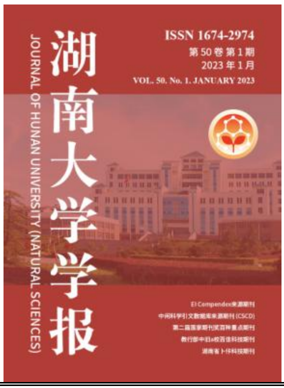

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Factors Influencing the Behavioural Intention of Patients with Chronic Diseases to Adopt IoT-Healthcare Services in Malaysia

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Abstract: The Internet of Things (IoT) in healthcare is the newest trend in the healthcare market. IoT allows healthcare providers to expand their reach beyond the usual clinical environment. They are driven to maximize the possibilities of digitally linked healthcare services to improve the user experience, diagnostic accuracy, and communication among healthcare professionals. Sensors, wearables, and health monitors have made healthcare cheaper, faster, and more effective. Despite the privileges of the IoT in healthcare services, the adoption rate of these services is still in the early stages. The aim of this research was to examine the adoption of IoT-enabled healthcare services among Malaysian chronic patients. To achieve this purpose, the study offered an integrated framework to investigate the influence of the identified factors on Behavioural Intention (BI) to adopt IoT healthcare services. The novelty lies in combining the Unified Theory of Acceptance and Use of Technology (UTAUT), the Theory of Organizational Environments for Technology Adoption (TOE), and the Social Exchange Theory (SE). Patients in Malaysia dealing with chronic illnesses were the subjects of an online survey. Eleven predicted predictive constructs' impacts were investigated using partial least square structural equation modeling. The findings revealed that individual and technological factors and their dimensions, significantly affected chronic disease patients' BI toward IoT-healthcare services adoption. Similar results were observed for the effect of BI on Use Behaviour (UB). Meanwhile, trust partially mediated the effect of individual and technological-related factors on BI.

Keywords: Internet of Things, chronic disease, adoption.

影响马来西亚慢性病患者采用物联网医疗服务行为意愿的因素

摘要：医疗保健中的物联网(物联网)是医疗保健市场的最新趋势。物联网允许医疗保健提供者将其范围扩大到通常的临床环境之外。他们致力于最大限度地发挥数字化医疗保健服务的可能性，以改善用户体验、诊断准确性以及医疗保健专业人员之间的沟通。传感器、可穿戴设备和健康监测器使医疗保健变得更便宜、更快捷、更有效。尽管物联网在医疗保健服务中享有特权，但这些服务的采用率仍处于早期阶段。这项研究的目的是检查马来西亚慢性病患

者对物联网医疗保健服务的采用情况。为实现这一目的，该研究提供了一个综合框架来调查已识别因素对采用物联网医疗保健服务的行为意向(双)的影响。新颖之处在于结合了技术接受和使用的统一理论(乌特)、技术采用的组织环境理论(脚趾)和社会交换理论(SE)。马来西亚患有慢性病的患者是一项在线调查的对象。使用偏最小二乘结构方程模型研究了11个预测预测结构的影响。研究结果表明，个人和技术因素及其维度显着影响慢性病患者对物联网医疗服务采用的双。双对使用行为(UB)的影响也观察到了类似的结果。同时，信任部分地调节了个人和技术相关因素对双的影响。
关键词：物联网、慢性病、收养。

1. Introduction

Healthcare is the most expensive service in many countries across the world. The current healthcare system is facing many challenges including high costs, lack of efficiency, and an increasing elderly population with chronic illness. In the last decade, IoT has revolutionized technology [1]. It provides clever and new technologies and services through which all devices connected to the Internet interact with each other [2]. Countries and industries are using the IoT to improve their competitiveness [3, 4]. There is no agreement on a universal definition of the Internet of Things (IoT). However, researchers refer to the "Internet of Things" as a network of objects connected over the Internet [3, 5]. Despite the benefits of IoT in healthcare, the adoption of this service remains low and in its early stages [6]. Nevertheless, there is a lack of information and studies on the adoption of IoT healthcare services among users and patients. Malaysia is no exception given the paucity of data on users' perspectives regarding the usage and adoption of IoT in the healthcare system [7], especially among chronic disease patients. The lack of a holistic approach to healthcare in general might contribute to the low adoption rate of IoT in healthcare. Most of the ongoing research in Malaysia and other countries focuses on the underlying technologies, factors, and services without considering the role of human-related factors and the social background. Therefore, there is a need to determine the reasons behind the lack of usage of smart healthcare services from the patients' perspective. Even such service provides many benefits to patients, but they are still having concerns related to the individual and the technological level. At the individual level, users find IoT complex and are unaware of the advantages that can be gained from using this technology [6, 8, 9]. At the technological level, information sensitivity, which includes security and privacy concerns during the collection and transmission of patient data [10, 11]. Given the low adoption of IoT among users, numerous theories have been employed in the literature to elucidate the behavioral intention to use and adopt technology, as well as understand the predictors and increase the explanatory power of IoT models [12-14]. Among the widely deployed models is the technology acceptance model (TAM), which was developed by Davis. Meanwhile, Venkatesh pointed out that TAM can explain only 54% of the variation in technology acceptance [15]. Building on TAM and seven other technology acceptance models and theories, Venkatesh developed a unified theory of acceptance and use of technology (UTAUT) [15]. The model can explain up to 69% of the variation in technology acceptance. However, both UTAUT and TAM were criticized for focusing on the individual aspects and being simplistic in predicting the adoption of a new technology [16]. Adopting a new technology is not only dependent on individual factors but also on the characteristics of the technology, such as security, privacy, and availability [16, 17]. To increase the explanatory power of technology adoption, previous studies have suggested a combination of two or more theories [18]. Therefore, this study responds to the suggestion and combines the UTAUT, which is an individual-based model, with the TOE, which is a multi-perspective framework. Since the IoT is considered a relatively new technology, previous studies have focused on well-established and developed countries, while those conducted in developing and emerging economies are relatively limited. Malaysia is a developing economy with a high level of technological advancement compared to other Middle Eastern and Southeast Asian countries. The IoT is deployed in several sectors, including the healthcare sector. Adopting IoT in healthcare can help reduce wait times, congestion, and lost patient records. However, few studies examine this issue [19]. Accordingly, this study determines the predictors of IoT adoption in healthcare services among patients with chronic diseases in Malaysia.

