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CLOUDIOT-BASED HEALTHCARE ADOPTION BY HEALTHCARE PROFESSIONALS: A CONCEPTUAL MODEL

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ABSTRACT

In hospitals and healthcare facilities, the conventional healthcare setting is highly monotonous and inefficient, and it does not scale up to meet the present demand for healthcare services. Driven by the increased world population aging and the spread of pandemics, it has become essential to build cohesive and organized healthcare systems that seek to reduce clinical costs and the burden placed on healthcare institutions. The fast development of new technologies has recently sparked a worldwide revolution dubbed the 4th Industrial Revolution that used to improve healthcare services and introduce the concept of Healthcare 4. An example is CloudIoT-based healthcare which contributes to the development of effective healthcare systems that manage and monitor hospitals and patients and improve the quality of healthcare services. Although there are many benefits to using this technology, there is a disparity between its advanced development and its actual usage among healthcare professionals. This research study determines a gap in the current research on investigating the factors influencing healthcare professionals' adoption of this technology since prior studies focused primarily on the functionality and design of its systems, while adoption of such systems is lacking in these studies. The most common models for predicting and evaluating technology acceptance and use are the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). The aim of this study is to review the relevant literature for these three models and provide a conceptual model for healthcare professionals' adoption of CloudIoT-based healthcare.

Keywords*: Healthcare systems; 4th Industrial revolution; Healthcare 4; CloudIoT-based healthcare; TAM; UTAUT; UTAUT2; Healthcare professionals' adoption*.

1. INTRODUCTION

The fast development of new technologies has sparked a worldwide revolution dubbed the 4th Industrial Revolution, which has affected social and economic systems throughout the world. Industry 4.0 appeared with the fast growth of the Internet of Things (IoT), Cloud Computing (CC), Big Data (BD), and Artificial Intelligence (AI), which was drastically altering human lives and making substantial contributions to the creation of new manufacturing techniques and processes. As part of the 4th Industrial Revolution, healthcare 4.0 uses several Industry 4.0 techniques to improve healthcare, revolutionizing the eHealth system [1], [2]. This research study sheds light on the integration of IoT and CC, known as CloudIoT, representing a key driver for the Fourth Industrial Revolution. In particular, we investigate the CloudIoT-based healthcare adoption from the healthcare professionals' viewpoint and identify the main factors affecting its adoption.

The IoT and CC are emerging technologies in the 21st century ICT revolution, where these two technologies complement each other with mutual benefits. Each of these technologies is very different from the other, but they work well together because of their complementary characteristics [3]. The CloudIoT, which combines CC with IoT, solves IoT-

related issues such as data access, data processing, data storage, privacy, and security. IoT can use CC's virtual resources to compensate for its technical limitations. The IoT characteristics, on the other hand, allow CC to expand its coverage to include real-world objects [1], [3]. In addition, scalability, availability, reliability, flexibility, and security are some properties provided by CC [4], while IoT, in turn, lacks such properties due to the high level of its devices' and protocols' heterogeneity. Such complementary properties, as well as low cost and ease of use, are considered the key drivers of CloudIoT [3]. The CloudIoT adoption enables novel services and systems relying on the extension of the cloud via things, allowing the cloud to cope with real-world situations, which gives rise to the paradigm of Things as a Service.
CloudIoT-based healthcare contributes to the development of effective healthcare systems that manage and monitor hospitals and patients, and its adoption provides new opportunities to the healthcare domain [5], [3]. Furthermore, CloudIoT improves the quality and process of healthcare by facilitating the collection and delivery of patients' data to the Cloud for processing and storage [6]. Chronic diseases that significantly affect people's health can be detected and treated earlier using CloudIoT-based healthcare monitoring and management services. Besides, CloudIoT can make it easier to cope with time-sensitive healthcare services by managing healthcare sensors in a transparent and effective way [7].

The CloudIoT paradigm allows a variety of IoT sensors to connect and exchange data throughout a network, resulting in robust and organized healthcare solutions [8]. The adoption of CloudIoT-based healthcare systems improves patient care and boosts medical infrastructure [9]. It also allows patients to continue with their daily business and activities, whereas, in the background, healthcare professionals track them and provide advice and recommendations [8]. Using CloudIoT in healthcare systems includes collecting patient data through wireless sensor networks, transferring patient data to the cloud in real-time, and processing the data using artificial intelligence algorithms [10], [11]. Affordably available bio-markers sensors capture precise patient data, and the data processing aid in early disease detection, enabling healthcare professionals to provide related medical treatments in time [12]. Thus, the concept of CloudIoT-based healthcare is to provide a ubiquitous healthcare service with a minimal cost.

Implementing the CloudIoT-based healthcare paradigm includes collaborating among several cutting-edge technologies, sensors nodes, mobile applications, and end-users into a single integrated system to track, collect, and analyze data [13], [3]. It comprises three basic components: sensors for data collection, communication devices that provide real-time data, and a cloud for data analysis and processing, including mining [3], [14]. A backend clinical care system may also be included in the paradigm, which continually retrieves information from cloud storage [15]. The CloudIoT offers a real-time health monitoring infrastructure to analyze patients' vital data, leading to averting preventable deaths. It also offers promising ways to improve healthcare services and functions by exploiting the advances in the Internet of things, cloud computing, big data, and artificial intelligence technologies in building robust healthcare systems.

The CloudIoT paradigm attracts a lot of interest and, as a result, offers up new research opportunities. For instance, VCC [16] is a CloudIoT-based healthcare project aimed at providing novel healthcare services to people with chronic conditions. Belli et al. [17] presented a CloudIoT architecture for managing e-Health massive stream applications. Furthermore, several systems with highly functional solutions [18], [19] have been created in response to the potential impact of CloudIoT on healthcare services. However, despite the significant benefits that such systems may provide for healthcare services, their adoption in the healthcare arena remains limited.

This research study determines a gap in the current research on investigating the factors influencing the adoption of CloudIoT-based healthcare. The cause of this gap is that prior studies focused primarily on the functionality and design of CloudIoT systems, while adoption of such systems was lack in these studies. It is commonly acknowledged that the adoption of innovative technologies and systems is dependent on several technical and personal factors. Thus, this research seeks to address this knowledge gap by deeply understanding the factors influencing healthcare professionals' acceptance of CloudIoT-based healthcare since their acceptance is a precondition for the successful adoption of such systems.

The most common models for predicting and evaluating technology acceptance and use are the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of

Technology (UTAUT), and the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). The aim of this study is to review the relevant literature for these three models and provide a conceptual model for healthcare professionals' adoption of CloudIoT-based healthcare. Figure (1) shows the steps followed in our research.

