Factors influencing the adoption of IoT healthcare products and services: An empirical study of the end consumers

Article history

Received:
2 April 2026

Received in revised form:
15 April 2026

Accepted:
20 April 2026

Published online:
15 June 2026

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Abstract

Internet of Things (IoT) technology has been increasingly applied across numerous industries. The healthcare sector, more than many others, requires advanced technologies such as IoT to enhance quality of life and improve access to healthcare and emergency services for millions of people. IoT healthcare technology enables providers to enhance the quality of patient care, communication, and diagnostic accuracy while enhancing efficiency and reducing costs. Despite the immense opportunities offered by IoT healthcare solutions, their adoption among end users remains limited due to concerns about privacy, perceived usefulness, complexity, ease of use, and high costs. Therefore, this study examines the main factors influencing customers' adoption of IoT healthcare products and services by integrating constructs from TAM, IDT, and Privacy Calculus Theory. The demographic data were analysed in SPSS, whereas SmartPLS was used for confirmatory factor analysis (CFA), partial least squares (PLS), and structural equation modelling (SEM). The findings indicate that perceived usefulness (PU), attitude, and observability significantly positively affect patients' willingness to adopt IoT-based healthcare technology. In contrast, perceived privacy risk, trialability, and cost did not have a substantial impact on adoption intention. The results of this research offer multiple theoretical and practical insights for the healthcare sector, as well as for researchers, policymakers, and product developers focused on implementing smart healthcare technologies

Keywords: *IoT Healthcare, Technology Adoption, Innovation Diffusion Theory, Privacy Calculus Theory, PLS-SEM*

1. Introduction

Healthcare professionals and administrators face many challenges in delivering affordable and adequate medical care. Recently, IoT has emerged as a key technology for addressing these issues [1]. The "Internet of Things" connects physical devices to the internet, enabling them to communicate and exchange data. While this concept is not new, an abundance of research has been conducted in this field, an increasing number of objects are becoming "smart" and connected [2]. The total number of connected devices is expected to grow from 15.9 billion in 2023 to over 32.1 billion by 2030, indicating the growing prevalence of the Internet of

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Things (IoT). By 2033, it is anticipated that China will have 8 billion IoT device users, with the consumer market representing around 60% of all devices, and this trend is expected to persist for the following decade [3].

IoT-enabled healthcare technologies use Radio-Frequency Identification (RFID), sensors, nanotechnology devices, and wearables to support real-time health monitoring, remote diagnosis, and personalised healthcare [4]. These uses improve efficiency, increase patient safety, and support informed health decisions [5], [6]. IoT will enhance individualized treatment and improve patient outcomes while saving healthcare management costs. It will facilitate early diagnosis and intervention, reduce unnecessary tests and frequent appointments, and lower overall costs and patient outcomes [7]. In addition, IoT use in telecare has accelerated due to the COVID-19 pandemic, enabling patients to manage their health remotely and minimizing the need for face-to-face consultations [8]. These rapid developments highlight both the advantages and future potential of IoT healthcare products and services in transforming the consumer healthcare sector.

Technology integration into daily life has changed consumer expectations, behaviors, and interactions. Smart objects with online communication and interoperability support remote control of devices and remove physical boundaries. IoT drives new business models in healthcare and accelerates its digital transformation [9]. The frequent applications in healthcare focus on tracking patients, ensuring correct equipment usage, and supplying medications to enhance efficiency and safety [10]. IoT is transforming healthcare by extending care beyond hospitals and empowering individuals to make healthier choices.

Despite these advantages, customer adoption remains stagnant [11]. Comprehensive research on user acceptance of IoT-based healthcare products remains limited. Key barriers include perceived complexity and limited awareness of the technology's benefits [12]. Furthermore, studies have primarily focused on technological infrastructure and organizational readiness rather than systematically investigating end-user adoption factors within the healthcare context [13]. Earlier studies on IoT in healthcare have mainly concentrated on technological aspects, including its applications and challenges [14]. However, [15] indicated that the gap highlights the need for further investigation into how individual user characteristics, preferences, and behaviors affect the acceptance and use of IoT technologies. Understanding users' perceptions of the usefulness, observability, and privacy concerns of IoT healthcare technologies is essential for influencing their behavioral intention.

Therefore, this study investigates the factors influencing patients' willingness to adopt IoT products and services. An integrated model is employed, combining the TAM, IDT, and privacy calculus to examine factors and constructs such as perceived usefulness, ease of use, observability,cost and privacy considerations affect users' behavioral intentions to adopt IoT-based healthcare technology. The remainder of the paper is organised as follows. Section 2 reviews the application of IoT in the healthcare sector. Section 3 outlines the conceptual model and formulates the research hypotheses. Section 4 explains the methodology adopted in the study, while Section 5 presents the empirical results. Finally, Sections 6 and 7 provide a discussion of the findings and outline the study's theoretical and practical implications.

