Behavior Intention of Chronic Illness Patients in Malaysia to Use IoT-based Healthcare Services

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***Abstract*—The Internet of Things (IoT) has emerged as a trend in the healthcare industry to develop innovative solutions that enhance patient outcomes and operational efficiency. Healthcare has become more accessible, affordable, and efficient to sensors, wearables, and health monitors. The healthcare industry's adoption of the Internet of Things is lagging behind other sectors despite its many benefits. This study aims to investigate the extent to which chronic patients in Malaysia are using healthcare services made possible by the Internet of Things. To that end, this study proposes a unified framework to examine how these highlighted factors affect Behavioral Intention (BI) with regard to adopting IoT healthcare services. The innovation here is in bringing together three distinct theories: i) the Technology-Organization-Environment Framework (TOE), which is a framework for understanding how companies adopt new technologies; ii) the Unified Theory of Acceptance and Use of Technology (UTAUT); and iii) the Social Exchange Theory (SE). Patients in Malaysia who are coping with long-term health issues were surveyed online. This study also employs SPSS and Smart Partial Least Square (Smart PLS) for data analysis. Eleven hypothesized predictive components have been investigated. The results showed that chronic illness patients' BI towards adopting IoT solutions was considerably impacted by both individual and technological factors and related aspects. The impact of BI on Use Behaviour (UB) also showed similar outcomes. Moreover, trust somewhat mediates the impact of both individual and technological factors on BI. The findings of this investigation will be beneficial to policymakers and suppliers of healthcare in that country. Additionally, the patients and their family members would gain benefits from the study due to the fact that the delivery of comprehensive treatment, especially in the field of chronic disease management, will be improved through IoT-healthcare services. The Internet of Things will also let medical staff function remotely and professionally.**

Keywords*—*Internet of things; IoT; chronic disease; adoption theories; adoption

I. Introduction

Chronic diseases have become one of the most important problems of the twenty-first century. It is considered a very serious global, national, and individual health problem. Globally, in 2019, they were responsible for nearly 42 million deaths (Global Burden of Disease Collaborative Network 2020) [1]. This proportion has increased over time, from 67% of deaths worldwide in 2010 to 74% in 2019 (Global Burden of Disease Collaborative Network 2020). Although the COVID-19 pandemic led to a considerable number of deaths due to communicable diseases in 2020 (WHO 2020) [1][2] Chronic diseases are generally defined as conditions that last for at least 1 year and require ongoing medical attention or limitation of daily living activities; approximately one in three adults is affected by multiple chronic conditions (MCCs), such as cardiovascular diseases, cancer, and diabetes.[2]. Their social and economic consequences can impact people's quality of life. Chronic conditions are becoming increasingly common and are a priority for action in the health sector [1].

In contrast, healthcare costs have been a significant global concern. The rising costs of healthcare can be attributed to various factors, including an aging population, an increase in chronic diseases, and costly administrative and technology expenses. These issues are being addressed by implementing more efficient healthcare models and investing in new technologies to improve patient outcomes and reduce costs.

In the previous decade, IoT has experienced exponential growth and revolutionized the application of technology in the healthcare industry [1]. It offers cutting-edge technology and services that enable communication between any two Internet-connected objects [2]. The Internet of Things (IoT) is being used by both nations and businesses to boost their competitiveness [2, 3].

No one has been able to agree on a single, comprehensive definition of the IoT. Researchers, however, use the term "Internet of Things" to refer to an online network of physical items [2-4]. The healthcare industry is slow to adopt IoT despite its many advantages [5]. In spite of the growing popularity of IoT healthcare services, there is a lack of data and research on how customers and patients are adapting to these technologies. The absence of information on users' opinions regarding the utilization and implementation of IoT in the healthcare system is notable. [6], Malaysia is no exception, especially for patients with chronic diseases.

The healthcare industry has indeed been slow in adopting IoT technologies, and a lack of a systemic approach could be a contributing factor. Despite ongoing efforts to promote the adoption of IoT in healthcare, other factors such as data privacy and security concerns, as well as the cost of implementing these technologies, remain challenges that need to be addressed [7]. Most current studies in Malaysia and elsewhere ignore the importance of human factors and social context in favor of studying the underlying technology, components, and services. Regarding the matter at hand, it is important to clarify the definition of service. The term refers to any devices, applications, or services offered by a smart healthcare provider that is related to the diagnosis, monitoring, prevention, or treatment of human disease or the assessment or care of human health. [8]. To achieve successful adoption of IoT healthcare services, it is important to consider the user's perspective [9]. Hence, it is crucial to examine the factors that lead to the low adoption of smart healthcare services from the patients' perspective. Despite the various benefits of this approach, patients have concerns at both individual and technological levels, as outlined below:

1) At the individual level, users may find it challenging to comprehend IoT and may not be aware of its potential benefits for their daily lives [5, 10, 11].

2) At the technological level, patient data sensitivity involves concerns about security and privacy during the collection and transfer of data [12, 13].

Although the Internet of Things is still a relatively new technology, most research on the Internet of Things has been conducted in mature economies, with limited studies in developing and emerging markets. The healthcare sector is one of the many industries that have adopted IoT lately.

Prior studies have proposed several hypotheses to elucidate the reasons behind the low adoption of the Internet of Things (IoT). Understanding these predictors can help improve the explanatory power of IoT models and ultimately address the issue of low adoption [14-16]. Davis's concept, the technology acceptance model (TAM), is one of the most popular in use today. Venkatesh's research has shown that while the Technology Acceptance Model (TAM) can explain a significant portion of the variation in technology acceptance, it has limitations in predicting adoption rates. Venkatesh subsequently developed the Unified Theory of Acceptance and Use of Technology (UTAUT), which expands on TAM and other models to provide a more comprehensive understanding of technology adoption. UTAUT can explain up to 69% of the variance in technology adoption, making it a valuable tool for researchers and practitioners seeking to understand and promote technology adoption [17].

However, UTAUT and other models such as the Technology Acceptance Model (TAM) have been criticized for their emphasis on individual aspects and generalizations in predicting the adoption of new technologies. Nonetheless, these models provide a useful starting point for comprehending technology adoption and can be supplemented with other factors, such as organizational culture, social influence, and technical factors, to develop a more complete comprehension of technology adoption [17].

While individual variables are crucial, the properties of the technology itself, such as its security, privacy, and accessibility, can significantly influence its adoption rates. These factors can make or break the chances of a technology being adopted [17, 18]. Recent research has demonstrated that combining two or more theories can improve the ability to explain technology acceptance [19]. In light of this recommendation, the present investigation synthesizes the UTAUT, an individual-based paradigm, with the TOE, a multi-perspective framework to identify the factors that encourage Malaysians with chronic diseases to use the Internet of Things (IoT) for their healthcare. The contributions of this study are:

1) Analysis of previous works to determine and investigate the behavior intention of chronic patients toward using IoT healthcare services.

2) Combining the UTAUT, TOE, and Social Exchange Theory to better understand IoT adoption in healthcare services.

3) Structural equation modeling (SEM) is deployed including the Smart Partial Least Square (Smart PLS) as part of the analysis process.

The paper is organized as follows: Section II shows the literature review including the related works. Section III presents the research framework and hypothesis. The methodology is shown in Section IV. All the results are presented and discussed in Section V; Section VI concludes the work, and finally, the limitation and future work are presented in Section VII.

II. Literature Review

This section provides background on the use of IoT in healthcare and its relevant information. It also presents a theoretical background to show the main focus of previous studies related to IoT in the healthcare sector and discusses existing frameworks and models related to the study in detail. Additionally, a summary of related works is presented, addressing and contrasting them to highlight the gap in existing research that this work is addressing and to show the difference between previous works and this work.

