NOVA IMS Information Management School

MDDM

Master's Degree Program in

Data-Driven Marketing

Patient Trust in the Use of AI Chatbots for Healthcare Purposes

A Cross-Cultural Study of Trust, Privacy Perceptions, and Adoption Factors in Portugal and Israel

Sara Pihas

Master Thesis

presented as partial requirement for obtaining a Master's Degree in Data-Driven Marketing

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STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism, any form of undue use of information or falsification of results along the process leading to its elaboration. I further declare that I have fully acknowledged the Rules of Conduct and Code of Honor from the NOVA Information Management School.

Lisbon, 11/07/2025

Sara Pihas

DEDICATION

I dedicate this thesis to my family, for their unconditional love and unwavering support throughout every stage of my life. To my mother, for the strength and courage she has always given me, and for never letting me give up. To my father, for being a constant example of perseverance and dedication.

To my professors and supervisors, thank you for the knowledge shared and guidance provided throughout this journey. A special thanks to my supervisor Catarina Neves, for her patience, availability, and invaluable input in making this work possible.

To all my colleagues and friends, I met during this master's program. Thank you for the support, and for making this experience lighter and more enjoyable.

And finally, I thank my sister for not letting me give up, for pushing through the challenges, and for making me believe that this journey was worth it.

ABSTRACT

This study investigates the factors shaping patient trust in the adoption of AI chatbots for healthcare purposes, using an extended UTAUT2 framework integrated with constructs from Bagozzi's self-regulation model. Drawing on 256 valid responses from Portugal and Israel, the research explores how performance expectancy, effort expectancy, hedonic motivation, habit, price value, trust, system quality and information quality influence both behavioral intention and actual use of AI chatbots in healthcare. Trust emerges as a critical driver, directly impacting use behavior and moderating key relationships such as those between service quality and intention to use. Multigroup analysis reveals cultural differences, with Portugal showing stronger alignment between intention and behavior, while Israel displays an intention behavior gap, emphasizing the importance of contextual and cultural factors in technology acceptance. The study contributes to theoretical understanding by highlighting the role of trust as both a direct and moderating influence and confirms that adoption dynamics vary across populations. Practically, it provides actionable insights for developers and healthcare providers aiming to enhance AI chatbot adoption by prioritizing usability, trust building features, and localized strategies. Ultimately, this research supports the design of inclusive, trustworthy AI tools that align with patient expectations in sensitive healthcare contexts.

KEYWORDS

Artificial Intelligence (AI); AI chatbot; AI in Healthcare; AI trust; UTAUT2; Patients' perceptions

Sustainable Development Goals (SDG):

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LIST OF ABBREVIATIONS AND ACRONYMS

AI – Artificial Intelligence

ML – Machine Learning

NLP – Natural Language Processing

UTAUT - Unified Theory of Acceptance and Use of Technology

PLS-SEM - Partial Least Squares Structural Equation Modeling

EE - Effort Expectancy

FC - Facilitating Conditions

HB - Habit

HM - Hedonic Motivation

IQ - Information Quality

IU - Intention to Use

PE - Performance Expectancy

PV - Price Value

SI - Social Influence

SQ - Service Quality

SQ_ - System Quality

TR - Trust

UB - Use Behaviour

STD - Standard Deviation

CR - Composite Reliability

AVE - Average variance extracted

VIF - variance inflation factor

IS - Information System

HTMT - Heterotrait-Monotrait Ratio

1. INTRODUCTION

The integration of Artificial Intelligence (AI) in the healthcare sector has been transforming how patients are interacting with new technologies such as medical information processing and automated services. AI chatbots have emerged from the health perspective as crucial tools to provide immediate healthcare assistance, from diagnostics to disease prediction (Mbunge & Batani, 2023). However, the adoption of these new technologies faces significant challenges regarding patient trust (Esmaeilzadeh, 2020). Nowadays, patient trust is critical for the effective delivery of healthcare services. Lack of confidence in AI systems can lead to patients not using them and missed opportunities to address health disparities through accessible and cost-effective solutions (Mbunge & Batani, 2023). In addition, concerns about data privacy and misdiagnosis in the use of AI in healthcare make it critical to understand and address patients' trust perception to ensure responsible technology adoption (Kamoonpuri & Sengar, 2023). The increase of AI applications, complementing advances in machine learning (ML) and public health demands, requires a timely exploration of these topics. In turn, this study is particularly relevant since healthcare providers and technology developers aim to meet ethical standards and the growing expectations of patients in a post-modern world pandemic where digital health has become indispensable (Wang & Wang, 2024).

Prior research has argued both optimism and concerns regarding AI in healthcare not only because some studies focus on the efficiency and accessibility of AI chatbots, while others emphasize the barriers to acceptance such as perceived risks and lack of transparency in AI decision-making processes, but also due to the limited number of studies about the perception of AI in healthcare (Esmaeilzadeh, 2020; Schaarup et al., 2023). These findings underscore the need for a nuanced understanding of trust concerns across diverse patient populations. The main objectives of this research are to identify and compare the specific trust concerns patients have when interacting with AI chatbots and to assess how these concerns differ across different demographic groups globally, more specifically in Portugal and Israel. The research goals are guided by three key questions:

1) How do patients perceive the security of their personal health information when using AI chatbots in healthcare services?
2) What factors influence patient trust using AI chatbots in healthcare services?
3) What factors influence patient willingness to use AI chatbots in healthcare services?
4) How do these perceptions differ across demographic groups in Portugal and Israel?

This research aims to contribute both theoretically and practically to the field of AI applied to healthcare. Theoretically, there is an advance in the understanding of social and psychological factors that shape patient interacts with AI chatbots, building on existing models of technology adoption and health behavior. Practically, it provides actionable insights for developers and healthcare providers to design safer and more reliable AI chatbots which could encourage broader use (Mbunge & Batani, 2023; Prakash & Das, 2024). By embracing a human and machine collaboration model, where AI chatbots enhance efficiency in routine healthcare tasks and human professionals focus on delivering empathetic and critical care, healthcare systems can foster trust and, improve patient outcomes for AI chatbots' integration in healthcare (Altamimi et al., 2023).

2. THEORETICAL BACKGROUND

2.1. AI CHATBOTS IN HEALTHCARE

AI chatbots are advanced systems powered by AI that are revolutionizing the healthcare industry by streamlining processes and enhancing patient experiences. These systems leverage natural language processing (NLP) and ML algorithms to facilitate human interactions between patients and virtual agents. NLP methods enable the extraction of information from unstructured data such as clinical notes and medical journals, transforming text into readable machine structured data. This enriched data can then be analyzed using ML techniques, which are also employed to process structured data like imaging, genetic, and electrophysiological records. ML approaches in medical applications often cluster patient traits or estimate the likelihood of disease outcomes (Jiang et al., 2017). Together, NLP and ML empower chatbots to perform diverse functions, such as managing appointment scheduling and prescriptions, assisting patients with preliminary symptom analysis, and answering medical inquiries (Wang et al., 2023).

2.2. PRIOR RESEARCH

The previous studies presented below in table 1 provide significant insights about the adoption and application of AI in the healthcare industry. Some of the key findings emphasize the critical role of initial trust in facilitating the adoption of AI technologies by healthcare professionals (Wang & Wang, 2024). The potential for AI chatbots to complement human medical professionals, enhancing efficiency and workflow, is also highlighted (Altamimi et al., 2023). Moreover, AI's capacity for disease prediction and patient care personalization has been underscored as a transformative benefit (Mbunge & Batani, 2023).

However, the studies also identify substantial barriers to adoption, including customer related challenges, technical limitations, and financial constraints (Kamoonpuri & Sengar, 2023). Addressing these challenges requires a focus on patient centered design, explainable AI models, and transparent data practices to build and sustain trust (Schaarup et al., 2023). Additionally, findings underscore the interconnected influence of trust, perceived risks, and demographic factors on patient adoption intentions and overall satisfaction (Esmaeilzadeh, 2020; Prakash & Das, 2024).

Overall, it is important to align technological advancements with user centric considerations to maximize the potential of AI driven solutions in the healthcare industry.

