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# The Impact of AI-Driven Chatbots and Virtual Assistants on Users' Satisfaction and Actual Usage in Digital Healthcare Services

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***Abstract**: The domain of healthcare is undergoing rapid digital transformation, with users increasingly expecting efficient and seamless interactions. AI-powered healthcare chatbots are emerging as key tools in reshaping patient communication and promoting personalised health behaviour goals that align with individual preferences, needs, and constraints. This study draws on four key theoretical models: expectation-confirmation theory, the Technology Acceptance Model, trust theory, and perceived risk. The proposed framework was evaluated using partial least squares structural equation modelling from 434 users in Saudi Arabia. The statistical analysis validates the proposed research framework, which posits that meeting user expectations and ease of use have a strong influence on satisfaction and perceived usefulness. Trust boosts continued use, while perceived risk is surprisingly insignificant. Continuance intention is the strongest predictor of actual chatbot usage behaviour. These results offer valuable insights for healthcare technology developers and providers aiming to improve user adoption of AI-driven healthcare chatbots. The findings suggest that meeting or exceeding user expectations (confirmation) is crucial for satisfaction. Ease of use remains a fundamental requirement for perceived usefulness. Building trust is essential for encouraging continued usage intention. Satisfaction and continuance intention drive actual usage behaviour.*

***Keywords**: Artificial Intelligence, Chatbots, Digital Healthcare, User Satisfaction*

***Nomenclature:***
AI: Artificial Intelligence
LLMs: Large Language Models
PR: Perceived Risk
ECT: Expectation-Confirmation Theory
TAM: Technology Acceptance Model
PU: Perceived Usefulness
PEOU: Perceived Ease of Use
CI: Continuance Intention

## I. INTRODUCTION

The COVID-19 pandemic pushed organisations to quickly adopt technological innovations to maintain operations and safeguard business continuity [1]. The domain of healthcare is going through a swift digital transformation, with advancements in artificial intelligence (AI) and large language models (LLMs) leading to this transformation [2].

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Likewise, LLMs enhance chatbots and virtual assistants that are enabled to generate human-like responses through leading generative AI chatbots (e.g., ChatGPT, DeepSeek, Gemini) that are increasingly being utilised across diverse fields [3, 4]. In fact, chatbots demonstrate the increasing integration of AI-driven methods across diverse domains, showcasing their versatility and capacity to enhance human capabilities while optimising user experiences in various domains, such as banking, education, e-commerce, and healthcare [5, 6]. AI-powered chatbots are conversational tools designed to mimic human interactions through text or voice inputs [5]. In healthcare, these chatbots are gaining popularity, driven by the increasing use of telemedicine and virtual healthcare services [7]. Despite AI chatbots' ability to interact naturally with many users at the same time, evidence shows that the positive impacts of this technology may not be shared equally among all demographics [8, 9, 10]. The rapid integration of AI-driven technologies in healthcare has led to the increasing adoption of chatbots and virtual assistants for tasks such as appointment scheduling, health education, and diagnostics [7].

It is essential to address the specific challenges users encounter when adopting new technology to facilitate their integration into society [11, 12]. While prior research has evaluated user satisfaction based on demographic factors [8, 10] Less attention has been given to cognitive and emotional factors, such as trust and perceived risk (PR). Researchers highlight significant differences in users' motivations, mental capacities, attitudes, and perceptions, all of which influence how they engage with emerging technologies [5, 8, 10]. Moreover, less work has been done to understand the psychological and behavioural factors that influence user satisfaction and continuous usage. PR concerns about data privacy may hinder user trust and satisfaction, yet are often underexplored in current studies. This study seeks to fill this gap by adopting an integrated theoretical framework to investigate user satisfaction and actual usage (USE) of AI health technologies. This study draws on four key theoretical models. Expectation-Confirmation Theory (ECT) is employed to examine post-adoption satisfaction, while the Technology Acceptance Model (TAM) addresses perceived usefulness (PU) and perceived ease of use (PEOU). Trust theory is applied to assess users' trust in AI technologies, and PR is included as a cognitive inhibitor that may hamper usage. The integration of ECT and TAM provides a comprehensive foundation for understanding user satisfaction and USE. This integrated model is commonly used in research on continuance intention (CI) and holds particular significance for AI-powered health applications.


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We aim to investigate the following research questions.
RQ1: How do PU, PEOU, and confirmation influence user satisfaction?
RQ2: What is the role of trust in AI in shaping user satisfaction and CI?
RQ3: How does PR influence trust and user satisfaction in digital healthcare services?
RQ4: What factors most significantly predict the USE of AI chatbots and virtual assistants?

The remainder of the paper is structured as follows: Section II presents an overview of the existing literature. In Section III, the research framework adopted in this study is explained. Moreover, the methodology, including research design, data collection, and data analysis, has been illustrated in Section IV. Section V discusses the statistical results, followed by a discussion concerning implications and limitations in Section VII. Lastly, Section VII presents the conclusion and outlines future directions.