2. Literature Review

2.1. IoT in Healthcare

Smart healthcare could be described as the use of mobile and electronic devices to facilitate disease detection, better medical management, and increasing quality of life [20, 21, 69]. The concept of smart healthcare is presented when IoT modules aid the basic roles of the health sector. The IoT has been the focus of international interest for several years. Several countries now consider healthcare services as one of the most significant challenges that affect the public and private sectors socially and economically [22]. It is expected that healthcare costs will account for 20%–30% of the GDP in some countries by 2050 [23]. Reducing costs is considered one of the significant benefits of IoT-healthcare innovation since the integration of devices and technology reduces operational costs and enhances the quality of healthcare services [24-26, 84]. Given that the rising cost will have a significant effect on patients' quality of life [22, 27], some researchers argue that adopting new technologies will assist in reducing costs effectively and facilitate a healthy life at a low cost [22, 28, 29].

Presently, IoT has been integrated into healthcare mainly in the areas of remote patient monitoring, information collection and transfer it in real time, and end-to-end connectivity. It also enables data communication, interoperability, and essential information analysis and communication between machines. IoT has been instrumental in transforming routine medical checks into more patient- and home-centered than hospital-centered techniques in medical diagnostics. IoT has therefore assisted in decreasing the expenses and occurrence of dangerous errors in healthcare systems, especially for disabled and chronic disease patients [30-32]. According to the national center for chronic disease prevention and health promotion (NCCDPHP), chronic diseases are defined as conditions that last for one or more years and require ongoing medical attention or limited daily activities [33]. Chronic diseases are the leading causes of death and disability in the United States. Common chronic diseases include hypertension, heart disease, and diabetes. Most chronic diseases are uncurable, but they can be managed in diverse ways to reduce the daily burden of the disease or the likelihood of its progression to more serious symptoms [34]. Chronic diseases are also known as the "silent global pandemic" because they are considered the major cause of death and disability worldwide [35]. Several studies have suggested that the implementation of IoT healthcare services is a solution for effective monitoring and the provision of better care to chronic disease patients [36-38]. Thus, IoT could be employed to ease the burden on family members and visits to the hospital, thereby increasing patients' quality of life. Against this background, previous studies in Malaysia either focused on the adoption of smart homes or the technicality of IoT usage in healthcare and the business sector [39-41]. However, the low adoption of IoT, especially among the chronic disease patients in Malaysia, was hypothesized to be associated with individual and technological factors [35].

2.2. Theoretical Background

In the context of technology adoption literature, there are eight widely known models, theories, and frameworks. Among these models, the newest is UTAUT. However, the most commonly used is TAM. Nevertheless, in the context of healthcare, these two models have been criticized for being simple and focusing only on the individual aspect of adoption. The technological aspect, which is more related to the ability and perception of the technology, has seldom been incorporated. To address this lack, the TOE is considered as a multi-perspective framework. It has technological, organizational, and environmental aspects. Again, the TOE is lacking for the individual aspects of technology adoption. For this reason, there is a need to combine the TOE with the UTAUT, as suggested by researchers. To increase the explanatory power of the proposed model, there is a need to include contextual variables such as trust in the service providers, and this can be covered by the social exchange theory (SE).

2.3. Existing Frameworks and Models of IoT

In the area of adoption research, there are eight prevalent models, theories, and frameworks. UTAUT is the newest of these models, whereas TAM is the most popular. Early work in technology adoption can be traced back to the theory of reasoned action (TRA). TRA was developed by Fishman and Ajzen [42]. The theory proposed that the human behavior is determined by the attitude and the subjective norms. Ajzen noted the limitation of the theory and added the perceived behavioral control along with the attitude and subjective norms to develop the theory of Planned Behavior (TPB) [43]. Davis developed the TAM model by building on TRA and TPB [44]. Table 1 provides an overview of the comparisons of technology acceptance theories and models and variance explained [45].