Table 1 – Literature Review

Authors	Topic	Theories	Method	Findings	Data
Wang & Wang, 2024	Analysis of trust factors for AI diagnosis in intelligent healthcare	UTAUT	Initial trust boosts model accuracy, crucial for AI adoption among doctors.	Optimize AI adoption factors among healthcare professionals.	190 participants
Altamimi et al., 2023	AI Chatbots in Medicine: A Supplement, Not a Substitute	Human-Machine Collaboration, Ethical AI Frameworks	Review of existing studies and analysis of AI chatbot applications in healthcare.	AI chatbots improve healthcare efficiency but can't replace humans. A collaborative model is optimal.	Case studies and reports on AI adoption of healthcare professionals
Mbunge & Batani, 2023	Deep learning and ML models in SSA healthcare	Deep learning, Disease Surveillance Models, Predictive Analytics	PRISMA and quantitative analysis.	AI models aid in detection, diagnosis, prediction, and monitoring, enhancing personalized care and decision making.	320 papers analyzed
Esmaeilzadeh, 2020	AI tools for healthcare purposes: consumers' perspective	Value perceptions	Clinical decision support from consumers' perspectives.	AI can improve outcomes but requires addressing risks before widespread use.	Survey of 427 respondents
Kamoonpuri & Sengar, 2023	Barriers to AI enabled virtual assistants	Diffusion of Innovations and Fuzzy AHP met hod	Fuzzy AHP model to identify and prioritize barriers.	Customer-related barriers are the most significant followed by technical and financial barriers.	Data from 37 experts working in AI, NLP, ML, and Data Science
Schaarup et al., 2023	Perception of AI in healthcare with diabetes and non-diabetes groups.	Multinomial logistic regression	Assess demographic and health factors' influence on AI perception.	Positive AI perceptions, but human interaction is key, focus on patient centered approaches, education, and explainable AI to build trust.	Survey of 8,420 participants
Prakash & Das, 2024	Trust in AI based health chatbots	Trust-in-technology framework	Partial Least Squares Structural Equation Modeling	Anthropomorphism, information quality, explainability, trust, and service quality affect trust in AI chatbots. Trust and risk influence usage intention.	202 participants
Wang et al., 2023	Users' intention to adopt healthcare chatbots	Mixed-method approach (interviews and qualitative data	Two-stage study, fuzzy set comparison analysis	Social features, combined with functionality, lead to high trust and satisfaction	34 out of 57 respondents selected

3. CONCEPTUAL MODEL AND HYPOTHESIS

The unified theory of acceptance and use of technology (UTAUT) is recognized as one of the most comprehensive and widely used models for analyzing technology acceptance. According to UTAUT, behavioral intention to use technology is shaped by four core constructs: effort expectancy, performance expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003). Building upon UTAUT, the extended UTAUT 2.0 framework incorporates three additional constructs: hedonic motivation, price value, and habit (Venkatesh et al., 2012). While UTAUT and UTAUT 2.0 are traditionally applied in quantitative studies, they can also serve as robust analytical frameworks for gaining deeper insights into complex phenomena (Wilson et al., 2021).

In addition, as illustrates Figure 1, based on Bagozzi self-regulation, and existing literature on perceived quality, perceived value, and technology adoption, we propose a research model that explores how users' emotional reactions mediate the relationship between their appraisal and their behavioral intention to use and actual usage, highlighting their role in sustaining AI chatbot adoption for healthcare purposes.

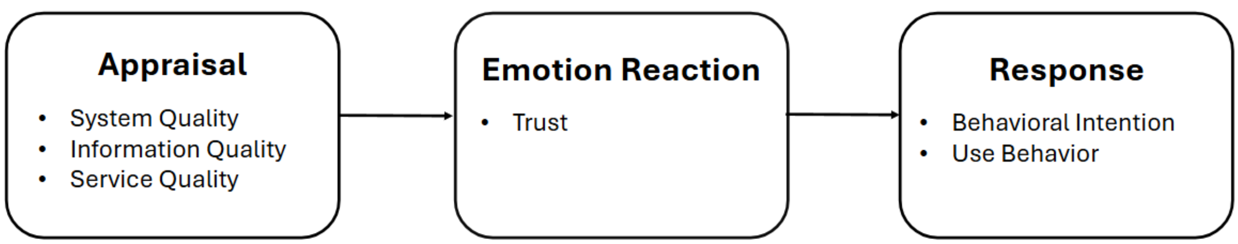

Figure 1- Conceptual construction of Bagozzi self-regulation framework

Fig. 2 illustrates the conceptual model, and the hypothesized relationships based on UTAUT 2.0 and Bagozzi's self-regulation framework. This research integrates UTAUT 2.0 framework with additional constructs related to perceived quality and trust, extending its application to the healthcare context. In this model, behavioral intention is influenced by key UTAUT 2.0 constructs, including performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit. Behavioral intention, in turn, impacts the actual use behavior regarding AI chatbots for healthcare purposes. This approach facilitates a comprehensive analysis of the factors influencing patient behaviors. Besides, it allows deeper insights into the challenges and opportunities for fostering trust in the implementation of AI chatbots for healthcare purposes. Beyond UTAUT 2.0 framework, the conceptual model integrates patient appraisal which includes system quality, information quality, and service quality, which play a crucial role in shaping trust toward AI chatbots used for healthcare purposes, exploring how patients' emotional reactions mediate the relationship between their appraisal and their behavioral intention and actual usage, highlighting their role in sustaining AI chatbot adoption for healthcare purposes. Control variables such as age, residence, gender and education degree are also considered to account for individual differences in AI chatbots adoption for healthcare purposes.

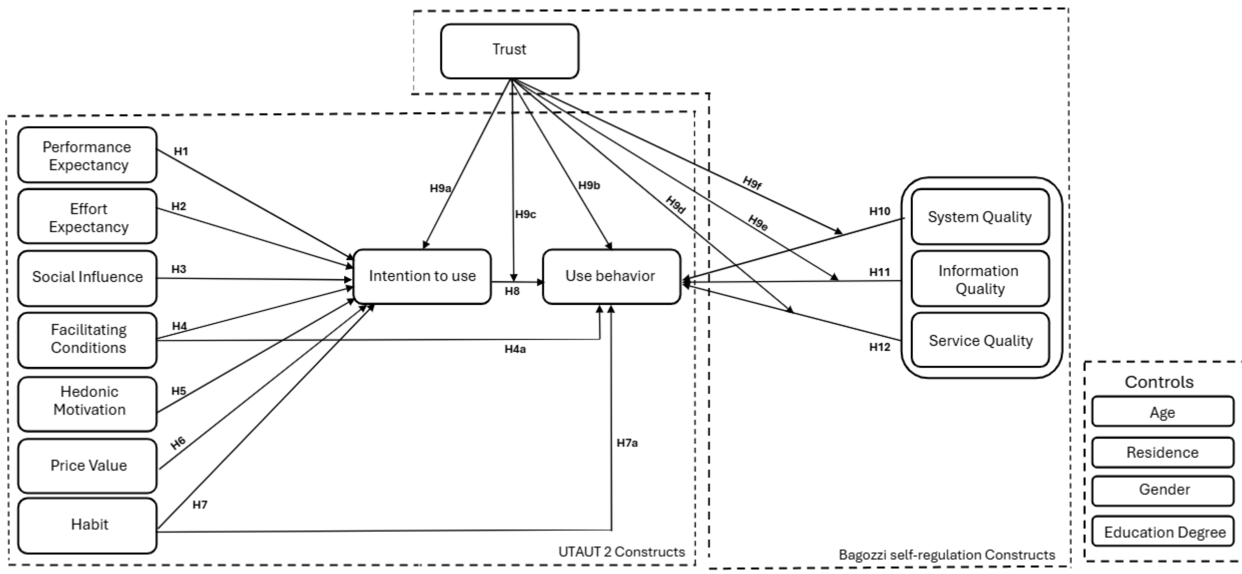

Figure 2 – Proposed research model (Adapted from Bagozzi, 1992; Venkatesh et al., 2012)

3.1. UTAUT 2 CONSTRUCTS

Each UTAUT 2.0 construct plays a crucial role in shaping the intention to use and subsequent use behavior in the context of AI chatbot adoption for healthcare purposes. Performance expectancy reflects the extent to which individuals believe that AI chatbots will enhance their healthcare experiences, such as improving efficiency or providing accurate medical guidance (Esmaeilzadeh, 2020). Effort expectancy stands for the perceived ease of using AI chatbots, influencing patient acceptance, especially among those less familiar with digital health technologies (Wilson et al., 2021). Social influence captures the impact of peers, medical professionals, or societal norms on individuals' willingness to engage with AI driven healthcare solutions (Schaarup et al., 2023). Facilitating conditions encompass the availability of necessary resources, support, and infrastructure that enable harmonious interaction with AI chatbots in medical settings (Wilson et al., 2021). Hedonic motivation acknowledges the role of enjoyment and patient engagement in encouraging adoption, particularly in AI driven healthcare systems that offer personalized (Yamoah & Acquaye, 2019) and interactive experiences (Park et al., 2023). Price value considers the perceived cost-effectiveness of AI chatbots, which can significantly impact adoption decisions, particularly in healthcare systems where financial considerations play a crucial role (Kamoonpuri

& Sengar, 2023). Lastly, habit reflects the extent to which prior experiences and repeated exposure influence continued use of AI chatbots for healthcare interactions (Wang et al., 2023). These constructs together shape behavioral intention, which subsequently drives use behavior, as patients evaluate the reliability, effectiveness, and convenience of AI powered healthcare support (T. Jiang et al., 2024). Thus, it was presented the following hypothesis:

H1. Performance expectancy has a significant positive effect on the intention to use.
H2. Effort expectancy has a significant positive effect on the intention to use.
H3. Social influence has a significant positive effect on the intention to use.
H4. Facilitating conditions has a significant positive effect on the intention to use.
H4a. Facilitating conditions has a significant positive effect on use behavior.
H5. Hedonic motivation has a significant positive effect on the intention to use.
H6. Price value has a significant positive effect on the intention to use.
H7. Habit has a significant positive effect on the intention to use.
H7a. Habit has a significant positive effect on use behavior.