## II. RELATED WORK

### A. Overview of Digital Healthcare Services

Digitalization is playing an increasingly pivotal role across nearly all sectors of society [13, 14]. The healthcare sector, however, has been relatively slow to adopt digital technologies and has only recently begun to digitalise its services on a broader scale [15]. From telemedicine and electronic health records to mobile health apps and AI-based tools, these innovations are transforming traditional healthcare delivery [16]. The integration of AI-driven chatbots and virtual assistants in healthcare is a relatively recent advance and is still emerging, and requires further exploration [11, 16]. Current studies suggest that AI-driven chatbots and virtual assistants can significantly enhance user engagement and improve healthcare accessibility [11, 17] [12]. However, to sustain long-term adoption, greater emphasis must be placed on improving the user experience of these AI-powered solutions [16]. Still, unequal access, digital literacy gaps, lack of clinical validation, and resistance to adoption by users are some prevalent challenges reported by researchers [12, 15, 18].

### B. AI-based Chatbots and Virtual Assistants in Digital Healthcare

Before telemedicine, users were required to find a physician and book an appointment, which involved switching between multiple websites [16]. Instead of conducting extensive research, a universal healthcare assistant could be conveniently leveraged through voice queries, leading to the development of virtual healthcare agents for automation [19]. Over the last decade, the adoption of AI healthcare assistants has increased significantly, mainly because of the COVID-19 pandemic [20]. AI-powered chatbots in healthcare offer diverse functionalities, such as real-time support, 24/7 availability, and personalised attention. [10]. Global developments in AI and the advent of Chatbots made the development of virtual agents feasible [21]. AI-based healthcare chatbots are a specific form of personalised assistants that automate tasks in the healthcare industry, where each system mimics human cognition and behaviour to assist the users. In this domain, the user can simulate visual (images), speech (voice), or textual input [21]. AI-driven virtual health assistants have been adopted in the U.S. for chronic disease management, aiding in automated patient tracking and behavioural guidance [21, 22]. Similarly, Japan is actively considering the deployment of socially assistive AI chatbots in eldercare facilities to boost patient well-being [23]. These solutions address both (medical and emotional) needs, yet AI remains underutilised in primary healthcare within low-resource settings.

### C. User Satisfaction in Digital Healthcare

Achieving and sustaining user satisfaction is a critical challenge for many service-oriented industries [24]. Satisfaction is defined as the sense of pleasure or dissatisfaction that results from comparing a product's perceived performance against one's expectations [25]. Similarly, researchers emphasised that service convenience plays a significant role in influencing customer satisfaction in technology-driven services [10, 26]. Golinelli et al. [27] Conducted a systematic review of AI applications in healthcare that highlighted how these technologies improved healthcare delivery and addressed challenges in remote care, contributing to better healthcare quality and USE. Moreover, Esmaeilzadeh et al. [10] explained that user satisfaction with chatbots is strongly influenced by utilitarian values (e.g., ease of use, accuracy, relevance, privacy). User satisfaction has a direct impact on users' willingness to reuse the chatbot and adopt its recommended actions, highlighting its mediating role. Researchers pointed out that poor usability, limited personalisation, lack of human interaction, accessibility issues, and inconsistent service quality across platforms are some prevalent challenges concerning user satisfaction [10, 27, 28]. In summary, the growth of digital health technologies underscores the need to understand user needs and preferences deeply. Identifying key factors that influence adoption can offer valuable insights for developing and evaluating successful digital health solutions.

### D. Research Gaps

To the best of our knowledge, limited empirical research has been done to investigate the relationship between user satisfaction and USE in the context of AI-driven chatbots and virtual assistants in digital healthcare services. Previous studies have focused on conceptual or traditional prototypes (rather than AI-enabled tools), lacking consideration of users' perceptions in real-world environments. Furthermore, the distinctive features of the healthcare domain require a more nuanced investigation of how users interact with and perceive these tools.

## III. RESEARCH FRAMEWORK

We used the hybrid framework based on ECT and TAM. ECT examines post-adoption satisfaction, focusing on how


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users' initial expectations compare with their actual experiences. The TAM assesses PU and PEOU, which are essential factors influencing users' acceptance and continued use of technology. Moreover, trust theory evaluates the level of trust users place in AI. The research framework is illustrated in Figure I. The various constructs of the research framework, along with their corresponding hypotheses, are explained in the subsequent subsections.

### A. Perceived Usefulness

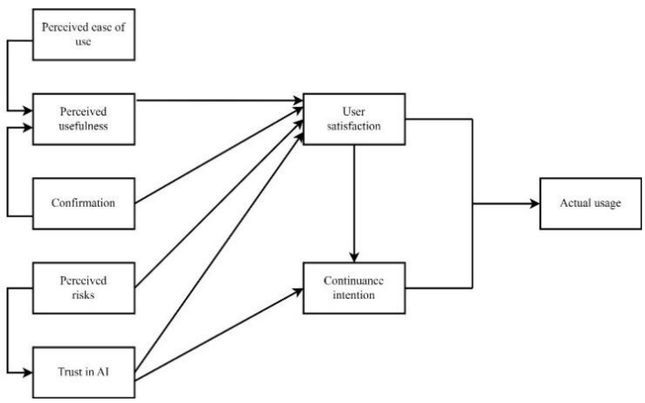
PU refers to an individual's belief that a technology enhances their efficiency and effectiveness in performing tasks or fulfilling roles [29]. In the context of AI-driven chatbots for digital healthcare, PU measures how well the chatbot improves user satisfaction and streamlines healthcare interactions. PU is a critical factor influencing the intention to adopt new technologies, as demonstrated in technology acceptance models [30].