A. *IoT in Healthcare*

IoT in healthcare refers to the integration of internet-connected devices and sensors with healthcare systems to gather, monitor, and analyze patient data in real-time [20, 21]. The use of IoT modules in the healthcare sector has led to the emergence of "smart healthcare," which aims to improve patient outcomes and healthcare services through the use of technology. The adoption of IoT is expected to continue to grow in the coming years. Providing quality healthcare at an affordable cost is one of the most pressing societal and economic issues facing many nations today [22]. In some nations, healthcare expenditures are projected to reach 20-30% of GDP by 2050 [23]. Combining devices and technology reduces operating expenses and enhances the quality of healthcare services, making cost savings a key advantage of IoT healthcare innovation [24-26]. In light of the fact that increasing expenses will have a significant impact on patients' quality of life, this is particularly essential [22, 27].

At the moment, IoT is mostly used in healthcare for patient tracking through remote devices, data gathering, instantaneous transfer, and full network accessibility. It also paves the way for machine-to-machine data exchange, interoperability, and the analysis and exchange of crucial information. In the field of medical diagnostics, IoT has been essential as a result of moving the emphasis away from the hospital and onto the patient and their residence.

Consequently, IoT has reduced healthcare system costs and the incidence of risky errors, particularly for patients with disabilities and chronic diseases. [28-30]. According to the National Center for Chronic Disease Prevention and Health Promotion (NCCDPHP), chronic disease refers to a long-term health condition that persists over an extended period, typically lasting for three months or more. These diseases generally do not have a definitive cure and often require ongoing medical management to control symptoms and prevent further complications. They can impact various aspects of a person's life, including physical functioning, mental well-being, and overall quality of life [31].

In the United States, chronic diseases account for a disproportionate share of deaths and disabilities. Hypertension, cardiovascular disease, and diabetes mellitus are all examples of common chronic disorders. Despite the lack of a cure, most chronic diseases can be managed in various ways to lessen the severity of symptoms or slow their course [32]. Chronic illnesses are the leading worldwide cause of mortality and disability [33], so much so that they have been dubbed the "silent global epidemic". As reported by the WHO, diabetes has become one of the primary contributing factors to premature illness and death in many countries, including Malaysia. As shown in Fig. 1, Malaysia's Ministry of Health Malaysia (2019) depicts that Malaysia occupies the first spot in terms of mortality rates among the population aged between 20 and 79 globally.

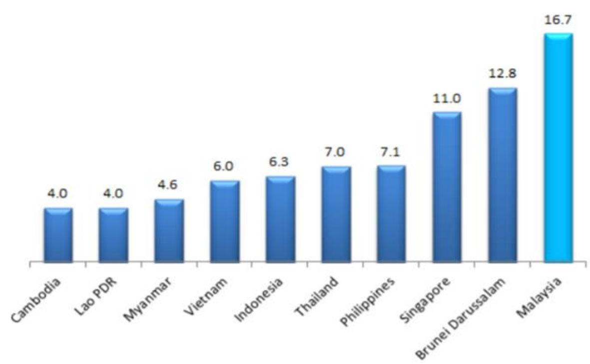

Fig. 1. Rate of death in Asian countries.

Several scholarly investigations have proposed that adopting Internet of Things (IoT) healthcare services could be the solution for improved monitoring and healthcare delivery to patients with chronic illnesses [6, 34, 35]. In this manner, the Internet of Things (IoT) could be used to improve patients' quality of life by reducing the stress placed on their loved ones and hospital visits. In light of this, prior research in Malaysia focused mainly on the development of smart homes, or specific information about Internet of Things deployment in sectors such as healthcare and industry [36-38]. However, it was hypothesized that individual and technological factors were responsible due to the poor rate of adoption of IoT, particularly among those suffering from chronic diseases in Malaysia [33].

B. *Technical Review*

A variety of authors have reviewed this topic, with different perspectives on the role that various factors play in enabling IoT in healthcare. Three major categories of factors are identified and discussed based on their significance to the success of the implementation of IoT in healthcare, such as factors related to the systems, factors related to individuals (end users), and other factors related to infrastructure and environments, as shown in Fig. 2.

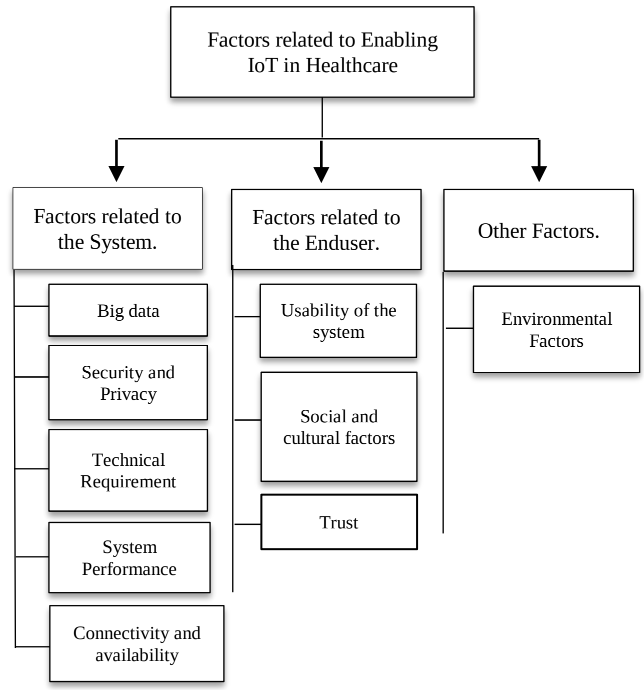

Fig. 2. Most related factor to enables IoT in healthcare.

1) *Factors related to the system:* It refers to the factors that impact a system's capacity to accomplish its intended purpose. These aspects are considered critical to the success or smooth functioning of Internet of Things services, such as big data, security and privacy, technological requirements, connectivity, and availability, and they represent the system factors required for a connected IoT in a healthcare context. Each of these elements is described briefly in the sections that follow.

a) Big data: The phrase "big data" is used to refer to a huge amount of data that exceeds the capacity of traditional storage and processing methods [39]. This deluge of information may be assembled or fragmented. How to reliably and securely acquire and retain data in systems has been a major topic of study in recent years [28, 40], as well as the means through which to preserve a strong level of integrity [25, 28]. How the system would handle a large amount of healthcare data collected from a variety of sensors was the topic of several studies [33]. Several studies voiced concerns about the speed and analysis of massive volumes of data [21, 40, 41] following data collection and processing [42, 43], data management [2, 44], and data monitoring. These potential difficulties must be addressed in order to assure the availability, dependability, and correctness of big data [28, 45] and to aid decision-makers in making sound decisions [43, 46].

b) Security and privacy: Both "security" and "privacy," which concentrate on data security, are related concepts. Security is mainly concerned with preventing authorized access to the system's data or information, whereas privacy relates to the protection of personally identifiable information. These words work better with modern healthcare software to protect patients' personal information [9, 24, 47]. Security risks, data breaches, insecure devices, and wearability are just some of the potential security and privacy issues that have been the subject of several studies [2, 4, 27, 48-50]. Data security and patient privacy must be prioritized for the longevity of any smart healthcare system [21, 51, 52].

c) Technical requirements: Besides the necessary basics, we should consider technical requirements [53, 54] leaks from energy storage systems and batteries [20, 55], low power consumption in operation [22, 56], leveraging IoT endpoints for use in intelligent decision-making, and power usage [50, 57-62] to improve communications and store information quickly [63]. Smart hospitals rely on connections to upload patient data, link medical equipment, and react fast (via sensors) [64]. Researchers focus on network connections and data transmission reliability [60, 65, 66] and handle problems like traffic [67]. Other studies improve service quality and performance [9, 60, 68].

d) Enhance system performance: Numerous aspects of the healthcare system are of interest to the authors in order to improve service quality in a timely and accurate manner. [40, 69], such as raising people's consciousness about the need to use medical equipment regularly, dealing with delays in responses or problems in latency [60, 70], and keeping up a high rate of data transfer quality [63, 71], also decreasing packet loss, determining the relationship between ICT and healthcare, and how ICT can help an individual [67]. Patients also get the best healthcare applications [20, 58, 65]. Some research has recommended early detection using improved monitoring systems [45, 72, 73] such as hypertension and blood pressure, and a deep learning-based vocal pathology detector to identify false main users [41, 74]. Rural healthcare should be egalitarian [40, 75]. Maintaining current technology and creating a smart healthcare engineering course to interest students [76, 77].

