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# Understanding AI Acceptance in Healthcare: A Mixed-Method Study on Trialability and Doctor-Patient Relationships

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***Abstract***

*The implementation of artificial intelligence is transforming healthcare practices by its ability to improve its practices. However, despite the benefits, its widespread acceptance remains a challenge. This study aims to advance the understanding of the key antecedents of AI acceptance by patients, using an extension of the TAM by incorporating trialability and doctor-patient relationships. A sequential mixed-method approach was employed, beginning with semi-structured interviews to identify adaptable factors in healthcare and then a survey to validate the qualitative findings through Structural Equation Modeling (SEM) via AMOS (version 24). The results confirmed that trialability significantly enhances AI adoption by lowering uncertainty, while strong doctor-patient relationships positively influence perceived usefulness. In addition, findings showed that Perceived usefulness is the strongest antecedent of AI adoption while perceived ease of use plays a secondary role. The study offers theoretical advancements in AI adoption models and practical insights by highlighting the need for healthcare providers and policymakers to emphasize AI trial opportunities and foster trust-based patient communication.*

***Keywords:*** *Artificial Intelligence, Technology Acceptance Model (TAM), Trialability, Doctor-patient relationship, Healthcare adoption.*

## Introduction

Artificial intelligence (AI) is considered as a transformative, general-purpose technology that is reshaping industries across the globe, with healthcare being one of the most impacted sectors (Malik et al., 2019; Brynjolfsson & McAfee, 2017; Cheng et al., 2022; Sobaih et al., 2025). Medical AI encompasses many applications, including auxiliary diagnosis, risk prediction, disease triage, health management, and hospital administration, all facilitated by advanced algorithms such as machine learning and deep learning (He et al., 2019). The promise of AI in Healthcare lies in its ability to revolutionize Patient care by improving diagnostic accuracy, enhancing treatment options, and optimizing operational efficiency (Olawade et al., 2024).

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Nevertheless, the successful adoption of AI in healthcare is a complicated process, shaped by several factors that go beyond technological capabilities. In other words, adoption is not only about deploying AI solutions; rather, it's about the ongoing use and integration of AI into everyday clinical workflows (Homburg et al., 2009; Olawade et al., 2024). However, for AI to meaningfully transform healthcare, it must become available to target users (healthcare providers and patients) and be implemented into operations to improve patient outcomes and healthcare delivery (Prakash et al., 2022). To increase adoption in the real world, AI tools must be trusted and accepted by patients, clinicians, health organizations, and authorities (Lekadir et al., 2025).

Patient acceptance is the keystone in the successful integration of AI into healthcare as they're the end users of this technology. An absence of appropriate levels of acceptance could lead to underutilization, causing inefficiencies, waste, and lost opportunities for further innovation (Kirlidog & Kaynak, 2013; Lee & See, 2004; Parasuraman & Riley, 1997; Chew & Achananuparp, 2022). On the other hand, High acceptance rate results in broad implementation, allowing AI to realize its full potential in enhancing patient outcomes, refining clinical workflows, and enabling more informed decision-making.

Different theories have been proposed to describe the adoption and utilization of technology in health settings. The Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) and the AI Device Use Acceptance Model (AIDUA) (Gursoy et al., 2019) have been employed to investigate the psychological, behavioral, and contextual variables influencing the acceptance of artificial intelligence technologies.

Among these, the best-known and empirically tested model is the Technology Acceptance Model (TAM), which informs and explains Information Technology (IT) adoption on the individual level (Cheng et al., 2022). The Technology Acceptance Model (TAM) (Davis, 1985, 1989) holds that perceived usefulness (PU) and perceived ease of use (PEOU) are the two major determinants when user acceptance is concerned. These constructs have been found to play a substantial role in clinical and patients' AI technology acceptance (Chakraborty et al., 2021; Roppelt et al., 2024; Sobaih et al., 2025).

Yet, although models like the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) provide valuable insight into patient attitudes and intentions to use technology, the character of artificial intelligence (AI) in the medical sector involves special factors such as greater mobility, greater risk, and less trust. These distinguish healthcare AI from other technological innovations, so a TAM or UTAUT-based model does not fully explain the intention to use AI (Fernández-Llamas et al., 2018; Cheng et al., 2022; Sobaih et al., 2025). While most of the existing literature expanded TAM or UTAUT to solve these problems, it is necessary to identify other determinants of AI use in healthcare organizations.

The primary purpose of this study is to advance the understanding of AI in healthcare settings and more precisely, the key antecedents of AI acceptance by patients, using an extension of the TAM. Unlike prior studies in the context of TAM, this research incorporates two relatively underexplored constructs of trialability and doctor-patient relationships to evaluate their impact on the acceptance of AI. A mixed-method approach was employed, combining both qualitative and quantitative phases to ensure a comprehensive examination of these factors. The qualitative phase allowed for the identification of key constructs, which were subsequently validated through quantitative analysis.

The novelty of this study is that it empirically investigates the doctor-patient relationship as a predictor of perceived usefulness of AI in healthcare, an aspect that, to our knowledge, had not been empirically examined before. By adding these relational and experiential variables to TAM, this study provides a fuller model for AI adoption explanation. This not only theoretically enriches the discourse by placing trust-based interactions in the context of technology acceptance models but also provides practical implications for the adoption of artificial intelligence in healthcare environments. The integration of trialability and doctor-patient relationship dynamics covers important gaps in existing academic literature, providing a customized model that accurately reflects the peculiar complexities associated with the adoption of technology in healthcare.

## Literature Review

## Overview of TAM

The original model by Davis, first introduced in 1989 and known as the Technology Acceptance Model (TAM), has becomét a widely-used foundation for understanding how users accept technology. TAM was originally developed to evaluate users' responses to Information Technology systems, but this concept is currently employed in many domains, including the sphere of healthcare. TAM has two primary constructs, perceived usefulness (PU), and perceived ease of use (PEOU). Such constructs can predict a user intention to adapt a new tech (Davis, 1989; Venkatesh et al., 2003; Sobaih et al., 2024). These constructs are critically valuable in the healthcare context as innovative solutions, including AI solutions, EHRs, and telemedicine, are increasingly essential to contemporary practice.

PU is defined as the extent to which a person believes that using a specific technology improves his/her performance. Research has indicated that PU significantly impacts healthcare professionals' and patients' initial lean towards the adoption of innovations including EHRs and telemedicine systems as these technological tools are recognized to provide assistance in enhancing patient care, and most importantly operational excellence (Holden & Karsh, 2010; Dou et al., 2017).

On the other hand, Perceived Ease of Use (PEOU) is degree of perceived ease or difficulty that users think they would encounter when using the technology. Studies have shown that technologies with user-friendly interfaces are adopted in clinical practices more easily. Perceived usefulness is particularly important for preventing resistance to new tools, including AI applications (Venkatesh & Bala, 2008; Sobaih et al., 2024; Wu & Wang, 2005) . Acceptance and adoption of a system is more easily achieved when users perceive the system as easy to use (Ye et al., 2019; Roppelt et al., 2024).

Venkatsh & Davis (2000) proposed an extension of the original TAM, namely TAM2, where other variables like subjective norms, image, perceived job relevance and perceived quality of output had been added to build a more detailed understanding of PU. They also incorporated other variables such as computer self-efficacy, computer anxiety and perceived external control to influence PEOU. These improvements allowed TAM to a better flexibility in different contexts. This was followed by TAM3 model which integrates the PEOU determinants with the extensions of TAM2 which enhances the model's capability in explaining the user behavior in several contexts (Bîlbîie et al., 2024).