- H1: PU positively affects USE.

### B. Perceived Ease of Use

In this study, we defined PEOU as the overall perception of users regarding their satisfaction and use of digital healthcare services through chatbots. The findings also concur with previous research on the TAM, which consistently finds that PU is a more powerful predictor than PEOU [31, 32, 33]. Moreover, users may adapt their behaviour to the new technologies if they perceive it to be easy [32] [34].

- H2: PEOU positively affects PU.




**[Fig.1: Research Framework]**

### C. Confirmation

In the context of AI-driven chatbots and virtual assistants in digital healthcare, CONF refers to users anticipating how effective and responsive technology will be in addressing their health-related requests or needs [35]. CONF is the comparison between the PU of the technology before use and its actual usefulness after use [36]. Based on the ECM, a positive association exists between users' expectations and post-experience confirmation of those expectations [37]. Hence, if users' expectations are confirmed after interacting with AI-driven tools in digital healthcare, they are likely to feel more satisfied and to perceive the technology as more useful.

- H3a: Confirmation positively affects PU.
- H3b: Confirmation positively affects USE.

### D. Trust

In this study, we define trust as the overall perception of users concerning the trustworthiness of AI-driven chatbots and virtual assistants in digital healthcare services. Even in digital healthcare environments, users seem to exhibit a higher degree of trust when interacting with AI-based systems compared to traditional online platforms. Drawing on existing literature, trust and satisfaction are recognised as closely related constructs. While trust is often considered a fundamental attribute of digital health, shaping how users respond to automated interactions, there is less evidence specifically examining trust in the context of AI-enabled healthcare tools [38, 39].

- H4a: Trust in AI positively affects USE.
- H4b: Trust in AI positively affects CI.

### E. Perceived Risk

In this study, PR refers to the potential adverse outcomes users associate with interacting with AI-driven chatbots and virtual assistants in digital healthcare services. The fourth industrial revolution has intensified the interconnectedness and interdependence between technological systems and users [40]. Identifying the various aspects of the PRs of these AI-enabled technologies in the healthcare context is, therefore, a crucial construct.

- H5a: PR negatively affects trust.
- H5b: PR negatively affects USE.

### F. User Satisfaction

Satisfaction is defined as the feeling of pleasure resulting from comparing an AI assistant's continued performance to initial user expectations [41]. This is often linked to CI and USE. In this study, user satisfaction refers to a user's evaluation of the digital healthcare service, encompassing all interactions and experiences, including those facilitated by AI systems. User satisfaction with AI-driven chatbots and virtual assistants can be a critical aspect for digital health providers.

- H6a: User satisfaction positively affects CI.
- H6b: User satisfaction positively affects USE.

### G. Continuance Intention

CI refers to an individual's conscious decision and willingness to continue using a product, service, or technology based on prior positive experiences, satisfaction, and perceived benefits [41]. In the context of digital healthcare services, this is particularly relevant, as users often rely on consistent and trustworthy digital communication. However, due to varying awareness levels about AI-based technologies, such as AI-driven chatbots across different countries and healthcare systems, the drivers of CI may not be uniform. In light of the existing literature on AI-based technologies, it is apparent that understanding the adoption and CI among users of these technologies in healthcare contexts remains inconclusive [42].



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- H7: CI positively affects USE

**Table I: Measurement Items for Research Constructs**

| Construct | Code | Measurement Item (English) |
|---|---|---|
| Perceived Usefulness | PU1 | Using the AI chatbot/virtual assistant improves my healthcare service experience. |
| | PU2 | The AI chatbot/assistant enables me to access healthcare information more efficiently. |
| | PU3 | I find the chatbot/assistant helpful for managing my health-related queries. |
| Perceived Ease of Use | PEOU1 | Interacting with the AI chatbot/assistant is clear and understandable. |
| | PEOU2 | It is easy for me to become skilled at using the chatbot/assistant. |
| | PEOU3 | I find the system easy to use without technical help. |
| Confirmation | CONF1 | My experience with the AI chatbot met my expectations. |
| | CONF2 | The chatbot's performance met my expectations. |
| | CONF3 | Overall, I am satisfied that the chatbot met my expectations. |
| Perceived Risk | PR1 | I am concerned about the accuracy of information provided by the chatbot. |
| | PR2 | I believe that relying on an AI chatbot for medical information may lead to incorrect decisions. |
| | PR3 | I worry about system errors or malfunctions while using the chatbot. |
| Continuance Intention | CI1 | I intend to continue using AI chatbots/assistants for digital health services. |
| | CI2 | I will frequently use AI-driven services for health-related purposes in the future. |
| | CI3 | I plan to rely on the chatbot/assistant when I need healthcare support. |
| Trust | TUR1 | I trust the chatbot to provide accurate information |
| | TUR2 | I feel confident that the chatbot will protect my privacy |
| | TUR3 | I find the chatbot is reliable in handling my requests |
| Actual Usage | USE1 | I often use the chatbot for government services |
| | USE2 | I intend to continue using the chatbot for similar needs in the future |
| | USE3 | I recommend using the chatbot to others seeking government services |
| User Satisfaction | SAT1 | I am satisfied with my overall experience using the chatbot |
| | SAT2 | The chatbot met my expectations for service quality |
| | SAT3 | I am pleased with the responses provided by the chatbot |