2) Factors related to the individual: Providers of healthcare must guarantee that user requirements and perspectives are prioritized. Several of the reviewed studies highlighted user problems and concerns, such as system performance, ease of use, accessibility to healthcare services, reliability of IoT devices, high cost, and trust [64, 78]. Thus, IoT aims to lower patients' expense burden by reducing hospital and clinic visits while providing precise and effective healthcare [22]. Most research has focused on these issues [73, 74]. Some have attempted to make smart gadgets and communication technology for remote monitoring systems more affordable [50, 56]. Thus, the notion of a "smart stone" has been embraced by some academics as a means of reducing elderly citizens' issues using mobile devices and tablets by limiting the system's involvement with the user [27]. This approach was also utilized to determine the primary elements impacting senior people's adoption of smart gadgets for health care [5]. IoT healthcare's major problem is user uptake. To determine the most important elements affecting technology adoption, researchers must dig deep [29].

3) Other factors: Some researchers have reported additional issues, particularly in terms of external influences [3], traditions, laws, and ordinance platforms [45, 75], healthcare information systems that use social media, and how they can improve patient care [50, 79], and the benefit of working in the healthcare industry for a long time [80]. An increase in the senior population is a direct result of the correlation between healthcare system improvements and a longer lifetime duration. Physical incapacity, long-term illness, and technological headaches are just a few of the difficulties that the elderly face [29].

C. Theoretical Review

In the study of how people embrace new technologies, there are eight prominent models, theories, and frameworks. UTAUT is the newest model available. TAM, however, is the standard. However, these two paradigms have been panned by healthcare experts for being overly simplistic and narrow in their concentration on the individual. Yet, the technological side, which is more concerned with technology's potential and public opinion of it, is rarely incorporated.

The TOE is an integrative paradigm that seeks to address this shortcoming from a variety of angles. It involves elements of technology, management, and ecology. Once again, the TOE is inadequate for the separate facets of technological diffusion.

Researchers have suggested that combined theories are able to explain the variation in adoption [81]. Few studies combined more than one theory to better explain the rise of the IoT [82]. Therefore, this study merges the TOE and UTAUT. The social exchange theory can be used to account for contextual factors like customer trust in service providers, which will boost the proposed model's ability to explain observed phenomena (SE).

1) Existing frameworks and models of IoT: The theory of reasoned action is a foundational concept in the history of technology adoption (TRA). Fishman and Ajzen created TRA [83]. According to the theory's central tenet, people's actions are driven by their attitudes and internalized values. Ajzen recognized the theory's flaws and developed the Theory of Planned Behavior (TPB) [84] by combining attitude, subjective norms, and perceived behavioral control. Davis combined TRA and TPB to create the TAM model [85].

According to research, UTAUT and TAM are commonly used models for measuring people's willingness to adopt new technologies, but they have been criticized for being too simplistic and narrow in focus. Meanwhile, the TOE framework, which includes elements from technology, organization, and natural phenomena, is considered more holistic but still lacks key components for effective technological integration. Therefore, combining the TOE and UTAUT models is necessary to gather data on both individual and technological aspects. By including the contextual variable of trust, the proposed model's explanatory power can also be enhanced.

TABLE I. SUMMARIZES THE DIFFERENCES AND SIMILARITIES BETWEEN SEVERAL THEORIES AND MODELS OF TECHNOLOGICAL ACCEPTANCE

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 Utilization (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 social exchange theory, people are more likely to adopt an innovation when they trust specific individuals or groups promoting it and when they believe that the benefits outweigh the risks and costs associated with its use are less [86, 87]. As a result, establishing and maintaining trust in the adoption of new technology is essential for promoting positive attitudes and behaviours toward innovation [64].

In previous studies, a combination of more than one theory was also investigated such as a study, that combined TAM and IDT to predict the adoption of IoT by users [32]. Before combining TAM, TRA, and TPB to foretell IoT adoption, Rahimi studied each one separately, and the results demonstrated that IoT adoption can be largely explained by three theories, or previously unconsidered constructs could be added to existing theories [82].

2) Discussion of related work: This section discusses and summarizes all the related works to IoT adoption studies; Table II shows the research gap and limitations found in the literature.

TABLE II. A SUMMARY OF RELATED WORKS

Ref.	Type of study	IV	DV	Theory	Respondent	Sample size	Findings
[4]	Empirical study (Mixed methods)	• Human detachment concerns, • Privacy concerns, • Life quality expectancy • Cost concerns • Enhance patient safety. • Lack of communicating and transferring data between doctors and patients.	Intention to use WSN-SHHS	• UTAUT • PAD	IoT users 18- and above	1- interview (the data collected from 15 home healthcare patients 2-survey the data collected from 140 respondents	Patients are more likely to embrace WSN-SHHS if they are concerned about human alienation than if they have high-performance expectations
[5]	Empirical study (Online survey)	• Performance Expectancy • Effort Expectancy • Social Influence • Facilitating Conditions • Technology Anxiety • Perceived Trust • Perceived Cost • Expert Advice	Behavioural intention	• UTAUT	IoT users 55 and above	254	The R2 value of 81.4% indicates that the established framework has satisfactory explanatory power. This suggests that a theoretical framework explaining the use intention of smart homes among the elderly in a health setting may be developed by combining UTAUT with other constructs.
[88]	Empirical study	• Data sharing • Expert support • Device • Task scope (monitoring, diagnosis, treatment) • Provider profession (Technology + medicine)	Behavioural intention to use IoT disease management service	• Nil	IoT users 20- above 50	493	Potential consumers' acceptance of an IoT healthcare service is predicted to be affected by the key factors mentioned in this research.
[20]	Empirical	• Attitude towards Adoption • Perceived usefulness • Perceived ease of use • Intrusiveness • Comfort	Behavioural intention to use IoT	• TAM	IoT users	273	The findings highlight the connection between IoT applications and the healthcare sector by focusing on four important user key-drivers that investigate intrusiveness (INTR).