TAM and all the related models have been employed extensively in examining AI acceptance in the healthcare context (See Table 1).

| **Study** | **Focus** | **Key Findings** |
|---|---|---|
| Alhashmi et al. (2020) | Extended TAM to study AI-based patient monitoring systems. | PEOU and PU significantly influence healthcare workers' intentions to adopt AI. |
| Liu and Tao (2022) | Explored trust's role in smart healthcare services. | Trust was more influential than PU in shaping behavioral intentions. |
| Roppelt et al. (2024) | Argued for adapting TAM with social influence and trust in healthcare. | Social influence and trust are crucial for AI adoption in healthcare. |
| Chatterjee et al. (2021a) | Integrated TAM2 with trust and attitude for healthcare CRM systems. | PU and PEOU were significant predictors of AI adoption. |
| Na et al. (2022) | Combined TAM with the Technology–Organisation–Environment (TOE) framework. | Technological traits, external variables, and personality positively influenced PU and PEOU, but environmental factors disrupted acceptance. |
| Panagoulias et al. (2024) | Proposed an AI explainability framework integrating TAM with REALM and machine learning. | Explainability and interpretability enhance trust and usability in AI systems, supporting transparency and validation. |
| Roy et al. (2024) | Examined physicians' behavioral intentions toward AI-based diabetes diagnostic tools. | PU, PEOU, and subjective norms positively impact intentions, while perceived risk negatively affects them. Experience moderates these relationships. |
| Chen et al. (2024) | Studied perceptions of ChatGPT in healthcare, focusing on usefulness, trust, and risks. | Trust and novelty were key factors for adoption. Tailored applications are needed to meet diverse user expectations. |
| Reddy (2024) | Explored generative AI integration using TAM and NASSS frameworks. | Generative AI can revolutionize healthcare but requires strategic adoption, change management, and real-world piloting. |

Table 1. Studies on AI Acceptance Using TAM Model

While TAM is useful in explaining AI adoption, Bao and Lee (2023), affirms that TAM lacks adequate capacity in predicting adoption of healthcare specific technologies such as AI. They propose certain contingent factors, including a regulatory environment as well as compatibility with clinical work arrangements. Subsequently, Zin et al. (2023) strengthened this criticism by explaining that TAM is insufficient in explaining the AI acceptance in healthcare. In response, this research extends TAM by incorporating variables such as trialability and the doctor-patient relationship to provide a more comprehensive framework for understanding AI acceptance in healthcare.

Acknowledging the constraints of the Technology Acceptance Model (TAM), this research adopts a mixed-methods approach to enhance the model by incorporating context-specific factors. In the initial phase, qualitative data collection was conducted to uncover variables uniquely relevant to AI adoption in healthcare. These insights were then tested in a subsequent quantitative phase to validate the findings within an expanded TAM framework. The following section delves into the qualitative results, providing new perspectives on the dynamics of AI acceptance within the healthcare domain.

## Research Model and Hypothesis

Given the multitude of factors influencing patient acceptance of AI in healthcare, a qualitative study was conducted to identify the most relevant determinants in the healthcare context. This phase involved semi-structured interviews with a diverse group of 43 participants, selected through a combination of purposive, snowball, and convenience sampling. This diverse sample included individuals from various professions, age groups, and genders, allowing for a broad understanding of the factors influencing AI acceptance. Notably, 73.2% of the participants were female, and the age range ranged from 21 to 60. Occupations varied widely including workers (7%), IT engineers (14%), professors (28%), students (19.5%), teachers (2.3%), unemployed individuals (4.7%), managers (2.3%), senior directors (2.3%), those in liberal professions (2.3%), and retirees (4.7%). The sample exhibits a diverse representation of individuals from various genders, age groups, and professional fields.

The interview guide was designed around three main phases: an introductory phase to gather perceptions of AI in general, a subject-focused phase exploring AI's impact on healthcare, and a deepening phase aimed at identifying factors that encourage AI adoption.

The thematic analysis, conducted independently by multiple researchers using NVIVO software, revealed that the findings of the qualitative study strongly align with the core variables of the TAM model, such as perceived usefulness and perceived ease of use. The data were coded and categorized into meaningful themes and sub-themes, and these results were systematically discussed among the researchers to reach an agreement on the final set of findings. In this study, one major theme, "factors influencing AI acceptance," was identified, with key sub-themes including perceived usefulness, perceived ease of use, trialability, and the relationship with the doctor. This thematic structure highlights the importance of these context-specific elements in shaping AI acceptance in healthcare.

To enhance the reliability of the qualitative phase, direct quotes from participants, as shown in Table 2, were used to support the emerging themes. The validation process involved two independent researchers who carefully examined and compared the sub-themes with the interview transcripts to ensure consistency. Additionally, the analysis was cross-referenced with concepts from existing literature, providing further validation of the study's findings and confirming their alignment with established research on technology acceptance (Charfi, 2012). These results present strong evidence for extending the traditional TAM framework by incorporating the elements of trialability and the doctor-patient relationship, highlighting the necessity of a more comprehensive model that reflects the specific dynamics of AI adoption in healthcare.

| **Theme** | **Subtheme** | **Number of citations** | **% of the theme** | **Verbatim** |
|---|---|---|---|---|
| Factors Influencing Patient Acceptance | Perceived Usefulness | 30 | 69.77% | *-"AI can make a full revolution in health care by enabling better diagnoses, treatments, and therefore saving lives. Ans as a result we as patients should not resist it."* |

| | | | | |
|---|---|---|---|---|
| to AI | | | | *-"AI in use within healthcare will help the doctors and staff make better decisions, leading toward good outcomes on my health and this is why I encourage all my family to accept it."*<br>*-"AI technology can automate repetitive and mundane tasks, freeing healthcare professionals to take up more complex and critical tasks."*<br>*-" I'm willing to use AI as it can analyze large bulks of data much faster compared to what any human mind would be capable of processing; hence, it always gives a quicker and more probable diagnosis and as a result, it can save my life."*<br>*-"It can also help in the forecast of health problems much earlier before they occur, thus enabling early interventions and better health outcomes."*<br>*-"By leveraging the power of AI for the evaluation of data collected from patients, health care providers are in a better position to craft treatment programs tailored to meet the needs and traits unique to each patient."*<br>*-"AI can lower health costs by improving efficiency, lessening administrative burdens, and optimizing error minimization."*<br>*-" It can also enable health professionals to monitor remotely, deliver more personalized care, and thus help reduce the rate of hospitalization."*<br>*-"AI can improve the accuracy of medical imaging and analysis, leading to earlier detection and better treatment of diseases."*<br>*"AI has the potential to uncover patterns and trends in patient data, paving the way for more targeted and effective treatments."*<br>*"Personally, I believe AI can significantly boost diagnostic precision and speed, ultimately leading to better patient outcomes. That's why I'm encouraged to embrace its use."* |

