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EXPLORING THE FACTORS AFFECTING THE DEPLOYMENT OF THE INTERNET OF THINGS IN HEALTHCARE ORGANIZATIONS IN THE UAE USING THE UTAUT MODEL

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ABSTRACT

Despite the growing interest in digital healthcare, the adoption of Internet of Things (IoT) technologies in healthcare organizations, remains limited and underexplored, particularly from the patients' perspective. This research investigates the key factors influencing the deployment of IoT-based healthcare devices among end users in public hospitals across the UAE. Drawing from the Unified Theory of Acceptance and Use of Technology (UTAUT), enhanced with constructs identified from existing literature, the study proposes a predictive adoption model. Data was gathered from 231 participants, and structural equation modeling was used to validate both the measurement and structural components of the model. The findings highlight that technological complexity, social influence, perceived health risks, facilitating conditions, perceived security and privacy, and relative advantages significantly shape users' attitudes (ATT), which in turn affect their behavioral intentions (BI) to adopt IoT healthcare devices. The study concludes that addressing these factors is critical for successful IoT implementation in healthcare. It contributes to Information Systems (IS) research by integrating new variables into the UTAUT model and offers practical insights for healthcare decision-makers and technology providers aiming to boost IoT adoption.

Keywords: *Healthcare, Internet of Things, Privacy, Security, UTAUT*

1. INTRODUCTION

The Internet of Things (IoT) represents a system comprising interconnected physical items, vehicles, gadgets, and various objects equipped with sensors, software, and connectivity to network [1]. These devices can collect and exchange data, enabling them to communicate and interact with each other autonomously. The overarching goal of IoT is to create a seamlessly connected environment where objects can share information, make decisions, and perform tasks to enhance efficiency, convenience, and productivity across various domains, including home automation, healthcare, transportation, and industrial processes. Positioned at the brink of a technological revolution, the assimilation of IoT is transforming sectors, communities, and the fundamental aspects of our day-to-day existence.

The incorporation of IoT into healthcare infrastructures has surfaced as a groundbreaking influence, offering the potential to drastically change the operations and service delivery of healthcare institutions [2]. According to Bhatt et al., [3], utilizing IoT as a viable technology offers a solution to the issue of overcrowded public hospitals. Wearable medical devices enabled by IoT have the capability to monitor a patient's condition and relay pertinent health data to hospital staff. This is particularly beneficial for individuals managing chronic conditions who frequently require medical consultations. Incorporating diverse IoT wearable gadgets like watches or smartphones not only has the potential to enhance patient outcomes but also to alleviate the burden on public hospital resources. The IoT possesses remarkable potential to yield superior outcomes through the utilization of cutting-edge technologies. In the medical field, it emerges as a groundbreaking concept, offering top-notch services to COVID-19 patients and facilitating precise surgical procedures [4].

IoT represents a promising technology capable of alleviating the strain on public hospital capacity. Wearable medical devices enabled by IoT can monitor patients' conditions continuously, transmitting pertinent health data to hospital physicians. This holds particular significance for individuals managing chronic illnesses who frequently require medical consultations [5]. By leveraging a range of IoT-enabled wearable devices, such as smartwatches or smartphones, lives can potentially be saved, while concurrently easing the burden on public hospital resources. While there's a recognized necessity for public health organizations to adopt this approach, its implementation remains limited and is at an early stage of development [5]. Nevertheless, despite numerous benefits, a recent comprehensive analysis of IoT adoption indicates that the integration and embrace of IoT in healthcare remain relatively limited [6]. Key challenges include: Behavioral resistance among healthcare professionals and patients, technological complexity and interoperability issues, Privacy and security concerns hindering trust in IoT-based healthcare solutions, and Lack of policy frameworks for IoT integration in public healthcare systems [10]. While prior studies have examined technical aspects of IoT adoption, there is insufficient empirical research on behavioral factors influencing end-user acceptance, particularly in the local context. Without addressing these barriers, healthcare institutions may struggle to leverage IoT's full potential for improving patient outcomes and operational efficiency.

As per findings by Al-Rawashdeh et al., [7], the integration of IoT applications among healthcare end users remains notably limited. Healthcare professionals pose significant obstacles to the effective implementation of IoT for delivering healthcare services. Although various studies have provided valuable perspectives on IoT adoption in healthcare, there remains a necessity for a comprehensive systematic review of the influential factors driving IoT adoption. The literature predominantly reflects contributions from developed nations equipped with the requisite infrastructure and expertise to leverage IoT technology [8]. Furthermore, scholarly attention is primarily directed towards the technical facets of integrating IoT healthcare devices, encompassing aspects such as connectivity, sensors, networking, and programming, with ongoing exploration into individual adoption and utilization of such technologies [9]. Literature suggests that current research predominantly focuses on the technical aspects of user adoption and interaction with IoT technologies, while the behavioral perspective remains relatively understudied [5]. There exists a notable gap in understanding regarding how the IoT influences individual and societal acceptance, with studies lacking clarity on this matter. Investigations into user experiences with IoT are still at an early stage, necessitating further exploration to identify factors that could encourage widespread adoption of IoT technologies.

Limited research has examined the issue of IoT adoption in developing countries, as noted by Maswadi et al., [10]. Furthermore, the reluctance to embrace change and integrate new technologies, along with non-compliance among healthcare personnel and deficiencies in policies for introducing and implementing IT-based solutions, have exacerbated an existing challenge, impeding the introduction of more intricate eHealth solutions like IoT [7]. Therefore, a clear understanding of behavioral factors influencing IoT adoption in healthcare is essential for designing user-centered solutions that address real concerns and encourage uptake. In the context of the UAE, where digital transformation in healthcare is a national priority, understanding user behavior can help policymakers and practitioners ensure the effective deployment of IoT-based solutions. This study adopts an extended Unified Theory of Acceptance and Use of Technology (UTAUT) framework to explore the behavioral intentions towards adopting IoT-based healthcare devices. Using data collected from 231 participants in UAE public hospitals, the study employs structural equation modeling (SEM) to evaluate both the measurement and structural models. By identifying the key determinants influencing IoT adoption, this research provides empirical evidence to inform both academic discourse and practical strategies for healthcare innovation. The integration of security, social influence, and facilitating conditions into the UTAUT model will significantly improve the prediction of IoT adoption in healthcare organizations compared to the original UTAUT framework.