Figure 1: Our research steps

2. LITERATURE REVIEW

2.1 Technology Introduction in the Healthcare Domain

In our hospitals and healthcare facilities, the conventional healthcare setup is extremely monotonous and inefficient, and it does not scale up to meet the present demand for healthcare services [20]. As the world's population continues to age and the spread of pandemics, it has become more important to build cohesive and organized healthcare systems that seek to reduce clinical costs and the burden placed on healthcare institutions [21], [22]. Thus, various factors and challenges drive further research studies in this field, including an increase in the number of older people worldwide, chronic and pandemic diseases, and increased demand on the healthcare systems [22], [9].

The use of IT in the healthcare domain with the goal of developing and providing healthcare services is referred to as "E-Health"[23], which has become a strategic imperative for building integrated healthcare. E-Health is a foundational step in developing new methods and innovative services for the healthcare community. In addition, it has the potential to improve healthcare quality and reduce costs and manage limited resources [24], [25]. Moreover, it enables healthcare professionals to be more responsive, provides high-quality services, enhances communication, offers up-to-date data, and boosts healthcare efficacy and efficiency [24], [26]. However, although IT implementation in the healthcare domain has many benefits, the healthcare domain is ranked at the bottom of all information-intensive industries when it comes to investments in IT [27]. Additionally, evidence reveals that most e-health projects do not advance as expected and that most of these projects are ultimately deemed failures, particularly when implemented in developing countries [28], [29].

Introducing IT is a two-way process: IT changes the way firms operate and end-users influence the future progress of technology. Consequently, this process could only succeed if end-users adequately support it [30]. In the healthcare research domain, many previous studies confirm that the healthcare professionals' acceptance of new technologies is the precondition for successful adoption.[31], [32]. Also, many healthcare projects implementation has failed due to the healthcare professionals' non-acceptance of such projects. For example, a telemedicine project aimed to enable innovations in the German healthcare field was postponed for more than five years because of doctors' non-acceptance of such technology, although most doctors perceive the potential advantages of the project [33]. In South Korea, even though telemedicine was first used at Seoul National University Hospital in 1988 as a trial E-health project, its advancement remains slow owing to physicians' opposition [34]. Doctors often show reluctance towards implementing new E-health systems since they may recognize them as a threat to their competence and they may be hesitant to use them.

Thus, as seen by the examples given above, the success of E-health systems is decided by the end-users (healthcare professionals). There are several studies that support this finding, and all share the same concerns about adopting new technology in healthcare organizations [35], [36], [37], [38]. Therefore, to avoid wasting investment on technology-based healthcare, organizations that adopt it must focus not only on the technical issues but also on the healthcare professionals' acceptability of such technologies.

2.2 Technology Acceptance Models

Several theoretical models have been presented over the last five decades to evaluate and analyze the adoption and behaviors associated with introducing and applying new technologies. Different factors have been presented by these models to understand their impact on individuals' adoption of technology. Among these models is the theory of reasoned action (TRA) [39], social cognitive theory (SCT) [40], the perceived characteristics of innovating theory (PCI) [41], the theory of planned behavior (TPB) [42], the motivational model (MM) [43], the model of PC utilization [44], the innovation diffusion theory (IDT) [45], the technology acceptance model (TAM)

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[46], the unified theory of acceptance and use of technology (UTAUT) [47], and the unified theory of acceptance and use of technology 2 (UTAUT2) [48]. They have been developed and validated as reliable measures of the extent to which technology is suited to consumer tasks [49]. This research stream began with TRA and continued with different theories, as shown in Figure (2). Yet, among these theoretical models, three have recently been employed more than others to evaluate technology adoption in the healthcare domain. These three models are shown in detail as follows:

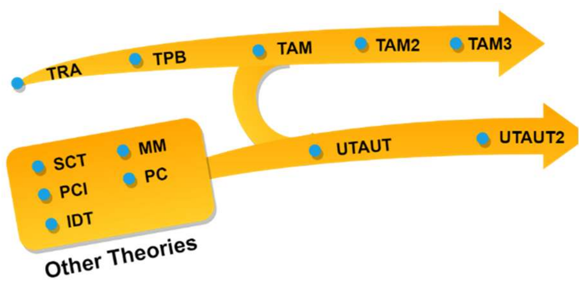

Figure 2: Research stream on technology acceptance theories.

First, the Technology Acceptance Model (TAM), introduced in 1989 by Davis [46] and has since been widely implemented and verified. It was initially formed based on the theory of planned behavior (TPB) and the theory of reasoned action (TRA) [50]. These three theoretical models are concerned with whether or not a person intends to conduct a specific action [51]. However, TAM, TPB, and TRA theories have different constructions. According to the original TAM model, the relations between external variables and attitude toward usage are mediated by the perceived ease of use and perceived usefulness. In turn, attitude affects behavioral intention, and behavioral intention affects actual usage [46], as shown in figure (3).

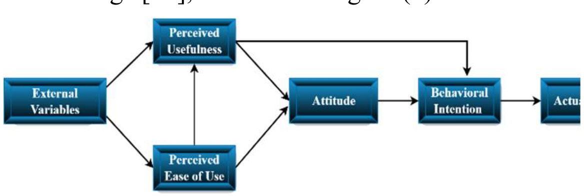

Figure 3: TAM model [46]

Second, Unified theory of acceptance and use of technology (UTAUT) model was developed by Venkatesh et al. [47], where they merged and synthesized eight previous theoretical models to obtain a precise and dependable viewpoint on user acceptance of technology. Variables of eight previous theoretical models were combined into four main factors and four moderating variables to develop the UTAUT [47]. Therefore, the UTAUT improves the adoption prediction by incorporating determinants of the previous theories, making it superior to all of them. When compared to other models of technology adoption, the UTAUT model offers a better adoption prediction rate. The TAM can predict 30 percent of adoption success, while TAM2 can predict 40 percent, whereas the UTAUT can predict 70 percent [47]. Figure (4) depicts the UTAUT model.