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|---|---|---|---|---|
| | Perceived Ease of Use | 15 | 34.88% | *-"I really found the AI-powered application very easy to use. In a few minutes, it was able to track symptoms and make personal recommendations."*<br>*"I was skeptical about trying this AI diagnostic tool, but it couldn't have been simpler. All I had to do was answer a few questions, and in seconds, I got a probable diagnosis."*<br>*"This AI-powered virtual assistant is incredibly user-friendly. Instead of searching for information myself, I just talk to it, and it tells me everything I need to know about my medication and treatment."*<br>*-"The symptom checker AI is much more convenient and easier to use for me. I do not have to wait for the appointment or leave my house when getting suggestions about my health concerns."*<br>*-"The AI chatbot helps me with the reminders for medication. It's way easier than setting reminders for my phone or handling all those pillboxes."*<br>*-"That AI-powered virtual assistant that works out an appointment for me and finds healthcare providers, it is just so simple to deal with. I don't have to sift through some confusing website or sit on hold on the phone."* |
| | Trialability | 39 | 90.70% | *-"I would be willing to try, on a trial basis, an AI-based system for healthcare administration so that I can experience firsthand the benefits derived from it.."*<br>*-"I'd rather have an opportunity to try it before committing; it will tell me if my needs and preferences using AI-based healthcare will be met by then."*<br>*-"It would be nice if the AI-based healthcare systems provided a type of trial period in which the patients can assess the efficacy, as well as the ease of use."*<br>*-"If there were a trial version for some AI-* |

| | | | | |
|---|---|---|---|---|
| | | | | *based healthcare system, I would want to try it out more rather than going forward and just using it."*<br>*-"A trial period for medical healthcare systems based on AI would give me a reason to increase my confidence in its capabilities and thus want to use it in the future."*<br>*"I'd like to give AI in healthcare a try and see how it could benefit me and improve my health."* |
| | Relationship with the Doctor | 27 | 62.79% | *-"Because I have had a strong relationship with my doctor and trusts his judgment, I would be more open-minded to seeing the benefits of AI if the recommendation came from him."*<br>*-"My doctor knows history and wishes; if they felt that the use of AI added any value, then confidence would be there indeed that the addition to my care is useful."*<br>*-"A good relationship with one's doctor means trusting their advice. If this doctor thinks that AI could improve one's health, then it would be something useful."*<br>*-"Since I had a good rapport with my doctor, if he uses AI, then I feel that is for good enough reason. That makes me more likely to consider AI as an effective tool in my treatment."*<br>*-"My doctor has always made good decisions for my health. If they believe this AI could be a big help, I'd trust that it's useful."*<br>*- "I'd only trust my doctor's opinion if they've known me and my needs for years—and even then, only if they feel AI would genuinely improve my care."* |

Table 2. Synthesis of Verbatims

This research uses the Technology Acceptance Model (TAM) as its foundational framework and modifies it to address the unique issues related to the adoption of healthcare technologies. To capture these complexities, the model has been extended to include variables like trialability and the doctor-patient relationship. These additions are crucial in informing the hypotheses of the conceptual model, which will be further tested and validated during the quantitative phase (see Figure 1).

Based on our current knowledge, limited research has rigorously investigated the relationship between individual-level determinants and healthcare-specific factors in influencing the acceptance of artificial intelligence. Studies that incorporate the Technology Acceptance Model with supplementary variables, such as trialability and the doctor-patient relationship, are notably lacking. Although most of the literature has focused on the technical and clinical barriers to artificial intelligence adoption, there remains a huge gap in understanding how these factors interrelate to influence the adoption behaviors of both patients and healthcare practitioners.

This study aims to bridge that gap by developing a comprehensive model that integrates key behavioral and contextual factors influencing AI acceptance in healthcare. In doing so, it not only advances theoretical understanding of AI adoption but also offers practical insights for successfully implementing AI in healthcare settings. These contributions respond to calls for more in-depth exploration of AI integration in healthcare systems (Char et al., 2020; Fernandes et al., 2020; Sobaih et al., 2025).

## Hypothesis

From the results of the qualitative study, two qualitative TAM constructs were identified: perceived usefulness and perceived ease of use as the two cognitive belief measures needed to assess intention to adopt artificial intelligence in healthcare environments. From the patients' point of view, perceived usefulness refers to the degree to which people think that the adoption of AI technologies will enhance the quality and effectiveness of their healthcare experiences, including improvements in diagnostic accuracy or optimization of treatment processes, or providing more tailored care (Davis, 1989). Perceived ease of use, on the other hand, reflects users' perceptions about the perceived difficulties or ease associated with the practical application of AI technologies and, hence, influences their likelihood to adopt those technologies in practice (Venkatesh et al., 2003).

A large body of literature indicates the strong relationship between these constructs and behavioral intention (BI). Studies have shown that when artificial intelligence technologies are perceived as beneficial, patients will be more inclined to adopt them (Chuah et al., 2016; Lunney et al., 2016). Moreover, ease of use not only increased the perception of usefulness but also had a direct impact on behavioral intention, as an easier-to-use system is more likely to be perceived as valuable and consequently adopted (Kleijen et al., 2004). These trends have emerged from the qualitative data gathered in this research study, with respondents indicating the significant function that the ease of integration and functionality has in their willingness to adopt artificial intelligence. Based on these qualitative insights and the voluminous literature that has supported TAM, we suggest the following hypotheses:

H1: Perceived usefulness positively influences healthcare professionals' and patients' intention to use AI.

H2: Perceived ease of use positively influences healthcare professionals' and patients' intention to use AI.

The qualitative findings from this study underscored trialability as a pivotal factor influencing AI adoption in healthcare, surpassing the traditionally emphasized constructs of perceived usefulness and ease of use in shaping behavioral intentions. Trialability, defined as the capacity to experiment with a new technology on a limited scale before committing to full adoption (Rogers, 2003), plays a crucial role in this context. In healthcare, enabling patients to engage with AI tools in practical, real-world scenarios can significantly mitigate uncertainty, foster trust in technology, and provide essential hands-on experience, ultimately enhancing the likelihood of adoption.

As noted by Al-Gahtani (2003), personal experience with innovations helps users to overcome uncertainties and to realize how technology can work in their specific contexts. This factor is very important in the health sector where new technologies are normally perceived as complicated or difficult to use. The availability of testing time for AI systems will, therefore, help to remove the apprehensions, thus reducing resistance to adopting the systems. Atkinson (2007) and Park and Chen (2007) highlight that innovations accompanied by practical experimentation are Likely to be adopted more quickly. Similarly, Chung and Holdsworth (2012) found that trialability is a strong predictor of adoption intention for emerging technologies, such as mobile commerce. In the healthcare sector, where decision-making often involves high risks, enabling users to have the opportunity to trial AI systems could be crucial in gaining widespread acceptance and adoption. Thus, the following hypothesis is proposed:

H3: Trialability has a positive influence on the intention to use AI in healthcare settings.

Insights obtained from the qualitative study, supported by extant literature, provide evidence that the doctor-patient relationship plays an important role in shaping patients' perceptions of artificial intelligence within the healthcare sector. This relationship refers to the social tie between health professionals and patients that acts as an essential factor in how patients perceive the introduction of AI technologies. Moreover, this relationship significantly influences consumers' general health outcomes, thus making it very relevant within the health sector dynamics (Yan et al., 2016; Wu et al., 2020). Positive interaction between doctors and patients is how trust is fostered, while it in turn determines the mindset of patients regarding the use of artificial intelligence technologies as constructive to healthcare. Peng et al. (2020) found that patients whose trust in their physicians is guaranteed are ready to accept technology-based interventions as part of healthcare. Similarly, earlier research highlights the key role that sound doctor-patient relationships play in chronic illness care and in developing acceptance of health technologies (Kaplan et al., 1989). In AI-related areas, trustworthy health care professionals are of critical importance to patients in gaining trust, particularly if such innovations have the endorsement of their physicians (Koopman et al., 2014).