2. Related works

2.1. Overview of IoT in Healthcare

The Internet of Things is regarded as the third wave of the Internet, following the Internet of People and the Internet of Information [16]. It has significantly transformed various industries, particularly healthcare. It is expected that over 75 billion gadgets will be interconnected worldwide by 2025 [17]. This expansion is anticipated to yield substantial benefits for healthcare. Currently, IoT products and services are employed to enhance patient care and outcomes by enabling advancements in remote monitoring [18], personalized treatment, and efficient health delivery services. IoT further provides the ability to save healthcare expenses and provide patients more control over their health [19].

Using IoT solutions within healthcare systems improves organizational processes. These services and products include tracking medical equipment, identifying drugs with RFID, and creating smart hospital wards that use wearables and mobile apps to manage health [16],[20]. The adoption of IoT is growing worldwide [21]. Smart hospitals and telemedicine are key parts of this trend, showing a clear focus on using IoT to improve healthcare service [3]. According to Precedence Research, the global IoT healthcare market is predicted to become 53.64 billion dollars in 2024 and grow to about USD 368.06 billion by 2034, indicating a 21.24% compound annual growth rate [22].

2.2. Opportunities and Challenges of IoT in Healthcare

The current healthcare system empowers patients' access to their medical information, supporting them to manage their well-being. Wearable health devices allow providers to deliver care anytime, fostering a continuous connection and emotional bond with technology [23]. According to [24], healthcare is being transformed by IoT, which is improving patient experiences and increasing efficiency for care teams and facilities. It overcomes geographic obstacles and enables rapid clinical responses. IoT also streamlines healthcare delivery, helping to predict health issues and manage patient care both in and out of hospitals [25].

Despite IoT significant promise in healthcare, it also poses challenges with data security, privacy, connectivity, compatibility, and cost. Ethical concerns surrounding IoT in healthcare arise from issues related to the handling of sensitive health data, including privacy of information, data sharing, autonomy, ownership of data, consent, and uncertain value within the care model. In addition, wearable technology like fitness monitors and smartwatches gathers an enormous amount of individual medical information [26]. The recent trending technologies, including IoT, blockchain, and AI integration, have demonstrated tremendous promise in the healthcare industry by improving the standard of medical treatment and boosting diagnostic accuracy. Additionally, they address critical issues pertaining to data security, integrity, connectivity, and medical records in healthcare systems [27].

Table 1. IoT Healthcare Technology Adoption

Author	Context	Theory / Model	Key Constructs	Key Findings
[28]	End consumers in India	UTAUT2	Attitude, BI, FC, Price Value, Health Risk	FC and price value did not significantly influence attitude; FC directly influenced BI.
[29]	Wearable healthcare users in Hong Kong	TAM, HBM	PU, Privacy, Health Belief, Adoption Intention	Health belief and information accuracy significantly influence PU and adoption intention; privacy was insignificant.
[30]	Chronic illness patients in Malaysia	TOE, UTAUT, SE	PE, EE, Trust, Privacy, BI	Individual and technological factors significantly affect BI; trust partially mediates these effects.
[31]	IoT consumers	TAM	PU, PEOU, Trust, Social Influence, BI	Attitude and BI are strongly impacted by PU and PEOU; social influence and trust have indirect impacts.
[32]	Gen Z & Millennials	TAM, TPB	Attitude, PU, Innovativeness, BI	Attitude, PU, innovativeness significantly influence IoT adoption intention.
[33]	Healthcare providers	TPB, Privacy Calculus	Attitude, Privacy, Risk, Trust, BI	Gender differences observed; risk perception showed limited impact on BI.
[34]	Smart home healthcare patients	UTAUT, PAD	PE, Human Detachment, Adoption	Human detachment concerns outweighed performance expectancy in adoption decisions.

The literature review shows that IoT adoption is shaped by individual, technological, security, health, and environmental factors. These influences are identified by theories such as TAM, UTAUT/UTAUT2, TOE, TPB, Privacy Calculus, and integrated models and are mainly supported by survey-based quantitative research and SEM analysis. Researchers have often studied factors like perceived usefulness, ease of use, facilitating conditions, trust, privacy, security, and health beliefs. However, most studies focus on general IoT applications or healthcare providers, and there is little research on how healthcare consumers adopt

IoT. To address this gap and build on prior research, this study integrates three theoretical models to examine the enablers and barriers influencing consumers' adoption of IoT healthcare products and services, directly addressing the need identified in prior literature.

