UNIVERSIDADE CATÓLICA PORTUGUESA

Artificial Intelligence in the Health sector

Understanding the determinants of adoption and intention to recommend the technology

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Dinis Tavares

Under supervision of
Prof. Gonçalo Baptista

Católica Porto Business School, Universidade Católica Portuguesa
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Abstract

Over the last years the integration of Artificial Intelligence (AI) in various industries has witnessed a significant impulse, leading to transformative changes in traditional business, practices, and processes. With an enormous potential to transform patient care, maximize operational efficiencies, and improve medical results, healthcare has emerged as a leading industry in the implementation of AI-driven technology. The increasing complexity of healthcare demands, coupled with advancements in AI and computational capabilities, has induced considerable interest in exploring the adoption and acceptance of AI within healthcare settings. This work contributes to this evolving exciting discourse by combining two well-known theories, Unified Theory of Acceptance and Use of Technology (UTAUT) and the Health Belief Model (HBM), with the Intention to Recommend the technology construct. This innovative research model was tested using structured equation modelling (SEM) with data mainly from a European country, providing useful new insights of the determinants of AI adoption in healthcare. Key findings from the study reveal that performance expectancy, social influence, and facilitating conditions significantly influence individuals' intentions to adopt AI technologies in healthcare, highlighting the importance of considering these factors for successful implementations in this sector. The study's originality and value lie in its comprehensive investigation into AI adoption dynamics, offering valuable insights for researchers and practitioners.

Keywords: Artificial Intelligence, Healthcare, UTAUT, HBM, Behavioural Intention, Intention to Recommend, Medicine.

Resumo

Ao longo dos últimos anos, a integração da Inteligência Artificial (IA) em tem tido um impulso significativo, levando a mudanças drásticas nas práticas e processos comerciais tradicionais. Com um enorme potencial para transformar o cuidado dos pacientes, maximizar a eficiência operacional e melhorar os resultados médicos, a saúde emergiu como uma indústria líder na implementação de tecnologia impulsionada pela IA. A crescente complexidade das necessidades na saúde, aliada aos avanços tecnológicos tem suscitado um interesse considerável em explorar a adoção e o consentimento da IA dentro de contextos de saúde. Este estudo contribui para esta evolução ao combinar duas teorias conhecidas, a Teoria Unificada da Aceitação e Uso da Tecnologia (UTAUT) e o Modelo de Crenças de Saúde (HBM), com a variável Intenção de Recomendar a tecnologia. Este modelo de pesquisa inovador foi testado usando uma modelagem por equações estruturais (SEM) com dados maioritariamente de um país europeu, facultando um ponto de vista diferente e útil sobre os determinantes da adoção de IA na saúde. As principais descobertas do estudo revelam que a expectativa de desempenho, a influência social e as condições facilitadoras influenciam significativamente a intenção das pessoas em adotar tecnologias de IA na saúde, destacando a importância de considerar esses fatores para implementações bem-sucedidas neste setor. A originalidade e o valor do estudo residem na sua investigação abrangente sobre as dinâmicas de adoção de IA, oferecendo uma visão valiosa para profissionais de saúde e de investigação.

Palavras-chave: Inteligência Artificial, Saúde, UTAUT, HBM, Intenção de adoção, Intenção de recomendar, Medicina

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1. Introduction

The world as we know it is rapidly changing. Artificial Intelligence (AI) is revolutionizing most industries and changing people's lives. In the last years this has become increasingly more evident in the healthcare industry, where the proliferation of applications has evolved from very basic but effective symptom checking devices to increasingly autonomous robotic physicians and surgeons. These changes have been providing opportunities to increase the accuracy of diagnosis and treatment of diseases, while also allowing to reduce administrative tasks (Britt, 2018; González & Gutiérrez, 2020).