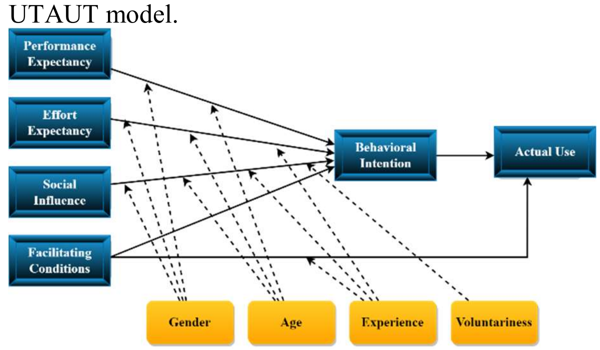

Figure 4: UTAUT Model [47]

Third, Unified theory of acceptance and use of technology 2 (UTAUT2), introduced in 2012 [48], and it has been widely used in a variety of ICT application areas since then [52], [53], [54], [55]. The UTAUT2 is one of the most recent research studies models for predicting technology adoption and a person's desire to do a specific behavior. Originally, the UTAUT2 is an updated version that was built to overcome the restrictions of the UTAUT [56]. Even though experts consider the UTAUT a full model, it has certain constraints [56], and these limitations led to the development of the UTAUT2 model [48]. By adding three factors (Price Value, Hedonic Motivation, and Habit), the UTAUT2 gives a more comprehensive perspective of the customer's behavioral intention, leading to improved insights into the customer's perception and even more accurate interpretations [48]. Despite its 2012 establishment, the UTAUT2 model has already obtained over 10000 citations on Google Scholar, highlighting its predictive power in the IS sector and beyond [57]. This offers encouragement for researchers to use the UTAUT2 model to understand technology-adoption issues of various situations where this may be done as a stand-alone model, or by integration with other models, or by extending the model with other variables [57]. Thus, the UTAUT2 has become recently a widely used model for examining the factors that influence users' adoption of new technological systems [58]. Figure (5) depicts the UTAUT2 model.

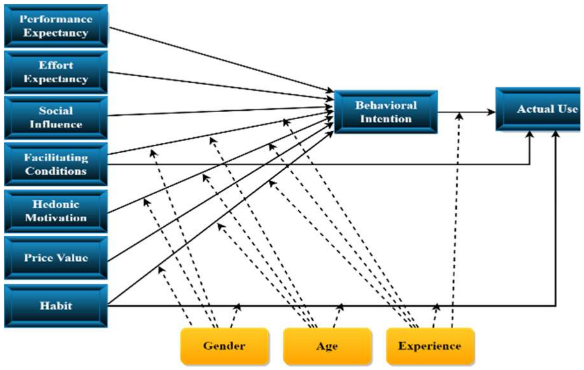

Figure 5: UTAUT2 Model [48]

2.3 E-health Acceptance and Use

Researchers have made many efforts to evaluate, forecast, and analyze the E-health systems' acceptance and actual usage by end-users. Among several technology acceptance models, TAM, UTAUT, and UTAUT2 are the most commonly used theories in this domain. Previous research studies have attempted to improve the explanatory power of these models by including factors from other models or adding new antecedents, mediators, or moderators to the original models' factors.

Fan et al. [38] integrated the UTAUT model with trust theory to study healthcare professionals' acceptance of artificial intelligence-based medical diagnosis support systems (AIMDSS). They evaluated the degree to which the integrated model could explain the healthcare professionals' decisions to adopt AIMDSS. Their integrated model has been shown to offer substantial extra explanatory power. The study's findings showed that the factor "initial trust" is the most significant factor influencing the healthcare professionals' acceptance of AIMDSS. This result suggests that healthcare professionals are conservative in their acceptance of technology, concentrating on trust in technology. In other words, healthcare professionals are cautious about embracing new technology since it has a direct impact on the health of their patients and the quality of healthcare.

Solangi et al. [36] integrated the UTAUT with Health Believe Model (HBM) and two external variables to study the adoption of IoT-based healthcare among healthcare professionals in Pakistan. The data was collected using a questionnaire from 1268 healthcare professionals, and the Structural Equation Modeling (SEM) was used to conduct the path analysis and test the hypotheses. The result indicated that performance expectancy, effort expectancy, facilitating conditions, doctor-patient relationship, and perceived severity significantly influence the healthcare professionals' adoption intention of IoT-based healthcare. In addition, adoption intention is not influenced by social influence and perceived susceptibility. An unexpected result of this study was that trust didn't influence healthcare professionals' adoption intention, which is inconsistent with the previous studies in the healthcare domain.

In Cameron, Bawack and Kamdjoug [59] investigated factors influencing physicians' intention to adopt the Health Information Systems (HIS) in hospitals. They extended the UTAUT with two external factors (Self-efficacy and Cost-effectiveness). A questionnaire was used to collect data from 228 clinicians, and SEM was employed to test the hypotheses. The result indicated that all the original UTAUT exogenous factors impacted the physicians' intention to adopt HIS, while the external factors did not. The result also showed that the performance of the UTAUT was poor in clarifying the physicians' intention variance to adopt HIS, as it only explained 12% of the variance. However, using age as a moderator variable increased clarifying variance up to 46%.

In Ethiopia, Shiferaw et al. [60] examined the factors affecting healthcare professionals' adoption intention of telemedicine during the outbreak of COVID-19 by extending the UTAUT model with two external variables (attitude and self-efficacy). A questionnaire was used to collect the data from 423 healthcare professionals, and SEM was used to evaluate the hypotheses. The analysis result indicated that the four UTAUT's exogenous variables in addition to self-efficacy significantly influenced healthcare professionals' attitudes towards the adoption of telemedicine. Besides, the healthcare professionals' behavioral intention was significantly affected by effort expectancy and attitude. An unexpected result was that performance expectancy did not influence the healthcare professionals' behavioral intention, inconsistence with the existing literature. However, the extended model performs well in predicting telemedicine acceptance by healthcare professionals as it explained 63.6% of their behavioral intention variance.

In United Arab Emirates, Alqudah and Shaalan [61] included the trust variable to the original UTAUT model as an antecedent of performance expectancy to study the physicians' acceptance of

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Queue Management Solutions (QMS). After collecting the data from 61 physicians, the SEM was used to conduct the path analysis and test the hypotheses. The result demonstrated that the physicians' behavioral intention was significantly affected by performance expectancy and facilitating conditions. Besides, performance expectancy was significantly influenced by trust, indicating its positive effect on physicians' beliefs. The extended model performed well in explaining the physicians' acceptance of QMS, as it explained 62.3% of their behavioral intention variance to adoption.

In Thailand, Vichitkraivin1 and Naenna [62] studied the medical staff adoption of healthcare robots by extending the UTAUT model with four external variables, namely, technical barrier, safety barrier, time barrier, and resistance to change. They used a questionnaire to collect the data from 466 respondents and used SEM to perform the analysis. The result showed that staff's behavioral intention was positively influenced by social influence, effort expectancy, and performance expectancy, whilst it was negatively influenced by the technical barrier and safety barrier. The result also revealed that the staff's actual use was significantly influenced by facilitating conditions and behavioral intention. Yet, even though the authors added four additional factors to the original model, its performance was poor in clarifying the staff's intention variance to adopt healthcare robots, as it only explained 25.4% of the variance.