## IV. METHODOLOGY

### A. Research Design

The research design focuses on identifying the impact of AI-driven chatbots and virtual assistants on user satisfaction and USE in digital healthcare services. The survey instrument was carefully designed to include constructs derived from the integrated theoretical model, ensuring both content validity and reliability through pilot testing and expert review, as shown in Table I. Data collection was conducted using a structured survey questionnaire that systematically captured the behaviours, attitudes, perceptions, and beliefs of participants.

### B. Data Collection

A cross-sectional exploratory survey design was employed, which plays a crucial role in user experience research, enabling the identification of differences and the uncovering of challenges that may impact satisfaction. This approach is beneficial for understanding broad trends and gathering feedback quickly, making it valuable where time and resources are limited [43]. Moreover, a survey was designed that is both cost-effective and time-efficient, making it ideal for collecting data from a large number of users. It ensures anonymity, provides standardised and quantifiable data for easy analysis [44]. The data were collected between January 2025 and March 2025 from users of AI chatbots/virtual assistants in healthcare services at two hospitals in Makkah city, Saudi Arabia. The participants were recruited through social media platforms and emails. Google Form was used for online surveys as it allows researchers to reach a large population easily, is less expensive compared to traditional methods, has faster response rates through real-time data collection, automatically records responses in spreadsheets, reducing manual data entry and minimizing errors, and responses are stored in formats suitable for analysis, for graphical representation and statistical summaries [45]. The online link was sent to the healthcare professionals, whereas hard copies of the questionnaire were distributed in the selected hospitals. The survey, which took approximately 10 minutes to complete, included a series of questions assessed using a 5-point Likert scale. To ensure accessibility, the survey was provided in Arabic, and 434 users have submitted the study.

### C. Data Analysis

In this study, we used SmartPLS, which involved Partial Least Squares Structural Equation Modelling (PLS-SEM), to explore and quantify relationships between variables in complex models [46]. Researchers widely use SmartPLS to construct models that integrate latent variables (unobservable constructs) and their measurable indicators [47, 48]. It also facilitates the estimation of path coefficients, which represent the strength and direction of relationships, and evaluates the reliability and validity of the constructs. Moreover, it provides a visual and analytical framework to uncover insights, enabling researchers to make informed decisions about theoretical models and practical applications across various domains [46, 47].

## V. RESULTS

Table II presents the demographic statistics for the respondents. We collected data from 434 users, comprising 184 males (42.4%) and 250 females (57.6%). Regarding age distribution, 89 users

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(20.5%) fell within the 18 to 30-year-old range. The 31 to 40 age group has the highest representation, with 143 users (32.9%). The 41 to 50 age group comprises 108 users (24.9%), while the oldest category, those over 50 years, includes 94 users (21.7%). The data highlight that most users are between 31 and 40 years old, while the smallest proportion is those aged 18-30 years.

**Table II: Demographic Statistics**

| Demographics | Category | Frequency | Percent |
|---|---|---|---|
| **Gender** | Male | 184 | 42.4% |
| | Female | 250 | 57.6% |
| **Age** | 18–30 | 89 | 20.5% |
| | 31–40 | 143 | 32.9% |
| | 41–50 | 108 | 24.9% |
| | More than 50 | 94 | 21.7% |

**Table III: Reliability of Each Construct with Interpretation**

| Constructs | Cronbach's Alpha Score | AVE Score | Interpretation |
|---|---|---|---|
| CI | 0.852 | 0.772 | CI demonstrates excellent reliability and validity, indicating that the measurement items for CI are consistent and accurately represent the construct. |
| CONF | 0.870 | 0.793 | CONF shows strong reliability and validity measures, suggesting that the items measuring confirmation of expectations are highly consistent and effectively capture the construct. |
| PEOU | 0.801 | 0.715 | PEOU demonstrates good reliability and validity, indicating that the measurement items are consistently and effectively capturing the PEOU construct. |
| PR | 0.732 | 0.786 | PR has the lowest Cronbach's alpha score among all constructs; however, the values still exceed the acceptable thresholds. Interestingly, PR has one of the highest AVE values, suggesting that, despite being slightly lower in internal consistency compared to other constructs, the items effectively capture a high proportion of the variance in the PR construct. |
| PU | 0.803 | 0.717 | PU shows good reliability and validity, indicating that the measurement items for PU are consistent and effectively capture the construct. |
| SAT | 0.876 | 0.802 | SAT demonstrates the highest reliability and validity measures across most indicators, suggesting that the measurement items for SAT are highly consistent and effectively capture the construct. |
| TUR | 0.796 | 0.710 | TUR shows good reliability and validity, indicating that the measurement items for trust are consistent and effectively capture the construct. |
| USE | 0.864 | 0.786 | USE demonstrates excellent reliability and validity, indicating that the measurement items for AU are highly consistent and effectively capture the construct. |