3. Research Model and Hypotheses

The research model and hypotheses in this study are based on integrated models of TAM, IDT, and the Privacy Calculus Theory to examine individuals' intention to adopt IoT healthcare products and services. This study used a quantitative approach. The model was tested using a questionnaire that included three TAM factors: perceived ease of use (PEOU), perceived usefulness (PU), and attitudes (AT). It also included two factors from IDT: trialability and observability. Additionally, privacy concerns and cost were included from the privacy calculus theory. By combining these factors, the model shows how usability, innovation, and privacy concerns together affect adoption. Figure 1 provides an overview of the proposed research model.

3.1. Technology Acceptance Model

TAM explains individual behaviour toward technology and addresses the limitations of the TPB and TRA. It also seeks to clarify the affecting factors of consumer adoption of an innovation and technologies [35], [36] The initial model suggests that usage of a system could be affected by consumer incentives, particularly by external variables including the functioning of the system's features and functionality [37], [38].

Perceived Usefulness: "Perceived usefulness refers to the degree to which a person believes that using a particular system will improve their performance or quality of life" [35]. The perceived usefulness constitutes the main variable in determining user acceptance of a system. IoT product adoption relies on attracting tech enthusiasts who are inclined to embrace IoT gadgets and have higher expectations for their use [39], [40].

H1: *Perceived usefulness is associated with the behavioural intention to adopt IoT healthcare products and services.*

Perceived Ease of Use: Perceived ease of use is defined as "the user's perception that interacting with a system requires minimal mental or physical effort." User acceptance and adoption depend on system simplicity of use. Easy-to-use IoT products and services improve intention to use. According to research, adoption declines when the product is complicated and not easy to use [35].Therefore,

H2: *Perceived ease of use has a positive effect on the behavioural intention to adopt IoT healthcare product and services.*

Attitude: According to Venkatesh and Davis [[41], describes an individual's overall assessment of utilising new technology, whether it be favourable or unfavourable. In contrast, behavioural intention reflects their planned decision to either adopt or avoid using it in the future. In order to study how attitudes develop, modern social psychologists typically employ cognitive or information-processing methods. Attitude (AT) and behaviour intention (BI) are positively correlated, as demonstrated by numerous studies [41].

H3: *Attitude has a positive effect on the intention behavioural to adopt IoT healthcare products and services.*

3.2. Diffusion of Innovation (DOI)

Innovation diffusion theory explains the process through which new ideas or technologies spread among members of a social system over time through specific communication channels [42].This model identifies key attributes that influence adoption decisions: relative advantage, compatibility, complexity, trialability, and observability [43]. It offers practical insights for policymaking, business strategies, and public health initiatives, and it remains essential in promoting social and technological advancement [44].

Trialability: The concept of trialability represents the extent to which a potential user experiments with an innovation prior to making a full adoption decision, for which an innovation can be tested on a limited scale. Previous studies support the significance of trialability in the adoption process. Trialability strongly influences IoT adoption by letting users try wearable fitness trackers, lowering risk, and building confidence [45]. This supports the diffusion of innovations theory, which sees trialability as key to adoption.

H4: *Trialability positively affects behavioural intention to adopt IoT products and services.*

Observability: Observability is "the degree to which the results of an innovation are visible to others." Existing studies show that observability greatly and positively affects consumer perceptions towards IoT services [45] Moreover, previous studies show that the increased visibility of individual expressions significantly raises users' perceived utility and usability [46].

H5: *Observability is positively associated with the intention to adopt IoT healthcare products and services*

3.3. Privacy Calculus Theory (PCT)

Privacy calculus theory demonstrates how individuals evaluate the balance between perceived benefits and dangers prior to disclosing personal information [47]. It derived from the behavioural calculus model proposed by Laufer and Wolfe [48], argues that the necessity to reveal personal information is grounded in a rational evaluation of risks and usefulness. The model posited that individuals assess both the reward and potential cost of sharing their personal information, considering the loss of privacy acceptable when specific benefits were guaranteed and the risks were moderate [48].

Perceived Privacy Concern: The safeguarding of personal privacy is a crucial adoption condition for continued use of technology, as health information is regarded as more sensitive than demographic or general transaction data [49]. [50] emphasizes that individuals are primarily concerned with security and privacy, expressing apprehensions regarding breaches and misuse. Similarly, [51] stated that perceived security and privacy issues are key determinants of consumers' intentions to use IoT devices.

H6*: Perceived privacy risk has a negative association with the behavioural intention to adopt IoT healthcare products and services*

Cost: In this context, cost represents the anticipated financial expenditure for consumers. Older individuals are more affected by cost concerns, while younger, more technologically adaptive users ("IoT natives") are less impacted. Perceived financial burden, along with usability and privacy concerns, consistently discourages both providers and consumers from implementing IoT healthcare solutions [52], [53].