This paper is organized into sections that provide an overview of existing literature, the theoretical framework, the research model and methodology, the results and hypothesis testing, followed by a discussion of findings, conclusions, practical implications, and limitations.

2. IOT IN HEALTHCARE SYSTEMS

The integration of IoT technologies within healthcare systems has emerged as a significant avenue for innovation, promising to revolutionize patient care, operational efficiency, and overall healthcare delivery [11]. IoT in healthcare involves the interconnected network of devices, sensors, and systems that collect, exchange, and analyze data to facilitate intelligent decision-making and

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automation. IoT applications in healthcare span a wide range of areas, including remote patient monitoring, telemedicine, medication adherence, predictive analytics, and smart hospital management. Remote monitoring devices enable continuous tracking of vital signs and health parameters, empowering healthcare providers to deliver personalized care and intervene proactively in case of emergencies. Telemedicine platforms leverage IoT technology to facilitate virtual consultations, enabling patients to access healthcare services remotely and reducing the burden on traditional healthcare facilities.

The adoption of IoT in healthcare holds numerous benefits, including improved patient outcomes, enhanced patient engagement and empowerment, reduced healthcare costs, and optimized resource utilization. By leveraging real-time data insights and predictive analytics, healthcare organizations can identify trends, anticipate patient needs, and optimize treatment protocols, leading to better clinical outcomes and operational efficiencies [12]. However, the widespread adoption of IoT in healthcare is not without challenges and barriers. Concerns regarding data privacy and security, interoperability issues among disparate systems and devices, regulatory compliance, and the need for robust infrastructure and technical expertise present significant hurdles to overcome. Addressing these challenges is crucial to ensure the successful implementation and scalability of IoT solutions in healthcare settings. Looking ahead, the future of IoT in healthcare appears promising, with ongoing advancements in sensor technology, artificial intelligence, and data analytics driving innovation and transformation. Emerging trends such as edge computing, blockchain, and 5G connectivity hold the potential to overcome existing limitations and unlock new opportunities for IoT-driven healthcare delivery models.

3. THEORETICAL FRAMEWORK AND HYPOTHESES DEVELOPMENT

When considering the acceptance of new technology, several theories are available to analyze individuals' choices and determine which innovations to adopt. Among these, the UTAUT model stands out as particularly effective. Ever since UTAUT's inception, it has been widely employed across diverse disciplines to investigate and elucidate technology adoption, primarily on an individual basis. Furthermore, studies have indicated that UTAUT's explanatory power is approximately 70%, surpassing the performance of its eight predecessors. These prior models had explained between 17% and 53% of the variance in behavioral intention (BI) before UTAUT was formulated [6].

This study employs UTAUT2, which suggests that technology adoption hinges on anticipated benefits and the expected physical and mental efforts involved [13]. UTAUT also encompasses additional factors such as social influence and facilitating conditions. The complexity of technology may impede its adoption, while perceived playfulness, especially in the case of wearable devices like IoT, can influence perceptions of effort. Additionally, the influence of others may alter users' perceptions of the benefits of new technologies such as IoT. Consequently, this research posits that the complexity of such technologies plays a significant role in defining effort expectancy (EE), while the social impact and perceived importance of the technology may determine performance expectancy (PE). UTAUT suggests that PE and EE affect technology adoption. Criticisms of UTAUT have highlighted its insufficient consideration of technological factors. To address this critique, this research considers the level of security provided by IoT as a crucial variable. Additionally, privacy (PV), which is integral to technological considerations, is significant in discussions involving technologies like IoT [14]. Furthermore, facilitating conditions are essential predictors in UTAUT, though their moderating role has been minimally explored.

The study proposed that attitude (ATT) is influenced by social influence (SI), perceived security and privacy (PSP), technological complexity (TC), perceived health risk (PHR), relative advantage (re), price value (PV), and facilitating conditions (FC). It was expected that both FCs would directly influence behavioral intention to adopt IoT in healthcare. The subsequent section elaborates on the hypotheses of this study. Refer to Figure 1 for the conceptual framework.

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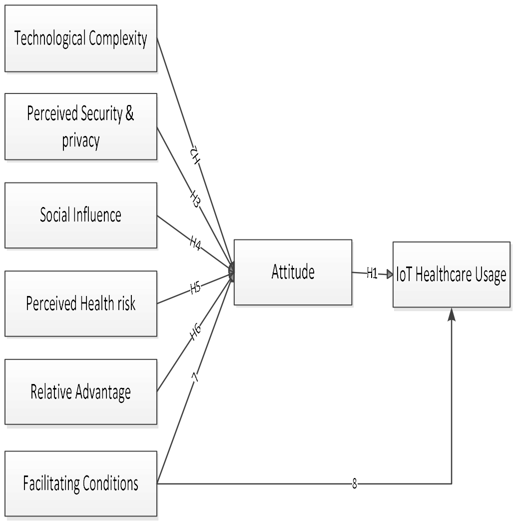

Figure 1: Conceptual Research Model.

Attitude (ATT)

Attitude (ATT) is defined as an individual's psychological inclination towards expressing preference or aversion towards an object following an assessment [15]. ATT plays a significant role in influencing behavior across various contexts. The Technology Acceptance Model (TAM), the Theory of Reasoned Action (TRA), and the Theory of Planned Behavior (TPB) all indicate that ATT serves as a predictor of Behavioral Intention (BI) to use a technology. Studies have examined the impact of healthcare professionals' ATT towards IoT on their BI to adopt the technology. Thus, an individual's ATT towards emerging technologies significantly affects their BI. Given that IoT-based healthcare devices represent a novel technology, we propose the following hypothesis:

H1: ATT towards IoT-based healthcare devices will influence end users' IoT usage.