3.2. INTENTION TO USE AND USE BEHAVIOR

As previously mentioned, intention to use significantly influences use behavior as UTAUT2 suggests that the stronger the intention to use a technology, the higher the likelihood of actual usage. In healthcare purposes, where AI chatbots are increasingly being deployed, a strong intention to use is often linked with increased interaction with these systems (Venkatesh et al., 2003). According to author (Esmaeilzadeh, 2020), the individuals who express a higher intention to use AI chatbots are more likely to rely on them for healthcare information and services. This connection underscores the importance of fostering positive intentions through effective communication, design, and trust building features.

H8. The intention to use positively influences use behavior.

3.3. SYSTEM QUALITY AND TRUST

System quality can be evaluated based on its effectiveness, efficiency, patient-centeredness, accessibility, equity, and safety – all of which can influence patient trust (World Health Organization, 2006). In the context of AI chatbots for healthcare purposes, system quality also plays a fundamental role in fostering patient trust. Emotional reaction factors, itrust, are shaped by cognitive appraisals. Trust refers to the belief that the service provider is honest and benevolent (Liang et al., 2011). Prior research has established that system predictability and availability significantly enhance patient trust (Vance et al., 2008). In the context of AI chatbots for healthcare, patients rely on system quality to assess the reliability and credibility of the service. When an AI chatbot efficiently delivers accurate health related information and ensures system stability, patients are more likely to perceive the service as trustworthy (Altamimi et al., 2023). As AI driven healthcare solutions continue to evolve, ensuring high system quality is crucial for strengthening patient trust. Hence, the following hypothesis was proposed:

H10. System quality positively influences trust when using AI chatbots for healthcare purposes.

3.4. INFORMATION QUALITY AND TRUST

In healthcare, information quality refers to patients' assessment of the information provided by AI chatbots based on their interactions when using these systems (Shiferaw et al., 2024). Indeed, high-quality information, characterized by accuracy, timeliness and completeness, enhances trust when using these systems (Delone & McLean, 2003). Moreover, the quality of information impacts trust. Patients tend to trust AI chatbots that deliver accurate and comprehensive health information (Shiferaw et al., 2024). As previously mentioned, when individuals use AI chatbots for healthcare purposes, high-quality information, characterized by structured and reliable answers, enhances their experience and fosters greater trust when using these systems. AI chatbots that prioritize accuracy, and clarity can positively influence patients' trust and emotional engagement with digital healthcare services (Xiong et al., 2022). Thus, it was proposed this hypothesis:

H11. Information quality positively influences trust when using AI chatbots for healthcare purposes.

3.5. SERVICE QUALITY AND TRUST

Service quality refers to how individuals assess a service provider's performance based on their personal experience with the service (Xiong et al., 2022), playing a crucial role in shaping patient trust, as individuals rely on healthcare services to provide accurate diagnoses, effective treatments, and secure handling of personal data. High service quality, characterized by reliability, responsiveness, and professionalism, fosters trust by ensuring that patients feel safe and well cared for (Swain & Kar, 2018). In AI driven healthcare, trust is influenced by factors such as the accuracy of chatbot generated recommendations, transparency in decision making, and robust data privacy measures (Shiferaw et al., 2024). When patients perceive AI chatbots for healthcare purposes as secure and reliable, they are more likely to trust and adopt them as part of their healthcare journey experience (Schaarup et al., 2023). Whereas, poor service quality, such as incorrect diagnoses, lack of personalization, or system errors, can lead to hesitation when using AI based medical assistance (Wang & Wang, 2024). Therefore, ensuring a high quality of AI healthcare services is essential to foster patient trust so the following hypothesis was proposed:

H12. Service quality positively influences trust when using AI chatbots for healthcare purposes.

3.6. THE ROLE OF TRUST

Trust is a crucial factor in the acceptance and use of AI based tools, particularly in healthcare contexts. Research demonstrates that individuals' trust in AI, particularly chatbots, significantly affects their intention to use and use behavior. Altamimi et al. (2023) note that trust in AI chatbots is essential because patients need confidence that these systems will deliver accurate and reliable information without compromising their privacy. In healthcare, where sensitive personal data is often shared, trust becomes even more critical, as users must believe in the chatbot's ability to act responsibly and securely (Shiferaw et al., 2024).

H9a. Trust positively influences the intention to use.
H9b. Trust positively influences the use behavior.

3.6.1. IMPACT ON USE BEHAVIOR MODERATED BY TRUST

The relationship between behavioral intention and actual use is significantly moderated by trust in AI systems. While a strong intention to use AI chatbots in healthcare is essential, the actual behavior depends on the user’s trust in the system. F. Jiang et al. (2017) suggest that when users perceive AI tools as trustworthy, they are more likely to follow through on their intentions and engage with these systems consistently. Similarly, (Prakash & Das, 2024) emphasize that trust enhances the effect of user intention on use behavior, making trust an essential moderator in predicting technology adoption. If patients trust that AI chatbots will safeguard their data and provide useful feedback, they are more likely to adopt these technologies (Park et al., 2023).

H9c. Trust will positively moderate the relationship between the intention to use and use behavior.
H9d. Trust will positively moderate the relationship between service quality and use behavior.
H9e. Trust will positively moderate the relationship between information quality and use behavior.
H9f. Trust will positively moderate the relationship between system quality and use behavior.

4. RESEARCH METHODOLOGY

4.1. INSTRUMENTAITON AND DATA COLLECTION TOOLS

An online survey was developed and distributed using the Qualtrics platform to collect data for evaluating the proposed research model. The survey begins with two targeting questions to ensure participants met the eligibility criteria: being 18 years of age or older and residing in either Portugal or Israel. Following the targeting section, the main body of the questionnaire consisted of 55 questions designed to assess patients' perspectives on the use of AI chatbots for healthcare purposes. For all constructs, equations were adapted from relevant studies published in reputable international journals on information technology, information systems, or business management. These questions were measured using a seven-point numerical scale, ranging from "1 – Strongly disagree" to "7 – Strongly agree". The final section included 6 demographic questions, which collected information on respondents' age group, gender, highest level of education, and familiarity with Nova Information Management School University. The survey was translated using Google Translate from the Qualtrics platform and made available in four languages: English, Portuguese, Italian, and Hebrew.

4.2. DATA COLLECTION

The questionnaire was pilot tested to prove its validity and reliability. This research's pilot study analyzes data collected from 36 patients, in which 30 individuals reside in Portugal and 2 individuals in Israel, and finally 4 individuals in other countries.

A pilot test of the questionnaire was conducted to assess its validity and reliability. The pilot study included responses from 36 patients, of whom 30 resided in Portugal, 2 in Israel, and 4 in other countries. Based on the analysis of the pilot data, no structural or content modifications were deemed necessary. The main data collection phase took place between February and March 2025, during which the survey was shared online through social media platforms and forums relevant to the topic. At the beginning of the questionnaire, AI chatbots used for healthcare purposes were briefly introduced, accompanied by a short explanation of the research objectives to provide context for respondents. A total of 446 responses were obtained, of which 256 (57%) were considered valid and complete for analysis, with 156 from Portugal and 100 from Israel. In terms of age distribution, most participants are 34 years old or younger: 55.1% in Portugal (47 aged 18–24 and 39 aged 25–34) and 40% in Israel (23 aged 18–24 and 17 aged 25–34), totaling 126 individuals (49.2%) under the age of 35. Regarding gender, most participants identify as female, with 59 in Portugal (37.8%) and 39 in Israel (39%), while 87 individuals (34%) identify as non-binary/third gender or preferred not to disclose their gender. As for education, the sample is highly educated: Portugal includes 43 participants with a bachelor's degree (27.6%) and 63 with a master's or doctoral degree (40.4%), while Israel includes 22 with a bachelor's degree (22%) and 30 with a master's or doctoral degree (30%), meaning that 61.7% of the total sample holds a higher education degree. Further details on the characteristics of the respondents are presented in Table 2. Finally, common-method bias was analyzed using two methods: (1) Harman one factor test, in which no indicator should explain more than 50% of variance, which was verified; and (2) adding a theoretically irrelevant variable, presenting a maximum shared variance of 0.035 (3.5%) with the other construct, which is considered low. Thus, no common-method bias was found.