H7: *Cost is associated with the intention to adopt IoT healthcare products and service among customers.*

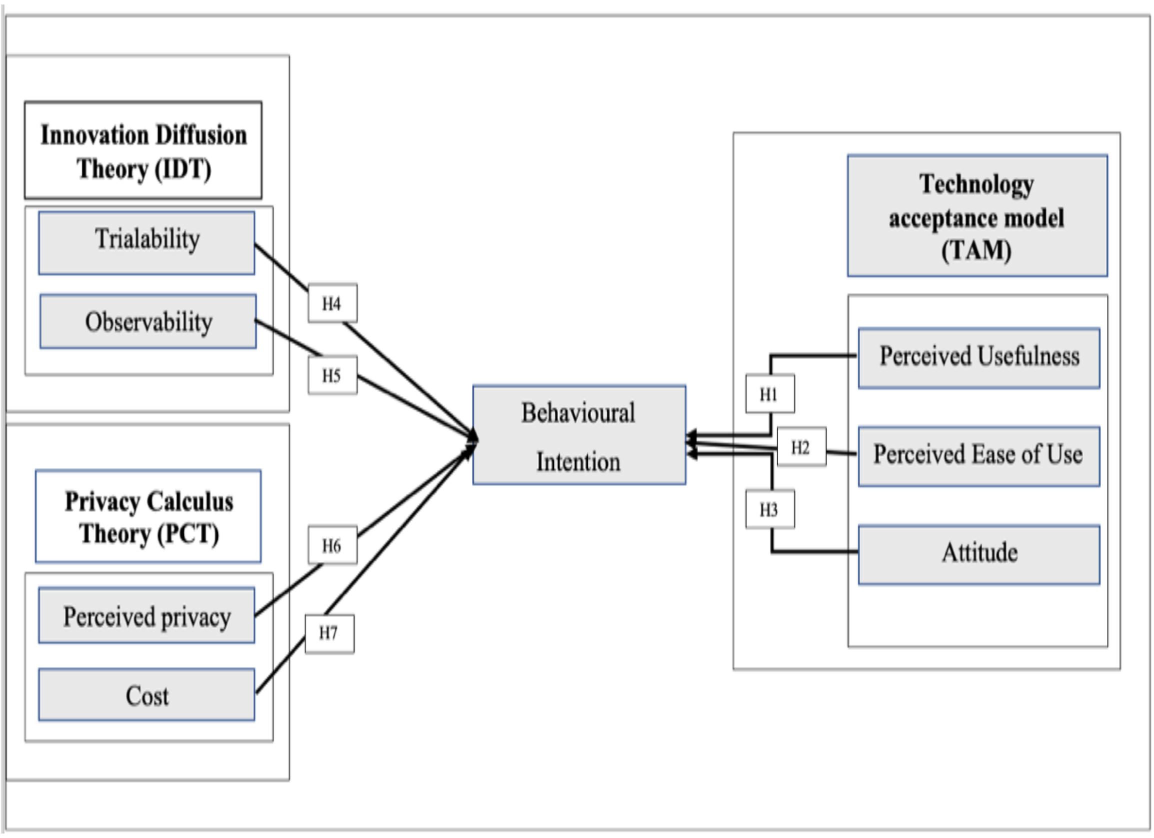

Figure 1. The Research Model

The model constructs derived from TAM, DOI, and Privacy Calculus Theory are integrated to examine factors influencing the behavioural intention for IoT healthcare technology.

4. Methodology

A quantitative research approach was employed to collect, analyze, and then address the research questions and evaluate the offered hypotheses. Quantitative studies may employ surveys, structured questionnaires, or experiments to gather data from participants [54]. To investigate the complicated relationships among different latent variables (PLS-SEM was applied; these constructs are inherent from the theories and models, including IDT, TAM, and privacy calculus theory). In exploratory research, PLS-SEM is useful for identifying key drivers and for the prediction of significant outcomes. The data were analysed with SmartPLS version 4.1.0.9, where both the measurement model and the structural model were assessed.

4.1. Population and Sample

In order to test the model and hypothesis, determining an appropriate sample size is very crucial. End consumers of IoT healthcare products who were over 18 years of age and owned a smart device are the target population for this study. The recommended minimum sample for a construct with at least seven requires a sample size of 300 to 500 participants [55] , [56]. To reach a wide range of respondents, convenience nonprobability sampling was used. Convenience sampling enables quick data collection from readily accessible participants, such as those in public places or online, given the emphasis on understanding general consumer opinions and intentions regarding IoT adoption in healthcare [57]. The data was distributed via an online survey instrument, Google Forms to reach the target population. After several months of data collection, 385 completed questionnaires were obtained from participants. This approach was appropriate for understanding consumer perceptions in a rapidly evolving technological context.