Technological complexity (TC)

The theory of diffusion of innovation (DOI) posits that the complexity of technology (TC) plays a role in shaping user intention toward adopting new technology. Individuals who lack awareness or understanding of technology may feel hesitant or uncertain about using it, as suggested by Pal et al. [16]. Complexity refers to "the degree to which an innovation is perceived as relatively difficult to understand and use" [17]. Essentially, innovations perceived as less complex tend to garner greater acceptance and adoption. The influence of perceived ease of use on IoT acceptance and adoption remains a subject of debate.

According to Lu [18], most research findings indicate favorable impacts of users' attitudes toward IoT stemming from perceived ease or complexity of use. The adoption of IoT in healthcare settings is not without its challenges, particularly concerning technological complexity factors that significantly affect user intention [19]. Technological complexity is a significant challenge in the adoption of IoT. IoT systems comprise a complex ecosystem of interconnected devices, sensors, networks, and data processing mechanisms. The integration of diverse technologies, communication protocols, and data formats contributes to the inherent complexity of IoT systems. Users are often required to navigate through intricate setup procedures, configure device settings, and troubleshoot connectivity issues, which can lead to frustration and resistance toward adoption. Literature illustrates that technology complexity and anxiety, particularly in the context of computer-related systems and information services are very common [5]. A study by Aghdam et al., [20] highlights interoperability as a key challenge in IoT adoption, particularly in healthcare, where the integration of diverse medical devices and systems is essential for delivering comprehensive patient care. Integrating IoT devices with existing systems while maintaining data integrity and interoperability requires careful planning and investment. Therefore, it is speculated:

H2: Technological Complexity influences users' attitudes (ATT) toward IoT healthcare usage.

Perceived security and privacy (PSP)

Perceived privacy and security play pivotal roles in shaping the adoption of IoT technology in healthcare. As healthcare systems increasingly integrate IoT devices to enhance patient care and operational efficiency, concerns regarding the confidentiality of personal health information and the security of connected devices have become paramount.

The term "perceived security" (PS) refers to how people feel about the IoT's security and reliability (Zhang et al., 2014). Numerous studies have underscored the importance of PS in the context of IoT applications [21]. Similarly, Chouk and Mani,[22] identified a positive relationship between PS and the utilization of smart services. Their findings suggest that increased PS contributes

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to the broader adoption of IoT. Conversely, PV pertains to the confidentiality of IoT use and users' concerns regarding the safeguarding of their personal information [23]. A high level of perceived privacy has been shown to significantly impact IoT usage.

Perceived privacy, referring to individuals' perceptions of the confidentiality of their personal information when using IoT devices, has been shown to significantly influence adoption behaviors. In a study by Kayali and Alaaraj [23], high levels of perceived privacy were found to be positively associated with the adoption of IoT technology. Healthcare professionals and patients alike value the assurance that their sensitive health data remains private and protected from unauthorized access or disclosure. Therefore, perceptions of privacy directly impact the willingness of users to embrace IoT solutions in healthcare settings. Similarly, perceived security, which encompasses individuals' beliefs about the reliability and protection of IoT systems against cyber threats and breaches, is a critical determinant of adoption. Research by Al-Rawashdeh et al., [24] highlights the importance of perceived security in influencing users' attitudes towards IoT technology. In the context of healthcare, where the integrity and availability of medical data are paramount, concerns about the security of IoT devices can significantly hinder adoption efforts. Dutta et al., [21] further emphasize the significance of perceived security in IoT applications, underscoring its role in fostering trust and confidence among users. Furthermore, studies have demonstrated a positive correlation between perceived privacy and security and the adoption of IoT technology across various domains. Chouk and Mani [22] found that increased perceived security was associated with higher usage of smart services, indicating the broader implications of security perceptions on technology adoption. Similarly, in the healthcare sector, where the stakes are particularly high due to the sensitive nature of patient data, perceptions of privacy and security exert a significant influence on adoption decisions. This study posits that elevated levels of perceived privacy and security will have a positive effect on the usage of IoT in healthcare.

H3: Perceived security and privacy influence users' behavioral intentions (BI) toward IoT- healthcare usage.

Social Influence (SI)

Social influence pertains to how individuals perceive important figures who influence their decision-making processes. UTAUT suggested that social influence is a crucial factor capable of impacting behavioral intentions [14]. This concept is deeply rooted in social psychology, where individuals are prone to conform to the beliefs and behaviors of those they consider significant. In healthcare settings, where collaboration and professional networks are integral, Social Influence manifests through various channels such as peer interactions, organizational culture, and leadership endorsements. According to Alomari and Soh [6], most prospective users lack adequate information about IoT. Thus, the impact of SI is even amplified in the decision-making process. The attitudes of healthcare professionals towards IoT adoption are significantly influenced by the opinions and behaviors of their peers, superiors, and opinion leaders within their professional communities. The mechanism through which Social Influence affects attitudes towards IoT adoption in healthcare is multifaceted. Firstly, social validation and peer approval reinforce positive attitudes towards technology adoption. When healthcare professionals observe their colleagues embracing IoT solutions and experiencing benefits, they are more likely to develop favorable attitudes toward incorporating similar technologies into their practice. Secondly, normative expectations within healthcare organizations contribute to the influence of Social Influence on attitudes. Healthcare professionals tend to conform to perceived norms and expectations regarding technology adoption established by their peers and organizational leaders. When IoT implementation is endorsed as a standard practice within the healthcare setting, individuals are more inclined to adopt positive attitudes towards its adoption to align with prevailing norms.

Several studies have explored the role of Social Influence in shaping attitudes towards IoT adoption in healthcare. For instance, a study by Arfi et al., [25] investigated the factors influencing physicians' intentions to adopt IoT-enabled medical devices. The findings revealed that perceived social pressure from colleagues and superiors significantly impacted physicians' attitudes towards using IoT devices in clinical practice. Similarly, research by Al-Rawashdeh et al., [7] demonstrated that social endorsement from influential peers positively influenced nurses' attitudes toward IoT-based patient monitoring systems. Hence, it is hypothesized that:

H4: SI significantly influences users' attitudes (ATT) toward IoT healthcare usage.