Table 2 - Sample characteritics

Country	Age	n = 256	%	Gender	n = 256	%	Education	n = 256	%
Portugal	18-24	47	30.1%	Male	49	31.4%	No school degree complete	11	7.1%
	25-34	39	25.0%	Female	59	37.8%	Primary school	16	10.3%
	35-44	17	10.9%	Non-binary/Third gender	27	17.3%	High school degree	23	14.7%
	45-54	16	10.3%	Prefer not to say	21	13.5%	Bachelor degree	43	27.6%
	55-64	26	16.7%				Master degree	47	30.1%
	> 65	11	7.1%				Doctoral degree	16	10.3%
Israel	18-24	23	23.0%	Male	22	22.0%	No school degree complete	14	14.0%
	25-34	17	17.0%	Female	39	39.0%	Primary school	14	14.0%
	35-44	15	15.0%	Non-binary/Third gender	20	20.0%	High school degree	20	20.0%
	45-54	14	14.0%	Prefer not to say	19	19.0%	Bachelor degree	22	22.0%
	55-64	22	22.0%				Master degree	19	19.0%
	> 65	9	9.0%				Doctoral degree	11	11.0%

5. DATA ANALYSIS AND RESULTS

To analyze the research model, the study employed partial least squares structural equation modeling (PLS-SEM), a variance-based approach recognized for its effectiveness in exploratory research and predictive modeling. The analysis of both the measurement and the structural models was conducted using SmartPLS 4, a widely used software for PLS-SEM applications.

5.1. MEASUREMENT MODEL

A measurement model assessment was conducted for the reflective constructs. All variables demonstrated composite reliability (CR) values exceeding the recommended threshold of 0.70 (see Table 3 below), confirming consistency reliability. Indicator reliability was examined by analyzing the factor loadings, with the guideline that loadings should generally exceed 0.70, and any item with loading below 0.40 should be removed. All item loadings (Appendix 1) are above 0.70, except for three items (FC1, IQ2 and PE2), which, while slightly below the threshold, remain above 0.40 and close to 0.70. Thus, indicator reliability is considered acceptable. Convergent validity was assessed through the average variance extracted (AVE), with all constructs presenting AVE values above 0.50 (Table 3), indicating that convergent validity has been achieved.

Table 3 – Constructs' descriptive statistics, CR, AVE, and correlations.

	Mean	STD	CR	AVE	EE	FC	HAB	HM	IQ	IU	PE	PV	SI	SQ	SQ_	TR	UB
EE	4.18	1.53	0.78	0.64	**0.80**												
FC	4.33	1.60	0.79	0.65	0.36	**0.81**											
HAB	3.69	1.47	0.79	0.56	0.25	0.19	**0.75**										
HM	4.03	1.47	0.75	0.60	0.26	0.19	0.30	**0.78**									
IQ	4.17	1.46	0.75	0.60	0.22	0.25	0.16	0.28	**0.77**								
IU	4.09	1.56	0.77	0.63	0.36	0.25	0.33	0.34	0.19	**0.79**							
PE	4.18	1.45	0.77	0.53	0.36	0.24	0.23	0.29	0.34	0.39	**0.73**						
PV	3.89	1.47	0.76	0.61	0.20	0.19	0.24	0.27	0.22	0.28	0.20	**0.78**					
SI	3.90	1.38	0.79	0.56	0.32	0.19	0.32	0.34	0.25	0.31	0.31	0.25	**0.75**				
SQ	4.17	1.46	0.75	0.61	0.19	0.23	0.34	0.25	0.29	0.34	0.26	0.27	0.22	**0.78**			
SQ_	4.45	1.56	0.80	0.66	0.24	0.27	0.11	0.16	0.36	0.26	0.28	0.31	0.15	0.34	**0.81**		
TR	4.03	1.50	0.77	0.62	0.23	0.10	0.26	0.22	0.27	0.35	0.25	0.19	0.35	0.26	0.18	**0.79**	
UB	3.98	1.50	0.79	0.66	0.18	0.14	0.35	0.26	0.28	0.26	0.25	0.18	0.33	0.26	0.24	0.30	**0.81**

Notes: Effort Expectancy (EE); Facilitating Conditions (FC); Habit (HB); Hedonic Motivation (HM); Information Quality (IQ); Intention to Use (IU); Performance Expectancy (PE); Price Value (PV); Social Influence (SI); Service Quality (SQ); System Quality (SQ_); Trust (TR); Use Behavior (UB); Standard Deviation (STD); Composite Reliability (CR); Average variance extracted (AVE); values in diagonal (bolt) are the square root of AVE.

Discriminant validity of the constructs was evaluated using three different approaches. First, the Fornell-Larcker criterion was applied, which states that the square root of a construct's AVE should be higher than its highest correlation with any other construct. As shown in Table 3, this condition was met. Secondly, indicator loadings were compared to cross-loadings to ensure that each indicator had a stronger correlation with its own construct than with others. Items below 0.4 were removed from the model. As reflected in Table 4, the final item loadings (highlighted in bold) are all greater than their corresponding cross-loadings. The third method used was the heterotrait-monotrait ratio (HTMT), where all values fell below the accepted limit of 0.90 (see table 4 below), further confirming discriminant validity.

In addition to the reflective constructs, the model also includes the use behavior construct derived from the UTAUT2 framework. To test for multicollinearity among its indicators, variance inflation factor (VIF) values were examined. All VIF values were below the threshold of 3.3, more specifically, the highest VIF value is 1.64, which is below the commonly accepted threshold of 3.3, suggesting that there are no multicollinearity issues.

Table 4 – Heterotrait-monotrait ratio

Construct	EE	FC	HAB	HM	IQ	IU	PE	PV	SI	SQ	SQ_	TR	UB
EE													
FC	0.79												
HAB	0.48	0.31											
HM	0.68	0.42	0.65										
IQ	0.61	0.55	0.39	0.83									
IU	0.85	0.52	0.66	0.90	0.54								
PE	0.74	0.47	0.39	0.66	0.79	0.78							
PV	0.51	0.50	0.52	0.76	0.66	0.74	0.45						
SI	0.63	0.33	0.52	0.75	0.57	0.61	0.53	0.54					
SQ	0.47	0.52	0.73	0.69	0.83	0.89	0.61	0.78	0.46				
SQ_	0.52	0.59	0.20	0.40	0.86	0.57	0.53	0.75	0.27	0.81			
TR	0.56	0.21	0.55	0.58	0.74	0.88	0.56	0.53	0.73	0.72	0.40		
UB	0.41	0.26	0.65	0.64	0.66	0.60	0.47	0.45	0.63	0.63	0.49	0.68	

5.2. STRUCTURAL MODEL

The estimation results of the structural model are presented in Fig. 3, including the R^2 values that reflect the variance explained by the model, along with the path coefficients and their respective levels of statistical significance. The structural model explains 32.5% of the variance in intention to use and 24.6% of the variance in use behavior. Among the UTAUT2 predictors, performance expectancy ($\hat{\beta}$ = 0.180; $p < 0.01$), effort expectancy ($\hat{\beta}$ = 0.145; $p < 0.05$), hedonic motivation ($\hat{\beta}$ = 0.134; $p < 0.05$), habit ($\hat{\beta}$ = 0.117; $p < 0.1$), and price value ($\hat{\beta}$ = 0.106; $p < 0.1$) significantly predict intention to use. However, facilitating conditions ($\hat{\beta}$ = 0.061; $p > 0.1$) and social influence ($\hat{\beta}$ = 0.014; $p > 0.1$) are not statistically significant predictors of usage intention. Regarding use behavior, habit ($\hat{\beta}$ = 0.260; $p < 0.01$) has a strong and statistically significant effect. In addition, facilitating conditions ($\hat{\beta}$ = 0.007; $p > 0.1$) is not a statistically significant predictor for use behavior. Additionally, intention to use ($\hat{\beta}$ = 0.038; $p > 0.1$) does not significantly influence use behavior in this model.

In terms of Bagozzi's constructs, trust ($\hat{\beta}$ = 0.183; $p < 0.01$) was found to be a statistically significant predictor of intention to use. Regarding use behavior, trust ($\hat{\beta}$ = 0.127; $p < 0.1$) system quality ($\hat{\beta}$ = 0.132; $p < 0.1$), and information quality ($\hat{\beta}$ = 0.154, $p < 0.5$) are statistically significant predictors, while service quality ($\hat{\beta}$ = 0.038; p > 0.1) is not. The moderation analysis showed that the interaction between trust and intention to use ($\hat{\beta}$ = -0.124, p > 0.1), as well as the interaction between trust and service quality ($\hat{\beta}$ = 0.126, p < 0.1) are statistically significant. However, the interactions between trust and system quality ($\hat{\beta}$ = 0.052, p > 0.1), and between trust and information quality ($\hat{\beta}$ = - 0.043; p > 0.1) are not statistically significant.