4.2. Design and measurement

The survey instrument, which consists of two primary sections, has been used, with the first section collecting demographic data from respondents and screening questions assessing their awareness and use of IoT healthcare products. The second section focused on constructs aligned with the study's objectives, measuring factors related to IoT healthcare adoption based on the three integrated theoretical frameworks. The study adapted measurement items from prior research to suit the context of IoT healthcare products. With only minor modifications, a pilot study was conducted, during which experts evaluated the instruments for validity and reliability. Primary data were collected from 385 participants using an online questionnaire with a five-point Likert scale. The survey assessed constructs such as perceived usefulness, observability, perceived privacy risk, and cost. These constructs were developed from the integrated model of TAM, IDT, and Privacy Calculus Theory.

4.3. Data Analysis

The data were analysed using SmartPLS version 4.1.0.9 and IBM SPSS Statistics to test and examine the hypothesis. A two-step data analysis approach was employed. Measurement model evaluation was the first step in order to determine if the constructs were reliable and valid. Following that, a structural framework was used to examine the relationships among the factors.

5. Evaluation and Results

5.1. Demographic details of respondents

To better understand consumers' willingness to adopt IoT healthcare products and services. Data were collected from 385 respondents. Demographic details collected from participants included gender, age group, education level, and income range. The gender distribution was balanced, with 207 males (53.8%) and 178 females (46.2%). Participants aged 25–35 constituted the largest group in the sample, with 182 respondents (47.3%). A large proportion of respondents had a bachelor's degree (49.6%), followed by those with a master's degree (30.6%). Doctorate holders accounted for 14.8%. Respondents with lower qualifications, such as a diploma, foundation, or secondary school, made up less than 5% collectively. Students formed the largest occupational category (54.0%). Private-sector employees accounted for 20.8%, and government employees accounted for 12.7%. The self-employed, the unemployed, and those in miscellaneous professions each accounted for less than 6%. In regard to monthly income, 42.1% reported earning less than $500 per month. Another 19.7% earned between $500 and $1,000. Only 10.4% reported incomes above $2,500 per month. A small proportion (3.9%) had no income. Student income and other sources accounted for less than 5% each.

5.2. Evaluation of the Research Model

To determine complex relationships of variables that cannot be observed directly, the PLS-SEM statistical method has been applied. This method is used to assess both reflective and formative factors and is appropriate for studying complex structures with small sample sizes [55]. This method was also used to examine the relationships among latent variables and to determine the extent to which the model explains changes in the primary constructs under study. The data analysis was conducted in two stages: measurement model evaluation and structural model evaluation. Both analyses were performed using SmartPLS.

5.3. Model Measurement model

A measurement model examines the relationships between each variable and its reflective indicators. Reliability testing focuses primarily on outer loadings, alpha value, and composite reliability. Conversely, convergent validity is established when indicator outer loadings exceed 0.70 and the Average Variance Extracted (AVE) is at least 0.50 [58]. In the present model, all eight constructs, namely, Trialability (TR), Observability (OB), Perceived Privacy Risk (PPR), Cost, Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Attitude Toward Use (AT), and Behavioral Intention (BI), were operationalized as reflective, indicator loadings ranged from 0.640 to 0.865, and the thresholds for reliability and validity were consistently achieved, as shown in Figure 2.