Perceived health risk (PH)

Perceived risk plays a crucial role in consumer decision-making, particularly within the service industry [26]. Perceived health risk (PH) is a crucial factor influencing the adoption of IoT technology in healthcare settings. As healthcare organizations increasingly leverage IoT devices to monitor patients remotely, deliver personalized care, and optimize treatment outcomes, concerns about the potential health risks associated with these technologies have become increasingly salient. Perceived health risk refers to individuals' perceptions of the potential adverse effects on their health resulting from the use of IoT devices in healthcare contexts [27]. These concerns may stem from worries about data accuracy, reliability of medical diagnoses, or potential harm caused by device malfunctions or errors. Research has shown that perceived health risk significantly impacts individuals' attitudes and behaviors towards adopting IoT technology in healthcare.

A study by Alraja et al., [28] investigated the influence of perceived health risk on the adoption of IoT-based health monitoring systems. The findings revealed that individuals who perceived higher health risks associated with using IoT devices were less likely to adopt them for healthcare purposes. This suggests that concerns about the safety and reliability of IoT technology can act as barriers to adoption, particularly in healthcare contexts where the consequences of inaccurate or unreliable data can have serious implications for patient well-being.

Moreover, perceptions of health risk may be influenced by factors such as device accuracy and regulatory compliance. For example, concerns about the accuracy of vital sign measurements or the security of patient data stored and transmitted by IoT devices can amplify perceived health risks among healthcare professionals and patients. Addressing these concerns through rigorous testing, certification, and compliance with healthcare regulations is essential for fostering trust and confidence in IoT-enabled healthcare solutions. Additionally, the perception of health risk may vary depending on individual characteristics such as age, health status, and previous experiences with technology. Older adults or individuals with chronic health conditions may be more cautious about adopting IoT devices due to heightened concerns about potential health risks. Al-Rawashdeh et al., [7] concluded that specialists are worried about the health risk if the technology is used in their health activities. Therefore, healthcare organizations and technology developers need to tailor their communication strategies and educational materials to address the specific concerns and needs of different user groups. Hence, the following hypothesis is formulated:

H5: Perceived health risk influences users' attitudes (ATT) toward IoT healthcare usage.

Relative advantage (RA)

Relative advantage, a key concept in the theory of diffusion of innovations, refers to the extent to which a new technology is perceived as superior to existing alternatives [17]. In the context of healthcare, relative advantage plays a significant role in shaping the adoption of IoT technologies, which promise to revolutionize patient care delivery, enhance clinical decision-making, and improve operational efficiency [21].

Healthcare organizations are increasingly turning to IoT solutions to address various challenges, such as remote patient monitoring, chronic disease management, and hospital resource optimization. The perceived relative advantage of IoT technology over traditional approaches, such as manual monitoring or paper-based record-keeping, is a critical factor influencing adoption decisions among healthcare professionals and organizations. Research by Lu [18] examined the factors influencing the adoption of IoT in healthcare settings. The study found that healthcare professionals perceived IoT technologies as offering significant advantages over conventional methods, such as real-time data monitoring, improved patient outcomes, and enhanced efficiency. These perceived benefits were instrumental in driving the adoption of IoT solutions across different healthcare domains. Moreover, relative advantage extends beyond clinical benefits to encompass organizational and economic advantages. For healthcare providers, IoT technology offers opportunities to streamline workflows, reduce administrative burden, and optimize resource utilization. Studies have shown that healthcare organizations that adopt IoT solutions experience improvements in efficiency, cost-effectiveness, and patient satisfaction [27]. Additionally, the perceived relative advantage of IoT in healthcare is influenced by factors such as usability, interoperability, and integration with existing systems. User-friendly interfaces, seamless integration with electronic health records, and compatibility with other medical devices contribute to the perceived value proposition of IoT solutions [27].

H6: RA has an influence on the ATT toward IoT-based healthcare devices.

Facilitating conditions (FC)

The successful integration of IoT technology in healthcare hinges on various factors, among which facilitating conditions (FCs) play a pivotal role. The term "FCs" refers to the availability of necessary resources and infrastructure for utilizing technology [29]. FCs encompass the resources and infrastructure necessary for the effective utilization of IoT devices in healthcare settings. Understanding FCs in this context entails recognizing the intricate web of elements, including device reliability, internet connectivity, data management systems, and user support mechanisms, all of which collectively shape users' experiences and perceptions of IoT technology in healthcare. According to Alarefi, [5], FC is proposed by UTAUT to have a direct effect on the BI. Users' attitudes towards adopting IoT in healthcare are intricately intertwined with their perceptions of the ease of use, usefulness, and compatibility of the technology with their needs. FCs exert a profound influence on these perceptions. For instance, the availability of robust infrastructure and technical support can instill confidence in users regarding the reliability and effectiveness of IoT devices for healthcare applications. Conversely, inadequate FCs, such as unreliable internet connectivity or insufficient training, may breed skepticism and hinder users' willingness to adopt IoT solutions in healthcare.

Behavioral intention, referring to individuals' readiness to engage in a specific behavior, is also shaped by FCs [27]. Users' perceptions of the feasibility of adopting IoT technology are heavily influenced by the presence or absence of facilitating conditions. When FCs are readily available and conducive to use, users are more likely to express a strong intention to adopt IoT solutions in their healthcare routines. Conversely, barriers posed by insufficient FCs may deter users from embracing IoT technology, despite recognizing its potential benefits.

Empirical evidence from previous research corroborates the hypothesis that FCs influence both attitude and behavioral intention toward IoT usage in healthcare. Studies have consistently demonstrated positive correlations between the availability of FCs and users' perceptions of technology usefulness and intention to adopt. Moreover, addressing FC-related barriers has emerged as a critical component of strategies aimed at promoting the successful implementation and acceptance of IoT solutions in healthcare settings. Therefore, the impact of facilitating conditions on attitude and behavioral intention to use IoT in healthcare is substantial and multifaceted. Recognizing the pivotal role of FCs in shaping user perceptions and intentions is paramount for designing effective strategies to foster the adoption and utilization of IoT technology in healthcare. By addressing FC-related challenges and fostering an environment conducive to innovation, stakeholders can harness the transformative potential of IoT to enhance healthcare delivery and improve patient outcomes [21]. Hence, it is hypothesized that:

H7: FCs significantly influence users' attitudes (ATT) toward IoT healthcare usage.