In Ghana, Lulin et al. [63] studied factors influencing nurses' acceptance and use of Electronic Health Records Systems (EHRS) using the UTAUT model. They employed SEM to analyze the data after being collected from 660 nurses using a questionnaire. The findings indicated that effort expectancy and performance expectancy significantly influenced the nurses' actual use through the mediating role of their behavioral intention. This result also showed that effort expectancy was the most significant determinant of behavioral intention, indicating the important role of users' perceived ease of use in the E-health adoption domain. Although the authors excluded the social influence and facilitating condition in their model, it explained 37% of the nurses' behavioral intention variance and 46% of their actual use variance.

Idoga et al. [64] examined factors influencing healthcare professionals' adoption of cloud-based healthcare technology in Nigeria using an extended UTAUT2 model with five external factors. They collected the data using a questionnaire from 300 healthcare professionals and tested the hypotheses using SEM. The result demonstrated that the factors (cloud-based health knowledge, performance expectancy, social influence, and IT infrastructure) significantly influenced the healthcare professionals' adoption intention. Besides, performance expectancy was the most important factor in predicting the adoption, indicating that healthcare professionals tend to adopt new technology if they perceive its usefulness to their tasks. However, although the authors include additional factors to the original UTAUT2 model, they did not mention whether the external variables increase the model's explanatory power.

In China, Wu et al. [65] studied factors influencing physicians’ acceptance and actual use of the M-health applications using an extended UTAUT2 with three external variables (cognitive trust, altruism, and online rating). They collected the data from 393 physicians using a questionnaire and tested the hypotheses using SEM. The findings indicated that physicians' behavioral intention was influenced by social influence, effort expectancy, altruism, and performance expectancy. Besides, the physicians' behavioral intention mediated the relations between actual use and the four factors: habit, cognitive trust, facilitating conditions, and online rating. These findings showed the importance of physicians’ intrinsic motivations (the three external variables) in explaining their acceptance and actual use of M-health applications. However, the model's predictive power was not evaluated in this study.

Francis [66] employed the UTAUT2 model to examine the factors influencing the physicians' behavioral intention to adopt Self-Monitoring Devices (SMD) in the United States. Using a questionnaire, the data was collected from 258 physicians, and the SEM was used to perform the path analysis and test the hypotheses. The findings revealed that performance expectancy, hedonic motivation, and price value significantly influenced the physicians' adoption intention. The findings also showed that performance expectancy was the most important factor in predicting the physicians' behavioral intention, which emphasizes the role of perceived usefulness in the technology-based healthcare adoption domain. Moreover, the findings revealed that the UTAUT2 performs well in explaining the physicians' intention variance to adopt SMD, explaining 80% of the variance.

In India, Dash and Sahoo [67] used the UTAUT2 model to study the determinants influencing physicians' adoption intention of E-consultation during the COVID-19 outbreak. SEM was used to conduct the path analysis and test the hypotheses after data was collected from 337 physicians through a questionnaire. The result indicated that performance expectancy, social influence, facilitating conditions, and effort expectancy influenced the physicians' intention, whereas price value and habit did not. It was also indicated that performance expectancy was the most significant predictor of physicians' adoption intention. However, the model's predictive power was not assessed in this study.

In Ghana, Owusu Kwateng et al. [68] examined factors influencing the healthcare personnel's adoption intention of HIS using the UTAUT2 model. They collected the data from 110 healthcare personnel and employed SEM to evaluate the hypotheses. The result demonstrated that the healthcare personnel's behavioral intention was significantly influenced by habit, hedonic motivation, and performance expectancy. Besides, performance expectancy was the most important determinant, indicating the important role of perceived usefulness in the E-health adoption domain. The result also showed that the model explained 62.6% of the behavioral intention variance, demonstrating a good predictive power.

Shahbaz et al. [69] investigated factors influencing hospitals employees' adoption of big data analytics systems in Pakistan using an extended TAM model with four external variables (Task-technology fit, Trust, Security, and Resistance to change). The data was collected using a questionnaire from 224 Hospitals employees, and SEM was used to test the hypotheses. The findings demonstrated that perceived usefulness, trust, security, perceived ease of use, and Task-technology fit significantly affected the hospitals' employees' behavioral intention. The findings also revealed that Resistance to change negatively moderated the relationship between employees' behavioral intention and their actual usage. This result shows that adding new constructs to the original TAM model can increase comprehension of technology-based healthcare acceptance behavior. Yet, the model's predictive power was low in this study, as it explained 45% of the behavioral intention variance and 25% of the actual use variance.

Pan et al. [70] extended the TAM model with three factors (subjective norms, perceived risk, and experience of using M-health) to study the medical practitioners'' adoption intention of Artificial intelligence-based healthcare services in China. The data was collected using a questionnaire from 484 medical practitioners, and SEM was used to perform the analysis and test hypotheses. The result indicated that the medical practitioners' intention was affected by attitude, usefulness, and experience using M-Health. The result also indicated that social influence only influenced the clinicians' behavioral intention, while it did not influence non-clinicians behavioral intention. In addition, perceived ease of use and perceived usefulness were shown to positively influence medical practitioners'' attitudes, while perceived risk was shown to only influence non-physicians' attitudes negatively. This result demonstrates that including additional factors into the original model may improve understanding of technology-based healthcare adoption behavior. Besides, it increases the predictive power of the model, as it explained 67.2% of non-clinicians behavioral intention variance and 71.5% of clinicians' behavioral intention variance.

Using an extending TAM model with recognized risk and technical infrastructure support factors, Shadangi et al. [71] examined factors influencing physicians' attitude and behavioral intention to adopt telemedicine in Pakistan. A questionnaire was used to collect data from 132 physicians and Regression analysis was used to evaluate the hypotheses. The result indicated that perceived usefulness, recognized risk, and perceived ease of use significantly influenced the physicians' attitudes and behavioral intentions. The result also showed that perceived usefulness is the most important factor in predicting physicians' attitudes and behavioral intentions towards telemedicine, supporting the significant role of perceived usefulness in adopting innovative eHealth technologies. However, although the extended model provided adequate explanations of the physicians' orientation for using telemedicine, its predictive power was not evaluated in this study.