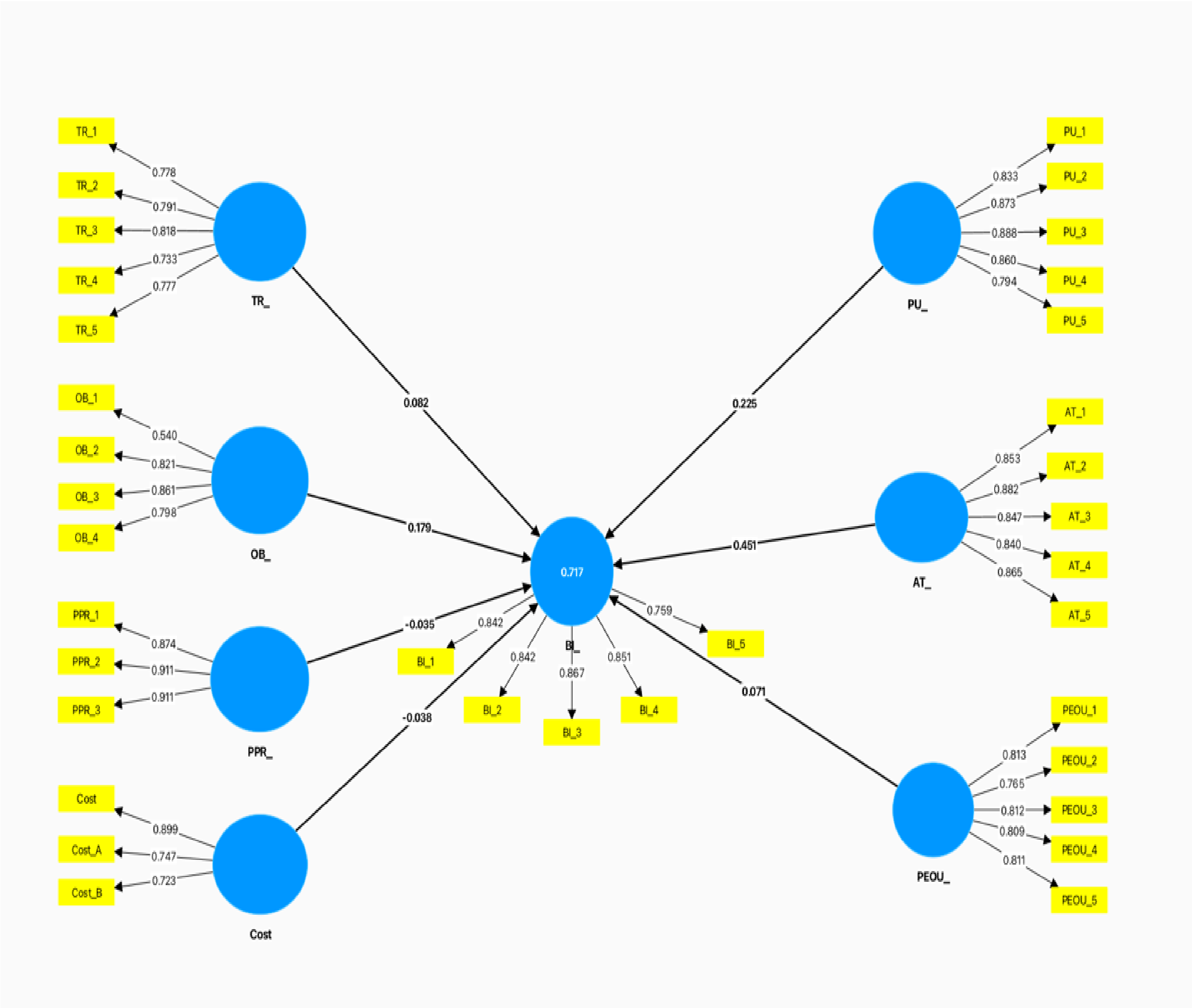

Figure 2. Structural Model of the Study

5.4. Factor Loadings, Convergent Validity, and Reliability Measures

The reliability of indicators reflects the extent to which each item is explained by its corresponding construct. A construct is reliable if its loadings are above 0.70, indicating that it explains over half of the indicator's variance. The loading between 0.4 and 0.7 may be kept if removing them does not improve the reliability. Loading values < 0.4 are usually removed [26]. All values of the factor loadings are more than the suggested level of 0.70, signifying adequate indication reliability. However, OB_1 (0.540) fell slightly below the acceptable limit; it was retained due to its theoretical relevance.

Table 2. Model Measurement model results

Constructs	Indicator	Factor Loading	Cronbach's Alpha	Composite reliability (rho_c)	AVE
Perceived Usefulness	PU_1	0.833	0.904	0.929	0.723
	PU_2	0.873			
	PU_3	0.888			
	PU_4	0.860			
	PU_5	0.794			
Observability	OB_1	0.540	0.754	0.846	0.586
	OB_2	0.821			
	OB_3	0.861			
	OB_4	0.798			
Perceived Privacy Risk	PPR_1	0.874	0.881	0.927	0.808
	PPR_2	0.911			
	PPR_3	0.911			
Cost	Cost	0.899	0.738	0.835	0.630
	Cost_A	0.747			
	Cost_B	0.723			

5.5. Discriminant Validity: Fornell–Larcker Analysis

When constructs that could be considered theoretically distinct demonstrate low correlations, discriminant validity is established, and these correlations are significantly lower than those observed for convergent validity. A lack of discriminant validity makes it unclear whether the results are genuinely supported by the data or influenced by the repeated use of the same construct, leading to unreliable conclusions. The value of discriminate should be more than 0.50 [59],[60].