Furthermore, studies have shown that FCs significantly influence users' behavioral intentions (BI) to adopt new technologies [7]. Previous research has demonstrated the impact of FCs on BI toward various technologies such as mobile banking, mobile payment systems, and food delivery applications. Therefore, the following hypothesis is proposed:

H8: FCs influence users' behavioral intentions (BI) toward IoT- healthcare usage.

4. RESEARCH DESIGN AND METHODOLOGY

This research adopts a quantitative, survey-based research design to investigate the links between independent factors and IoT usage in healthcare. Similar approaches have been used in IoT adoption studies across healthcare [7], smart homes [10], and fintech [23]. Unlike exploratory qualitative designs, this method enables statistical validation of hypothesized relationships. The use of SEM follows precedents in UTAUT extensions [21], but diverges by incorporating healthcare-specific factors. To collect data for the study, a survey instrument with 25 items was created. The survey serves as the cornerstone of the research methodology, employing cross-sectional techniques for data collection .The study population consists of patients attending medical facilities in the UAE. Convenience sampling is employed to gather data due to the absence of a comprehensive database on individuals with chronic illnesses. A questionnaire serves as the primary research instrument, comprising questions sourced from various prior studies. The survey comprises two segments: the

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first delves into participant demographics, while the second evaluates IoT adoption through a five-point Likert scale.

To collect field data, the administration of four public hospitals was approached to aid in distributing the questionnaire. A total of 346 surveys were sent out, with follow-up reminder emails sent to encourage additional responses. Consequently, 231 questionnaire responses were received and valid, and a response rate of 64.4% has been achieved. With a sample size of 231 participants, the study aimed for a reliable analysis using Structural Equation Modelling (SEM). Following suggestions by Kline [30], a sample size of approximately 200 (refer to Table 2) was deemed suitable for SEM. Sample size determination also considered the type of test applied in data analysis, with larger samples generally reducing error rates in result generalization [31]. Prior to administering the official survey, pilot testing was conducted to verify the reliability and validity of the items.

The reliability of the questionnaire was assessed using Cronbach's Alpha, yielding a high reliability. Table 1 presents the Cronbach's alpha values for the instrument's measures. The majority of the measures achieved an alpha value above 0.74, indicating strong reliability. As a result, no modifications or refinements to the questionnaire were necessary to enhance the alpha coefficients.

Table 1: Reliability Tests

Factor	***No Items***	***Cronbach's alpha***
Attitude	1	0.82
Technological Complexity	3	0.81
Perceived Security & privacy	4	0.74
Social Influence	4	0.78
Perceived Health risk	4	0.80
Relative Advantage	4	0.81
Facilitating Conditions	5	0.83

The data underwent analysis via SEM to examine initial data, validate measurements, and evaluate structural elements of the proposed model. Analysis findings were utilized to estimate indicator weights, loadings, and path coefficients between exogenous and endogenous variables. Additionally, tests were conducted for convergent and discriminant validity to affirm the survey instrument's validity. Survey reliability was assessed using Cronbach's alpha and composite reliability tests, facilitated by the SPSS statistical tool.

Table 2: Respondents demographic data

Measure	**Item**	**Frequency**	**Percentage**
Gender	Male	155	67%
	Female	76	33%
Age	20-40	18	7.7%
	41-60	168	72.7%
	> 60	45	19.4%
Education Level	High School	59	25.5%
	Bachelor	71	30.7%
	Higher Degrees	101	43.7%
Employment	Self Employed	114	49.3%
	Private Sector	48	20.7%
	Public Sector	69	29.8%

5. DATA ANALYSIS AND FINDINGS

This section discusses the results obtained from evaluating the proposed model in this study. The study employed Structural Equation Modeling (SEM) to assess the model's efficacy in adopting mobile cloud computing and evaluating its performance. SEM was chosen due to its capability to analyze multiple relationships simultaneously, unlike other statistical methods such as multiple regression or multivariate analysis of variance, which can only analyze relationships between individual variables. Typically, SEM follows a two-step process, comprising the measurement model and structural model. Initially, exploratory factor analysis (EFA) is carried out to enhance the measurement model. Subsequently, confirmatory factor analysis (CFA) is employed to evaluate the structural model. The analysis of data through SEM was conducted using the AMOS software, chosen for its accessibility and suitability for this study. The subsequent sections present the findings of the proposed model analysis, categorized into two types of analyses: measurement analysis and structural model analysis.

5.1 Exploratory factor analysis (EFA)

To evaluate the reliability of the measurement model, this study utilized Exploratory Factor Analysis (EFA) in conjunction with Principal Components Analysis (PCA) to determine factor loading and reliability using Cronbach's alpha (α) for each construct within the proposed model. EFA, aimed at identifying the most relevant items for each construct, played a crucial role in this assessment. Table 3 provides an overview of the results, including Cronbach's alpha (α) for reliability analysis and factor loading values for all

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constructs. Initially, for reliability analysis, Cronbach's alpha (α) was employed to gauge internal consistency among items within the same construct, following Byrne’s [32] recommendation of considering values above 0.7 as acceptable. As shown in Table 2, all latent constructs exhibited satisfactory reliability, with Cronbach's alpha exceeding 0.7.

Subsequently, Principal Components Analysis (PCA) with Varimax rotation was conducted to uncover the underlying structure for each factor in the research model. PCA relied on factor loading values, with each item demonstrating factor loadings surpassing 0.7, as suggested by Campbell and Fiske [33]. Any item with a factor loading below 0.7 was considered for removal from the construct's structure. The outcomes presented in Table 2 confirmed that all items were appropriately loaded onto the factors, each displaying loadings above 0.7, thereby affirming the identification of all constructs.