Table 1 Technology acceptance theories/models comparison [45]

Theory/Model	Explained Variance
1. Theory of Reasoned Action (TRA)	0.36
2. TAM	0.54
3. Motivation Model (MM)	0.38
4. Theory of Planned Behavior (TPB)	0.47
5. Combined Technology Acceptance Model and Theory of Planned Behavior (C-TAM-TPB)	0.39
6. Model of PC Usage (MPCU)	0.47
7. Innovation Diffusion Theory (IDT)	0.40
8. Social Cognitive Theory (SCT)	0.36
9. Unified Theory of Acceptance and Use of Technology (UTAUT)	0.69

According to the literature, UTAUT and TAM are the most commonly used models to assess people's attitudes toward adopting new technology; these two models were critiqued for being too simplistic and focusing only on the individual aspect in terms of technology adoption. In contrast, the technological aspect that relates more to the capability and perception of technology is seldom included. Furthermore, the TOE is seen as a multi-perspective framework that includes technological, organizational, and environmental components. Similarly, the TOE lacks the individual elements of technology adoption. Therefore, it is necessary to integrate the TOE and UTAUT to collect information on individual and technological aspects. Bringing together these two models and the contextual variable, trust, will also increase the explanatory power of the proposed model. The social exchange theory can address trust. A combination of more than one theory was also found in the previous studies. For instance, in the study of Liu, TAM and IDT were combined to predict the adoption of IoT by users [35]. Rahimi tested TAM, TRA, and TPB separately before combining them to predict IoT adoption and findings showed that three theories can explain IoT adoption with an explanatory power of less than 30% [27].

3. Research Framework and Hypotheses

This research intends to examine the factors that predict IoT adoption among Malaysian patients with chronic diseases. The study deploys UTAUT, TOE, and social exchange theory. In UTAUT, performance expectancy, effort expectancy, and social influence are all considered individual factors. Security, privacy, and availability are technological factors. Additionally, the facilitating condition from UTAUT is considered a technical factor since it relates to the technology's infrastructure and facilitating conditions for using the technology. Trust based on social exchange theory is proposed as a mediator. UTAUT proposes that gender and experience are moderating variables. In this study, the gender and experience of patients with chronic diseases will be deployed as moderating variables. Fig. 1 shows the conceptual framework of this study.

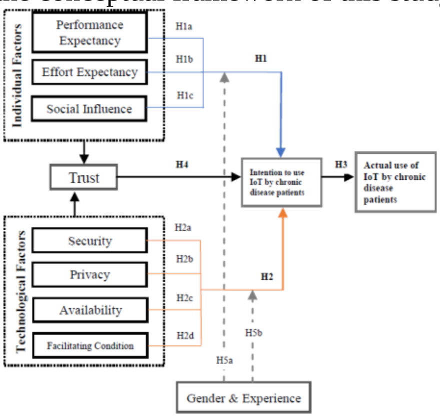

Fig. 1 The research framework (Developed by authors)

3.1. Individual Factors

Individual factors consist of three variables: performance expectancy (PE), effort expectancy (EE), and social influence (SI). Previous studies have examined the effect of these variables and found a positive and significant effect of these factors on the intention to use IoT. In this study, the influence of individual factors on IoT adoption is expected to be positive and significant. Accordingly, it is assumed:

H1: Individual factors positively affect the BI to use IoT-healthcare service by chronic disease patients.

3.1.1. Performance Expectancy (PE)

PE is "the level to which an individual believes that adopting the system would assist them in achieving improvements in job performance" [15]. Venkatesh discovered that PE is the strongest predictor of behavioral intention (BI) to adopt technology [15]. According to Pai and Huang, PE impairs the ability of BI to use health information systems [46]. Carlsson found that physical activity had a direct positive impact on the intention to use mobile devices [47]. Studies have shown experimentally that the bigger the PE, the greater the likelihood that mobile health services will be adopted [48]. As a result, the following hypothesis was proposed in this study:

H1a: PE has a positive impact on the BI to use IoT-healthcare services by chronic disease patients.

3.1.2. Effort Expectancy (EE)

EE is described as "the degree of simplicity associated with system use" [49]. Studies reveal that EE has a significant impact on users' intentions to adopt and accept a health information system. EE, for instance, has been recognized as a significant component that directly influences the intention of users to use mobile health monitoring systems, e-health services through a smartphone, clinical decision support systems, and mobile health [16, 48]. Pal discovered that the influence of effort expectation on IoT-healthcare is substantial [6]. Therefore, it is assumed:

H1b: EE has a positive impact on the BI to use IoT-healthcare service by chronic disease patients.