Table 3. Discriminant Validity (Fornell–Larcker)

	AT	BI	Cost	OB_	PEOU	PPR	PU	TR
AT	0.858							
BI	0.805	0.833						
Cost	0.400	0.342	0.794					
OB	0.557	0.614	0.335	0.765				
PEOU	0.685	0.651	0.388	0.549	0.802			
PPR	0.381	0.340	0.442	0.429	0.332	0.899		
PU	0.791	0.752	0.406	0.543	0.677	0.369	0.850	
TR	0.679	0.651	0.436	0.609	0.572	0.438	0.643	0.780

The Fornell-Larcker criteria were used to assess the discriminant validity. The AVE square root of each variable exceeded the correlations with the other respected variables. It clearly demonstrates that every construct in the model measures a distinct topic and is empirically unique.

5.6. Structural Model Path Analysis

PLS-SEM was employed to evaluate path coefficients, and the following table presents an overview of the findings. Based on the result, attitude positively influences behavioral intention (AT → BI; $\beta = 0.451$, $p < 0.001$), supporting hypotheses on IoT healthcare product and service adoption.

Table 3. Results of the Structural Model

Path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AT_ -> BI_	0.451	0.449	0.053	8.491	0.000
Cost -> BI_	-0.038	-0.037	0.036	1.053	0.292
OB_ -> BI_	0.179	0.179	0.046	3.885	0.000
PEOU-> BI_	0.071	0.072	0.050	1.409	0.159
PPR_ -> BI_	-0.035	-0.035	0.037	0.943	0.346
PU_ -> BI_	0.225	0.225	0.059	3.837	0.000
TR_ -> BI_	0.082	0.083	0.057	1.429	0.153

Note: p-values were obtained from consistent bootstrapping (5,000 subsamples, two-tailed test, $\alpha = .05$). Bold indicates significance at $p < .05$. p-values in red indicate non-significant paths ($p \geq .05$).

The results indicate strong statistical support with a high path coefficient and significant t-value, indicating that positive attitudes toward IoT healthcare technologies enhance users' intention to adopt these solutions. Likewise, PU significantly improved BI ($\beta = 0.225$; $p < 0.001$), confirming H1 and H3. The findings show that individuals who perceive IoT healthcare technologies as valuable and beneficial in improving their health management and communication with healthcare providers are more inclined to adopt them. In addition, observability (OB) ($\beta = 0.179$, $t = 3.885$, $p < 0.001$) significantly predicts BI, supporting H5 and [61] DOI theory, which highlights observability's role in enhancing adoption through visible benefits.

However, TR ($\beta = 0.082$, $p = 0.153$) and PEOU ($\beta = 0.071$, $p = 0.159$) did not show significant effects on BI, failing to support H2 and H4, suggesting that ease of use and trialability may not directly drive adoption in this context, contrary to [61] Perceived privacy risk result shows (PPR; $\beta = -0.035$, $p = 0.346$) and the cost variable ($\beta = 0.082$, $p = 0.153$) did not have a statistically significant effect, offering no support for H6 and H7. This suggests that concerns related to privacy and financial cost, although emphasized in the Privacy Calculus Theory (PCT) and prior research [62] do not significantly hinder adoption. In general, the findings highlight that perceived usefulness, favorable attitudes, and observability are key drivers of IoT healthcare adoption. At the same time, ease of use, trialability, privacy risks, and costs play less direct roles, potentially due to contextual factors or indirect effects not captured in the model.

6. Discussion

The results shed light on how variables from TAM, IDT, and PCT collectively impact users' decisions to adopt IoT healthcare products and services. The findings revealed partial support for the proposed model, suggesting that while specific constructs significantly influence adoption, others have limited or no effect on users' behavioural intentions. Perceived usefulness, attitude toward adoption, and observability emerged as significant positive predictors of behavioural intention in healthcare. However, cost, ease of use, trialability, and privacy risk were not proven to be significant predictors.

Hypothesis 1 (H1) proposed that behavioural intention is linked to the perceived usefulness (PU) of IoT healthcare products and services. The results supported this hypothesis. The prior research by [63] , [64] finding aligns with this research. Similarly, [NO_PRINTED_FORM] [65] found that the perceived usefulness factor of utilizing IoT health products was significantly impacted by behavioral intention, whereas perceived usefulness was not predicted by personality attributes. In contrast, Hypothesis 2 suggests that PEOU results indicate a positive relationship, but it is not statistically significant. In contrast to the hypothesis 1 result, prior IS/IT research has indicated that TAM factors significantly influence behavioral intention [66].

Moreover, Hypothesis 3 (H3) was confirmed, with attitude (AT) emerging as the strongest predictor of willingness to adopt ($\beta = 0.451$, $t = 8.491$, $p < 0.001$). The findings of this hypothesis demonstrate that users possess a positive and favorable disposition towards acceptance. An additional investigation indicated that customers' overall good attitude and happiness with IoT will motivate them to stay invested in using it both presently and in the future [67].