Table 3: Internal consistency analysis using Exploratory Factor Analysis

Constructs	Items	Factor loadings (>0.7)	Cronbach’s Alpha (α ⩾ 0.70)
Attitude	ATT1	0.814	0.842
Technological Complexity	TC1	0.811	0.823
	TC2	0.723	
	TC3	0.812	
Perceived Security & privacy	PSP1	0.785	0.723
	PSP2	0.723	
	PSP3	0.814	
	PSP4	0.894	
Social Influence	SI1	0.890	0.875
	SI2	0.823	
	SI3	0.713	
	SI4	0.814	
Perceived Health risk	PH1	0.823	0.898
	PH2	0.804	
	PH3	0.823	
	PH4	0.843	
Relative Advantage	RA1	0.843	0.804
	RA2	0.893	
	RA3	0.825	
	RA4	0.803	
Facilitating Conditions	RA1	0.856	0.882
	RA2	0.743	
	RA3	0.835	
	RA4	0.802	
	RA5	0.834	

5.2 Measurement analysis

Ensuring research precision requires scrutinizing the instrument's reliability and measurement quality before embarking on the main analysis. This process entails evaluating the relationships between the factors outlined in the proposed model and the corresponding measurement items through two analytical methods: reliability and validity analysis. Composite reliability, which measures the consistency among items within the same construct, is considered highly reliable if it surpasses 0.7, and acceptable if it falls between 0.6 and 0.7 [34]. As shown in Table 3, all of the constructs in this study exceeded the minimum threshold for composite reliability, indicating high overall reliability.

Convergent validity was assessed using Average Variance Extracted (AVE), with an acceptable value set at 0.5 or higher as recommended by Hair et al. [35]. Based on the recommendation of Hair et al., [34], the best results of convergent validity can be obtained if standardized loading estimates are 0.7 or higher, the estimation of AVE is greater than 0.5 and the estimation of reliability is above 0.7. Following the above-mentioned recommendation, this research study assumed the minimum cut-off criteria for factor loadings, AVE, and composite reliability as 0.7 > 0.5 > 0.7 respectively, in assessing the convergent validity Results from Table 4 reveal that all AVE values for the constructs met or exceeded this threshold. Conversely, discriminant validity was evaluated by comparing the square root of AVE with correlations between the constructs. For discriminant validity to be established, the square root of AVE for each latent construct should exceed the estimated correlation between the constructs [36]. The results presented in Table 5 demonstrate that the square root of AVE for all constructs exceeded the correlations between them, providing sufficient evidence of discriminant validity. Overall, the study offers reliable and valid measurements for the proposed model.

Table 4: Results of composite reliability and convergent validity

Constructs	Composite Reliability (CR > 0.7)	Average Variance Extracted (AVE > 0.5)
Attitude	0.85	0.71
Technological Complexity	0.89	0.67
Perceived Security & privacy	0.92	0.73
Social Influence	0.82	0.69
Perceived Health risk	0.81	0.63
Relative Advantage	0.88	0.73
Facilitating Conditions	0.86	0.69

Table 5: rotated pattern matrix (factor loading)

Constructs	ATT	TC	PSP	SI	PH	RA	FC
ATT	**0.82**						
TC	0.483	**0.85**					
PSP	0.473	0.412	**0.79**				
SI	0.318	0.418	0.464	**0.85**			
PH	0.480	0.309	0.368	0.437	**0.89**		
RA	0.415	0.517	0.479	0.493	0.326	**0.84**	
FC	0.518	0.497	0.437	0.474	0.467	0.456	**0.82**

5.3 Structural model analysis

In this section, an analysis of the proposed model is carried out on a structural level, divided into two parts. The first part assesses how well the proposed model fits with the collected data, using a Goodness of Fit (GoF) analysis. The following section focuses on testing the hypotheses proposed in the research model.

To evaluate how well the measurements align with the proposed research model, a Confirmatory Factor Analysis (CFA) was conducted, examining various model-fit indicators. These indicators include Chi-square/degree of freedom (χ^2/df), Goodness-of-Fit Index (GFI), Adjusted Goodness-of-Fit Index (AGFI), Root Mean Square Error of Approximation (RMSEA), Standardized Root Mean Square Residual (SRMR), Normed Fit Index (NFI), Non-Normed Fit Index (NNFI), Comparative Fit Index (CFI), and Incremental Fit Index (IFI). In this study, the Goodness of Fit (GoF) analysis played a crucial role in Structural Equation Modeling (SEM), serving as a vital step to evaluate how well the proposed model aligns with the obtained data [37]. Upon reviewing the results presented in Table 6, all factors of the model demonstrated a good fit with the data, as indicated by the model fit indices. Specifically, the values of the model fit indices, including χ^2/df, GFI, AGFI, RMSEA, SRMR, NFI, NNFI, IFI, and CFI, were determined to be 3.63, 0.934, 0.961, 0.048, 0.056, 0.982, 0.981, 0.919, and 0.982, respectively. Thus, the analysis confirms that the proposed model is well-suited to the collected data.

Table 6: Results of model fit indices

Fit indices	Measurement model	Research model	Criteria
X2/Df	3.63	3.89	<5.00
GFI	0.934	0.946	>0.90
AGFI	0.961	0.983	>0.80
RMSEA	0.048	0.042	<0.06
SRMR	0.056	0.067	<0.08
NFI	0.982	0.939	>0.90
NNFI	0.981	0.969	>0.90
IFI	0.919	0.991	>0.90
CFI	0.982	0.964	>0.90

5.4 Hypotheses testing

After confirming the alignment of the proposed model with the gathered data, the hypotheses within the research model were subjected to standardized path analysis. This examination aimed to analyze the relationships between the constructs outlined in the proposed model. The summarized results in Table 7 validated all hypotheses within the research model, indicating statistically significant positive effects.

Table 7: Hypotheses test results

H. No	Stand. coefficient Weights (β)	SE (P)	C.R.	Label
H1	0.501*	0.004	42.432	Significant
H2	0.393*	0.008	33.723	Significant
H3	0.473*	0.002	29.325	Significant
H4	0.446*	0.010	32.301	Significant
H5	0.503*	0.003	28.383	Significant
H6	0.493*	0.012	30.392	Significant
H7	0.347*	0.003	34.191	Significant
H8	0.422*	0.007	33.028	Significant

It was presumed that a relationship achieved statistical significance at the 0.05 level when the critical ratio (CR or t-value) exceeded ±1.96 [35]. All causal paths in the model were scrutinized based on the path estimates and CR (t-value). Findings indicated that t-values for twenty-two causal path estimates exceeded 1.96 (the critical value) and were significant at $p \leq .05$. However, only t-values for eight causal paths were statistically significant. The parameter estimates can be found in Table 6, and the overall structural model is illustrated in Figure 2.

