle-aged hospital staff with low education, such as diploma and below, and clinical professionals in the hospital during awareness and training program sessions. It is likely that these identified groups might require some extra assistance to understand the concepts related to mIoT. It is also possible that they might not ask for assistance by themselves due to peer pressure and perceived shame. Thus, if it is possible, two versions (beginner and intermediate) of mIoT awareness and training program sessions should be introduced in the hospital, so the participants can choose according to their self-perceived abilities.

Based on demographic differences, the study participants showed varying preferences and expectations toward mIoT. For instance, young and non-clinical participants have shown PTA as a significant facilitator for the adoption, while older and clinical participants have indicated otherwise. Thus, this element should be considered carefully and moderated opinion should be promoted regarding PTA to accommodate both groups. Although PTA is a relatively new determinant for the adoption of e-health, it holds substantial importance for mIoT due to the nature of the technology. Therefore, hospital administrators have to be very careful about their presentation and explanation to the staff.

VII. Limitations and Research Implications

This research provides a substantial basis to future mIoT studies in the Kingdom of Saudi Arabia and elsewhere in the Gulf region. The study incorporated a modified UTAUT model and named it UTAUT-HS. The model showed significant variance (above 70%), which indicated that it was a good fit to explain the mIoT adoption behaviour. In addition, the model also showed some interesting findings, which as per the researchers' knowledge, have yet to be observed in any mIoT studies.

These findings include the most decisive role of CESE in adopting mIoT. Though CESE can be considered a subset of EE, based on the current study findings, it has narrowed the scope of EE to CESE, which can help future researchers tailor their research direction toward more targeted needs. However, the current study must assert that the UTAUT-HS model should be tested with a much larger sample (including many doctors from different specialisations and hospitals) as the current study speculates some other EE concerns (which are not shown in the current study) from the physicians. Furthermore, PTA is another factor that is initially not included in any of the original past technology adoption models (TRA, TPB, TAM, UTAUT, etc.). Now, this factor is substantially crucial with respect to mIoT and again, it should be tested with a large sample, including a sufficient number of doctors.

Also, it is suggested that more direct questions (e.g., 'mIoT including AI can make me redundant' etc.) should be included in PTA, which may overlap with the job security factor or perhaps another construct of job security can be included in the model to explore the severity of this matter. Apart from the current research, some other recent qualitative studies have highlighted these concerns. Another noteworthy finding concerning the UTAUT-HS model was the moderators' significant influence, including age, gender, education, and occupation. The current study found a wide range of significant differences among different demographic groups. While most of the differences were related to the degree (in one direction) to which a factor was known or perceived (e.g., males knew more about mIoT than females), some were in the opposite direction. PTA positively influenced BI for the younger participants, while it was non-significantly negative for the older counterparts.

Unexplored and unreported contrasting findings concerning a comparatively sensitive construct such as PTA can have grave consequences for the stakeholders responsible for introducing mIoT in the Kingdom. Thus, it is suggested that future studies include all potential demographics as moderators in the model to identify these conflicting perceptions. However, as asserted before, a much larger sample size would be required to execute these suggestions. Last, but not least, the UTAUT-HS may have universal relevance concerning mIoT adoption. Thus, researchers conducting studies in healthcare outside the Kingdom, particularly in the Western world, are suggested to employ UTAUT-HS to test its relevance.

VIII. Conclusion

The study concludes that CESE, PE, PTA and SI are the significant determinants that can influence the adoption of mIoT among the hospital care staff in the Kingdom of Saudi Arabia. The model (UTAUT-HS) included in the study showed a 71.2% variance in BI, which demonstrated a good fit and showed that the majority of the factors predicting mIoT adoption were included in the model. Among all determinants, CESE demonstrated the most substantial effect suggesting that computer and English language competence is a significant sub-determinant of the overall Effort Expectancy for mIoT adoption and should be prioritised during the development and introduction of these technologies. However, the element of PTA cannot be disregarded as it provided critical insights related to occupation and power dynamics in the hospitals and respective attitudes towards mIoT adoption. Future large-scale studies are recommended in KSA and elsewhere to validate the relevance of UTAUT-HS for mIoT adoption in the healthcare sector.

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APPENDIX

TABLE X. TABLE OUTER LOADING RESULTS OF THE INDICATOR

Study variables	BI	CC	CESE	EE	PE	PTA	SI
PE1					0.824		
PE2					0.935		
PE3					0.901		
PE4					0.863		
EE1				0.914			
EE2				0.934			
EE3				0.940			
EE4				0.909			
SI1							0.930
SI2							0.948
SI3							0.957
SI4							0.942
CESE1			0.935				
CESE2			0.928				
CESE3			0.943				
CESE4			0.921				
PTA1						0.832	
PTA2						0.941	
PTA3						0.908	
PTA4						0.875	
CC1		0.950					
CC2		0.932					
CC3		0.935					
BI1	0.965						
BI2	0.966						