Ref.	Type of study	IV	DV	Theory	Respondent	Sample size	Findings
[32]	Empirical	• Convenience • Safety • Interaction • Low-cost • Usefulness • Ease of use • Quality of technological service • Compatibility • Trust • Perceived value • Social factors • Product image	Behavioural intention to adopt mobile healthcare	• TAM • IDT	IoT users	Nil	The results highlight the significance of cultural norms, product perception, and customer confidence in pushing product adoption.
[70]	Empirical	• Health concern • Health information concerns • Privacy concern • Challenge appraisal. • Threat appraisal • Problem-focused coping. • Emotion-focused coping	• Challenge appraisal. • Threat appraisal • Problem-focused coping. • Emotion - focused coping. • Extended use	• coping model of user adaptation • (CMUA)	Users of IoT 20-above 50	260	This research helps us better understand how customers' restrictive habits affect the widespread adoption of wearable healthcare equipment.
[89]	Empirical	• Security • Privacy • Compatibility • Complexity • Behavioural control • Confirmation • Utilization	Cloud health information system utilization	• TRA	The user of IoT 25-30	259	There was a statistically significant impact from doctors' confirmation and behavioural control systems' compatibility, complexity, security, and privacy. The use of technology by doctors was improved by both confirmation and behavioural control.
[45]	Empirical	• Privacy and Security associated with medical records. • Data reliability, and Data authentication • Real-time monitoring • Real-time detection • Real-time diagnosis	Smart health monitoring system	• Nil	User of IoT	183	Present a framework that will transform the concept of automated health monitoring systems.
[75]	Empirical	• Relative advantage • Quality • Security • Inter-operability • Perceived usefulness • Perceived ease of use • Implementation intention	Use behavior	• TAM	User of IoT	Nil	The significant impact of intention is influenced by factors such as perceived ease of use and usefulness, relative advantage, interoperability, perceived quality, and perceived security. The perceived usefulness is influenced by the relative advantage, whereas the apparent simplicity of operation is impacted by interoperability. The objective had a significant influence on the utilization of IoT.
[82]	Empirical	• Perceived usefulness • Perceived ease of use • Attitude • Subjective norms • Perceived behavioural control	Behavioural intention	• TAM • TRA • TPB	User of IoT	Nil	The adoption of IoT is significantly impacted by the perceived user-friendliness and utility of the devices. Furthermore, the factors of attitude and subjective norms are significant predictors in the adoption of technology. The adoption of IoT is not significantly influenced by perceived behavioural control. Each of the three models has the

Ref.	Type of study	IV	DV	Theory	Respondent	Sample size	Findings
							capacity to account for the proportion of the variability observed in the Internet of Things (IoT).
[90]	Empirical	• Perceived Advantage • Technological Innovativeness • Compatibility • Trialability • Image • Perceived Vulnerability • Perceived Severity • Perceived privacy risk • Cost • Perceived Ease of Use • Attitude • Perceived Usefulness	Behavioural Intent to Adoption	• Technology acceptance model (TAM) • Innovation diffusion theory (IDT) • Technological innovativeness (TI) • protection motivation theory • privacy calculus theory	Users of IoT	426	The results of the entire model indicate that perceived advantage (PA), image, and perceived ease of use (PEOU) have a substantial impact on the intention to adopt IoT healthcare technology solutions. PA is a more significant factor in determining PEOU among males than females, according to the findings. Men are more affected by issues of appearance, privacy concerns, and feeling insecure than women.

From the literature, it is obvious that the number of experimental studies is greater than the number of theoretical studies, which seems logical given that a good service must be provided to patients by developing an efficient healthcare system to deliver the best customer service. After ensuring that the service is worthwhile enough, we turn to theoretical studies to examine the intention of people to adopt these services in their daily lives, as well as highlight the users' concerns about these services to give a clear indication to the providers to put more effort into providing a better experience with IoT healthcare services.

It can be seen from Table II that the number of studies pertaining to the adoption of IoT in the healthcare sector is limited. Most previous studies adopted an experimental rather than empirical approach. As can be seen in the summary table (Table I), the empirical, quantitative, and adoption studies are focused on the factors or predictors of IoT adoption among users. Most of the studies employed TAM to explain the behaviour toward adopting IoT.

Among these studies, perceived ease of use (PEOU) and perceived usefulness (PU) were found to be critical for the adoption of IoT [20]. Similar findings were derived in the study of Liu who indicated that social norms, trust, as well as PEOU and PU were the predictors of IoT adoption [32]. Rahimi deployed TAM and also reported that PEOU and PU were critical for the adoption of IoT, along with TAM the researcher also examined the validity of TRA and TPB [82]. Studies using TAM were also conducted by many researchers [90, 91]. The empirical studies also deployed other theories of technology adoption, such as UTAUT. In a study by Pal, the UTAUT model was applied along with variables such as anxiety, trust, and cost to understand the adoption of IoT by the elderly in four Asian countries [5]. The findings showed that the variables of UTAUT along with trust and cost were important predictors of IoT adoption among the elderly population. Meanwhile, Meri used the theory of reasoned actioned (TRA) to predict the adoption of IoT [89]. Previous research has shown that several different theories often work together. In Liu's research, for instance, TAM and IDT were coupled to anticipate user adoption of the internet of things [32]. Rahimi tested TAM, TRA, and TPB individually and then combined them to predict IoT adoption [82].

In conclusion, theoretical studies in the area of IoT adoption in healthcare are still limited, and there is a need to go in-depth due to its importance in providing distinguished healthcare services for patients. This can contribute to reducing the number of deaths and improving overall healthcare outcomes. Furthermore, findings revealed that a combination of more than two theories is needed to develop a comprehensive model that captures the complex nature of IoT healthcare service adoption.

III. Research Framework and Hypothesis

IoT adoption among patients with chronic diseases is a topic of increasing interest in the healthcare industry. In Malaysia, where chronic diseases are prevalent, understanding the factors that predict IoT adoption is crucial. This research aims to explore these factors using the Unified Theory of Acceptance and Use of Technology (UTAUT), the Technology-Organization-Environment (TOE) framework, and the social exchange theory. According to UTAUT, individual factors such as performance expectancy, effort expectancy, and social influence play a significant role in predicting IoT adoption.

IoT adoption is also affected by technological factors such as security, privacy, and availability. Due to the sensitive nature of health data, security concerns arise, while privacy concerns refer to the preservation of users' personal information for the availability of Internet of Things devices and their associated services.

Facilitating conditions, which are a component of UTAUT, are also crucial IoT adoption predictors. These conditions pertain to the infrastructure and resources necessary for the effective use of IoT devices. For instance, the availability of dependable internet connectivity and technical support can have a significant impact on the adoption decisions of end consumers.

According to social exchange theory, trust is a crucial mediator for predicting IoT adoption. Patients with chronic diseases may be hesitant to implement IoT devices out of concern for the technology's dependability and precision. Having confidence in the technology and its purveyors can help mitigate these concerns and boost adoption rates.

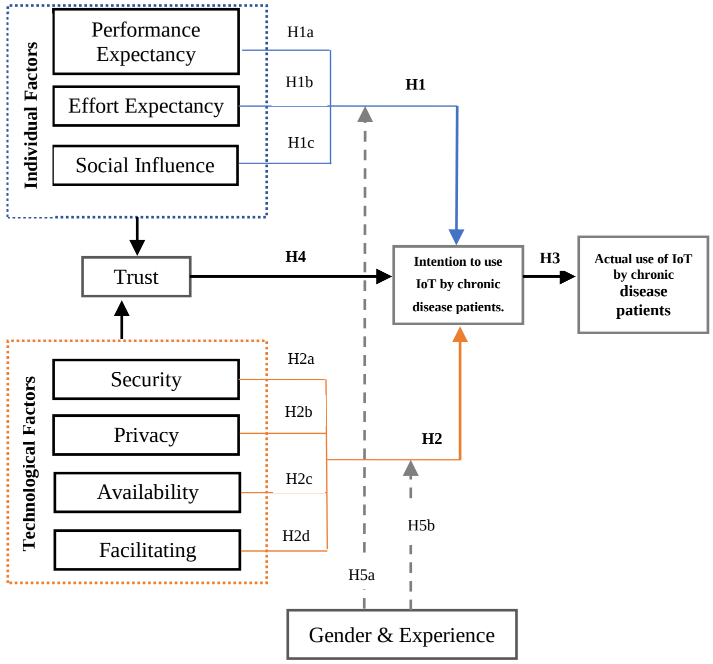

Fig. 3. The research framework.