Overall, from the 19 tested hypotheses, 12 were supported, demonstrating a good level of explanatory power of the model, particularly for intention to use. These findings highlight the relevance of both traditional UTAUT2 variables and extended constructs from the information system (IS) quality domain in understanding technology adoption behavior.

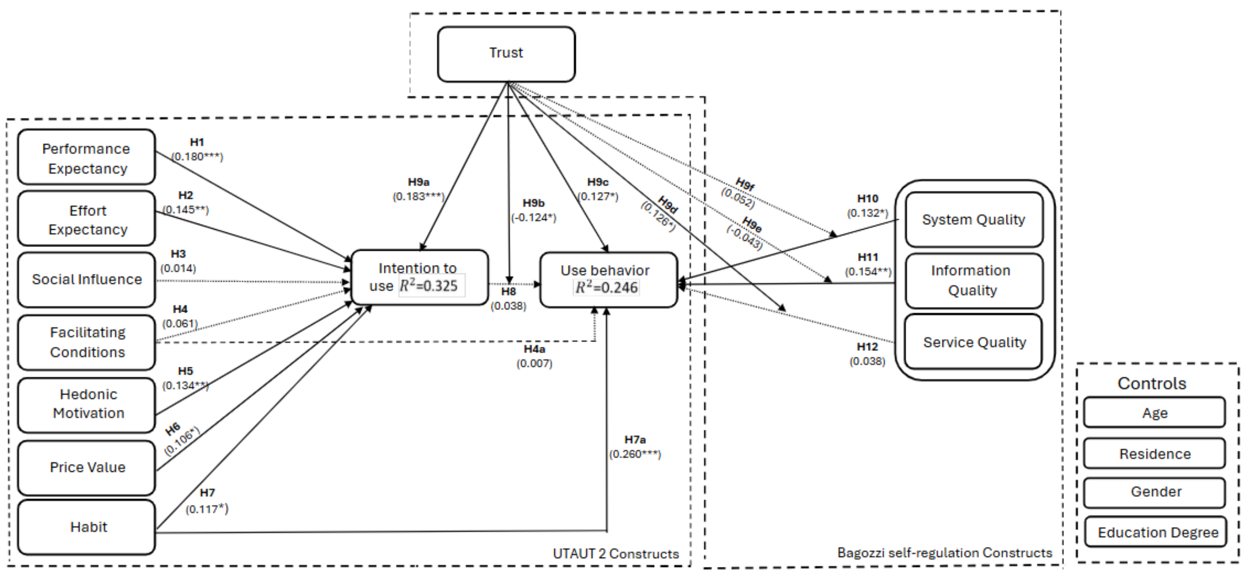

Figure 3 - Structural model results (variance-based technique)
*Notes: standardised coefficients; ***p < 0.01; **p < 0.05; *p < 0.10.*

6. DISCUSSION

This study aimed to understand the drivers behind patients' intention to use, actual use of AI chatbots in healthcare, using an extended UTAUT2 model enriched with constructs from Bagozzi’s self-regulation framework. The findings deliver valuable insights into the mechanisms that influence patient engagement with AI technologies for medical purposes, particularly in relation to trust and quality perceptions.

The results confirm that intention to use is significantly influenced by performance expectancy, effort expectancy, hedonic motivation, price value, and habit. These relationships align with core UTAUT2 assumptions, suggesting that patients are more likely to adopt chatbots when they believe these tools are useful, easy to use, enjoyable, cost effective, and can integrate into their routines. Among these, performance expectancy and effort expectancy stood out as particularly influential, highlighting the importance of chatbots delivering valuable health outcomes with patients’ minimal effort. Interestingly, social influence and facilitating conditions did not significantly affect the intention to use. A possible explanation remains in the personal and private nature of healthcare decisions where individuals may rely more on their own judgment rather than being influenced by others or external infrastructure when deciding to use AI chatbots. People often make health choices independently and may not discuss them with friends, family, or colleagues, which reduces the impact of social pressures or available resources. Contrary to expectations, intention to use did not significantly predict use behavior, suggesting an attitude behavior potential gap between patients stated intentions and their actual use. This discrepancy may reflect situational barriers, lack of urgency, or continued uncertainty about chatbots. Notably, habit also showed a direct and significant influence on use behavior, indicating that repeated interaction with AI chatbots can develop into routine behavior, which is crucial for a long term adoption.

Beyond the UTAUT2 constructs, trust emerged as a significant predictor of both intention to use and use behavior. This highlights how essential it is for patients to feel confident that chatbot systems are reliable, accurate, and secure, especially in a sector as sensitive as healthcare. Moreover, system quality and information quality were significant in predicting use behavior. These findings underline the importance of ensuring that AI chatbots provide reliable system performance and trustworthy, high quality information to gain patients' technology adoption. On the other hand, service quality did not have a significant effect, which might indicate that users prioritize technical reliability and content accuracy over service related elements, such as responsiveness or personalization, when it comes to health interactions.

Overall, the model explained a considerable portion of the variance in both intention to use (R^2 = 0.325) and use behavior (R^2 = 0.246), supporting the relevance of the proposed constructs in understanding the adoption of AI chatbots in healthcare. These insights suggest that developers and healthcare providers should focus on improving chatbot performance, ease of use, reliability, and trustworthiness to encourage wider adoption.

6.1. MULTIGROUP ANALYSIS

A multigroup analysis was conducted to compare the predictors of intention to use and use behavior of AI chatbots in healthcare across two countries: Portugal and Israel. The model explained a higher variance in intention to use in Israel (R^2 = 39.4%) compared to Portugal (R^2 = 33.8%), whereas the opposite was observed for use behavior, with Portugal showing greater explanatory power (R^2 = 33.2%) than Israel (R^2 = 19.6%). Among the predictors of intention to use, effort expectancy ($\hat{\beta}$ = 0.374, $p < 0.01$) and price value ($\hat{\beta}$ = 0.165, $p < 0.1$) were statistically significant only in Israel. In contrast, facilitating conditions ($\hat{\beta}$ = 0.152, $p < 0.1$), habit ($\hat{\beta}$ = 0.205, $p < 0.05$), and performance expectancy ($\hat{\beta}$ = 0.163, $p < 0.05$) were significant only in Portugal. Trust was statistically significant in Portugal ($\hat{\beta}$ = 0.167, $p < 0.1$), but not in Israel ($\hat{\beta}$ = 0.170, $p > 0.1$). Regarding use behavior, trust ($\hat{\beta}$ = 0.233, $p < 0.05$) was a significant predictor only in Israel, while habit ($\hat{\beta}$ = 0.331, $p < 0.01$) and system quality ($\hat{\beta}$ = 0.235, $p < 0.01$) were significant only in Portugal. Additionally, a negative and significant interaction between trust and intention to use was observed in Portugal ($\hat{\beta}$ = -0.163, $p < 0.1$), but not in Israel. Out of the 19 hypotheses tested, 9 showed statistically significant differences between the two countries, indicating that nearly 50% of the hypothesized relationships differ across contexts in terms of statistical significance.

The results of the multigroup analysis revealed significant differences between countries in the factors predicting both the intention to use and the use behavior of AI chatbots in healthcare. As it was previously mentioned, Israel exhibited a higher variance explained in intention to use than Portugal, however this did not translate into use behavior, where Portugal demonstrated a substantially higher explanatory power compared to Israel. One notable finding reinforcing this disparity is that in the Israeli sample, intention to use did not significantly predict use behavior ($\hat{\beta}$ = -0.082, $p > 0.1$), highlighting the presence of an attitude behavior gap in the Israeli context, where individuals express favorable attitudes or intentions that do not consistently result in use behavior (Yamoah & Acquaye, 2019). Several plausible explanations may account for this gap. Despite individuals in Israel perceiving AI chatbots as useful and easy to use (evidenced by the significance of effort expectancy and price value), as mentioned previously situational barriers such as limited availability of reliable chatbot services, lower trust, or insufficient integration into existing healthcare platforms and, lack of urgency, or continued uncertainty about chatbots may prevent the actual use. Additionally, cultural attitudes toward digital health technologies may contribute to cautious behavior, especially in the absence of strong habitual or social reinforcements. In contrast, Portuguese respondents demonstrated a stronger alignment between intention and use behavior, possibly due to greater familiarity with digital health tools, higher digital readiness, or stronger trust in healthcare institutions. Interestingly, in Portugal, habit and system quality emerged as significant predictors of use behavior, reinforcing the idea that consistent user experience and integration in healthcare routines are key to long term adoption. These findings highlight the importance of not only fostering positive attitudes toward AI health tools but also ensuring that infrastructural, cultural, and experiential enablers are in place to bridge the gap between intention and action. Additionally, structural differences such as health system policies, digital literacy, or user readiness may shape the role of predictors like habit, system quality, and facilitating conditions, which varied significantly across countries. These findings underscore the importance of considering cultural and behavioral contexts when designing and implementing digital health technologies, especially when trust, intention, and use behavior do not uniformly align across populations.