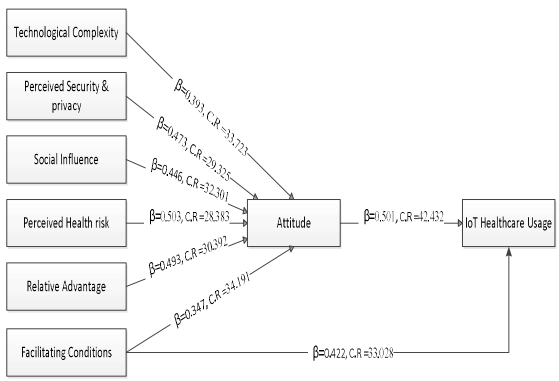

Figure 2: Structural Model

6. DISCUSSION AND IMPLICATIONS

The growing interest in healthcare IoT technology among both corporations and scholars stems from its innovative approach to facilitating communication between healthcare providers and patients. Additionally, it holds significant promise as a tool to enhance the healthcare sector. This research aims to explore the utilization of IoT among patients in the UAE who received treatment at public hospitals. IoT, a relatively novel technology, holds promise in reducing stress and enhancing patient care. This study aimed to explore the factors influencing IoT adoption in UAE healthcare organizations using an extended UTAUT model. The results demonstrate that social influence ($\beta = 0.446$), perceived security/privacy ($\beta = 0.473$), and facilitating conditions ($\beta = 0.422$) were the strongest drivers of adoption, while technological complexity ($\beta = 0.393$) and perceived health risk ($\beta = 0.503$) acted as barriers. These findings directly address our objective to identify behavioral and technological drivers of IoT adoption, highlighting the need for targeted interventions to improve trust and usability in UAE healthcare settings.

Drawing from the well-known UTAUT model and additional factors from the literature, this research identifies factors influencing behavioral intention through ATT. The proposed model underwent evaluation using SEM, with data collected from 231 participants via a survey questionnaire. The hypotheses formulated in the study found support in the data. FCs were found to directly and significantly impact behavioral intention towards the technology.TC, PSP, SI, PH, and RA were observed to significantly influence BI via ATT, with ATT exerting the strongest effect on adoption intention.

ATT refers to an individual's psychological inclination to express favor or aversion toward an object following an assessment. In this study, ATT was hypothesized to have a significant positive effect on IoT adoption in healthcare through hypothesis H1 (ATT → IoT healthcare usage). The results of parameter estimates ($\beta = 0.501$, t-value = 42.432) were found to be statistically significant at $p = 0.001$. These findings indicated that the hypothesis was significantly accepted and implied that ATT towards IoT-based healthcare devices will influence end users' IoT usage. The finding that ATT had a direct effect on IoT adoption in healthcare was consistent with the findings of different studies [21, 28]. Correspondingly, Kim [38] discovered that the majority of IoT users exhibit a favorable outlook on utilizing IoT devices, attributing higher quality to the transmitted information. Similarly, Liu et al., [39] observed that most users of IoT in healthcare expressed positive opinions about its valuable functions, particularly in areas like inventory or material tracking, as well as identification and authentication, which could enhance the effectiveness, convenience, and safety of healthcare services.

The hypothesized relationship between technological complexity and ATT toward IoT adoption IN healthcare measured through hypothesis H2 (TC → ATT) worded as "Technological Complexity influence users' attitudes (ATT) toward IoT healthcare usage" was found to be significant and supported based on the parameter estimate results ($\beta = 0.393$, t-value = 33.723, $p = 0.001$). The significance of technological complexity is also supported by Alqahtani et al. [40], who suggested that 15% of all EHR adoption barriers in Saudi Arabia were linked to the perceived complexity of the systems. When users lack technology knowledge, they frequently feel anxious when contemplating its use [16].

Hypothesis H3 (PSP → ATT) was worded as" Perceived security and privacy influence users' behavioral intentions (BI) toward IoT- healthcare usage". Results of parameter estimates ($\beta = 0.473$, t-value = 29.325) indicated that this hypothesis was found to be statistically significant at p = 0.001 level. The favorable impact of perceived security on behavioral intention (BI) implies that when the security level offered by IoT is high, patients tend to develop a positive attitude toward the technology. Similarly, the influence of perceived privacy on the usage of IoT healthcare devices indicates that a high level of privacy serves as an encouraging factor for patients in Saudi Arabia to utilize such devices. These findings align with previous studies by Pinochet et al. [41] and Alarefi [5] regarding the relationship between perceived security and BI. Certain organizations hesitate to embrace IoT due to concerns over potential privacy breaches especially in contexts involving medical data, where preserving user privacy and anonymity is paramount. This is crucial due to legal and regulatory obligations, which subsequently impact trust in adopting IoT within the healthcare sector [28].

The study also explored the influence of social factors on attitude and found a significant correlation between them. The result of the hypotheses revealed that the effect of SI on ATT is positive at B=0.446, C.R=32.301, and P<0.001 which provides support for H4. This implies that if positive recommendations spread among users, the attitude towards adopting IoT in healthcare will improve. Social influence originates from the individuals surrounding a person, and if those individuals express positivity, the individual will hold a favorable perception towards using the technology. Previous studies have shown that Social Influence (SI) affects attitude [5, 21], and the findings of this study are in line with these earlier findings. In the healthcare context, many studies have found a substantial role of SI in technology acceptance among doctors and physicians [6]. Social Influence (SI) holds significant importance for the adoption of IoT, particularly in the UAE. This is attributed to factors such as the nature of the technology (including wearable devices, apps delivering real-time data to patients, enhancing patient control over health data, etc.) and societal norms.