According to UTAUT, there are moderating factors, such as gender and experience. We will use gender and chronic disease patient experience as moderating factors in this investigation. Fig. 3 illustrates the research framework used in this study.

A. *Individual Factors*

Performance expectancy (PE), effort expectancy (EE), and social influence (SI) are considered individual factors in the context of IoT adoption. Previous studies have shown that these factors have a significant positive effect on the intention to adopt IoT *[92]*. Based on this, it is expected that individual factors will also have a positive and significant impact on IoT healthcare service adoption in this study. Thus, it is hypothesized that:

H1: Individual variables influence positively the BI to adopt IoT-healthcare services by patients with chronic diseases.

1) Performance Expectancy (PE): The term "performance expectancy" refers to the degree to which a person feels that using a certain piece of technology will assist them in doing their duties in a manner that is both more effective and efficient [93]. In the context of the Internet of Things (IoT), this term refers to the extent to which an individual believes that making use of IoT devices will improve their overall performance when carrying out a given set of responsibilities. According to Venkatesh's findings, PE has been identified as the most influential factor in determining an individual's behavioural intention (BI) toward technology adoption. This was reported in reference [93]. According to Pai and Huang PE impairs the ability of BI to utilize health information systems [43]. Carlsson revealed that performance expectations have a direct positive effect on an individual's intention to use mobile devices. This means that if an individual believes that using a mobile device will help them perform their tasks more efficiently and effectively, they are more likely to have the intention to use it [94]. The greater the PE, the more likely it is that mobile health services will be embraced, according to experimental studies [95]. Therefore, the following hypothesis was put up for this investigation:

H1a: PE has a positive effect on the BI for chronic disease patients to adopt IoT-healthcare services.

2) Effort Expectancy (EE): The ease of use (or EE) of a system is defined as "the degree of simplicity" [96]. Researchers have found that EE has a substantial effect on users' propensity to embrace a health information system. Clinical support for decision systems, mobile health monitoring systems, and e-health solutions accessible via smartphones are all examples, and portable well-being has all been shown to be positively influenced by EE [17, 95]. Pal found that effort expectancy has a major impact on the adoption Internet of Things in healthcare [5]. Hence it entails that:

H1b: EE has a positive effect on the BI for chronic disease patients to utilize IoT-healthcare services.

3) Social Influence (SI): "How important it is to other people that you accept the new technology" [93] is how social influence is defined as it relates to technology adoption. Liu concludes that SI is a crucial factor and has a significant effect on the spread of mobile medical services. Pal also looked into how peer pressure affects the uptake of smart homes to improve the health of the elderly [5]. Literature reviews have found a similar pattern: people are more inclined to adopt new technology when they see other people using it, too [97]. It is hypothesized in this investigation that individuals with chronic diseases will be influenced to accept and use IoT-healthcare services:

H1c: SI has a positive effect on the BI for chronic disease patients to adopt IoT-healthcare services.

B. *Technological Factors*

The TOE relies heavily on technological aspects. Their impact on the spread of various technologies has been the subject of several studies. According to Lian's research, technological factors have a significant effect on cloud computing's uptake in Taiwan [101]. Cloud computing adoption in the public sector has been the subject of several studies, including one by Polyviou and Pouloudi [107], who showed that technological characteristics were significant predictors of cloud adoption among public sector personnel. In India, cloud computing has been slow to catch on, according to research by Gangwar [90]. Thus, it is hypothesized in this study that technical factors will have a beneficial impact proceeding the behavioural intention of Malaysians with persistent illness to implement IoT healthcare. Accordingly, it is assumed:

H2: Technological factors have a positive effect on the BI for chronic disease patients to adopt IoT-healthcare services.

1) Security: The healthcare industry is facing serious security challenges. Without adequate safeguards, billions of sensitive medical files are kept on unprotected servers. Concerns regarding the safety of patient data and infrastructure have grown in tandem with the prevalence of ransomware attacks. In the present study, we define security as the confidence that patients with chronic diseases have in IoT healthcare services as safe places to save and share their personal information [98]. Security was introduced as a technological aspect by Lian, Senyo, and Alkhater [92, 99, 100]. So, this research takes into account security as a factor of the technological factors. Numerous studies have looked into how people's perceptions of risk influence their decisions about whether or not to adopt new technology. According to Junqi's research, [75] security concerns significantly affect whether or not a healthcare system is adopted. It is hypothesized as:

H2a: Security has a positive effect on the BI for chronic disease patients to adopt IoT-healthcare services.

2) Privacy: When it comes to the use of IoT devices in healthcare, privacy is a key problem. Medical devices such as (but not limited to) pacemakers, insulin engines, and individual monitors are frequently used in hospitals to keep tabs on patients' vital signs. In order to exchange data, these gadgets join a wireless network. Multiple hackers have broken through these systems as of late, taking the information for their end. If patients find out later that their doctors are using Internet of Things devices on them, they may feel violated. The term "privacy" refers to "the extent to which individuals with chronic diseases perceive that their personal information is secure" [98]. Researchers have taken privacy into account as a technological aspect in the spread of cutting-edge tools in a variety of contexts. For the Internet of Things to be widely used in healthcare, researchers have shown that protecting patients' personal information is crucial [2, 52, 101]. Hence, it is assumed that:

H2b: Privacy has a positive effect on the BI for chronic disease patients to adopt IoT-healthcare services.

3) Availability: Availability, which is one of the sub-constructs of technological factors, is the perception of how much personalized and uninterrupted connection and communication an individual has with other individuals and networks through ubiquitous technology [94]. Lack of internet connectivity is one of the main barriers to utilizing telehealth/telemedicine, as 68% of health care professionals reported this as their top concern in adopting these new technologies [17]. When formulating the TOE model, Tornatzky and Fleischer took into account accessibility to technology as a technological component [102]. Pathinarupothi, who noted that availability is vital for remote monitoring, and impacts the amount to which users are ready to embrace IoT, is one of the researches that looked at how accessibility affected IoT uptake [69]. The willingness of users to employ the Internet of Things is affected by factors such as availability. According to research in the field of technology adoption, such as the Phaphoom study, availability is crucial for the spread of cloud computing [103]. Positive findings on the impact of availability on BI to use IoT by Malaysians with chronic diseases are anticipated in this research. So, the following is postulated:

H2c: Availability has a positive effect on the BI for chronic disease patients to adopt IoT-healthcare services.

4) Facilitating Condition (FC): The variable "FC" is one of the constructs of the Unified Theory of Acceptance and Use of Technology (UTAUT). "FC" stands for "facilitating conditions," which refers to “the extent to which a user believes that an organizational and technical infrastructure exists to support the system's use” [104]. The FC was directly related to the employment of cutting-edge technology by the researchers that deployed UTAUT [93, 105, 106]. The extent to which a user is pleased with and finds value in an IT application has been shown in other research to be a major predictor of that user's intention to involve with new technologies [107]. Consequently, if the FC for a new system is high, it's likely that its users will be pleased with it and want to keep using it. Academic technology adoption was found to be significantly influenced by FC [106]. As a result, it stands to reason that FC has a significant impact on patients' propensity to engage in IoT-based healthcare services. Then, it is theorized as:

H2d: FC has a positive effect on the BI for chronic disease patients to adopt IoT-healthcare services.