The qualitative findings from our study align closely with these observations, demonstrating that patients who place trust in their doctors are more inclined to accept recommendations regarding the use of AI in managing their health. These individuals exhibited lower levels of resistance to AI, evaluating its benefits through the lens of their physicians’ expertise and credibility. Consequently, the doctor-patient relationship emerges as a pivotal element in enhancing the perceived value and fostering the adoption of AI technologies within healthcare settings. Thus, we propose the following hypothesis:

H4: The relationship with the doctor positively influences the perceived usefulness of AI in healthcare.

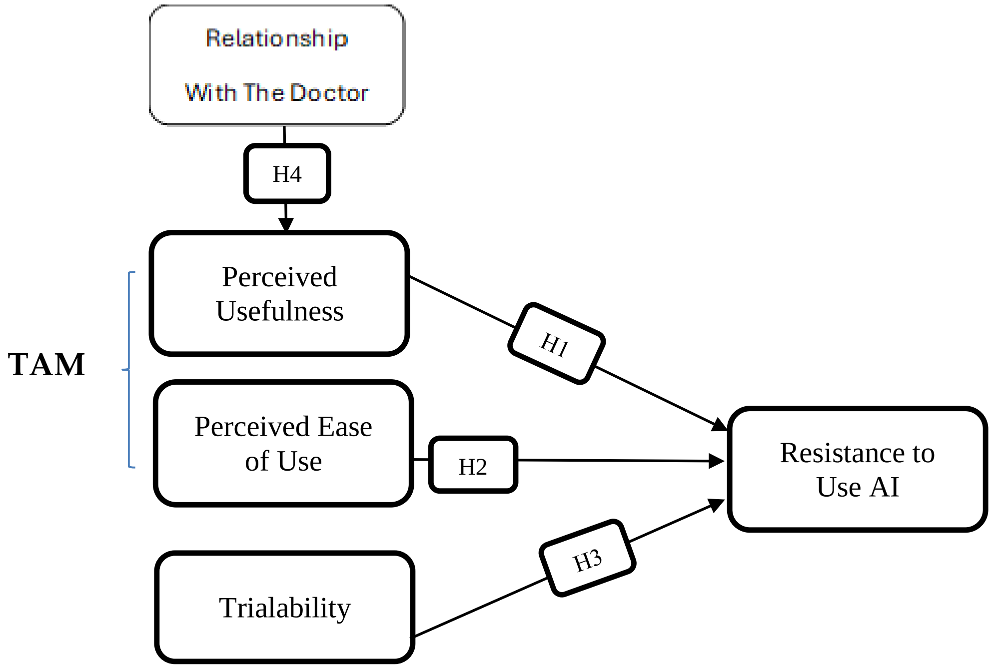


Figure 1. Conceptual Model

## Method

The next stage of this research, which is quantitative, focuses on the validation of the factors identified in the previous qualitative stage. For this purpose, a structured questionnaire was prepared to collect information on factors influencing the acceptance of artificial intelligence by Tunisian patients within the health sector.

### Data Collection

The survey method was chosen as the best way to collect quantitative data, following the suggestions of Saunders, Lewis, Thornhill (2012) and Creswell (2013). Particularly, online surveys were preferred for their capability in reaching a wide and varied number of respondents (Zikmund, 2010). To better response rates, a mix of self-administered and interviewer-administered survey tools was used to allow respondents provide clarifications when needed (Saunders et al., 2009).

Non-probability sampling methods, including purposive sampling, convenience sampling, and snowball sampling, were adopted to ensure a representative sample of the target population (Cavana, Delahaye & Sekaran, 2001; Guarte & Barrios, 2006). A Likert scale was integrated in the survey design to measure key attitudes toward AI acceptance consistently (Evrard et al., 2009). Since most respondents were Tunisian, the questionnaire was translated into French to ensure it was culturally and linguistically appropriate (Hafeez-Baig, 2010).

A pilot testing of the questionnaire was conducted before the actual data collection began, for the improvement of its content based on respondents' feedback about clarity and to also streamline its length. This was necessary to ensure the questionnaire was reliable and valid (Temessek, 2008).

Respondents were informed that the survey was purely for academic purposes and that some demographic data, such as gender, age, and level of education, would be collected. Participation was on a totally voluntary and anonymous basis, and respondents were allowed to fill out the survey at their leisure. All data collected was stored in a manner that secured the confidentiality and privacy of the participants (Li et al., 2022; Martikainen et al., 2020).

This structured approach is used to rigorously evaluate the extended TAM framework through integration of additional variables—trialability and relationship with the physician—to ensure the robustness and validity of the research model

**Measurement Scale**

The study adopted established scales from previous studies to measure the main constructs related to AI acceptance in the healthcare context (Table 3). Scales for PU and PEoU from Davis' original Technology Acceptance Model—TAM, 1989—with contextual adjustments informed by the studies of Kim and Park (2012), Sun et al. (2013), and Ye et al. (2019). To assess trialability defined as the comfort people feel about trying new technologies, items were modified from Rogers' Innovation Diffusion Theory (2003).

The construct of Intention to Use AI incorporated elements from Davis' TAM model, further enriched by insights from Holden and Karsh (2010), emphasizing user readiness to adopt AI in healthcare. Additionally, trust in healthcare providers was assessed using the doctor-patient relationship scale, examining how these dynamic impacts the perceived usefulness of AI tools (Koopman et al., 2014). Table 3 presents the factors included in the research model, along with their measurement items. These constructs were measured using a Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree").

| **Constructs Measurement items** | **Constructs Measurement items** | **Author** |
|---|---|---|
| Perceived Usefulness (PU) | PU1 AI Technology would help me to cope with preventable diseases at an early stage<br>PU2 AI Technology would be a good supplement to traditional healthcare approaches and fit with my medical philosophy<br>PU3 Using AI technology would improve the quality of my health care.<br>PU4 Using AI technology would improve my access to healthcare services.<br>PU5 Using AI technology would be useful in my health management routine (Routine check-ups, Treatment, Diagnosis)<br>PU6 Using AI will be useful to manage my health information<br>PU7 Using AI will enable me to manage my health tasks | Davis, 1989; Kim & Park, 2012; Sun et al., 2013; Ye et al., 2019 |

| | | |
|---|---|---|
| | more quickly<br><br>PU8 I will experience more self-management in my health care by using AI | |
| Perceived Ease of Use (PEoU) | PEoU1 Using AI Technology to manage my health would be easy<br><br>PEoU2 Interaction with AI Technology when managing my health would be clear and understandable<br><br>PEoU3 I would find it easy to get the AI Technology to do what I want it to do<br><br>PEoU4 AI Technology would offer a more convenient way for me to cope with my disease without queuing for registration in hospitals and would save me time and money. | Davis, 1989; Kim & Park, 2012 |
| Trialability (TRI) | TRI1 Before deciding on whether or not to adopt AI technology, I would need to use it on a trial basis<br><br>TRI2 Before deciding on whether or not to adopt AI technology, I would need to properly try it out<br><br>TRI3 I would be permitted to use the AI technology on a trial basis long enough to see what it can do | Rogers, 2003; Al-Gahtani, 2003 |
| Intention to use (IU) | IU1 I intend to use AI Technology in the future to manage my health conditions<br><br>IU2 I intend to use AI Technology frequently in my medical treatment, daily health management, and Diagnosis.<br><br>IU3 I intend to recommend that other people use the AI Technology in Health Management<br><br>IU4 I would like my doctor to use AI technology. | Davis, 1989; Holden & Karsh, 2010 |
| Relationship with the doctor (RWD) | RWD1 Doctors are my most trusted source of health information<br><br>RWD2 When I have a health concern, my first step is to contact a doctor | Koopman et al., 2014 |