### A. Reliability and Validity Evaluation

The statistical analysis revealed that all constructs demonstrate good internal consistency and reliability (α > 0.7), as shown in Table 3. Moreover, the composite reliability values are excellent across all constructs, indicating strong internal consistency. Composite reliability is generally considered a more appropriate measure than Cronbach's alpha in PLS-SEM because it accounts for different indicator loadings. The AVE score > 0.5 indicates good convergent validity. The statistical analysis revealed that all constructs significantly exceeded the 0.5 threshold; the highest values were observed for SAT (0.802), CONF (0.793), USE (0.786), and PR (0.786); the lowest, but still excellent, was TUR (0.710). All AVE values are well above the recommended threshold, indicating that each construct explains more than 50% of the variance in its indicators. The high reliability and validity metrics suggest that the measurement instrument is robust and appropriate for the research context of AI healthcare chatbot adoption. Based on reliability and validity metrics, SAT, CONF, and USE demonstrate the most robust measurement properties, while PR, although still acceptable, shows slightly lower reliability compared to the other constructs. The measurement model meets all established criteria for reliability and validity in PLS-SEM analysis, supporting the appropriateness of the research instrument for investigating user adoption of AI healthcare chatbots.

Discriminant validity confirms that a construct is truly distinct from other constructs in the model by empirical standards. This is crucial for establishing that constructs measure different concepts and are not redundant with each other [49]. Statistical analysis showed that there are the strongest correlations observed between USE and CI (0.715), which makes theoretical sense as CI should strongly predict USE; SAT and CONF (0.751), aligning with ECT theory by confirming that meeting expectations strongly relates to USE; and USE and CONF (0.671), indicating a strong relationship between CONF and USE. The weakest correlations involved PR with almost all constructs (< 0.25), suggesting that PR operates relatively independently of other constructs, consistent with earlier findings where PR's relationships were not statistically significant, as shown in Table IV. A particularly low correlation was observed between PR and SAT (r = 0.055), further supporting the conclusion that PR does not significantly impact USE. Theoretically relevant correlations include PU and PEOU (r = 0.632), aligning with TAM theory, where PEOU influences PU; TUR and CI (r = 0.637), confirming the relationship between TUR and CI; and USE and SAT (r = 0.690), supporting the expectation that user satisfaction leads to increased USE. The high correlation between CONF and SAT (r = 0.751) highlights the importance of meeting user satisfaction in healthcare chatbot contexts, reinforcing the strong relationship between these constructs. The moderate-to-high correlations between TUR and both CI and SAT validate TUR as a significant factor in the model, consistent with the substantial path coefficients. The Fornell-Larcker analysis provides strong evidence that all constructs in the model exhibit sufficient discriminant validity. This discriminant validity evidence, combined with the previously established reliability and convergent validity, confirms that the measurement model meets all necessary quality criteria for robust PLS-SEM analysis, providing a solid foundation for the conclusions drawn from the structural model testing.


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**Table IV: Discriminant Validity**

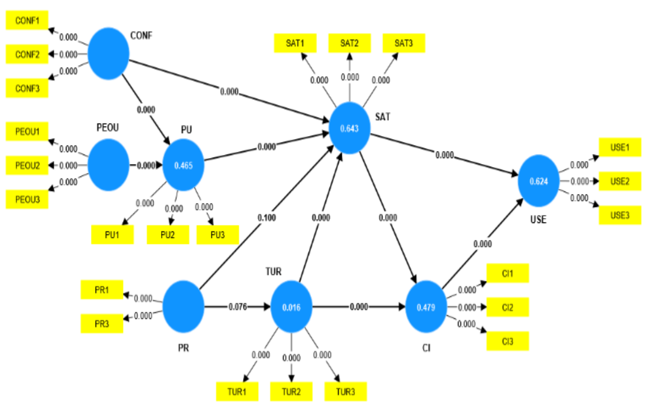
| | CI | CONF | PEOU | PR | PU | SAT | TUR | USE |
|---|---|---|---|---|---|---|---|---|
| CI | 0.879 | | | | | | | |
| CONF | 0.565 | 0.890 | | | | | | |
| PEOU | 0.478 | 0.601 | 0.846 | | | | | |
| PR | 0.085 | 0.023 | 0.140 | 0.887 | | | | |
| PU | 0.550 | 0.584 | 0.632 | 0.246 | 0.847 | | | |
| SAT | 0.584 | 0.751 | 0.608 | 0.055 | 0.630 | 0.895 | | |
| TUR | 0.637 | 0.540 | 0.457 | 0.127 | 0.444 | 0.565 | 0.843 | |
| **USE** | 0.715 | 0.671 | 0.503 | 0.105 | 0.613 | 0.690 | 0.540 | 0.887 |

## B. Structure Model Evaluation

Once the reliability and validity of the measurement model were confirmed, the structural model was assessed. This section outlines the key steps involved in evaluating the structural model.