C. Behavioural Intention (BI) and Use Behaviour

Is a catch-all phrase covering research into how people engage with and make use of technological systems. From marketing to the law, BI has found a home in many industries. Yet, the field is most commonly associated with the study of human-machine interactions in the social sciences. A definition of BI is the extent to which a person has deliberated over whether or not to engage in a particular course of action in the future [106] Individual's subjective evaluation of whether or not they should engage in the desired behavior (UB) [93]. Individuals' subjective evaluation of whether or not they should engage in the desired behavior (UB) [93]. Most earlier models of technology acquisition such as TAM and UTAUT have connected the BI to the UB [85, 93]. Gao observed a substantial correlation between BI and UB in their research [106]. Many investigations [108-110] have found the same thing. Therefore, in this study, it is hypothesized as:

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

D. Mediating Role of Trust

Patients with chronic conditions who have faith in the integrity of IoT-healthcare services are said to have "high levels of trust" [98]. Users were more likely to adopt new technologies when they had a positive impression of the companies providing those services [111]. Lansing and Sunyaev concluded, using a classification system based on how trust plays out in trying out new gear, that trust was underappreciated in this context and that the variable trust mediated the relationship between the factors of success of acquisition and utilization goals [112]. Ghazizadeh, Lee, and Boyle used trust as an intermediary among PEOU, helpfulness, and BI [113]. The conclusions revealed that trust completely mediated the consequence of PEOU on BI.

According to Social Exchange Theory, trust is a critical aspect that might impact an individual's desire to employ technology in healthcare. As stated in previous studies, patients who have trust in IoT healthcare technology are more likely to use, learn from, and realize its advantages. Furthermore, a trust may influence how individual and technological factors influence an individual's behavioural intention to adopt new technology. The research hypothesis is that trust will play a mediating role in the relationship between individual and technological factors and patients' behavioral intention (BI) to adopt Internet of Things (IoT) healthcare services. In other words, the study proposes that trust will act as a link between these factors and patients' willingness to use technology in healthcare. It is theorized as follows:

H4a: Trust mediates the effect of individual factors on BI to adopt IoT-healthcare service by chronic disease patients. H4b: Trust mediates the effect of technological factors on BI to adopt IoT-healthcare service by chronic disease patients.

E. Moderating Effect of Gender and Experience

Recent research has examined the impact of gender and experience on the relationship between UTAUT constructs and people's intentions to use technology. The results suggest that gender and experience can have a significant influence on people's attitudes towards technology, and should be taken into account when introducing new technological solutions [93]. Another point should be highlighted that the user's background and familiarity with the internet, computers, and other forms of information technology is another important factor to consider when introducing new technology solutions. The Unified Theory of Acceptance and Use of Technology (UTAUT) has also recognized that people are more likely to use technology when they have a high level of familiarity with it. This suggests that prior experience with technology can influence people's attitudes toward new technology and may impact their willingness to adopt it.

Rezvani used gender and professional experience to moderators the relationships between TAM and privacy and connectedness. [38]. The findings showed that these two characteristics affected the perceived utility (PU), perceived ease of use (PEOU), privacy, and desire to use IoT. Based on the UTAUT paradigm, this study hypothesizes that gender and experience affect the connection between individual and technological factors and patients' adoption of IoT. Accordingly, the following is hypothesized:

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

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

IV. METHODOLOGY

A. Population and Sample Size

This section describes the characteristics of the participants included in this research, how they were selected as well as the study's sample size.

1) Population: The population is described as "the entire group of people, events, or things that can be observed or measured." [114]. This definition is quite wide and might include anything from individual people to entire societies. Other researchers defined population as "the intended group that shares similar characteristics with the group in which the researcher wishes to generalize the research findings" [64]. When collecting data, it is important to choose the population carefully to ensure collecting relevant and reliable data. In the current research, the population of this study is patients suffering from chronic diseases in Malaysia. Presently, there are no specific statistics that reflect the number of patients with chronic diseases in Malaysia. However, the prevalence of chronic illnesses such as diabetes, hypertension, and heart disease is increasing among patients in Malaysia.

This study focuses on the Klang Valley area given that it is an urban area with the highest population in Malaysia amounting to 8.4 million people according to the World population review. Approximately 1.2 million of these patients are estimated to have one or more chronic conditions according to the Ministry of Health, Malaysia.

2) Sampling: The sample size is defined as "a process of selecting a number of individuals from a population to be tested or studied" [115]. The selection of a target population is critical to ensure that the sample is representative of the larger population of interest [114]. According to the Ministry of Health, about 1,000,000 Malaysians with chronic conditions live in the Klang Valley. SEM data analysis requires a sample size of 100–200 [116]. Kline said that SEM samples are typically 200 [117]. According to Krejcie and Morgan [118] and Sekaran [114], 384 respondents are a substantial and acceptable sample for this study's population.

B. Questionnaire Design

A standardized, closed-ended questionnaire was used to compile information for this investigation. The variables are measured in accordance with standards established by earlier research into the spread of IoT healthcare services. There are three sections in this questionnaire as it is shown in Fig. 4:

1) The first section explains the purpose of the questions.

2) The second section collects demographic data from respondents, such as age, gender, usage of IoT services, familiarity with IoT, expertise with IoT, and whether they have any chronic diseases.

3) The third section contains items designed to measure technological and individual characteristics, as well as research variables like behavioral intention, trust, and actual usage behavior.

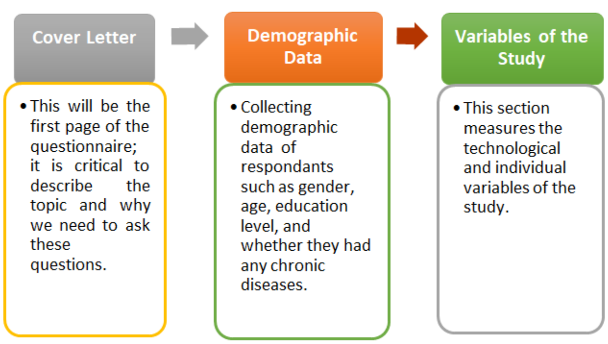

Fig. 4. The questionnaire sections.

Items are graded on a 5-point Likert scale, with 1 representing strongly disagreeing and 5 representing strongly agreeing. Compared to seven- and ten-point Likert scales [119-121], Likert scales are utilized because they have been found to be more accurate in gauging respondents' thoughts and feelings. The "closed-ended" nature of these questions makes them easier to answer than open-ended questions that ask respondents to describe how they feel about an issue or topic. These types of questions also increase the reliability of the data and make it easier to analyze the data and interpret the results [122].

C. Preliminary Test

After the questionnaire was designed, and before collecting actual data, it was crucial to conduct a preliminary test to ensure that the questions were appropriate, to obtain accurate results [123]. Particularly if the questions of the questionnaire were adopted from earlier studies, there is a need to modify the questions in a way to fit the new purpose of the research, As it has been done in this investigation were the questionnaire adopted from previous studies [124-126].

Pre-test and pilot studies were conducted in this study. The purpose of this test is to determine errors and ambiguity, make sure that questions are clear enough and understood by respondents, as well as identify any technical problems that may prevent the results from being reliable and accurate [64, 114].

D. Data Collection Procedures

Several approaches can be used for collecting data via surveys in research studies, including online and mail surveys, telephone interviews, face-to-face interviews, and drop-off surveys [114]. The present study aligns with previous research that investigated the adoption of IoT in healthcare and deployed a survey approach to collect the data due to the cost-effectiveness, convenience, and time of the studies [15, 38, 90]. Surveys also enable researchers to collect a large number of responses in a relatively short period [114]. Given that the data collection process occurred during the lockdown of COVID-19, an online survey may be the best option, as it allows patients to complete the survey at a time that is convenient for them and reduces the amount of contact between the patient and the researcher during that period. respondents who met the inclusion criteria were selected to complete the questionnaire. An online questionnaire was deployed for the data collection.