Table 3. Measurement Scales

**Data Analysis**

The quantitative data were subjected to a structured analysis process, which unfolded in five distinct stages. Initially, IBM SPSS software was used to conduct Exploratory Factor Analysis (EFA) and to assess reliability through Cronbach's alpha. Subsequently, AMOS software was used for Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM). Table 4 summarizes the key stages of data analysis, detailing the objectives of each phase and the anticipated outcomes:

| Phase | Objective | Outcome | Software |
|---|---|---|---|
| Demographic Analysis | To analyze respondent profiles (age, gender, etc.) | Understanding participant characteristics | SPSS |
| Validity & Reliability | To assess the internal consistency of measurement scales (e.g., Cronbach's alpha) | Ensures that the scales are reliable | SPSS |
| Exploratory Factor Analysis | To identify underlying factors and determine variance explained by each factor | Refines measurement model, identifies key structures | SPSS |
| Confirmatory Factor Analysis | To confirm the factor structure and assess model fit | Validates the model's alignment with the data | AMOS |
| Structural Equation Modeling | To evaluate causal relationships between variables and assess overall model fit (RMSEA, CFI, TLI) | Tests the hypotheses and evaluates how well the model explains AI acceptance in healthcare | AMOS |

Table 4. Phases of Data Analysis, Objectives, and Software Used

## Results

## The Demographic Results

A total of 450 participants took part in this study, with 228 respondents (50.7%) identifying as male and 222 (49.3%) as female, ensuring a balanced gender representation. The age distribution was predominantly within the 18-24 (27.6%) and 25-34 (25.8%) age groups, reflecting a younger participant base more inclined towards adopting AI technologies in healthcare.

The participants came from diverse occupational backgrounds, with 31.6% being students, 24.9% identifying as executive managers/directors, and 22.7% working as teachers/professors. In terms of educational background, 34.7% held a bachelor's degree, while 32.0% had achieved a doctoral degree, suggesting a highly educated cohort.

Given the 21 scale items to be tested and adhering to the minimum sample requirement of 5:1 subject-to-parameter ratio, at least 105 questionnaire responses would have been sufficient for the analysis (Bentler & Chou, 1987). Therefore, with 450 participants, the sample size significantly exceeds the threshold and is considered more than adequate for robust analysis.

Participants' AI knowledge levels varied, with 56.4% having basic knowledge, 2.2% having no knowledge, and another 2.2% reporting advanced knowledge of AI. This variation in AI proficiency provides a comprehensive understanding of how different familiarity levels might influence AI acceptance in healthcare settings. The general characteristics of the sample are presented in Table 5.

| | | Frequency | Percentages % |
|---|---|---|---|
| Gender | Male | 228 | 50.7 |
| | Female | 222 | 49.3 |
| | Total | 450 | 100,0 |
| Age | 18-24 years old<br>25-34 years old<br>35-49 years old<br>50-64 years old 90<br>65 years old and above | 124<br>116<br>84<br>90<br>36 | 27.6<br>25.8<br>18.7<br>20.0<br>8.0 |
| | Total | 450 | 100,0 |
| Education | Primary Education<br>Lower Secondary Education<br>Upper Secondary Education<br>Post-secondary non-Tertiary Education<br>Bachelor's degree or equivalent tertiary education level<br>Master's degree<br>Doctoral degree<br>Engineering Degree | 2<br>6<br>16<br>8<br>156<br>104<br>144<br>14 | 0.4<br>1.3<br>3.6<br>1.8<br>34.7<br>23.1<br>32.0<br>3.1 |
| | Total | 450 | 100,0 |
| Occupation | Teacher/Professor | 102 | 22.7% |
| | Executive Manager/Director | 112 | 24.9% |
| | Worker | 46 | 10.2% |
| | Engineer | 22 | 4.9% |
| | Unemployed | 8 | 1.8% |
| | Retired | 18 | 4.0% |
| | Total | 450 | 100,0 |
| Level of knowledge of AI | Minimal Knowledge | 78 | 17.3% |
| | Basic Knowledge | 254 | 56.4% |
| | Adequate Knowledge | 98 | 21.8% |
| | Superior Knowledge | 10 | 2.2% |
| | Total | 450 | 100,0 |

Table 5. Demographic Characteristics of Respondents

## EFA results

Exploratory Factor Analysis (EFA) was carried out to assess the validity and consistency of the five main constructs: PU, PEOU, Trialability, Relationship with the Doctor, AI usage intention (Table 6). Internal consistency of each of the constructs was assessed using Cronbach's Alpha coefficients for reliability. The analysis results further showed that all the constructs had good reliability levels as presented in the following table. More specifically, Perceived Usefulness obtained a Cronbach's Alpha of 0.966, Perceived Ease of Use 0.953, Trialability 0.952, Relationship with the Doctor 0.848 and Intention to Use AI 0.944. These results indicate that the observed constructs have strong psychometric features, and their applicability for examining the factors that influence AI use in the context of healthcare is appropriate. The KMO Index, Bartlett's Test for the suitability and Cross- Validity, Explained Variance has been summarized in the following table as well as their reliability indices using Cronbach's Alpha.

| Construct | Factorial Structure | KMO Index | Bartlett's Test (p-value) | Cronbach's Alpha | Explained Variance (%) |
|---|---|---|---|---|---|
| Perceived Usefulness | Unidimensional | 0.920 | 1985.500 (p=0.000) | 0.966 | 80.924% |
| Perceived Ease of Use | Unidimensional | 0.902 | 1500.865 (p=0.000) | 0.953 | 87.777% |
| Trialability | Unidimensional | 0.889 | 1120.250 (p=0.000) | 0.952 | 91.290% |
| Relationship with the Doctor | Unidimensional | 0.847 | 1256.412 (p=0.000) | 0.848 | 86.829% |
| Intention to Use AI | Unidimensional | 0.944 | 1770.865 (p=0.000) | 0.944 | 85.910% |

Table 6. EFA and Reliability Results for Measurement Constructs

## Confirmatory Factor Analysis (CFA)

CFA was performed to test the structure and validity of the measurement model. Various fit indices were considered in order to determine the appropriateness of the model, including Chi-square (Chi2), Goodness of Fit Index (GFI), Adjusted Goodness of Fit Index (AGFI), Root Mean Square Residual (RMR), and Root Mean Square Error of Approximation (RMSEA). The analysis also highlighted the examination of convergent and discriminant validity around the core constructs, which are central to the understanding of AI acceptance in the healthcare context.