3.1.3. Social Influence (SI)

SI is defined as "the extent to which a person believes it is vital that others feel he or she should adopt the new technology" [15]. Liu evaluated the influence of social norms on the adoption of mobile health care and found that social norms had a significant impact [35]. Pal also investigated the impact of social influence on the adoption of smart houses for elderly healthcare [6]. Similarly, literature reviews have also shown that people are more likely to use a new technology if others are also using it [50]. In this study, it is expected that the social influence on chronic disease patients will lead them to adopt and use the IoT-healthcare.

H1c: Social influence positively affects the BI to use IoT-healthcare by chronic disease patients.

3.2. Technological Factors

The technological-related factors include security, privacy, availability, and facilitating conditions. Technological factors are the core components of the TOE. Several studies have examined their effect on the adoption of different technologies. Lian has indicated that technological constructs have a fundamental impact on the adoption of cloud computing in Taiwan [51]. Other studies such as Polyviou and Pouloudi, which were conducted on the adoption of cloud computing by the public sector, have found that technological factors were important predictors of the adoption of cloud by employees in the public sector [52]. Gangwar found that technological factors significantly affected the adoption of cloud computing in India [53]. Thus, in this study, it is expected that technological factors will affect positively the behavioral intention to use IoT healthcare by chronic disease patients in Malaysia. Accordingly, it is assumed:

H2: Technological factors positively affect the BI to use IoT-healthcare service by chronic disease patients.

3.2.1. Security

Security has become a major issue in the healthcare field. Billions of personal health records are stored on insecure servers without proper protection. The rise in ransomware attacks has also raised concerns over the security of patient records and systems. Governments around the world have passed legislation to protect the privacy of patients' personal data, but enforcement is lacking in many developing countries. In this study context, security is defined as the degree to which chronic disease patients' belief that IoT services are secure platforms for storing and sharing personal data [54]. Lian, Senyo, and Alkhater incorporated security as a technological factor [50, 55, 56]. Thus, security is considered in this study as one factor of the technological construct. Several researchers have examined the effect of security on the behavioral intention to adopt the technology. Junqi found that security has a significant effect on the adoption of the healthcare system [9]. It is hypothesized as:

H2a: Security has a significant effect on the BI to use IoT-healthcare service by chronic disease patients.

3.2.2. Privacy

Privacy is a major concern when using IoT devices in healthcare. Hospitals often use medical devices such as pacemakers, insulin pumps, and patient monitoring equipment to monitor patients' health. These devices connect to a wireless network to send and receive data. Recently, several hackers have hacked into these devices and used the data for their own purposes. People might worry about their privacy if their healthcare providers use IoT devices without informing them. Privacy is defined as "the degree to which the chronic disease patients believe that IoT services are safe and protects their sensitive data" [53]. Researchers have considered privacy as one of the technological factors in the adoption of advanced technologies in various settings. Researchers indicated that privacy is essential for adopting IoT applications in healthcare [4, 17, 57]. Hence, it is assumed that:

H2b: Privacy has a significant effect on the BI to use IoT-healthcare service by chronic disease patients.

3.2.3. Availability

Availability is the third sub-construct of technological factors, and it refers to "an individual's perception of the extent to which ubiquitous technology provides a personalized and uninterrupted connection and communication with other individuals and networks" [58]. The lack of availability for patient care services can impact patient outcomes and have negative consequences. Improving internet access at healthcare facilities can help increase access to high-quality healthcare and improve patient experiences [59]. Tornatzky and Fleischer developed the TOE model and considered the availability of the technology as a technological factor [60]. Among the studies that have included and tested the effect of availability on the adoption of IoT is the study of Pathinarupothi, who pointed out that availability is important for remote monitoring, and it affects the degree to which users are willing to use the IoT [59]. Other Studies in the field of technology adoption, such as the study of Phaphoom, found that availability is critical for adopting cloud computing [61]. In this study, the effect of availability on BI to adopt IoT by chronic disease patients in Malaysia is expected to be positive. Thus, it is hypothesized as follows:

H2c: Availability has a significant effect on the BI to use IoT-healthcare service by chronic disease patients.

3.2.4. Facilitating Condition

FC is one of the variables of UTAUT and refers to "the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system" [62]. Researchers who deployed UTAUT linked the FC to the direct use of new technology [15], [63], [64]. Others suggested that the FC is mainly determined by the organizational and managerial support provided by institutions such as hospitals or universities or by the users themselves [16]. Moreover, some studies have demonstrated that the user's level of satisfaction with the IT application and perceived usefulness were the strongest predictors of their FC with new technologies [10]. Therefore, a high FC suggests that users are satisfied with a new system and are willing to continue using it in the future. Researchers found that FC has a direct significant effect on the actual use of educational technology [64]. Accordingly, it is expected that FC has a strong effect on the behavioral intention of patients to use IoT healthcare. Therefore, it is hypothesized as:

H2d: FC has a significant effect on the BI to use IoT-healthcare service by chronic disease patients.