Among the initial 384, we received 252 valid responses. As Kline stated that SEM responses more than 200 are satisfactory [117], such results are regarded adequate. SPSS 24.0 and Smart PLS 3.3 are used to analyze the data. Missing values, outliers, normality, and multicollinearity checks are all part of SPSS's preliminary analysis. The measurement type and the structural version are both a part of the main analysis conducted using Smart PLS.

V. Results

A. Descriptive Information

The respondent descriptions and variables for the study are included here. The former was reported in terms of frequencies and percentages, while the latter was represented statistically by means of each variable. The level of education, gender, age, chronic illness, frequency of use, and method of accessing IoT healthcare of the respondents are shown in Table III.

Factors and their associated descriptions are shown in Table IV. The average score for performance expectation (PE) was 3.29, indicating that most respondents agreed with the items used to calculate PE. The majority of respondents moderately agreed with the items evaluating effort expectancy (EE), as seen by its mean score of 3.39. Similar results for social impact could be shown (SI). The degree of individual-related elements had an overall mean score of 3.31. All of the factors taken into account under individual-related aspects in this study were moderately supported by respondents, it may be concluded.

TABLE III. DESCRIPTIVE INFORMATION OF RESPONDENTS

	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 services	Yes	79	31.4
	No	173	68.6
Tool to access IoT healthcare services	Smartphone	39	15.5
	Devices in the house	19	7.5
	Wearable devices	21	8.4
	Not using	173	68.6

Table V lists the four dimensions of the level of technologically related factors: security, privacy, availability, and facilitating conditions. Security, privacy, availability, and facilitation conditions have comparable mean scores of 3.20, 3.18, 3.38, and 2.96. A substantial level of agreement with the associated items or measures was determined in this study to be a mean score greater than 2.5. In light of this, the majority of respondents showed moderate agreement with all of the technologically linked criteria examined in this study. This is mirrored in Table IV's total mean score, which is 3.18.

TABLE IV. DESCRIPTIVE STATISTICS OF INDIVIDUAL FACTORS

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

TABLE V. TECHNOLOGY-RELATED FACTOR DESCRIPTIONS

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
Facilitating conditions	2.96	-	Moderate
Overall mean score	3.18	-	Moderate

The trust-related descriptive data are shown in Table VI. As a result, the overall average is 3.33, suggesting a moderate degree of agreement with the trust-measuring statements.

According to Table VII, the overall average grade for that behavioral intention (BI) is 3.30. All items used to gauge BI severity have received moderate agreement from participants, as indicated by the mean score being larger than 2.50.

Table VIII displays the outcomes for the frequency of use. The majority of respondents only somewhat agreed with the assertions pertaining to real behavior, as indicated by the mean score of 3.41 for actual behavior (AB).

TABLE VI. DESCRIPTIVE STATISTICS OF TRUST

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
The overall mean of trust	3.33	-	Moderate

TABLE VII. DESCRIPTIVE STATISTICS OF BEHAVIOURAL INTENTION

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
The mean of behavioural intention	3.30	-	Moderate

TABLE VIII. ACTUAL BEHAVIOUR DATA WITH DESCRIPTIVE STATISTICS

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

B. *Structural Equation Modeling*

Structural Equation Modeling (SEM) is a statistical method for analyzing the relationships between multiple variables [127]. SEM can be used for a variety of purposes, including testing theoretical models, investigating complex relationships between variables, and examining causal relationships [128]. Some of the advantages of SEM include its ability to handle multiple variables, account for measurement errors, and test complex models. Additionally, SEM allows researchers to test both direct and indirect effects between variables, making it a powerful tool for hypothesis testing and theory development [129]. The structural equation model assessment is divided into two models. The first model is the first-order variables while the second model is the second-order variables. The steps of assessing the SEM-PLS are shown in Fig. 5. By using SEM, researchers can gain valuable insights into the factors influencing the behavioral intention of chronic disease patients to adopt IoT-healthcare services in Malaysia.

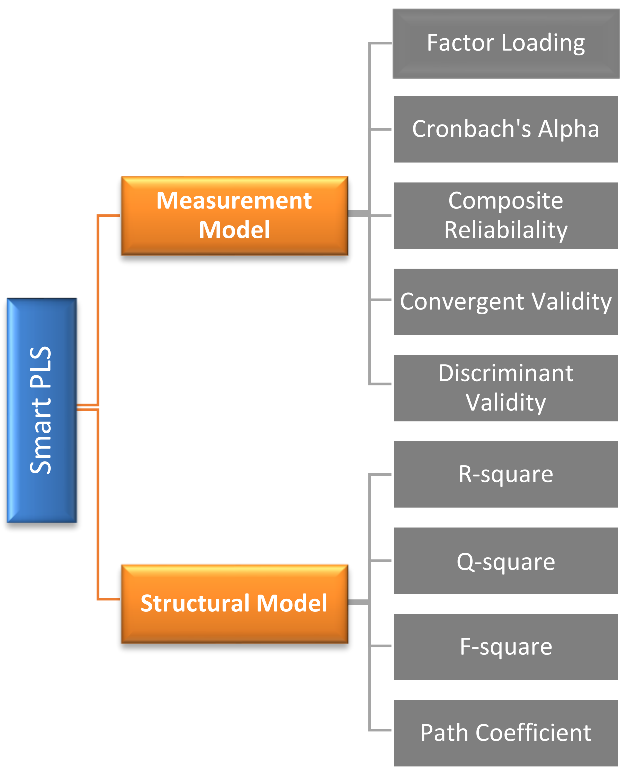

Fig. 5. Steps of assessing SEM-PLS.

1) Measurement model assessment: First-Order Measurement Model Assessment of SEM evaluates a structural equation model where all variables are measured by a single indicator, while Second-Order Measurement Model Assessment evaluates a structural equation model where one or more latent variables are themselves measured by other latent variables. Both assessments involve examining the reliability and validity of the measures used to operationalize the latent variables in the model to ensure that the measurement model provides a good fit to the data and accurately reflects the underlying constructs of interest [129, 130].

The finalized measurement model of this study is presented in Fig. 6, comprising the main constructs (1) individual-related factors (second order) and their dimension, performance expectancy, effort expectancy, and social influence (first order), and (2) technological-related factors (second order) and its dimension, which consist of the first-order variables; availability, security, privacy, and facilitating conditions. The factor loadings of the items on their respective variables and the loading of the first order on the second order are also presented.

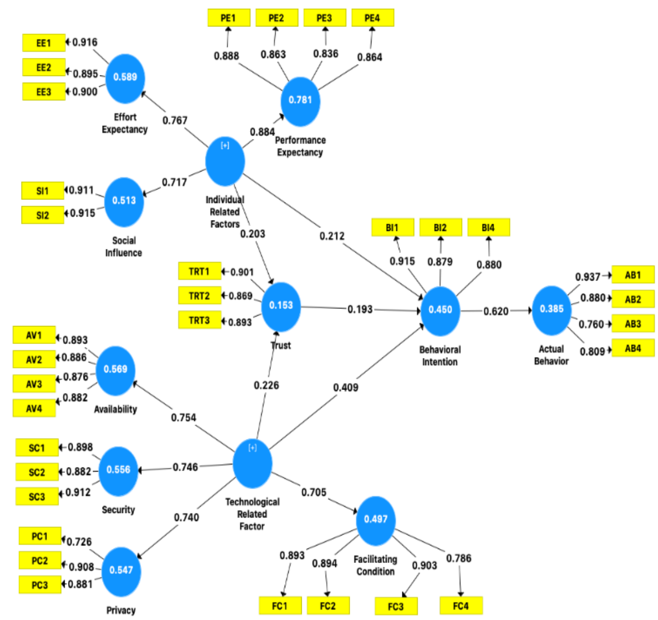

Fig. 6. Measurement mode.