## C. Direct Effects

In statistical analysis, a direct effect refers to the influence of an independent variable on a dependent variable that is not mediated by any other variables [50]. Figure II illustrates the structural equation model for AI healthcare chatbot adoption, featuring several key structural relationships with standardised path coefficients and $R^2$ values. The high $R^2$ value for SAT, along with its position as a mediator between multiple constructs and outcomes, highlights its central role in the model.




**[Fig.2: Structural Model]**

The very low $R^2$ for TUR confirms that PR explains almost none of the variance in TUR, consistent with the non-significant path coefficient. The USE is strongly predicted by both user satisfaction and CI, supporting the dual influence channels. The relationship between PEOU and PU is confirmed, supporting the integration of TAM principles in the context of healthcare chatbot adoption. The direct path from CONF to SAT demonstrates the importance of meeting user expectations in driving satisfaction. It confirms the strong explanatory power of the model for key outcomes (USE, SAT, CI) while also highlighting the limited role of PR. Moreover, the complex interrelationships between cognitive factors (PU, PEOU), affective factors (SAT, TUR), and behavioural outcomes (CI, USE) in the adoption of healthcare chatbots have been observed. The high $R^2$ values for the primary dependent variables validate the theoretical integration approach that the model successfully captures the key determinants of AI healthcare chatbot adoption and usage.

PU positively affects USE, with a path coefficient (PU → SAT) of 0.270 and a P-value of 0.000 (< 0.05), supporting the hypothesis. PEOU positively affects PU, as indicated by a path coefficient (PEOU → PU) of 0.440 and a P-value of 0.000 (< 0.05), confirming that users who find the AI chatbot easy to use also perceive it as more useful. CONF has significant positive effects on both PU and USE, with a path coefficient (CONF → PU) of 0.320 and P-value of 0.000 (< 0.05), and (CONF → SAT) of 0.495 and P-value of 0.000 (< 0.05). These results show a more substantial effect on USE. TUR in AI also significantly affects both USE and CI, with path coefficients (TUR → SAT) of 0.184 and (TUR → CI) of 0.451 and 9.732, and P-values of 0.000 in both cases, with a more substantial impact on CI. PR, however, does not show significant effects, with a path coefficient (PR → TUR) of 0.127 and P-value of 0.076, and (PR → SAT) of -0.046 and P-value of 0.100. These results do not support the hypothesis, and notably, the relationship between PR and TUR is unexpectedly positive. SAT has a positive effect on both CI and USE, with path coefficients (SAT → CI) of 0.329 and (SAT → USE) of 0.414 and P-values of 0.000. Finally, CI has a positive influence on USE, as indicated by the path coefficient (CI → USE) of 0.473 and a P-value of 0.000, confirming a strong relationship. The results of hypothesis testing are shown in Table V.

**Table V: Hypothesis Testing**

| Hypothesis | Path | Coefficient | t-value | p-value | Result |
|---|---|---|---|---|---|
| H1 | PU → SAT | 0.270 | 5.294 | 0.000 | Supported |
| H2 | PEOU → PU | 0.440 | 9.420 | 0.000 | Supported |
| H3a | CONF → PU | 0.320 | 7.685 | 0.000 | Supported |
| H3b | CONF → SAT | 0.495 | 7.889 | 0.000 | Supported |
| H4a | TUR → SAT | 0.184 | 3.863 | 0.000 | Supported |
| H4b | TUR → CI | 0.451 | 9.732 | 0.000 | Supported |
| H5a | PR → TUR | 0.127 | 1.772 | 0.076 | Not supported |
| H5b | PR → SAT | -0.046 | 1.645 | 0.100 | Not supported |
| H6a | SAT → CI | 0.329 | 6.113 | 0.000 | Supported |
| H6b | SAT → USE | 0.414 | 9.347 | 0.000 | Supported |
| H7 | CI → USE | 0.473 | 9.372 | 0.000 | Supported |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The findings strongly support the ECT framework, where CONF has a significant influence on both PU and user satisfaction with AI healthcare chatbots. CONF has the most substantial direct effect on user satisfaction among all predictors, highlighting the importance of meeting user expectations. The TAM relationships are also confirmed, with PEOU having a significant impact in PU, and PU having a substantial effect on USE. The PEOU → PU relationship is notably strong, emphasizing the importance of user-friendly design in healthcare chatbots. TUR plays a significant role in both user satisfaction and CI, with a powerful effect on CI. Contrary to expectations, PR does not significantly affect either TUR or USE.