6.1.1. MODERATING ROLE OF TRUST

The results in Figure 4 reveal that trust plays a moderating role in shaping the relationship between key predictors and use behavior, particularly intention to use and service quality. In the case of intention to use, the effect of trust becomes especially relevant at lower levels of intention where trust leads to different levels of use behavior, further highlighting its role as a differentiating factor in this context. For individuals with low intention to use, those who exhibit high levels of trust still demonstrate relatively higher levels of use behavior, suggesting that trust can compensate for a lack of initial intent. Conversely, for individuals with low trust, low intention to use results in equally low use behavior, reinforcing the idea that trust can act as a behavioral catalyst in hesitant users. Interestingly, for high levels of intention, trust does not significantly alter use behavior, indicating a diminishing moderating effect when intention is already strong.

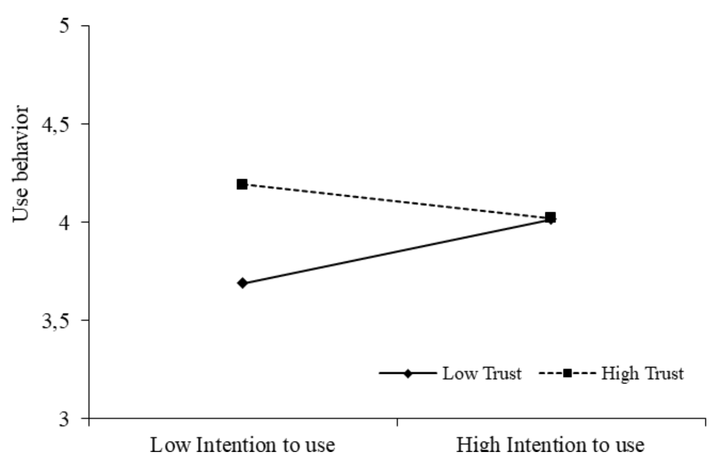

Figure 4 - Moderator effect of trust on intention to use

Similarly, the relationship between service quality and use behavior is also moderated by trust as it is showed in Figure 5. The impact of service quality on use behavior also differs depending on levels of trust. Among patients with high trust, service quality has a strong positive effect on use behavior, whereas this relationship is less pronounced for those with lower trust levels. These findings underscore the crucial role of trust not only as a direct predictor in some contexts but also affects how strongly other factors, like intention to use and service quality, impact the adoption of AI chatbots in healthcare.

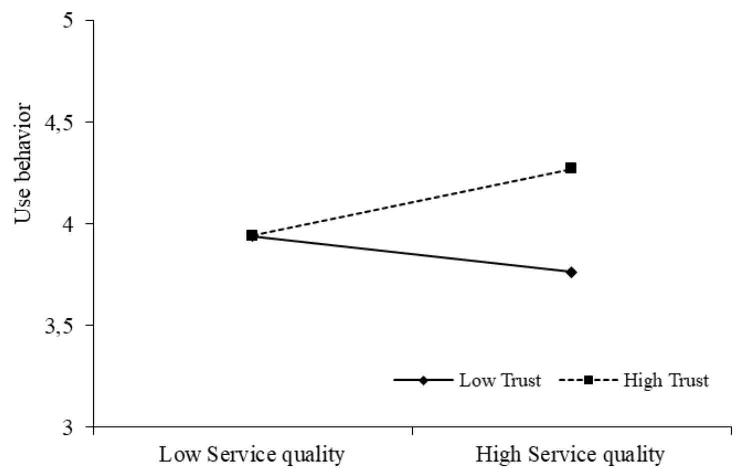

Figure 5 - Moderator effect of trust on service quality

6.2. THEORETICAL IMPLICATIONS

This study contributes important theoretical insights to the literature on AI adoption in healthcare, particularly by examining not only patients' intention to use AI chatbots but also their actual use behavior. This broader approach provides a deeper understanding of how patients engage with healthcare chatbots beyond intention alone. Applying the UTAUT2 model in this context reinforces its theoretical robustness and adaptability for emerging healthcare technologies. The findings highlight the role of constructs such as performance expectancy, habit, and effort expectancy in shaping adoption with AI chatbots. Trust is identified as a key moderating factor, influencing not only use behavior but also alters the strength of the relationships between other predictors, such as service quality, intention to use and use behavior. Moreover, perceptions of trust may vary across cultural contexts, suggesting that trust is not a universal construct, but one shaped by local norms and expectations around data privacy, technology, and healthcare systems. The multigroup analysis provides additional theoretical depth by revealing significant differences between populations, indicating that the strength and nature of drivers' adoption are not uniform across all populations. These findings underscore the importance of context specific models when studying technology acceptance in different healthcare systems. By confirming the relevance of these constructs, the study strengthens the theoretical foundation for researching AI in patient care and advances understanding of the mechanisms driving or hindering chatbot adoption. It also contributes to resolving ongoing debates around patient openness to AI by demonstrating how performance expectancy, habit, and trust shape both attitudes and behavior.

6.3. MANAGERIAL IMPLICATIONS

Healthcare providers and technology developers can draw several practical insights from this study regarding the implementation and promotion of AI chatbots in healthcare. One of the most notable findings is the strong influence of performance expectancy and trust on patients' intention to use and actual usage of AI chatbots. This suggests that if patients perceive the chatbot as reliable, helpful, and efficient in delivering care related services, they are more likely to adopt. For developers and healthcare institutions, this means placing a strong emphasis on usability, response accuracy, and clear communication of the chatbot's capabilities. Although social influence and facilitating conditions did not significantly impact patients' intention to use AI chatbots, their potential role should not be entirely dismissed. It is possible that, in different contexts or with targeted implementation strategies, these factors could still support adoption for instance, through trusted healthcare provider endorsements or by making chatbots easily accessible via familiar platforms. Marketing and communication strategies should be tailored to reinforce trust and highlight how chatbots can assist in real world healthcare tasks, such as appointment scheduling, symptom assessment, pre and post visit follow ups. Additionally, the practical implications extend to improving digital health literacy across patient populations, especially among those less technologically inclined. Training programs, tutorial videos, or even in clinic demonstrations could help overcome initial reluctance and promote greater adoption. Finally, the significant gap in AI adoption across age groups and cultural contexts observed in this study indicates the importance of localized, demographically sensitive and effective rollout strategies. Tailoring chatbot features and messaging to reflect patients' specific healthcare needs and cultural expectations could improve use, ultimately supporting the larger goal of creating digital health tools that can be used widely and fairly by everyone.

6.4. LIMITATIONS AND FUTURE RESEARCH

This study’s findings should be interpreted considering several limitations. First, the data were collected through a survey conducted during a specific time frame, which provides a snapshot of patients' perceptions and behaviors but may not capture evolving trends. Given the dynamic nature of technology adoption, particularly in the healthcare sector, future research could benefit from conducting longitudinal studies to monitor changes in patients’ intentions and user behaviors over time. Second, although this study focused on patients from Portugal and Israel, the sample size per country, combined with limited age and racial diversity and the overrepresentation of younger individuals, may restrict the generalizability of the findings. Broader and more representative samples across diverse cultural contexts and healthcare systems would improve the robustness and applicability of future results. In particular, cultural and contextual differences that influence technology acceptance warrant further exploration through cross cultural research. Third, while the research model integrates well established constructs, it may omit relevant variables that shape the adoption of AI chatbots in healthcare. Factors such as emotional responses, ethical concerns, institutional trust, and fear of job displacement may significantly influence patient behavior. Incorporating qualitative or mixed methods approaches in future studies could uncover deeper motivations and contextual influences not captured only through quantitative methods. Moreover, although the study captured both intentions and self-reported use behavior, it relied entirely on patients’ self-reports rather than observed behavior. This may introduce biases such as recall inaccuracies or social desirability, and future studies could incorporate behavioral tracking or experimental designs to better capture real world chatbot usage patterns. Finally, the model developed in this study is specific to AI chatbots in healthcare. Future research could test and extend this framework across other digital health technologies, such as AI driven mental health tools, remote patient monitoring systems, and symptom checkers, to compare adoption dynamics across sectors. Additionally, the limited number of existing studies on AI perception in healthcare, particularly among Gen Z patients and technologically disadvantaged populations, highlights the need for more inclusive research. Addressing challenges such as data privacy concerns, algorithmic bias, and the lack of regulatory frameworks remains crucial to supporting the responsible and equitable integration of AI technologies into health systems.