3.3. Behavioural Intention and Use Behavior

BI is the umbrella term for all studies on how people use and interact with technology. BI is used in various fields, from marketing to law. However, the term is used most often in the social sciences to refer to the study of how individuals interact with computers and electronic devices. BI is defined as "the degree to which a person has formulated conscious plans to perform or not perform some specified future behavior. UB is defined as the individual's positive or negative feeling about performing the target behavior [15]. Most previous theories of technology adoption, such as TAM and UTAUT, have linked the BI to UB [15, 49]. Akinnuwesi investigated the effect of BI on UB and found a significant effect between the two variables [17]. Several studies have derived similar results [64-67]. Therefore, in this study, it is hypothesized as:

H3: BI has a significant effect on the actual use of IoT healthcare services by patients with chronic diseases.

3.4. Mediating Role of Trust

Trust can be defined "as chronic disease patients' confidence in the reliability and trustworthiness of the services offered by IoT-healthcare services" [53]. The perception of the service providers as trustworthy, honest, and working in the interest of the user enhanced trust and increased the adoption of technology [68]. Based on a typology of the role of trust in the adoption of new technology, Lansing and Sunyaev concluded that trust received less attention in the context of technology adoption and that the variable trust played a mediating role between the success factor of adoption and usage intentions [50]. Social Exchange Theory (SET) proposed trust as an important factor that affects an individual's intention to perform an action. Thus, in this study, it is expected that when patients trust the technology of IoT healthcare, they will tend to use, learn from, and benefit from it. Thus, the effect of individual and technological factors on BI may be affected by the level of trust. Hence, in this study, it is proposed that trust will mediate the effect of the constructed individual and technological factors on the BI to use IoT healthcare by patients. Accordingly, it is hypothesized as follows:

H4a: Trust mediates the effect of individual factors on BI to use IoT-healthcare service by chronic disease patients.

H4b: Trust mediates the effect of technological factors on BI to use IoT-healthcare service by chronic disease patients.

3.5. Moderating Effect of Gender and Experience

Venkatesh included gender and experience as moderating variables. According to UTAUT, gender can play an essential role in the decision to adopt [15]. Additionally, the experience or education, also known as the knowledge of using IoT and information technology or the internet, is a determining factor in the adoption. UTUAT pointed out that when knowledge or experience is high, the users tend to use the technology, and vice versa. In the study of Rezvani, gender and experience were deployed as moderators between the variables of TAM and privacy as well as connectivity [41]. The findings showed that both variables have affected the relationship between PU, PEOU, privacy, and intention to adopt IoT. In this study, based on the conceptualization of UTAUT, the study proposes that gender and experience are moderators between individual and technology factors on the one hand and the adoption of IoT by patients on the other hand. Accordingly, the following is hypothesized:

H5a: Gender moderates the effect of individual and technological factors on the BI to use IoT-healthcare services by chronic disease patients.

H5b: experience moderates the effect of individual and technological factors on the BI to use IoT-healthcare service by chronic disease patients.

4. Methodology

4.1. Research Population and Sampling

The population of this study is composed of patients having chronic diseases. An online survey instrument has been developed to measure the perceptions of chronic disease patients about smart healthcare in their daily lives. The survey was conducted on Malaysian chronic patients under any age. The sample size of this study using the formula of Krejcie and Morgan is 384 respondents [70]. Before distributing the questionnaire to the participants, opinion has been sought from two independent experts for ensuring the questionnaire's validity and relevance. The survey instrument was structured into three parts. The first part is an introduction that presents the purpose of the questionnaire. The second part will be related to the background information of the respondents, such as their age, gender, IoT services they use, knowledge about IoT, and experience in using IoT.

4.2. Research Instruments and Mathematical Tools

This study uses a structured and closed-ended questionnaire to collect data from the respondents. The measurements of the variables were adopted from previous studies investigating the adoption of IoT healthcare services. The questionnaire consists of three parts: (1) an introduction that presents the purpose of the study; (2) the respondents' background information, such as age, gender, usage of IoT services, knowledge about IoT, and experience in using IoT; and (3) the specific research variables, such as behavioral intention, trust, and actual use behavior, as well as items designed to measure the technological and individual factors. Specifically, the items are evaluated using five Likert scale, where 1 = strongly disagree and 5 = strongly agree. The Likert scale is used as the measurement scale as it has been demonstrated in previous studies to be more efficient in assessing respondents' ideas and views compared to seven- and ten-point Likert scales [71, 72]. A total of 263 responses were obtained from the original 384. Such responses are considered sufficient since Kline argued that responses above 200 are sufficient when using the SEM [73]. The data were analyzed using SPSS version 24.0 and Smart PLS version 3.3. Preliminary analysis conducted using SPSS included missing values, outliers, normality, and multicollinearity. Additionally, the main analysis using Smart PLS includes the measurement model and the structural model.

5. Results

5.1. Descriptive Information

This section contains the respondents' descriptive information and the study variables. The former was provided in frequencies and percentages, while descriptive information about the variables was summarized using the mean score value. The respondents' education, gender, age, chronic disease, usage of IoT healthcare, and tool to access IoT healthcare.