**Table VI: Results of Indirect Effects Measurements**

| | Original Sample | Sample Mean | Standard Deviation | P Values |
|---|---|---|---|---|
| SAT -> CI -> USE | 0.155 | 0.155 | 0.029 | 0.000 |
| PR -> TUR -> SAT -> CI -> USE | 0.004 | 0.004 | 0.003 | 0.160 |
| PEOU -> PU -> SAT -> USE | 0.049 | 0.049 | 0.013 | 0.000 |
| PR -> TUR -> CI | 0.057 | 0.058 | 0.033 | 0.084 |
| TUR -> CI -> USE | 0.213 | 0.213 | 0.032 | 0.000 |
| CONF -> PU -> SAT | 0.086 | 0.086 | 0.020 | 0.000 |
| PEOU -> PU -> SAT -> CI -> USE | 0.018 | 0.019 | 0.006 | 0.003 |
| CONF -> PU -> SAT -> CI | 0.028 | 0.029 | 0.009 | 0.002 |
| CONF -> SAT -> CI -> USE | 0.077 | 0.077 | 0.016 | 0.000 |
| PEOU -> PU -> SAT | 0.119 | 0.119 | 0.027 | 0.000 |
| CONF -> SAT -> CI | 0.163 | 0.163 | 0.031 | 0.000 |
| PEOU -> PU -> SAT -> CI | 0.039 | 0.040 | 0.012 | 0.002 |
| PR -> SAT -> USE | -0.019 | -0.018 | 0.011 | 0.094 |
| PU -> SAT -> CI | 0.089 | 0.090 | 0.025 | 0.000 |
| PR -> TUR -> CI -> USE | 0.027 | 0.027 | 0.016 | 0.081 |
| TUR -> SAT -> USE | 0.076 | 0.076 | 0.022 | 0.000 |
| CONF -> SAT -> USE | 0.205 | 0.206 | 0.035 | 0.000 |
| PR -> TUR -> SAT -> CI | 0.008 | 0.008 | 0.006 | 0.165 |
| PR -> SAT -> CI -> USE | -0.007 | -0.007 | 0.005 | 0.143 |
| PR -> SAT -> CI | -0.015 | -0.015 | 0.010 | 0.126 |
| CONF -> PU -> SAT -> USE | 0.036 | 0.036 | 0.010 | 0.000 |
| PU -> SAT -> USE | 0.112 | 0.112 | 0.026 | 0.000 |
| PR -> TUR -> SAT | 0.023 | 0.024 | 0.015 | 0.127 |
| PR -> TUR -> SAT -> USE | 0.010 | 0.010 | 0.007 | 0.146 |
| CONF -> PU -> SAT -> CI -> USE | 0.013 | 0.013 | 0.004 | 0.002 |
| TUR -> SAT -> CI -> USE | 0.029 | 0.028 | 0.009 | 0.003 |
| TUR -> SAT -> CI | 0.060 | 0.060 | 0.019 | 0.002 |
| PU -> SAT -> CI -> USE | 0.042 | 0.042 | 0.012 | 0.001 |

This surprising finding suggests that in the context of healthcare chatbots, users may not associate PR with decreased TUR or USE. The strong relationships between USE, CI, and SAT validate the behavioural component of the model. CI has the most substantial direct effect on USE (0.473), confirming its role as a key predictor of chatbot adoption. The extended ECT-TAM framework is largely validated, with 9 out of 11 proposed relationships showing statistical significance. The most potent effects are observed in the PEOU → PU, CONF → SAT, CI → USE, and TUR → CI relationships, suggesting these are the most critical factors in healthcare chatbot adoption. These results offer valuable insights for healthcare technology developers and providers aiming to improve user adoption of AI-driven healthcare chatbots. The non-significant relationships between PR and both TUR and user satisfaction warrant further investigation, as they contradict theoretical expectations. This might indicate that in healthcare contexts, other factors may moderate or mediate these relationships.

## D. Indirect Effects

The statistical analysis of indirect impacts revealed that user satisfaction influences usage through CI, confirming that user satisfaction drives usage by fostering the intention to continue, as shown in Table VI. TUR also affects USE primarily by building CI and, through a longer path, by enhancing USE, which then increases CI. CONF plays a central role by affecting USE, which then drives both CI and SAT. It also works through PU, which leads to increased SAT, then CI, and ultimately USE. These multi-step paths show CONF's pervasive influence through various mechanisms. PEOU contributes to PU, which enhances SAT and drives both CI and USE. This supports the TAM model, highlighting that PEOU is a foundational driver of perceived value and system engagement. PU enhances SAT, which in turn drives CI and USE, further validating its central role in the model. TUR has dual channels of influence: it directly builds CI and indirectly works through USE, confirming its broad impact on user behaviour. PR, by contrast, shows no statistically significant indirect effects through any pathway. The effects are inconsistent in direction and magnitude, suggesting that PR does not have a meaningful influence on outcomes in this context. Key insights include the prominence of TUR and CONF as the most potent mediators, the consistent significance of complex multi-step mediation paths, the minimal role of PR, the validation of TAM constructs, and the multifaceted influence of TUR across both direct and indirect channels.

These findings enhance our understanding of the complex mechanisms through which various factors influence the adoption and usage of AI healthcare chatbots. CONF has pervasive effects through multiple pathways, making it a critical factor for developers/ Healthcare chatbots must consistently deliver on promised functionality to drive positive outcomes. While TUR exerts a significant influence through multiple pathways, PR has a limited impact on outcomes. This suggests focusing on building TUR might be more productive than addressing risk perceptions in healthcare chatbot design. User satisfaction mediates many significant relationships, confirming its central role in the framework. Enhancing user satisfaction should be a priority for healthcare chatbot developers. Understanding these specific mediating paths allows for targeted interventions. For example, to improve USE, one could focus on either enhancing TUR (which works strongly through CI) or CONF (which works strongly through SAT). The significance of these complex mediating paths validates the integration of ECT and TAM with trust and risk constructs.