7. CONCLUSION

Based on the UTAUT2 framework and extended constructs from trust and IS quality, this study proposed a detailed model to evaluate the acceptance and use of AI chatbots for healthcare purposes. Through structural equation modeling and a multigroup analysis comparing Portugal and Israel, the study provides both theoretical and practical contributions. The findings reveal that key predictors such as performance expectancy, effort expectancy, price value, hedonic motivation, trust, habit, system quality, and information quality influence patients' intention to use and use behavior of AI chatbots, although their effects and others vary between countries. In particular, Israeli participants exhibited high levels of intention to use, yet this did not translate into use behavior, revealing an attitude behavior gap likely shaped by trust concerns or contextual limitations. In contrast, Portuguese patients showed a stronger alignment between intention to use and use behavior, with habit and system quality playing central roles in sustained use. These results highlight the importance of considering cultural, behavioral, and infrastructural factors when deploying AI tools in healthcare. Beyond theoretical contributions, the findings emphasize the need for patient centered design strategies that enhance trust, usability, and integration into healthcare routines. This research aims to inspire further studies exploring how demographic and contextual variables influence digital health adoption, ultimately contributing to the equitable and effective implementation of AI in healthcare systems.

BIBLIOGRAPHICAL REFERENCES

Altamimi, I., Altamimi, A., Alhumimidi, A. S., Altamimi, A., & Temsah, M.-H. (2023). Artificial Intelligence (AI) Chatbots in Medicine: A Supplement, Not a Substitute. *Cureus*. https://doi.org/10.7759/cureus.40922

Bagozzi, R. P. (1992). The Self-Regulation of Attitudes, Intentions, and Behavior. *Social Psychology Quarterly*, *55*(2), 178. https://doi.org/10.2307/2786945

Delone, W. H., & McLean, E. R. (2003). The DeLone and McLean Model of Information Systems Success: A Ten-Year Update. *Journal of Management Information Systems*, *19*(4), 9–30. https://doi.org/10.1080/07421222.2003.11045748

Esmaeilzadeh, P. (2020). Use of AI-based tools for healthcare purposes: A survey study from consumers' perspectives. *BMC Medical Informatics and Decision Making*, *20*(1), 170. https://doi.org/10.1186/s12911-020-01191-1

Jiang, F., Jiang, Y., Zhi, H., Dong, Y., Li, H., Ma, S., Wang, Y., Dong, Q., Shen, H., & Wang, Y. (2017). Artificial intelligence in healthcare: Past, present and future. *Stroke and Vascular Neurology*, *2*(4), 230–243. https://doi.org/10.1136/svn-2017-000101

Jiang, T., Sun, Z., Fu, S., & Lv, Y. (2024). Human-AI interaction research agenda: A user-centered perspective. *Data and Information Management*, 100078. https://doi.org/10.1016/j.dim.2024.100078

Kamoonpuri, S. Z., & Sengar, A. (2023). Hi, May AI help you? An analysis of the barriers impeding the implementation and use of artificial intelligence-enabled virtual assistants in retail. *Journal of Retailing and Consumer Services*, *72*, 103258. https://doi.org/10.1016/j.jretconser.2023.103258

Liang, T.-P., Ho, Y.-T., Li, Y.-W., & Turban, E. (2011). What Drives Social Commerce: The Role of Social Support and Relationship Quality. *International Journal of Electronic Commerce*, *16*(2), 69–90. https://doi.org/10.2753/JEC1086-4415160204

Mbunge, E., & Batani, J. (2023). Application of deep learning and machine learning models to improve healthcare in sub-Saharan Africa: Emerging opportunities, trends and implications. *Telematics and Informatics Reports*, *11*, 100097. https://doi.org/10.1016/j.teler.2023.100097

Park, G., Chung, J., & Lee, S. (2023). Effect of AI chatbot emotional disclosure on user satisfaction and reuse intention for mental health counseling: A serial mediation model. *Current Psychology*, *42*(32), 28663–28673. https://doi.org/10.1007/s12144-022-03932-z

Prakash, A. V., & Das, S. (2024). (Why) Do We Trust AI?: A Case of AI-based Health Chatbots. *Australasian Journal of Information Systems*, *28*. https://doi.org/10.3127/ajis.v28.4235

Schaarup, J. F. R., Aggarwal, R., Dalsgaard, E.-M., Norman, K., Dollerup, O. L., Ashrafian, H., Witte, D. R., Sandbæk, A., & Hulman, A. (2023). Perception of artificial intelligence-based solutions in healthcare among people with and without diabetes: A cross-sectional survey from the health in Central Denmark cohort. *Diabetes Epidemiology and Management*, *9*, 100114. https://doi.org/10.1016/j.deman.2022.100114

Shiferaw, M. W., Zheng, T., Winter, A., Mike, L. A., & Chan, L.-N. (2024). Assessing the accuracy and quality of artificial intelligence (AI) chatbot-generated responses in making patient-specific drug-therapy and healthcare-related decisions. *BMC Medical Informatics and Decision Making*, *24*(1), 404. https://doi.org/10.1186/s12911-024-02824-5

Swain, S., & Kar, N. C. (2018). Hospital service quality as antecedent of patient satisfaction – a conceptual framework. *International Journal of Pharmaceutical and Healthcare Marketing*, *12*(3), 251–269. https://doi.org/10.1108/IJPHM-06-2016-0028

Vance, A., Elie-Dit-Cosaque, C., & Straub, D. W. (2008). Examining Trust in Information Technology Artifacts: The Effects of System Quality and Culture. *Journal of Management Information Systems*, *24*(4), 73–100. https://doi.org/10.2753/MIS0742-1222240403

Venkatesh, Morris, Davis, & Davis. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly*, *27*(3), 425. https://doi.org/10.2307/30036540

Venkatesh, Thong, & Xu. (2012). Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology. *MIS Quarterly*, *36*(1), 157. https://doi.org/10.2307/41410412

Wang, X., Luo, R., Liu, Y., Chen, P., Tao, Y., & He, Y. (2023). Revealing the complexity of users' intention to adopt healthcare chatbots: A mixed-method analysis of antecedent condition configurations. *Information Processing & Management*, *60*(5), 103444. https://doi.org/10.1016/j.ipm.2023.103444

Wang, X., & Wang, Y. (2024). Analysis of trust factors for AI-assisted diagnosis in intelligent Healthcare: Personalized management strategies in chronic disease management. *Expert Systems with Applications*, *255*, 124499. https://doi.org/10.1016/j.eswa.2024.124499

Wilson, J., Heinsch, M., Betts, D., Booth, D., & Kay-Lambkin, F. (2021). Barriers and facilitators to the use of e-health by older adults: A scoping review. *BMC Public Health*, *21*(1), 1556. https://doi.org/10.1186/s12889-021-11623-w

World Health Organization. (2006). *Quality of care: A process for making strategic choices in health systems*. 38.

Xiong, L., Wang, H., & Wang, C. (2022). Predicting mobile government service continuance: A two-stage structural equation modeling-artificial neural network approach. *Government Information Quarterly*, *39*(1), 101654. https://doi.org/10.1016/j.giq.2021.101654

Yamoah, F. A., & Acquaye, A. (2019). Unravelling the attitude-behaviour gap paradox for sustainable food consumption: Insight from the UK apple market. *Journal of Cleaner Production*, *217*, 172–184. https://doi.org/10.1016/j.jclepro.2019.01.094

APPENDIXES

APPENDIX A (Loadings and cross-loadings)