Hypothesis H5 (PH → ATT) was worded as “Perceived health risk influences users' attitudes (ATT) toward IoT healthcare usage”. Results of parameter estimates (β = 0.503, t-value = 28.383) indicated that this hypothesis was found to be statistically significant at p = 0.001 level. These results indicated that risk perception was a key factor in determining IoT adoption. This factor significantly influences adoption, highlighting the need for firms to employ diverse communication methods to ensure consumers feel comfortable with this technology and alleviate any related anxieties. The finding that Perceived health risk influence users' attitudes (ATT) toward IoT healthcare usage is consistent with the findings of different studies such as Alraja et ., [28], Dutta et al.,[21], Alomari and Soh,[6], and Al-Rawashdeh et al.,[7]. Furthermore, according to hypothesis H6 (RA → ATT), relative advantage is supposed to have a significant direct effect on attitude. However, the results of parameter estimates (β = 0.493, t-value = 30.392) indicated a significant relationship between RA and ATT. Therefore, this hypothesis was supported. The perceived benefits of using IoT-based healthcare devices over traditional methods of consulting a doctor were viewed as more advantageous. This aligns with prior research, which similarly identified Relative Advantage (RA) as a significant factor influencing attitude [21, 27, 42]. Those studies also concluded that the perceived advantages can impact the acceptance of IoT-based healthcare systems.

Finally, facilitating conditions can be referred to as the belief that organizational and technical infrastructures exist to support the use of the system. In the proposed hypothetical model, two hypotheses were proposed to investigate the effect of facilitating conditions on ATT and IoT healthcare usage. Hypothesis H7 (FC → ATT) worded as “FCs significantly influence users' attitudes (ATT) toward IoT healthcare usage” was proposed. Results of parameter estimates (β = 0.347, t-value = 34.191, p = 0.001) suggested that this hypothesis was found to be statistically significant. These results reflected that high facilitating conditions would increase users‘ beliefs toward the acceptance of IoT. In other words, it can be asserted that facilitating conditions such as infrastructure, technical support, and training exist to support the adoption of IoT in healthcare. Conclusively, it could be possible that participants develop positive attitudes toward IoT if adequate facilitating conditions are available Similarly, hypothesis H8 (FC → IoT Usage) proposed that “FCs influence users' behavioral intentions (BI) toward IoT- healthcare usage” shows a significant result. Parameter estimate results (β = 0.422, t-value = 33.028) indicated that this hypothesis was found to be statistically significant at p = 0.001 level. Similar to the findings of this research study, empirical findings of many previous research studies in similar contexts also found a positive correlation between these constructs [5, 21, 24]. Out of these factors, FC had the most potent effect.

This research contributes to IoT literature in public health organizations in emerging economies, focusing on the behavioral aspect rather than the technological one. It identifies factors influencing patients' IoT usage, explaining roughly half of the BI variance using a combination of TAM3 and UTAUT. The findings could aid decision-makers in UAE healthcare organizations and similar nations, emphasizing the importance of enhancing social influence, risk, and ease of use in promoting IoT adoption. Promoting positive word-of-mouth through various channels and incorporating gamification elements into IoT apps are recommended. Simplifying IoT usage, emphasizing its benefits, ensuring application security, and disseminating information effectively is crucial for fostering a conducive environment for IoT adoption.

Recent literature on healthcare IoT adoption has evolved along three main trajectories: (1) technical implementation studies, (2) professional adoption research, and (3) patient acceptance analyses. This work contributes most significantly to the third category while incorporating elements from the first two. Methodologically, the use of SEM with an extended UTAUT framework aligns with current best practices [7], though the study advances the field by incorporating health-specific constructs absent in generic IoT adoption models. Compared to the smart hospital framework proposed by Casillo et al. [9], the model provides greater granularity in behavioral factors rather than architectural considerations. In terms of key findings, the results confirm the importance of security/privacy concerns identified in European contexts [25] while revealing cultural specificities - notably the heightened role of social influence in UAE settings compared to Western populations. This complements Alarefi's [5] Saudi study but suggests national-level variations within GCC countries.

The findings from this research establish a foundation, enabling a deeper grasp of the obstacles and prospects linked to healthcare professionals' integration of IoT technology. Moreover, the studies in question predominantly employed quantitative approaches over qualitative ones, with some employing mixed methods. Indeed, employing diverse methodological approaches allows for flexibility in research design. While this study advances understanding of IoT adoption in UAE healthcare. The focus on patient perspectives in public hospitals excludes healthcare professionals, whose adoption barriers (e.g., workflow integration) may differ significantly. Additionally, the cross-sectional design and self-reported data also limit causal inferences, while the sample's age skew (72.7% aged 41–60) may not fully represent broader demographics. Cultural nuances, such as trust in institutional data governance, were implied but not explicitly tested. Future research could address these gaps by incorporating mixed methods, longitudinal designs, and comparative studies across public/private healthcare systems to strengthen generalizability and practical applicability.

7. CONCLUSION

In conclusion, this study aimed to identify and examine the key factors influencing patients' behavioral intention (BI) to adopt IoT-based healthcare devices in public hospitals in the UAE. Aligning with the study objective to identify adoption barriers and enablers, the results confirm that SI, PSP, and TC significantly shape BI (H1–H8). Notably, PSP's strong influence ($\beta = 0.473$) addresses our focus on privacy concerns, a key gap in prior IoT-healthcare studies. Beyond confirming the relevance of the UTAUT model, this research contributes to the literature by extending the framework with context-specific variables such as perceived health risk and perceived value, which have not been widely studied in prior IoT-healthcare research. The integration of these variables into the UTAUT model and the use of structural equation modeling (SEM) to validate their significance provide a more holistic and context-aware perspective on technology adoption in healthcare.

This study's contributions are twofold: First, it advances the theoretical understanding of IoT adoption by end users in developing healthcare contexts, particularly within the Gulf region—a setting that is underrepresented in current literature. Second, it offers practical implications for healthcare policymakers and technology developers by identifying critical behavioral and technological enablers that can inform strategies for successful IoT implementation. While the findings are context-bound to public hospitals in the UAE, they open avenues for future research to explore the longitudinal impacts of IoT on healthcare

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outcomes, as well as to investigate the interaction of cultural, demographic, and organizational factors with emerging technologies such as AI and blockchain. Ultimately, this study underscores the importance of aligning technological capabilities with human-centric adoption drivers to ensure that IoT solutions in healthcare deliver meaningful and sustainable improvements.

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