Table 2 Descriptive information on the respondents (The authors)

	Label	Frequency	Percent
Education	Less than high school	4	1.6
	High School or Less	21	8.3
	Diploma	93	36.9
	Bachelor	120	47.6
	Master	10	4.0
	PhD	4	1.6
Gender	Male	157	62.3
	Female	95	37.7
Age	18–30 years	10	4.0
	31–40 years	41	16.3
	41–50 years	88	34.9
	51–60 years	113	44.8
Chronic disease	Yes	252	100.0
Usage of IoT healthcare	Yes	79	31.4
	No	173	68.6
Tool to access IoT healthcare	Smartphone	39	15.5
	Devices in the house	19	7.5
	Wearable devices	21	8.4
	Not using	173	68.6

Table 3 depicts the descriptive information of the individual related factors. Performance expectancy (PE) recorded a mean score of 3.29, which indicates that the respondents agreed with the items measuring the variable. Meanwhile, effort expectancy (EE) reflected a mean score of 3.39, which reflects that most respondents moderately agreed with the items measuring the factor. Similar findings could be observed for social influence (SI). The overall mean score for the level of individual-related factors was 3.31. In conclusion, respondents moderately agreed with all the factors considered under individual-related factors in this study.

Table 3 Descriptive statistics of individual factors (The authors)

Code	Mean	Std. Deviation	Level
PE1	3.34	.983	Moderate
PE2	3.25	.935	Moderate
PE3	3.29	.898	Moderate
PE4	3.28	.920	Moderate
Performance expectancy	3.29	-	Moderate
EE1	3.26	1.038	Moderate
EE2	3.49	.998	Moderate
EE3	3.42	1.036	Moderate
EE4	3.39	.999	Moderate
Effort expectancy	3.39	-	Moderate
SI1	3.41	.931	Moderate
SI2	3.15	.996	Moderate
SI3	3.17	1.193	Moderate
Social influence	3.24	-	Moderate
Overall mean score	3.31	-	Moderate

The level of technological factors is presented in Table 4, comprising four dimensions: security, privacy, availability, and facilitating conditions. The corresponding mean scores for security, privacy, availability, and facilitation conditions are 3.20, 3.18, 3.38, and 2.96, respectively. In this study, mean scores greater than 2.5 were considered to reflect moderate agreement with the corresponding items or measures. Hence, most respondents demonstrated moderate agreement with all the technological factors investigated in this study. This is reflected in the overall mean score (3.18), as shown in Table 4.

Table 4 Descriptive statistics of technological factors (The authors)

Code	Mean	Std. Deviation	Level
SC1	3.21	.986	Moderate
SC2	3.22	1.000	Moderate
SC3	3.18	.985	Moderate
Security	3.20	-	Moderate
PC1	3.08	1.019	Moderate
PC2	3.09	1.018	Moderate
PC3	3.04	1.021	Moderate
PC4	3.51	1.004	Moderate
Privacy	3.18	-	Moderate
AV1	3.45	1.057	Moderate
AV2	3.32	1.069	Moderate
AV3	3.38	1.048	Moderate
AV4	3.36	1.025	Moderate
Availability	3.38	-	Moderate
FC1	3.04	.950	Moderate
FC2	2.90	.973	Moderate
FC3	2.96	1.011	Moderate
FC4	2.95	1.066	Moderate

Continuation of Table 4

Facilitating conditions	2.96	-	Moderate
Overall mean score	3.18	-	Moderate

Table 5 presents the descriptive information of trust. Resultantly, the overall mean is 3.33, which indicates that respondents displayed moderate agreement with the statements used in measuring trust levels.

Table 5 Descriptive statistics of trust (The authors)

Code	**Mean**	**Std. Deviation**	**Level**
TRT1	3.27	.952	Moderate
TRT2	3.44	1.030	Moderate
TRT3	3.29	.952	Moderate
TRT4	3.32	1.172	Moderate
Overall mean of trust	3.33	-	Moderate

The overall mean score for the level of behavioral intention (BI) is 3.30, as shown in Table 6. Given that the mean score is greater than 2.50, most respondents have moderately agreed with all the items measuring behavioral intention levels.

Table 6 Descriptive statistics of behavioral intention (The authors)

Code	**Mean**	**Std. Deviation**	**Level**
BI1	3.29	1.009	Moderate
BI2	3.29	.931	Moderate
BI3	3.36	1.297	Moderate
BI4	3.27	1.016	Moderate
Mean of behavioral intention	3.30	-	Moderate

Table 7 presents the results for the level of use behavior. The mean score for actual behavior (AB) is 3.41, which indicates that most respondents moderately agreed with the statements relating to actual behavior.

Table 7 Descriptive statistics of actual behavior (The authors)

Code	**Mean**	**Std. Deviation**	**Level**
AB1	3.52	1.261	Moderate
AB2	3.37	1.185	Moderate
AB3	3.08	.979	Moderate
AB4	3.67	1.156	Moderate
Overall Mean	3.41	-	Moderate

5.2. Results of Hypothesis Testing

The hypothesis testing performed in this study includes the direct, mediating, and moderating effects. All the hypotheses were evaluated based on 5,000 bootstrapping and p-value less than 0.05, as suggested by Hair [74]. Table 2 combines the results to present the hypotheses of the direct effect.