Construct	EE	FC	HAB	HM	IQ	IU	PE	PV	SI	SQ	SQ_	TR	UB
EE2	**0.754**	0.212	0.236	0.218	0.208	0.259	0.344	0.182	0.257	0.126	0.199	0.163	0.187
EE3	**0.842**	0.355	0.165	0.200	0.153	0.315	0.239	0.135	0.257	0.169	0.184	0.202	0.113
FC1	0.337	**0.681**	0.091	0.104	0.199	0.135	0.217	0.171	0.131	0.126	0.273	0.069	0.068
FC3	0.283	**0.918**	0.190	0.185	0.207	0.242	0.192	0.155	0.172	0.231	0.203	0.088	0.138
HAB1	0.215	0.196	**0.719**	0.238	0.164	0.210	0.250	0.222	0.258	0.265	0.092	0.186	0.264
HAB3	0.122	0.109	**0.733**	0.167	0.082	0.257	0.130	0.042	0.228	0.244	0.064	0.225	0.232
HAB4	0.215	0.120	**0.797**	0.264	0.123	0.266	0.141	0.265	0.232	0.253	0.093	0.183	0.297
HM1	0.194	0.159	0.234	**0.824**	0.197	0.291	0.166	0.246	0.210	0.219	0.137	0.184	0.209
HM3	0.214	0.131	0.232	**0.727**	0.239	0.240	0.296	0.167	0.330	0.165	0.117	0.148	0.199
IQ2	0.220	0.093	0.195	0.241	**0.641**	0.164	0.261	0.210	0.238	0.260	0.248	0.221	0.158
IQ3	0.151	0.256	0.090	0.207	**0.888**	0.144	0.278	0.154	0.170	0.210	0.311	0.210	0.264
IU1	0.309	0.156	0.243	0.308	0.100	**0.832**	0.359	0.222	0.277	0.297	0.217	0.337	0.207
IU3	0.259	0.241	0.278	0.230	0.212	**0.747**	0.242	0.229	0.202	0.230	0.187	0.214	0.210
PE1	0.232	0.144	0.173	0.231	0.210	0.313	**0.756**	0.078	0.286	0.120	0.160	0.155	0.194
PE2	0.310	0.138	0.164	0.182	0.319	0.226	**0.697**	0.162	0.206	0.245	0.207	0.229	0.184
PE3	0.255	0.240	0.162	0.212	0.241	0.294	**0.735**	0.210	0.187	0.224	0.241	0.174	0.163
PV2	0.142	0.091	0.197	0.198	0.162	0.240	0.171	**0.824**	0.186	0.148	0.251	0.088	0.107
PV3	0.165	0.223	0.177	0.227	0.185	0.200	0.140	**0.733**	0.207	0.290	0.239	0.213	0.180
SI1	0.270	0.108	0.267	0.220	0.189	0.214	0.230	0.178	**0.719**	0.144	0.084	0.276	0.315
SI2	0.172	0.107	0.167	0.210	0.211	0.228	0.214	0.166	**0.741**	0.155	0.180	0.276	0.253
SI3	0.275	0.203	0.276	0.322	0.152	0.244	0.257	0.214	**0.778**	0.189	0.064	0.232	0.186
SQ2	0.135	0.191	0.248	0.132	0.164	0.269	0.212	0.178	0.082	**0.732**	0.246	0.198	0.183
SQ3	0.155	0.174	0.277	0.248	0.276	0.257	0.196	0.241	0.246	**0.822**	0.274	0.211	0.220
SQ1_	0.200	0.253	0.069	0.165	0.303	0.228	0.212	0.242	0.071	0.262	**0.821**	0.135	0.196
SQ3_	0.187	0.189	0.112	0.101	0.285	0.189	0.236	0.270	0.167	0.283	**0.806**	0.157	0.189
TR1	0.193	0.063	0.269	0.171	0.199	0.274	0.265	0.191	0.292	0.242	0.088	**0.740**	0.183
TR4	0.172	0.088	0.157	0.169	0.224	0.285	0.139	0.109	0.261	0.179	0.185	**0.833**	0.280
UB1	0.138	0.133	0.287	0.183	0.192	0.198	0.223	0.185	0.273	0.238	0.202	0.251	**0.806**
UB2	0.158	0.087	0.286	0.242	0.265	0.227	0.177	0.106	0.267	0.184	0.182	0.234	**0.816**

Notes: Effort Expectancy (EE); Facilitating Conditions (FC); Habit (HB); Hedonic Motivation (HM); Information Quality (IQ); Intention to Use (IU); Performance Expectancy (PE); Price Value (PV); Social Influence (SI); Service Quality (SQ); System Quality (SQ_); Trust (TR); Use Behaviour (UB).

APPENDIX B. (Multigroup analysis for Israel and Portugal)

	Israel	Portugal
Intention to use (R-Squared)	**39.4%**	**33.8%**
Effort expectancy	0.374***	0.017
Facilitating conditions	0.019	0.152*
Habit	-0.038	0.205**
Hedonic motivation	0.138	0.104
Performance expectancy	0.122	0.163**
Price value	0.165*	0.078
Social influence	0.063	0.076
Trust	0.170	0.167*
Use Behavior (R-Sqaured)	**19.6%**	**33.2%**
Trust	0.233**	0.062
Facilitating conditions	0.101	0.002
Habit	0.137	0.331***
Information quality	0.185	0.114
Intention to use (R-Squared)	-0.082	0.052
Service quality	0.106	-0.001
System quality	0.051	0.235***
Tust x Intention to use	-0.061	-0.163*
Tust x Service quality	0.001	0.110
Trust x Information quality	-0.021	-0.029
Trust x System quality	0.058	0.133

APPENDIX C. (Measurement items)

Older 18 years old	SDF1	Are you over 18 years old?	
Age	SDF2	What's your age group?	
Residence	SDF3	In which country you currently reside?	
Gender	SDF4	What's your gender?	
Education Degree	SDF5	What is your highest education degree?	
Famliarity Nova IMS	SDF6	What is your level of familiarity with NOVA IMS (Nova Information Management School)?	
Perfomance Expectancy	PE1	I find AI chatbots for healthcare purposes useful in my daily life.	Adapted from Tam et al., 2020
	PE2	Using AI chatbots for healthcare purposes increases my chances of achieving things that are important to me.	
	PE3	Using AI chatbots for healthcare purposes helps me accomplish things more quickly.	
Effort Expectancy	EE2	My interaction with AI chatbots for healthcare purposes is clear and understandable.	
	EE3	I find AI chatbots easy to use for healthcare purposes.	
Social Influence	SI1	People who are important to me, would think that I should adopt an AI chatbot for healthcare purposes.	
	SI2	People who influence my behavior, would think that I should adopt an AI chatbot for healthcare purposes.	
	SI3	People who are in my social circle, would think that I should adopt an AI chatbot for healthcare purposes.	
Facilitating Conditions	FC1	I have the resources necessary to use AI chatbots for healthcare purposes.	
	FC2	I have the knowledge necessary to use AI chatbots for healthcare purposes.	
	FC3	AI chatbots for healthcare purposes are compatible with other technologies I use.	
	FC4	I can get help from others when I have difficulties using AI chatbots for healthcare purposes.	
Hedonic Motivation	HM1	Using AI chatbots for healthcare purposes is fun.	
	HM2	Using AI chatbots for healthcare purposes is enjoyable.	
	HM3	Using AI chatbots for healthcare purposes is very entertaining.	

Price Value	PV1	AI chatbots for healthcare purposes are reasonably priced.	Adapted from Tam e tal., 2020
	PV2	AI chatbots for healthcare purposes are a good value for the money.	
	PV3	At the current price, AI chatbots for healthcare purposes provide a good value.	
Habit	HAB1	The use of AI chatbots for healthcare purposes has become a habit for me.	
	HAB3	I must use AI chatbots for healthcare purposes.	
	HAB4	Using AI chatbots for healthcare purposes has become natural to me.	
Behavioral Intention	IU1	I intend to use AI chatbots for making health decisions when health needs (e.g., providing advice, booking appointments) arise in the future.	Adapted from Venkatesh et al., 2003
	IU3	I plan to use AI chatbots for making health decisions when health needs arise in the future.	
Use Behavior	UB1	I often use AI chatbots to search for diagnosis.	Adapted from Neves et al., 2025
	UB2	I oftern use AI chatbots to make health decisions.	
	UB3	I often use AI chatbots to monitor my health.	
System quality	SQ1_	AI chatbots for healthcare purposes have a fast response time.	Adapted from Xiong et al., 2022
	SQ3_	I can use AI chatbots for healthcare purposes at any time.	
Information quality	IQ2	AI chatbots for healthcare purposes provide satisfactory information formats.	
	IQ3	AI chatbots for healthcare purposes provide me with the information I need.	
Service quality	SQ2	AI chatbots for healthcare purposes respond quickly to my needs.	
	SQ3	AI chatbots for healthcare purposes provide services that meet my needs.	
	SQ4	AI chatbots for healthcare purposes understand my needs.	
Trust	TR1	AI chatbots for healthcare purposes offers a good level of privacy.	
	TR4	AI chatbots for healthcare purposes are trustworthy.	

APPENDIX D. (Ethics Approval)

De: Qualtrics Survey Software <noreply@qemailserver.com>
Enviado: quinta-feira, 10 de julho de 2025 15:21:57 (UTC+00:00) Dublin, Edinburgh, Lisbon, London
Assunto: NOVA IMS | Ethics Committee - APPROVED

NOVA IMS Information Management School

This is to certify that

Project No.: **DDMKT2025-7-103715**

Project Title: **Patient Trust in the Use of AI Chatbots for Healthcare Services**

Principal Researcher: **Sara Pihas**

according to the regulations of the Ethics Committee of NOVA IMS and MagIC Research Center this project was considered to meet the requirements of the NOVA IMS Internal Review Board, being considered **APPROVED** on 7/10/2025.

It is the Principal Researcher's responsibility to ensure that all researchers and stakeholders associated with this project are aware of the conditions of approval and which documents have been approved.

The Principal Researcher is required to notify the Ethics Committee, via amendment or progress report, of

- Any significant change to the project and the reason for that change;
- Any unforeseen events or unexpected developments that merit notification;
- The inability of the Principal Researcher to continue in that role or any other change in research personnel involved in the project.

Lisbon, 7/10/2025

NOVA IMS Ethics Committee
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NOVA Information Management School
Instituto Superior de Estatística e Gestão de Informação

Universidade Nova de Lisboa