## Goodness-of-fit indices for the measurement model

Indices for model fit suggest that the measurement model is within the thresholds that represent an acceptable fit. The CMIN/DF ratio was noted to be 2.50, which is within the recommended range of 0.5 to 3, confirming a good model fit. An RMSEA of 0.048 was observed, which is below the recommended cut-off level of 0.08, and RMR at 0.030 was also within the threshold of less than 0.05. The GFI and AGFI values were noted to be 0.92 and 0.90 respectively, both of which are above the accepted minimum threshold of 0.90. Similarly, the comparative fit indices comprising CFI (0.960), NFI (0.935), and IFI (0.950) exceeded the required threshold of 0.90. These results indicate that the model demonstrates strong fitness and hence allows for further structural analysis.

## convergent and discriminant validity

Convergent validity of the constructs was confirmed through various measures, including factor loadings, squared multiple correlations (SMC), composite reliability (CR), and average variance extracted (AVE). As presented in Table 7, all factor loadings surpassed the recommended benchmark of 0.7, and AVE values were higher than 0.6, meeting the guidelines established by Fornell & Larcker (1981) and Bagozzi & Yi (1991) for assessing convergent validity. The AVE values, specifically, ranged from 0.740 to 0.870, indicating that a significant proportion of the variance in the indicators is attributed to the latent variables. Additionally, all CR values were above 0.8, demonstrating strong internal consistency and reliability. This analysis confirms that the items within each construct are tightly correlated, supporting the conclusion that the constructs exhibit solid convergent validity.

| | **Factor Loadings** | **SMC** | **CR** | **AVE** |
|---|---|---|---|---|
| **Perceived Usefulness (PU)** | | | 0.966 | 0.781 |
| PU1 ←-PU | 0.818 | 0.669 | | |
| PU2 ←-PU | 0.824 | 0.679 | | |
| PU3 ←-PU | 0.859 | 0.738 | | |
| PU4 ←-PU | 0.871 | 0.759 | | |
| PU5 ←-PU | 0.911 | 0.83 | | |
| PU6 ←-PU | 0.931 | 0.867 | | |
| PU7 ←-PU | 0.944 | 0.892 | | |
| PU8 ←-PU | 0.904 | 0.817 | | |
| **Perceived Ease of Use (PeoU)** | | | 0.954 | 0.838 |
| PeoU1 ←- PeoU | 0.926 | 0.857 | | |
| PeoU2 ←- PeoU | 0.941 | 0.886 | | |
| PeoU3 ←- PeoU | 0.944 | 0.892 | | |
| PeoU4 ←- PeoU | 0.849 | 0.721 | | |
| **Trialability (TRI)** | | | 0.953 | 0.870 |
| TRI1 ←- TRI | 0.908 | 0.825 | | |
| TRI2 ←- TRI | 0.939 | 0.882 | | |
| TRI3 ←- TRI | 0.952 | 0.906 | | |
| **Intention to Use AI (IU)** | | | 0.940 | 0.797 |
| UI1 ←- UI | 0.951 | 0.905 | | |
| UI2 ←- UI | 0.904 | 0.817 | | |
| UI3 ←- UI | 0.89 | 0.793 | | |
| UI4 ←- UI | 0.822 | 0.676 | | |
| **Relationship With the Doctor (RWD)** | | | 0.851 | 0.740 |
| RWD1←- RWD | 0.9 | 0.809 | | |
| RWD2←- RWD | 0.819 | 0.67 | | |

Table 7. Validity testing for the constructs of the global measurement model

**Discriminant Validity**

Discriminant validity was evaluated using the Fornell-Larcker criterion, as illustrated in Table 8. This method establishes discriminant validity by ensuring that the square root of the Average Variance Extracted (AVE) for each construct is higher than the correlation values between that construct and the others. In our analysis, the diagonal values (in bold) indicate the square root of the AVE for each construct, and these values surpass the correlations with other constructs, confirming that discriminant validity has been achieved.

For example, the AVE square root for Perceived Usefulness (PU) is 0.883, which is higher than its correlation with other constructs, such as Perceived Ease of Use (PEoU) at 0.709, Trialability (TRI) at 0.567, Relationship with the Doctor (RWD) at 0.611, and Intention to Use AI (IU) at 0.632. Likewise, the AVE square root for other constructs, including PEoU (0.915), TRI (0.932), RWD (0.892), and IU (0.860), all meet the necessary criteria, confirming that each construct is distinct from the others in the model.

These findings offer substantial evidence endorsing the discriminant validity of the constructs used in the study and suggesting that none of the employed constructs is intrinsically interlinked with any other construct.

| | PU | PEoU | TRI | RWD | IU |
|---|---|---|---|---|---|
| PU | **0.883** | 0.709 | | 0.611 | 0.632 |
| PEoU | 0.709 | **0.915** | 0.431 | 0.456 | 0.519 |
| TRI | 0.567 | 0.431 | **0.932** | 0.684 | 0.669 |
| RWD | 0.611 | 0.456 | 0.684 | **0.892** | 0.621 |
| IU | 0.632 | 0.519 | 0.669 | 0.621 | **0.86** |

Table 8. Discriminant Validity (Fornell-Larcker)

## Structural Model Evaluation (SEM)

In this phase, SEM techniques were used to assess the viability of the conceptual model. The testing of the proposed model was carried out in two phases. Firstly, the goodness-of-fit of the entire structural model was checked. In this stage, various fit indices were analyzed to confirm that the model satisfactorily represents the data. In the second phase, the relationships hypothesized within the conceptual framework were tested. This involved examining both the statistical significance and the direction of the causal paths between the constructs. The results of this analysis allowed for an evaluation of the research hypotheses, determining the strength and relevance of the relationships proposed in the model. The structural model exhibits satisfactory fit indices, supporting the model's adequacy for hypothesis testing. The adjusted CMIN/DF ratio is 2.80, which is within the acceptable range of $1 < \text{CMIN/DF} < 3$, indicating a reasonable model fit. The RMSEA is reported at 0.075, falling below the threshold of 0.08, indicating a satisfactory level of fit. Additionally, the RMR stands at 0.040, comfortably within the acceptable limit of less than 0.05. The GFI and AGFI values are 0.890 and 0.850, respectively, demonstrating a reasonable fit, even though they fall slightly below the ideal threshold of 0.90. Lastly, the comparative fit indices, including CFI (0.920), NFI (0.872), and IFI (0.887), all approach or exceed the minimum threshold of 0.90, supporting the overall structural model adequacy.

## Hypothesis testing

This section examines the direct effects of key factors, such as Perceived Usefulness, Perceived Ease of Use, Trialability, and the Relationship with the Doctor, on patients' intentions to adopt AI in healthcare settings (Table 9). The findings largely supported hypothesized relationships, confirming significant associations between these factors and the intention to use artificial intelligence (AI). Most importantly, the relationship with the doctor emerged as the strongest predictor of perceived usefulness, with a standardized coefficient of 0.621, thus illustrating the central role of trust and communication in shaping patients' perceptions of the benefits of AI.

The intention to adopt artificial intelligence was also strongly influenced by trialability, with a coefficient of 0.511. This shows that the possibility of allowing patients to try out AI technologies before their full implementation is very important. This, in a way, decreases uncertainty and could build confidence in using the system. The other strong driver was Perceived Usefulness with a coefficient of 0.367, further solidifying that patients will be more willing to adopt AI where they perceive evident benefits.

While perceived ease of use had a positive, albeit smaller, effect on the intention to adopt AI (standardized coefficient = 0.120), the results indicate that aspects related to perceived usefulness and trialability are more central in the decision-making processes of patients.