Table 8 Results of Testing the Hypotheses (The authors)

H	**Factors**	**B**	**Std.**	**T-value**	**P Values**	**Sig.**
H1	Individual Related factors -> BI	0.238	0.082	3.032	0.002	Yes
H1a	Performance Expectancy -> BI	0.158	0.072	2.180	0.016	Yes
H1b	Effort Expectancy -> BI	0.043	0.057	0.752	0.230	No
H1c	Social Influence -> BI	0.153	0.072	2.121	0.019	Yes
H2	Technological factors -> BI	0.454	0.072	6.288	0.000	Yes
H2a	Security -> BI	0.199	0.064	3.119	0.001	Yes
H2b	Privacy -> BI	0.042	0.063	0.665	0.253	No
H2c	Availability -> BI	0.107	0.055	1.971	0.045	Yes
H2d	Facilitating Condition -BI	0.238	0.054	4.400	0.000	Yes
H3	Behavioural Intention ->AB	0.620	0.047	13.217	0.000	Yes

The first hypothesis predicted the effect of individual-related factors (H1) and its dimensions: performance expectancy (H1a), effort expectancy (H1b), and social influence on behavioral intention. The findings revealed that the direct effect performance expectancy and social influence on BI were important as the corresponding p-values were less than 0.05. Thus, hypotheses H1, H1a, and H1c are supported. In contrast, the effect of effort expectancy on BI is not significant; thus, H1b is rejected.

The second hypotheses proposed that technological-related and its dimensions, security (H2a), privacy (H2b), availability (H2c), and facilitating conditions (H2d), have a significant influence on behavioral intention. Security, availability, and facilitating conditions exhibited p-values less than 0.05, thus implicating that hypotheses H2, H2a, and H2c, and H2d are accepted. Nevertheless, the effect of privacy on BI was not significant, which led to the rejection of H2b. For H3, the effect of behavioral intention on use behavior is significant at p-value less than 0.05. Therefore, H4 is supported.

6. Discussion

The research framework was developed in this study by combining the UTAUT, TOE, and SE models. The hypothesized relationships between all constructs were investigated in the structural model. These relationships represent the 11 hypotheses relating to the direct effects between the factors and BI and then with actual use of the service. The findings of this study revealed that individual factors and their dimensions, including performance expectancy (PE) and social influence (SI), significantly affected chronic disease patients' behaviour intention (BI) toward IoT-healthcare services adoption. The present findings are consistent with previous studies reporting a significant effect of individual factors on the technology adoption [75, 76]. The findings from our study indicate that performance expectancy has a significant positive relationship with intentions to use IoT devices in healthcare. This agrees with the finding reported by previous studies [77] and [78], who also found that users with high PE have greater potential to adopt such a service than others. Previous studies disagree with the present findings of this study as EE represented an unimportant factor of UTAUT to adopt a new technology. Studies found that EE affected the BI to use new technology [78, 79]. However, a few studies also reported that EE demonstrated an insignificant effect on the usage of a new technology such as mobile banking, e-learning, and online purchase, thus aligning with the present results [80]. An explanation of this finding is that the patient can only anticipate the outcomes or the benefits to be obtained from these services, and it is unlikely that the user has any idea of the effort that is required on his part to participate in the services. This is especially true in the case of patients who have chronic diseases where the time taken for their medications and treatments has become an integral part of their lives. Therefore, the researchers need to focus on the other factors that can influence the adoption of such services to maximize the benefits of these novel systems in the healthcare industry.