## VI. DISCUSSION

The statistical analysis examined user adoption of AI-driven healthcare chatbots through an extended theoretical framework integrating the ECT, TAM, and constructs of trust and PR. To respond to RQs, the comprehensive assessment of measurement quality, path relationships, and model fit revealed strong support for most hypothesised relationships, with particularly notable influences of confirmation, trust, satisfaction, and CI on USE behaviour. Our findings align with the ECM and TAM, which emphasise that when users perceive a technology as applicable and their expectations are met (confirmation), satisfaction increases. Moreover, Trust in AI emerged as a critical antecedent to both user satisfaction and CI. Users who perceived the AI system as reliable, transparent, and aligned with their interests were more likely to continue using it and express satisfaction with it. These results support prior work emphasising the role of trust in reducing perceived uncertainty, especially in healthcare contexts. However, the consistent non-significance of PR's relationships contradicts theoretical expectations because risk perceptions apparently function differently in healthcare technology contexts. This finding suggests a need to reconsider how risk is conceptualised or measured in healthcare AI applications.

The findings of this research enhance the understanding of the complex mechanisms through which various factors influence the adoption and usage of AI healthcare chatbots. Confirmation (meeting expectations) has pervasive effects through multiple pathways, making it a critical factor for developers and providers to focus on. Healthcare chatbots must consistently deliver on promised functionality to drive positive outcomes. While trust exerts a significant influence through multiple pathways, PR has a limited impact on outcomes. This suggests focusing on building trust might be more productive than addressing risk perceptions in healthcare chatbot design and marketing. User satisfaction mediates many significant relationships, confirming its central role in the framework. Enhancing satisfaction should be a priority for healthcare chatbot developers. Understanding these specific mediating paths allows for targeted interventions. For example, to improve USE, one could focus on either enhancing trust (which works strongly through CI) or confirmation (which works strongly through SAT). The significance of these complex mediating paths validates the integration of ECT and TAM with trust and risk constructs. This integrated approach provides a more comprehensive understanding of healthcare chatbot adoption than any single theoretical framework.

### A. Theoretical Implications

The results validate the integration of ECT and TAM with trust constructs in the context of healthcare chatbots. The ECT components show strong effects (CONF → SAT, CONF → PU). Similarly, the TAM relationships are confirmed (PEOU → PU, PU → SAT). Moreover, trust emerges as a crucial factor influencing both satisfaction and CI. The consistent non-significance of PRs' relationships contradicts theoretical expectations because risk perceptions apparently function differently in healthcare technology contexts. This finding suggests a need to reconsider how risk is conceptualised or measured in healthcare AI applications. The significant indirect effects reveal the complex mechanisms through which factors influence actual usage. Both cognition-based paths (through PU) and emotion-based paths (through satisfaction) significantly influence usage. Trust operates through two channels: directly influencing CI and indirectly impacting outcomes through satisfaction.

### B. Practical Implications

The findings indicated that confirmation emerged as the strongest predictor of satisfaction, suggesting that healthcare chatbots must consistently deliver on promised functionality. Moreover, trust significantly affects both satisfaction and CI, so trust-building should be prioritised over addressing risk perceptions. Furthermore, PEOU significantly affects PU, and simple, intuitive interfaces remain crucial for the adoption of technology. Satisfaction mediates many key relationships and directly affects usage; therefore, developers should focus on enhancing features and experiences that promote satisfaction. Lastly, CI strongly predicts actual usage and features promoting repeated engagement should be emphasised.

### C. Limitations and Future Work

The fit indices suggest room for theoretical refinement, and the inclusion of additional constructs or relationships may enhance model comprehensiveness. The unexpected findings regarding PR warrant further investigation, and different dimensions or measures of risk might be more relevant in healthcare contexts. Moreover, demographic, cultural, or healthcare-specific moderating variables could enhance understanding, so the relationship between PR and trust might vary across different user groups.

## VII. CONCLUSION

This study contributes to both theory and practice by expanding the ECT-TAM model with PR in a healthcare context, offering actionable insights for developers and policymakers to enhance AI adoption, and addressing concerns about safety and data privacy in digital health interactions. The comprehensive analysis of the extended ECT-TAM framework provides strong empirical support for most hypothesised relationships in the context of AI healthcare chatbot adoption. The integrated theoretical approach offers valuable insights into the complex mechanisms that drive user satisfaction, CI, and actual usage. The findings highlight the critical roles of confirmation, trust, satisfaction, and CI while challenging assumptions about PR. Healthcare technology developers should focus on meeting user expectations, building trust, enhancing usability, and creating a satisfying user experience to drive the adoption and sustained usage of AI healthcare chatbots. These insights contribute to both theoretical understanding and practical implementation in this rapidly evolving domain of digital healthcare.

## DECLARATION STATEMENT

I must verify the accuracy of the following information as the article's author.

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