In the United States, Almojaibel et al. [72] studied factors affecting healthcare practitioners' acceptance of tele-rehabilitation using the TAM model. The data was collected from 222 pulmonary rehabilitation healthcare practitioners, and regression analysis was used to assess the hypotheses. The result indicated the significant role of perceived usefulness and ease of use in explaining the healthcare practitioners' intention to use tele-rehabilitation. The result also showed that perceived usefulness was the most significant predictor of the adoption intention. However, the model's predictive power was not assessed in this study.

Using a modified UTAUT model, Shiferaw and Mehari [35] studied the acceptance and use of Electronic Medical Record Systems (EMRS) in Ethiopia. The data was collected using a questionnaire from 423 healthcare professionals (doctors and nurses), and the SEM was used to conduct the path analysis and test the hypotheses. The result indicated that performance expectancy and social influence affected healthcare professionals' behavioral intention through the mediating role of attitude. In addition, effort expectancy significantly influenced the healthcare professionals' behavioral intention, and self-efficacy affects effort expectancy. Self-efficacy, behavioral intention, effort expectancy, and facilitating conditions influenced the actual use. These results indicate healthcare professionals tend to use the system based on its quality and functionality. However, although the authors added two external variables and modified the original UTAUT model's relations, they didn't evaluate the model's predictive power.

In Malaysia, Enaizan et al. [73] studied the healthcare professionals' acceptance of the Electronic Medical Record Systems (EMRS) by extending the UTAUT2 model with security, privacy, and trust factors. They collected the data from 375 healthcare professionals and used SEM to test the hypotheses and model's fit. The findings indicated that security, privacy, and the original UTAUT2 model's exogenous variables significantly influence the healthcare professionals' behavioral intention to adopt EMRS through a mediating role of trust. These results indicate the significant role of privacy, security, and individual factors such as performance expectancy in shaping trust in the eHealth domain. These findings imply that healthcare professionals are cautious about embracing new technology and placing their confidence in it since the health of patients and the quality of healthcare are directly impacted by such technology. However, even though the findings showed the importance of the additional factors (security, privacy, and trust) in explaining the acceptance of EMRS, the model's predictive power was not assessed in this study.

A summary of reviewed research studies is presented in Table (1).

Table 1: Summary of reviewed research studies

Authors	Technology / System	Population / sample	Model Used	External Variables	Country
[38]	AIMDSS	Healthcare Professionals N= 191	UTAUT	Task complexity, Personal innovativeness, Technology characteristics, Propensity to trust, Perceived crisis, and Initial trust (mediator variable).	China
[36]	IoT-based healthcare	Healthcare Professionals N= 1268	UTAUT	Cue to action, Trust, Doctor-patient relation, Perceived susceptibility, Perceived severity, and Health risk (moderator variable)	Pakistan
[59]	Health Information Systems	Physicians N= 228	UTAUT	Self-efficacy and Cost-effectiveness	Cameron
[60]	Telemedicine	Healthcare Professionals N=423	UTAUT	Self-efficacy and Attitude (mediator variable)	Ethiopia
[61]	Queue Management Solutions	Physicians N= 61	UTAUT	Trust	UAE
[62]	Healthcare Robots	Medical Staff N= 466	UTAUT	Technical barrier, Safety barrier, Time barrier, and Resistance to change	Thailand
[63]	Electronic Health Records Systems	Nurses N= 660	UTAUT		China

[64]	Cloud-based healthcare technology	Healthcare Professionals N= 300	UTAUT2	IT infrastructure, Security, Self-efficacy, Cloud-based health knowledge, and Information sharing (moderator variable)	Nigeria
[65]	M-health Applications	Physicians N= 393	UTAUT2	Cognitive trust, Altruism, and Online rating	China
[66]	Self-Monitoring Devices	Physicians N= 258	UTAUT2		United States
[67]	E-consultation	Physicians N= 337	UTAUT2		India
[68]	Health Information Systems	Healthcare Personnel N= 110	UTAUT2		Ghana
[69]	Big Data Analytics Systems	Hospitals Employees N= 224	TAM	Task-technology fit, Trust, Security, and Resistance to change (moderator variable)	Pakistan
[70]	Artificial intelligence-based healthcare services	Medical Practitioners N= 484	TAM	Subjective norms, Experience of using M-health, and Perceived risk (moderator variable)	China
[71]	Telemedicine	Physicians N= 132	TAM	Recognized risk and Technical infrastructure support	Pakistan
[72]	Tele-rehabilitation	Healthcare Practitioners N=222	TAM	Pulmonary rehabilitation type (moderator variable)	United States
[35]	Electronic Medical Record Systems	Healthcare Practitioners N=423	UTAUT	Self-efficacy and Attitude (mediator variable).	Ethiopia
[73]	Electronic Medical Record Systems	Healthcare Practitioners N=375	UTAUT2	Security, Privacy, and Trust (mediator variable).	Malaysia

3. METHODOLOGY

This study conducted a search of the relevant literature in the field of the adoption of eHealth. Besides, since CloudIoT-based healthcare is a relatively new paradigm and the literature lack studies on its adoption, this study reviewed the technology acceptance models to select a suitable theory as a basis for this research. This research sought a theoretical foundation with strong prediction power, particularly pertinent to the user's settings, to find a theory that encompasses almost all factors influencing the adoption intention of CloudIoT-based healthcare. However, any stand-alone model's constructs are not enough, and the model should be modified or extended when applied in the healthcare domain, as suggested by many researchers [48], [74]. Thus, along with selecting the proper model, many factors that deem suitable have also been set to add to the original model. Afterward, using the chosen factors and technology adoption model, a conceptual model and hypotheses were developed for studying the adoption of CloudIoT-based healthcare.

4. THE CONCEPTUAL MODEL FOR CLOUDIOT-BASED HEALTHCARE TECHNOLOGY ACCEPTANCE

After reviewing the relevant literature, an extended UTAUT2 model with additional external factors has been proposed, as depicted in Figure (6). The UTAUT2 model has been chosen based on its high predictive power and its recently widely used for examining the factors that influence users' adoption of new technological systems. Besides, the additional external factors have been selected based on their high support in prior studies. These factors might help the original UTAUT2 model's variables explain the healthcare professionals' adoption of CloudIoT-based healthcare. Yet, since CloudIoT is still an emerging technology that healthcare professionals are not widely used, especially in Jordan, measuring actual use would lead to an erroneous conclusion regarding adoption. Thus, the behavioral intention has been used in this study as the dependent variable rather than actual use. In our research, behavioral intention refers to the extent to which healthcare professionals are willing to adopt CloudIoT-based healthcare.