SI findings align with the reports from several previous studies. For instance, SI was critical in the adoption of technology among various groups of patients and users [78]. Studies also documented that SI affects the BI intention to use either an existing or novel technology [17, 79]. Similar results were observed for technological-related factors and their dimensions, including security, availability, and facilitating conditions. The findings indicate that technological factors have a significant effect on chronic disease patients' BI in using IoT healthcare services. The researcher found that technological factors were pertinent and have a significant effect on the adoption of technology in the public sector [51]. Another study has been conducting in India discovered that technology factors affected the adoption of new technology [52]. Findings of previous studies are in agreement with the findings of this study, which investigated the effect of security and found a significant effect on IoT-healthcare services adoption [25, 81, 85]. The second hypothesis under the technology context predicted that the effect of privacy on BI is significant. The hypothesis was proven to be untrue as privacy displayed an insignificant effect on BI toward using IoT adoption. This insignificant effect could be because patients understood the difficulties in sharing their information with a third-party till Malaysia's local laws were enacted to protect patients' privacy. Furthermore, the reasons behind these results may be data ownership and shared responsibility between doctors and patients. Given the fact that participants in this study were only patients and not doctors, they may not have had the right ownership over their own medical data due to their doctor's role in maintaining the patient's data and keep their privacy. This finding aligns with a previous study in which privacy had no significant effect on mobile health adoption [24]. However, the present findings are inconsistent with the reports from previous studies investigating the effect of privacy on the adoption of IoT [6, 65]. The findings also indicate that the effect of availability on BI is positive and significant. The positive effect of availability could be because patents found that IoT healthcare services should be accessible at any time and from anywhere. Many studies found that the availability of the technology is critical for the BI to use a new technology [20, 54, 59, 69]. Thus, availability is essential for the BI toward using IoT by chronic disease patients. The results of testing the hypotheses revealed that the facilitating condition (FC) had a positive and substantial effect on the BI. In line with the current results, researchers who used UTAUT linked FC to BI to use a new technology [15, 61, 62]. This suggests that FC is crucial to the BI for IoT adoption among patients with chronic diseases. The third hypothesis proposed that BI significantly affects the UB of IoT among patients with chronic diseases. The findings indicate that BI is an important driver of UB. Researchers in the context of IoT adoption also confirmed the effect of BI on UB. Researchers found that BI has a significant effect on UB [17, 49]. These studies are consistent with the findings of this study. Previous studies have investigated the mediating role of trust among various variables in the context of technology acceptance. In the study of Solangi, trust displayed a significant effect on the BI to use IoT [82]. Al-Momani also documented that trust has an important effect on IoT adoption [83]. In the UTAUT model, Venkatesh indicated that education and experience moderated the effect of UTAUT variables on BI [15]. The findings indicate that the prediction is untrue. Gender did not moderate the effect of individual factors on BI neither the effect of technological factors on BI toward using IoT by chronic disease patients. A possible explanation of the insignificant moderating effect of gender is the fact that the IT knowledge level among the patients was similar among male and female patients; this result is in line with other research which reached the same findings [17]. Additionally, the IoT is easy to use by both genders. In terms of experience or education, this study proposed that education will moderate the effects of individual and technological-related factors on BI toward using IoT by chronic disease patients. The findings showed that this assumption is true.

7. Conclusion, Limitations, and Future Work

This study was conducted to examine the factors affecting chronic disease patients' BI toward IoT adoption. The study found that chronically patients were more likely to adopt IoT healthcare services in the form of wearable devices if they were provided with more information regarding their condition, and if they felt that IoT devices would help improve their quality of life. The findings of this study revealed that individual factors and their dimensions, including performance expectancy (PE) and social influence (SI), significantly affected chronic disease patients' behaviour intention (BI) toward IoT-healthcare services adoption in Malaysia. The present findings are consistent with previous studies. Similar results were observed for technological-related factors and their dimensions, including security, availability, and facilitating conditions. The effect of BI on UB was also significant. Meanwhile, trust partially mediated the effect of individual and technological-related factors on BI. The latter relationship was moderated by education. The novelty of this study can be delighted by combining the UTAUT and TOE along with SET to increase the explanatory power of the model. The integrated model was tested using structural equation modeling (SEM) techniques in a sample of Malaysian patients with chronic disease. The findings of the study provide meaningful implications for healthcare providers. They can use these findings to develop effective strategies to increase the adoption of IoT healthcare services by chronic disease patients. Furthermore, there are limited studies in developing countries on IoT healthcare services adoption. Given that this study was conducted in Malaysia, it remains an exceptional contribution to the present literature of IoT in the context of developing countries. Whereas other IoT studies focused on TAM, a combination of theories was used in this study to elucidate the factors influencing IoT adoption among chronically ill individuals in Malaysia.

The research findings will be highly beneficial to healthcare policy makers and providers as it provides a better understanding of the potential of using IoT healthcare services in Malaysia. As well as the study will benefit both the patients and their family members as the adoption of IoT healthcare services will enhance the delivery of comprehensive care, specifically for managing chronic diseases. Meanwhile, healthcare personnel will equally benefit from this research as IoT will assist them in executing their duties professionally and remotely.

The limitations are worthwhile to be mentioned in this study. This study was conducted on patients with chronic diseases. Thus, the present findings are limited to chronically ill individuals. Therefore, it is recommended that researchers extend the population to include more individuals, such as patients with minor illnesses and those who regularly should visit hospitals. In terms of study location, this study investigated the adoption of IoT healthcare services among patients with chronic diseases in the Klang Valley, Malaysia. Thus, the findings of this study are restricted to this population, and the researchers might recommend replicating this study among patients in other countries to enable a more comprehensive comparison of the findings between countries.

The moderating effects of gender and experience/education were examined in this study. Based on the paucity of data regarding the moderating role of these variables in the adoption of IoT among users, more research is needed to further comprehend the underlying relationships. Meanwhile, trust as a mediator in this study explained parts of the relationship between the investigated variables. Future studies are recommended to examine the potential role of this variable to operationalize trust on the internet, with service providers, and in hospitals.

This study combined UTAUT, TOE, and SET to develop a model employed in investigating the research variables. A similar strategy could be used in future work to better explain the variation in IoT adoption. For instance, the combination of TAM and DOI or TAM and TPB or TAM, TOE, and DOI can be deployed to examine their power in explaining the adoption of IoT or other technologies.

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