To summarize, this research brings forth the indispensable roles of the doctor-patient relationship, trialability, and perceived usefulness in affording artificial intelligence adoption within the healthcare sector, where ease of use remains secondary yet nonetheless important.

| Hypothesis | Standardized Structural Coefficient | Critical Ratio (CR) | P-value | Validation |
|---|---|---|---|---|
| H1: Relationship with Doctor → Perceived Usefulness | 0.621 | 12.148 | 0.000 | Confirmed |
| H2: Perceived Usefulness → Intention to Use AI | 0.367 | 9.039 | 0.000 | Confirmed |
| H3: Perceived Ease of Use → Intention to Use AI | 0.120 | 3.019 | 0.003 | Confirmed |
| H4: Trialability → Intention to Use AI | 0.511 | 12.407 | 0.000 | Confirmed |

Table 9. Summary of Hypotheses Testing Results

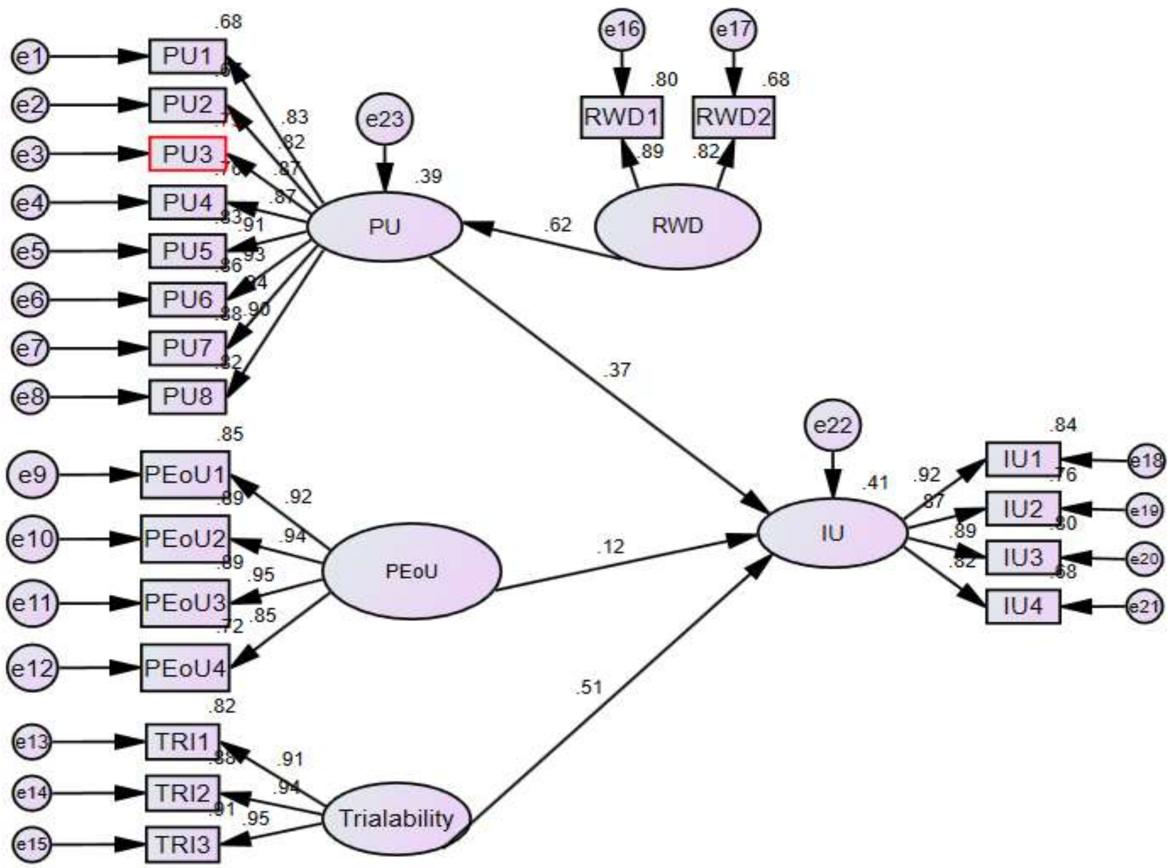


Figure 2. Structural Model

## Discussion

The main objective of this study was to analyze the determinants of the acceptance and intention of patients to use artificial intelligence in healthcare. Grounded in the Technology Acceptance Model (TAM), this research combined the traditional TAM constructs—perceived usefulness (PU) and perceived ease of use (PEOU)—but also expanded the model by introducing two additional factors: trialability and the relation with the doctor (RWD). These extensions were made specific to the context of the healthcare Technology Adoption model, where patient experience and trust in doctors play a major role.

The findings in this study underline the key role of core constructs in Technology Acceptance Model—namely, perceived usefulness and perceived ease of use—in determining intentions by patients to adopt AI in healthcare. Perceived usefulness is defined as an indication of the degree by which patients perceive that, through AI, their experiences in healthcare will improve and a critical determinant. This finding is in line with previous research that noted perceived usefulness as one of the leading predictors of technology adoption in healthcare settings (Deng et al., 2014; Li et al., 2019; Tural et al., 2020; Zin et al., 2023). In this regard, respondents who viewed artificial intelligence as beneficial and promoting efficiency in healthcare were more likely to show willingness to adopt these technologies.

Perceived ease of use, although important, plays a somewhat secondary role to perceived usefulness (PU). The idea that technology should be easy to use is still relevant, especially in healthcare settings where patients may not be highly skilled in using technology. However, as prior research has shown (Gefen et al., 2003; Sobaih et al., 2024; Sobaih and Abu Elnasr 2025), when the usefulness of technology is recognized, ease of use becomes less of an issue. This phenomenon has been observed in contexts where the perceived practical advantages of a system outweigh the potential challenges related to usability. As artificial intelligence becomes integrated into healthcare systems, improvement in both perceived usefulness and ease of use will be critical to increasing patient acceptance and utilization of such technologies (Venkatesh et al., 2003; Koul & Eydgahi, 2018; Kelly et al., 2023; Sobaih et al., 2025).

These findings demonstrate the strong predictive power of TAM in explaining patient attitudes and intentions toward adopting AI in healthcare and confirm the applicability of PU and PEOU in this sector. More importantly, they could provide useful insights for health providers and policymakers who aim at increasing patient engagement with AI technologies. By adopting this approach, health institutions can bring the many tangible benefits that artificial intelligence can offer, while simultaneously creating ease of interaction with a view to cultivating a generally receptive atmosphere for innovations driven by AI.

This also provides insights into the direct relation of trialability with the intention to use artificial intelligence in healthcare contexts. Results of this study show a strong positive relation, meaning that if given a chance to try out AI-driven healthcare systems, the likelihood of their adoption among patients would be considerably improved. Trialability reduces uncertainties because the user can directly perceive the concrete benefits of the technology, therefore increasing confidence and motivation to adopt it in their health practice. This is consistent with previous research that have emphasized trialability in the adoption of technology, since it provides a safe space for prospective users to become familiar with new systems before making long-term commitments (Rogers, 2003; Almela, 2023; Pinho et al., 2021; Ayanwale et al., 2024; Sobaih et al., 2025).