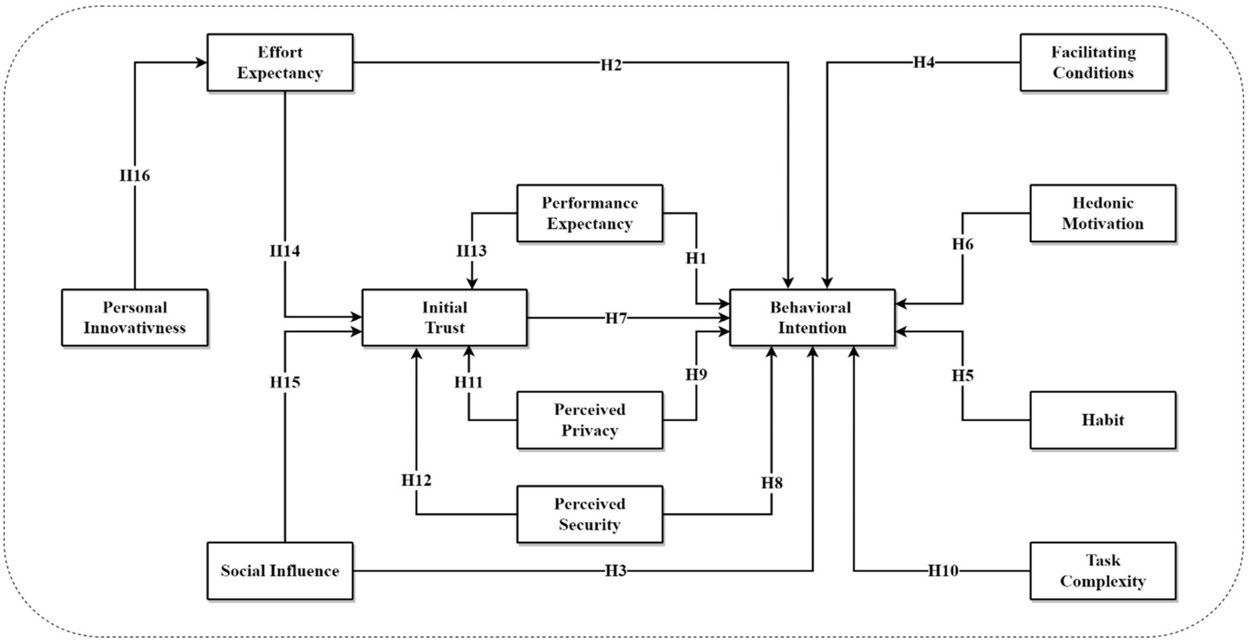

Figure 6: The extended UTAUT2 model

4.1 UTAUT2 and CloudIoT-Based Healthcare Adoption

4.1.1 Performance Expectancy

The term "Performance Expectancy (PE)" refers to "the degree to which an individual believes that using a new system or technology will help him/her to attain job performance" [47]. The adoption of innovative technologies would be more probable among users who perceive that the technology offers benefits to their daily tasks. In the CloudIoT-based healthcare context, PE indicates the individual's perception of such technology in healthcare problem-solving and improves its quality. Owusu Kwateng et al. [68] found that PE is the essential factor in encouraging healthcare professionals to use HIS. Also, according to Solangi et al. [36], PE is a key predictor of healthcare professionals' adoption intention of IoT-based healthcare technology. Similarly, in their empirical study, Vichitkraivin1 and Naenna [62] reported that the medical staff's adoption of healthcare robots is influenced significantly by PE. Based on the above, we propose the following hypothesis:

***H1**: PE significantly influences the healthcare professionals' behavioral intention to adopt CloudIoT-based healthcare technology.*

4.1.2 Effort Expectancy

The term "Effort Expectancy (PE)" refers to "the degree of ease associated with the use of the system" [47]. EE also has to do with how much effort it is for the user to use a given system. The UTAUT and UTAUT2 models emphasize EE as a critical construct, and it has also been used in most technology adoption studies in the healthcare domain. Wu et al. [65] found that EE is a significant factor in explaining physicians' adoption of M-health applications. Similarly, Shiferaw et al. [60] reported that the healthcare professionals' adoption of telehealth is affected significantly by EE. Also, according to Solangi et al. [36], EE is a significant factor in explaining healthcare professionals' adoption of IoT-based healthcare technology. In this study, EE reflects the healthcare professionals' subjective evaluation that CloudIoT-based healthcare would be easy and effortless. Since CloudIoT-based healthcare is a novel concept to most healthcare professionals, EE would have a

correlation with behavioral intention. In line with the above, we formulate the following hypothesis:
H2: *EE significantly influences the healthcare professionals' behavioral intention to adopt CloudIoT-based healthcare technology.*

4.1.3 Social Influence

The term "Social Influence (SI)" refers to “the degree to which an individual perceives that important others believe he or she should use a certain system or technology” [47]. People are influenced to a greater or lesser extent by others, particularly those closest to them, such as family members, colleagues, and friends. The views of these individuals, whether positive or negative, would impact end-users when deciding whether or not to use a certain system or technology. Previous research studies have shown that SI has a significant impact on healthcare professionals' intention to adopt new technologies, such as healthcare robots [62], cloud-based healthcare technology [64], and electronic medical records [35]. Thus, there is a logic that influential people in healthcare professionals' social circles will influence their decision to adopt CloudIoT-based healthcare technology. Consequently, we suggested the following hypothesis:
H3: *SI significantly influences the healthcare professionals' behavioral intention to adopt CloudIoT-based healthcare technology.*

4.1.4 Facilitating Conditions

The term "facilitating Conditions (FCs)" represents "the individual’s perception of the degree to which organizational and technical infrastructure support the use of the new system or technology" [47]. FCs are a form of convenience condition that impacts the system utilization. The lack of resources and technical support may lead to end-users hesitance adopting of technology. End-users must have the knowledge, training, skills, support, and resources required to use CloudIoT-based healthcare technology. Many research studies in the e-Health domain revealed the significant role of FCs in explaining the healthcare professionals' adoption intention, such as IoT-based healthcare [36], Health Information Systems [59], and telemedicine [60]. Thus, the availability of skills, support, and resources would influence the healthcare professionals' behavioral intention to adopt CloudIoT-based healthcare. Consequently, we formulate the following hypothesis:
H4: *FCs significantly influence the healthcare professionals' behavioral intention to adopt CloudIoT-based healthcare technology.*