While attitude showed a significant effect, hypothesis 4 (H4) trialability was found not to be significantly influencing behavioural intention to adopt IoT products and services. A prior study by [68] showed no significant relationship or effect on intention to use. Hypothesis 5 (H5) was also supported, which shows the relationship between observability and behavioural intention among customers. Previous research is consistent with this finding [44]. The findings illustrate that customers recognize and acknowledge the usefulness and features of IoT technology, which increases their likelihood of adoption.

Contrary to expectations, perceived privacy risk ($\beta = -0.035$, $p = 0.346$) and cost ($\beta = 0.082$, $p = 0.153$) were not significant predictors of behavioural intention. These results suggest that privacy and cost concerns are not the primary barriers to IoT healthcare adoption among the surveyed consumers. One possible explanation is that users increasingly trust technology providers or consider privacy trade-offs acceptable in exchange for the perceived health benefits. Similarly, cost may not be a decisive concern, as respondents may view IoT healthcare products as worthwhile investments in their personal well-being.

Overall, the supported relationships reinforce the applicability of established technology adoption theories in the healthcare context, emphasizing that behavioral intention is largely shaped by attitudinal and perceptual factors. These insights highlight the importance of studying these factors to design user-friendly, demonstrably beneficial, trustworthy, and affordable IoT healthcare solutions to enhance consumer acceptance and adoption.

6. Theoretical and Practical Implications

The implications of this study include both theoretical and practical. The most significant theoretical contribution of this research lies in its framework that examines the influencing factors affecting IoT healthcare product and service adoption by integrating TAM, DOI, and the Privacy Calculus Theory. This integration strengthens the conceptual framework for understanding IoT adoption. Furthermore, the study findings and framework provide insights and recommendations for healthcare providers, product managers, system developers, and medical specialists. The framework highlights the substantial impact of perceived usefulness and positive attitudes on adoption, demonstrating that users who perceive IoT products as beneficial are more inclined to adopt them. This contribution advances the health information technology literature and supports the healthcare industry in addressing adoption barriers.

In practice, this study benefits business managers, policymakers, and healthcare stakeholders by determining the primary factors influencing IoT adoption. Policymakers and medical professionals can use these insights to create frameworks for policies that address both behavioral and technology adoption challenges. Companies can enhance observability by designing transparent IoT features, like real-time health alerts (e.g., glucose or heart-rate monitoring), and promote perceived usefulness through marketing strategies, such as success stories, to improve consumer attitudes and adoption intentions. Additionally, addressing perceived privacy risks and pricing can further reduce reluctance.

7. Conclusion and Limitations

This study identified factors influencing IoT healthcare adoption using the integrated TAM, IDT, and PCT models. Despite IoT’s potential, adoption remains limited due to user hesitancy. By focusing on end users, this research gives an early behavioural analysis of IoT healthcare adoption. The main findings indicate that adoption decisions are significantly influenced by perceived usefulness, attitude, and observability. Perceived cost, perceived privacy risk, trialability, and ease of use, however, do not. These findings highlight the need to provide users with tangible benefits and results.

From a practical perspective, product designers and healthcare service providers must prioritise the most influential adoption factors in their IoT-enabled healthcare solutions. Companies can harness these insights to create IoT services that spark positive consumer attitudes and solid adoption intentions. By boosting observability with transparent features such as real-time feedback and health-monitoring reports, organisations can amplify perceived usefulness and drive ongoing engagement. Policy-wise, incorporating IoT into healthcare could enhance patient care and encourage the adoption of innovation. Offering incentives, including improved patient monitoring, customised treatment plans, or more efficient operations, might further encourage patient involvement. Policymakers and healthcare business leaders may leverage these insights to develop policy frameworks and adoption strategies that emphasise transparency, visible value creation, and user trust by integrating technological and behavioural considerations, as the earlier finding suggested.

This study has some drawbacks despite its contributions. This research relied on cross-sectional data collected from end consumers; therefore, the results may not be easily generalized to other cultural environments. Response bias may be introduced by self-reported, closed-ended survey data. Generalizability is further limited by the sample size. Future research should validate the model in diverse healthcare settings with larger samples. Researchers should consider longitudinal or mixed-method approaches to improve causal interpretations. Studying actual usage behavior, not just behavioural intention, will deepen understanding. Future research may further examine moderating variables like gender, age, or prior IoT experience. Overall, this study provides practical and theoretical insights for integrating IoT into consumer-centered healthcare systems.

Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this paper.

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