Lastly, this research presents compelling findings that demonstrate a correlation between the doctor-patient relationship and the perceived usefulness of artificial intelligence adoption in hospitals. This outcome is consistent with prior studies which have identified the quality of interaction between patients and healthcare providers as a significant determinant of patients' assessments regarding the effectiveness of health technology (Dou et al., 2017). A trustful relationship between the patients and health professionals, specifically, would strengthen the patients' belief in technological advances and their respective advantages, thus increasing the perceived usefulness (Koopman et al., 2014).

A lot of the fear associated with using new technologies can be allayed by the level of trust and rapport developed during consultations with health professionals; this is because patients would probably act on the recommendations of health professionals and regard the technology as helpful to the management of their condition (Deng et al., 2014). Likewise, good doctor-patient relationships, nurtured by open communication and credible health advice, increase the likelihood of patients accepting potential benefits associated with new technologies, including artificial intelligence. If patients perceive physicians to be well-informed regarding health issues, they then become more willing to accept and use AI tools since they consider these new technologies as being complementary to the professional health services they currently avail themselves of. This is further supported by research showing that interactions with health providers influence patients' intentions to use new health technologies positively (Peng et al., 2020), thus bringing in another layer of association between perceived usefulness and the intention to adopt artificial intelligence in medical contexts. This also highlights the value of AI responsible use to generate positive long term outcomes (Sobaih 2024).

## Theoretical Implications

This paper makes several important theoretical contributions, particularly in extending the Technology Acceptance Model (TAM) toward understanding the adoption of artificial intelligence in the healthcare context. To our best knowledge, this study is the very first empirical investigation of the relationship between doctor-patient relationships and perceived usefulness in the context of AI in healthcare. By introducing this new variable, relationship with the doctor—RWD—into the TAM framework, our study will enhance the understanding of how interpersonal trust and communication with health providers significantly influences patients' perceptions of artificial intelligence technologies (Koopman et al., 2014; Dou et al., 2017).This adds a new dimension to the TAM literature, which has traditionally focused on technological factors without fully accounting for the relational dynamics in healthcare settings (Venkatesh & Davis, 2000; Sobaih et al., 2025).

Moreover, the conceptual model presented in this study is unique. It integrates the original TAM factors of perceived usefulness and perceived ease of use with trialability and the doctor-patient relationship which have not been properly addressed in the case of the implementation of AI in the healthcare industry by Rogers (2003).

Moreover, the study uses both quantitative and qualitative data to increase the findings' credibility significantly. The qualitative phase of the study allowed for the exploration of patients' awareness and perception of AI technologies and the relational factors while the quantitative phase statistically validated these factors and affirmed the reliability of the proposed extended TAM model. Together these research methods increase the level of explanation provided by the model, with the aim of providing a broader framework suited to the characteristics of healthcare technology adoption.

The addition of trialability also underlines the importance of uncertainty mitigation in the adoption of innovative technologies in the health sector. The ability of patients to try out AI tools before their adoption can increase their confidence in technology, particularly in a context where people may feel a sense of vulnerability or fear of technological interventions (Rogers, 2003).

Therefore, this study adds value to the existing broader TAM literature by establishing the importance of these additional variables and by employing a mixed-methods approach, and it underlines the need to modify the TAM framework to capture new contexts, including AI in healthcare. The results of this study stress the need to keep enhancing and broadening the TAM model to capture contemporary nascent technology use issues with concern to security-conscientious settings such as healthcare. Qualified and quantitative data combined for developing an extended model here; therefore, our work significantly complements the existing TAM studies, as it may be used in subsequent research to identify further variables impacting AI acceptance.

## Practical Implications

The practical implications of this study hold considerable significance for healthcare practitioners, artificial intelligence developers, and policymakers. A comprehensive understanding of the critical factors that affect the adoption of artificial intelligence can inform the development and implementation of AI-based tools within healthcare settings, thereby enhancing patient outcomes and overall healthcare efficiency. First, AI developers should focus on the creation of systems that are usable and beneficial to patients, since these two factors—perceived usefulness and ease of use—are the strongest predictors of adoption. The key to driving adoption rates will be to ensure that the technologies provide real, perceivable benefits to the patients' healthcare experiences.

Moreover, this study shows the value of affording patients the opportunity to try out artificial intelligence technologies. Allowing patients the opportunity to experience AI tools in a controlled environment will help health providers decrease uncertainty and develop greater trust in technology. This real-world insight can be applied by AI developers and healthcare organizations in designing pilot programs or demo versions of AI tools that allow patients to get acquainted with the technology before committing to it in the long term.

Secondly, providers would need to recognize the important place that they hold in developing patients' perceptions of artificial intelligence technologies. One such finding from the research identifies that patients are more open to using AI tools because of trusting health professionals and perceiving technological advancements as an extension to their current care. On their part, healthcare professionals should then be prepared with the expertise to appropriately communicate the value of AI and integrate them when interacting with patients. Establishing trust and maintaining open communication between doctors and patients will be essential in promoting AI adoption.

Lastly, the implications of the findings for the design of healthcare systems should be considered by policymakers. The policies encouraging the integration of artificial intelligence in healthcare should focus not only on technological infrastructures but also on human factors influencing adoption. Health systems can increase the overall effectiveness of the implementation of AI through the creation of environments that make patients feel comfortable and confident in using AI tools.

In summary, these insights give developers of AI, healthcare professionals, and policymakers a framework that strategically improves the acceptance and adoption of artificial intelligence in health care. The theoretical and practical considerations noted in this research can be addressed in order for stakeholders to institute a more patient-centered framework for the adoption of AI, thereby optimizing both technology innovation and patient trust.

## Limitations and Future Directions

It should be noted that this study offers useful information about the factors affecting AI adoption in health care facilities but still has some limitations. First, due to its specificity of the geographical area for investigation, the research could be generalized only to the certain aspects of the healthcare field and particular population. Subsequent studies should perhaps extend to more cultural and health service system diverse locations to enhance generalizability. Moreover, although this study expands the TAM framework by the introduction of a new set of variables, such as the doctor-patient relationship and trialability, several factors related to the context were not considered, including privacy, ethics, or satisfaction. This study raises other possibilities that future studies could investigate to develop a better model of AI in healthcare. Finally, the cross-sectional design of this study limits any potential causal inferences between variables. Future research should therefore adopt experimental or longitudinal designs that will help establish the causality mechanisms operating to shape acceptance of AI in healthcare contexts.

## Conclusion

This research extends the Technology Acceptance Model (TAM) to examine AI adoption in healthcare by introducing two novel factors: of the different constructs – the doctor-patient relationship (RWD) trialability. Our findings underline the crucial importance of trust and communication between patients and healthcare providers in influencing perceptions of the utility of artificial intelligence, hence adding a new perspective to the Technology Acceptance Model literature. This study also emphasizes the importance of trialability by showing that allowing patients to try out AI technologies can reduce uncertainty and encourage their adoption in a healthcare setting.

Both perceived usefulness and perceived ease of use continue to have important effects on AI adoption as hypothesized by TAM. Testing the impact of the doctor-patient relationship in this research on perceived usefulness of technology contributes important theoretical advancements in Technology Adoption and healthcare sectors.

The usage of both qualitative and quantitative analysis in the present model strengthens the model and provides broader possibilities in the context of its application. The result of this study has significant practical implications, especially for the AI developers, health care systems, and health care policy makers who might draw from technological factors and relational factors to improve the integration of AI in health care systems. Further research should be conducted in the context to increase understanding of detailed specifics of the model.

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**Conflicts of Interest** "The authors declare no conflicts of interest."

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