4.1.5 Habit

Habit is defined as the extent to which individuals do their actions automatically because of previous knowledge or experience [48]. It is not only about repeating old behaviors and routines but also about behaving unintentionally and uncontrollably [75]. Since healthcare professionals use different technologies for payment, communication, education, and shopping, we suppose they have acquired an online services habit and will adopt CloudIoT-based healthcare services. Besides, previous research studies in the eHealth acceptance domain showed that HT positively influences the healthcare professionals' behavioral intentions [65], [68], [73]. Thus, CloudIoT-based healthcare is more likely to be adopted by healthcare professionals whose habits direct their use of technology. Consequently, we propose the following hypothesis:
H5: *HT significantly influences the healthcare professionals' behavioral intention to adopt CloudIoT-based healthcare technology.*

4.1.6 Hedonic Motivation

The term "Hedonic Motivation (HM)" represents "the extent to which an individual perceives pleasure and enjoyment when using a certain system or technology" [48], and it has been found to have a significant influence in predicting technology acceptance in different settings, such as blended learning [76], online purchase [77], and augmented reality applications [78]. However, in the healthcare context, healthcare professionals may pay more attention to the quality of healthcare services than gaining pleasure or enjoyment. Thus, the impact of HM on healthcare professionals' behavioral intention could be less significant in such context than its impact in other domains. Yet, CloudIoT-based healthcare technology may excite pleasure or curiosity of being a trend. Consequently, we propose the following hypothesis:
H6: *HM significantly influences the healthcare professionals' behavioral intention to adopt CloudIoT-based healthcare technology.*

4.2 Trust and CloudIoT-based healthcare adoption

The term "Trust (TR)" is described as the individual's readiness to depend on another party who has confidence in it [79]. TR is fundamental for people in the virtual world in which the physical aspect and absolute clarity are both lacking [80]. Given the lack of experience with CloudIoT-based healthcare among Jordanian healthcare professionals, this study focuses on the initial trust, which refers to confidence without previous use. TR assists in the reduction of complexity by excluding undesired future actions by others [81]. In the healthcare context, healthcare professionals are cautious when determining whether to embrace a particular technology since it may affect the quality of healthcare services and thus their patients' lives [38]. In CloudIoT-based healthcare, with trust, healthcare professionals will exclude the negative consequences of using this technology, like misanalysis and sensor faults, which might ultimately affect their decision to utilize it. Prior research studies revealed the significant role of trust in explaining the healthcare professionals' adoption of innovative technologies, supporting our argument. For example, Fan et al. [38] showed that "initial trust" is the most significant factor influencing the healthcare professionals' acceptance of AIMDSS. Enaizan et al. [73] revealed the vital role of trust in mediating the relationship between individual factors and behavioral intention for healthcare professionals in the context of EMRS adoption. Also, Shahbaz et al. [69] found that trust is a significant determinant of healthcare professionals' adoption of big data analytics systems. Thus, we formulate the following hypothesis:

H7: *TR significantly influences the healthcare professionals' behavioral intention to adopt CloudIoT-based healthcare technology.*

4.3 Perceived security and CloudIoT-based healthcare adoption

The term "Perceived Security (PS)" is defined as the extent to which an individual feels that using a given technology or system to gather and exchange data is safe and sound [82]. In the healthcare industry, where sensitive patient data is at stake, the perception of security is critical and may inhibit or induce individuals to use a specific system or technology. Many security issues are related to technological systems, such as failure, misuse, or intrusion. However, motivated by the potential influence CloudIoT has on enhancing healthcare services, many proposed CloudIoT-systems have focused on possible solutions to these security issues. Prior research studies have shown the significant role of PS in explaining the users' adoption intention in different research contexts, such as online marketing [83], EMRS [73], IoT-based smart campus [84], and CC [85]. In the CloudIoT-based healthcare context, we argue that the healthcare professionals' perception of the security level of the different entities involved in the system, such as sensors, means, and analytical tools, would significantly influence their intention to use such technology. Thus, we formulate the following hypothesis:

H8: *PS significantly influences the healthcare professionals' behavioral intention to adopt CloudIoT-based healthcare technology.*

4.4 Perceived privacy and CloudIoT-based healthcare adoption

Privacy is associated with protecting information, which basically includes unauthorized access by external parties, which represents a significant concern for healthcare systems. When it comes to healthcare, it refers to the extent to which data on patients and healthcare professionals is shared with third parties. Several previous studies have pointed out that privacy is critical when implementing e-Health services [86], [73], [87]. Besides, Soceanu et al. [88] revealed that Perceived Privacy (PP) has a favorable influence on the healthcare professionals' view that the system is suitable and usable in the healthcare domain. In the CloudIoT-based healthcare context, we argue that PP would have a significant role in explaining the healthcare professionals' adoption intention. Thus, we propose the following hypothesis:

H9: *PP significantly influences the healthcare professionals' behavioral intention to adopt CloudIoT-based healthcare technology.*

4.5 Task complexity and CloudIoT-based healthcare adoption

The term "Task complexity (TC)" refers to the extent of difficulty involved in accomplishing a specific task [89]. Healthcare activities involve several tasks, including the easy and the complex ones. If healthcare professionals realize how complex their tasks are, they are more inclined to accept assistance to improve their performance [90]. Previous research studies have identified TC as an influential variable in the technology adoption domain [38], [91]. Nevertheless, the utility of TC varies depending on the functions that technology plays for tasks of various complexity. CloudIoT may be seen as more beneficial for more complex tasks (collecting patient vital data, analysis of patient data, and diagnosis) by healthcare practitioners than for

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simpler ones. Based on the above, we formulate the following hypothesis:

H10: *TC significantly influences the healthcare professionals' behavioral intention to adopt CloudIoT-based healthcare technology.*

4.6 Trust's antecedents

Here we turn to explore trust antecedents to fully understand its role in CloudIoT-based healthcare adoption. According to previous research studies on trust in the technology acceptance context, many potential variables might predict trust. These variables may be categorized into three primary classes: personal attributes, technology attributes, and organizational attributes [38]. In our research, we identified five antecedents: performance expectancy, effort expectancy, perceived security, social influence, and perceived privacy. In the following section, we discuss the logic behind selecting these antecedents.

4.6.1 Initial trust, perceived security, perceived privacy, effort expectancy, and performance expectancy

According to Li et al. [92], Individuals' general perceptions of a particular technology would eventually influence their trust formulation in such technology. Based on the above, we identified the four factors: Perceived security, perceived privacy, performance expectancy, and effort expectancy, as kinds of a particular technology's general perceptions. The first factor refers to the extent to which an individual feels that using a given technology or system will be safe and sound, while the second refers to the extent to which an individual feels that critical data will not be shared with a third party. In addition, the third factor refers to the user's expectations that the new technology will improve his daily activities, and the last one refers to the user's expectations that using a new system or technology will be effortless. These are tangible reflections of technology attributes that might contribute to forming the initial trust as described above.