2) Structural model: The structural model is used to test hypotheses about the relationships among the variables and to estimate the strength and direction of those relationships [131]. The assessment of the structural model involved four criteria: R-square, Q-square, F-square, and the path coefficient. By integrating both the structural and measurement models, structural equation modeling provides a comprehensive analysis of the relationships among latent variables and their corresponding indicators.

C. *Result of Hypotheses Testing*

All three types of hypotheses—direct effect, mediating effect, and moderating effect—were examined here. Following Hair [74], all hypotheses were tested using a p-value of less than 0.05 and a bootstrapping sample size of at least 5,000. The direct effect hypotheses are summarized in Table IX.

The first hypothesis (H1) and its three components (H1a), (H1b), and (H1c) predicted the impact of personally relevant factors on behavioural intent. With p-values smaller than.05, the results showed that both performance expectation and social influence had a substantial direct impact on BI.

TABLE IX. THE OUTCOME OF THE TESTS OF THE HYPOTHESES

H	Factors	B	Std.	T-value	P Values	Significant
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 related 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

H1, H1a, and H1c are all supported by this level of evidence (p 0.05). Since the expected effect of effort on BI was not statistically significant, H1b cannot be true. The second hypothesis claimed that technological factors, including security (H2a), privacy (H2b), availability (H2c), and facilitating conditions (H2d), had a major impact on behavioral intention. The p-values for security, availability, and enabling conditions were less than 0.05, implying that hypotheses H2, H2a, H2c, and H2d are accepted. Yet, the impact of privacy on BI proved insignificant, leading to the rejection of H2b. The impact of BI on user habits is substantial for H3 with a p-value of just under 0.05. As a result, H4 is supported.

Trust can mediate the relationship between different factors and people's behavioral intention (BI) to use technology. Specifically, the direct effect of trust as a mediator is significant, meaning that trust plays an important role in shaping people's attitudes toward technology. The indirect effect of technological-related factors via trust on BI is also significant, indicating that people are more likely to use technology when they trust it and perceive it as reliable. Similarly, the effect of individual-related factors on BI through trust as a mediator is also significant, suggesting- that people's personal characteristics and beliefs can impact their trust in technology, which in turn influences their intention to use it.

The results indicate that education plays a moderating role in this relationship, meaning that it can influence the strength of the association between individual/ technological - related factors and BI.

D. *Discussion of Hypotheses Testing*

The study found that individual factors, specifically performance expectancy (PE) and social influence (SI), significantly affected the patients' behavior intention (BI) towards adopting these services. The results are consistent with previous studies, suggesting that these factors are crucial in determining patients' willingness to adopt IoT healthcare services. While EE has an insignificant effect on BI, The explanation for this finding is that patients may only anticipate the benefits of these services without fully understanding the effort required to participate in them, in addition, since many individuals have grown accustomed to using contemporary gadgets in their daily lives, it has become easier for them to adapt to new technologies.

The second main hypothesis proposed that technological-related factors have a significant impact on BI, and the results indicated that these factors do have a significant effect on patients' BI. The findings suggest that technological factors are crucial in determining patients' willingness to use IoT healthcare services. This indicated that an increase in the level of technological-related factors will cause an increase in BI toward using IoT healthcare services among these patients. The results of the hypotheses testing revealed that security, availability, and facilitating conditions have a positive and significant impact on the BI, except for the privacy factor. The insignificant effect of privacy on chronic disease patients' behavioral intention (BI) towards adopting IoT healthcare services, may be due to patients' understanding of the difficulties in sharing their information with a third-party. This understanding may be attributed to Malaysia's local laws that protect patients' privacy, which could have influenced patients' willingness to use IoT healthcare services.

According to the third hypothesis, BI has a significant impact on the UB of IoT healthcare services among chronic disease patients. The findings indicated that BI is an important driver of UB.

The fourth hypothesis was related to the mediating effect of trust between individual and technological-related factors and chronic disease patients’ BI towards using IoT healthcare services. The findings of the mediating analysis reflected that trust partially mediated the effect of individual-related factors on BI toward IoT adoption. Likewise, trust mediated the effect of technological-related factors on BI in facilitating IoT usage among chronic disease patients. This indicates that trust in the service providers can explain part of the relationship between individual and technological-related factors and BI.

The last hypothesis of this study predicted that gender and experience moderate the effect of individual and technological factors on BI towards using IoT by chronic disease patients. The findings indicated that the prediction was untrue. Gender did not moderate the effect of individual factors on BI nor the effect of technological factors on BI towards the use of 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. In addition, 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 towards using IoT by chronic disease patients. The findings showed that this assumption is true.

VI. Conclusion

The ultimate goal of this research is to examine the factors that influence patients' behavioral intention toward IoT adoption when dealing with chronic illnesses. The study found that patients who were provided with more information about their illness and believed that IoT devices could improve their quality of life were more likely to adopt IoT healthcare services in the form of wearable devices.

To enhance the model's explanatory capacity and originality, the investigation combined the UTAUT and TOE models with SET. The researchers used structured equation modeling (SEM) methods to test the integrated model on a group of Malaysians with chronic illnesses.

The study's findings indicate that individual factors and their dimensions, such as performance expectancy (PE) and social influence (SI), had a significant impact on chronic disease patients' behavior intention (BI) towards IoT healthcare services adoption in Malaysia. These results align with previous studies. The study also observed similar outcomes for technological-related factors and their dimensions, including security, availability, and facilitating conditions. Additionally, the effect of BI on UB was significant. Trust partially mediated the effect of individual and technological-related factors on BI, while education played a moderating role in the latter relationship.

This research is unique in the current literature on the Internet of Things (IoT) because it was undertaken in Malaysia. This study explored a number of hypotheses to shed light on what influences IoT adoption among Malaysians with chronic illnesses, as opposed to the narrower focus of TAM in other studies. Understanding the possibility of implementing IoT healthcare services in Malaysia Legislators and suppliers in the healthcare system are going to find the study results quite helpful. Patients and their loved ones would benefit from this research since the widespread implementation of IoT healthcare services will improve the quality and efficiency with which chronic disease management is handled. Meanwhile, healthcare workers will benefit from this study as well, since the IoT will facilitate the remote performance of their duties.

VII. Limitations and Future Work

Several limitations should be highlighted in this investigation. Patients with long-term illnesses were the focus of this research. This means that the results only apply to people who have a chronic illness. In light of this, it has been proposed that scientists increase the size of the sample numbers, such as those with mild diseases and frequent hospital visitors. This research looked into the use of Internet of Things healthcare services by people living with chronic diseases in Klang Valley, Malaysia. Researchers may therefore suggest conducting a global study with patients from diverse nations would allow for an additional thorough international comparison of results, as the current study's findings are specific to this demographic.

In this research, we looked at how gender and level of experience/education can act as moderators. There is a lack of information about how these factors influence users' decisions to use IoT, so more research will be needed to better understand the underlying relationships. Some of the observed associations between the studied variables and trust can be attributed to the role of trust as a mediator. To better operationalize trust in online interactions, in service delivery, and in healthcare settings, it is advised that future research investigate the possible role of this characteristic.

In this work, UTAUT, TOE, and SET were integrated to form a model for examining the research aspects. In subsequent works, a similar method could be utilized to more adequately illustrate the aforementioned IoT adoption variation. 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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