Previous research studies addressed the relationships between security, privacy, and initial trust. For example, Enaizan et al. [73] examined the healthcare Practitioners' adoption intention of EMRS based on an extended UTAUT2 model with trust, privacy, and security. Their result confirmed that security and privacy significantly influenced the healthcare Practitioners' trust in such systems. Another study on the adoption of Big Data Analytics Systems in the healthcare domain revealed the effect of security on shaping the initial trust in these systems [69]. Also, Liu and Tao [93] revealed the relationship between privacy and trust in the adoption of smart healthcare services, where the loss of privacy leads to a loss of trust in such services. In the CloudIoT-based healthcare context, the healthcare professionals' perception of security and privacy would increase their trust in the reliability of such systems. Thus, we proposed the following two hypotheses:

H11: *PS significantly influences the healthcare professionals' trust in CloudIoT-based healthcare technology.*

H12: *PP significantly influences the healthcare professionals' trust in CloudIoT-based healthcare technology.*

Many research studies also addressed the effect of performance expectancy and effort expectancy on the initial trust. For instance, in their empirical study, Fan et al. [38] found that PE and EE are two prominent antecedents in shaping the healthcare professionals' trust in AIMDSS. Another study confirmed the influence of PE and EE on trust in the context of EMRS [73]. Regarding CloudIoT-based healthcare, we argue that healthcare professionals who have high expectations for needed effort and the system's performance are more likely to shape an initial trust in the system. Thus, we proposed the following two hypotheses:

H13: *PE significantly influences the healthcare professionals' trust in CloudIoT-based healthcare technology.*

H14: *EE significantly influences the healthcare professionals' trust in CloudIoT-based healthcare technology.*

4.6.2 Initial trust and social influence

Although social influence plays a vital role in predicting users' behavioral intention, it also has a significant role in shaping users' technology trust. Many research studies support this argument in different IS research contexts, such as Mobile Social Network Games (M-SNGs) [94], Mobile Wallets [95], and AIMDSS [38]. A person is more prone to depend on the views of influential people in shaping the trust when he lacks sufficient experience and hands-on operation of a specific technology. As such, when healthcare professionals see a new eHealth technology is preferred and accepted by their colleagues and close people, they tend to

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believe in the technology. This study argues that Jordanian healthcare professionals' perception that close people think they should use CloudIoT-based healthcare would influence their initial trust since they don't have previous experience with this technology. Thus, we proposed the following hypothesis:

H15: *SI significantly influences the healthcare professionals' trust in CloudIoT-based healthcare technology.*

4.7 Personal Innovativeness and Effort Expectancy

The term "Personal Innovativeness (PI)" represents the extent to which an individual is relatively earlier than others in using a new system or technology [96]. People have diverse responses to innovations due to their different propensities and characteristics. Individuals with high levels of inventiveness are more likely than others to be able to master new technologies, and they often think of their use as simple and less complex [38]. Since the effort expectancy is a measure of how difficult it is to use a certain technology, many previous research studies investigated the effect of PI on EE. For instance, Fan et al. [38] showed that PI had a significant influence on EE in the context of AIDMSS adoption. Also, Wu et al. [97] revealed that PI has a favorable influence on the healthcare professionals' view that the M-health applications are easy and simple to use. Based on the above, we assume that PI favorably affects EE in the context of CloudIoT-based healthcare, and we propose the following hypothesis:

H16: *PI significantly influences the healthcare professionals' EE in CloudIoT-based healthcare technology.*

5. DISCUSSION

This study uses different technology acceptance models and mainly draws on the UTAUT2 model to propose a conceptual model for CloudIoT-based healthcare adoption. In addition, the literature on several eHealth technologies was reviewed and synthesized in order to propose 15 hypotheses that aim to explain the healthcare professionals' intention to adopt CloudIoT-based healthcare. In the following, we present the two main implications of our study.

5.1 Theoretical Implications

First, determining the factors influencing the acceptance of CloudIoT-based healthcare in this study offers an initial explanation of this technology's adoption. We built a conceptual model in order to explain the healthcare professionals' intention to adopt this paradigm, including the development of hypotheses concerning relations between the factors, which existing literature lacks. Second, we extended the UTAUT2 model by adding five new factors and modifying the relationships between the factors. Therefore, this study's conceptual model has well alignment with previous studies that recommended extending or modifying any theoretical model when studying the acceptance of technology in a specific context.

5.2 Practical Implications

This study provides insights into CloudIoT-based healthcare that contributes to developing effective healthcare systems. Understanding the factors influencing the acceptance of CloudIoT-based healthcare technology enables stakeholders to be more conscious of issues that must be considered to boost the adoption process. Thus, the proposed conceptual model can help different stakeholders seeking to enhance the adoption of this technology. For instance, given that trust can serve as a mediator between several factors and behavioral intention, CloudIoT providers should take into consideration the factors that may increase the healthcare professionals' trust in such systems. Consequently, understanding the impact of several factors, such as security, privacy, and effort expectancy on trust helps CloudIoT-based healthcare providers better develop their systems.

The current study is a conceptual paper that explores the literature as well as theoretical support to boost the adoption of CloudIoT-based healthcare systems. We are aware that there is a lack of data to back up the argument that is stated in this research; nonetheless, we plan to gather data and conduct an empirical study in order to validate the proposed model and hypotheses. Accordingly, using a questionnaire to collect the proper data, the future study will empirically investigate the proposed model as well as the hypotheses that were established. Healthcare professionals with knowledge or expertise in eHealth in Jordan will be the target group of the study.

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6. CONCLUSION

The implementation of CloudIoT-based healthcare technology contributes to developing effective healthcare systems that manage and monitor hospitals and patients and improve the quality of healthcare services. However, although there are many benefits to using these systems, healthcare professionals use very few of such systems. As part of our literature study on technology acceptance models, we found few research studies on the factors that influence the adoption of CloudIoT compared to other technologies. Thus, we proposed a conceptual model for adopting CloudIoT-based healthcare technology by healthcare professionals. Based on reviewing the existing literature on the acceptance of innovative technologies in the healthcare sector, we sought a theoretical foundation with strong prediction power, particularly pertinent to the user's settings. Additionally, along with selecting the proper model, many factors that deem suitable have also been set to add to the selected theoretical model. Consequently, based on the UTAUT2 model, we proposed our conceptual model.

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