The rapid development and integration of AI-driven technologies in healthcare plays a pivotal role in improving patient outcomes and elevating the overall quality of healthcare services (IBM Education, 2023). These advancements empower physicians not only to offer patients more precise and comprehensible explanations of their medical conditions and treatment options (Lyu et al., 2023), but also to enhance the diagnostic process. By efficiently harnessing AI-assisted methods, doctors can evaluate potential diagnoses more effectively and discard less likely hypotheses, ultimately leading to improved patient care, (Lin et al., 2020; Sauerbrei et al., 2023).In various research studies, AI also demonstrated its capability to enhance human judgment, support healthcare decision-making, and show potential for improving treatment efficiency in the future. Leveraging a range of cognitive capabilities, AI aids in the development of novel and precise analytical procedures for medical images (Odhiambo et al., 2023).

Despite the benefits, the automatization of patient provider relationships also raises concerns regarding patient trust, loyalty, and satisfaction, which are a

crucial part of this business (González & Gutiérrez, 2020; Loh, 2018). Regarding these concerns, some argue that empathy forms a cornerstone of person-centred care, being considered the gold standard for doctor-patient relationships, improving satisfaction, and decreasing malpractice, improving health outcomes (Sauerbrei et al., 2023). Empathy holds significant importance, as it serves as a catalyst for compassion, which can be described as the feeling of warmth, concern, and care for others, along with a strong motivation to enhance the client's well-being (Sauerbrei et al., 2023). Therefore, empathy proves invaluable as it serves as a precursor for compassion, which automatized systems cannot provide. Yet, nowadays, since time is often insufficient for doctors to develop this kind of relationship with their clients, AI also comes up as a possible solution for this problem, enabling doctors to have more meaningful conversations with their patients, while delegating certain tasks to the machine (Sauerbrei et al., 2023).

This work's main goal is to emphasize the unique contributions and added value of this study in the context of AI acceptance in healthcare. This goes beyond merely understanding the antecedents of AI tools acceptance, it provides a comprehensive evaluation of success and willingness to recommend AI technology, which is crucial for its implementation and integration into healthcare systems. Unlike previous studies, this research delves into the nuanced dynamics of AI adoption, offering insights into patients' openness to use and recommend these technologies, thereby filling a gap in the literature. Furthermore, the innovative aspect of this study lies in its integrated model, which combines the Unified Theory of Acceptance and Use of Technology (UTAUT) with the Health Belief Model (HBM). By synthesizing these frameworks, the research offers a holistic understanding of the factors driving AI acceptance in healthcare, surpassing the limitations of previous studies that may

have focused on isolated constructs or failed to capture the complexity of adoption dynamics.

The contribution to knowledge is significant as this study uncovers novel insights into the interplay between various factors influencing AI adoption, shedding light on previously unexplored aspects of technology acceptance in the healthcare sector. By elucidating the mechanisms underlying patients' attitudes and intentions towards AI technology, the research advances our understanding of how these innovations can be effectively integrated into healthcare practices, ultimately improving patient care and outcomes. Moreover, the findings of this study hold practical implications for healthcare practitioners, policymakers, and technology developers. By identifying key determinants of AI acceptance and recommendation intentions, the research equips stakeholders with valuable insights to design tailored interventions, policies, and technologies that promote the successful adoption and utilization of AI in healthcare settings. This not only enhances the efficiency and effectiveness of healthcare delivery but also contributes to better patient experiences and outcomes, ultimately driving positive societal impact.

The structure of this study reflects a systematic approach to investigating the adoption of AI in healthcare. The introductory chapter provides an overview of the research problem and objectives, setting the stage for the subsequent chapters. Following the introduction, the literature review chapter offers a comprehensive examination of theoretical frameworks and previous research relevant to AI adoption and technology acceptance in healthcare contexts. The research model chapter delineates the conceptual framework utilized in this study. The methods chapter that follows, outlines the data collection procedures, measurement instruments, and analytical techniques employed, ensuring the

rigor and validity of the research findings. Subsequently, the data analysis and results chapter present the empirical findings derived from structural equation modelling (SEM) analysis, elucidating the relationships between key constructs and hypotheses. The discussion chapter synthesizes the findings, highlighting their theoretical implications, managerial insights, limitations, and avenues for future research. Finally, the conclusion chapter offers a succinct summary of the study's contributions, implications, and recommendations, concluding with reflections on the broader implications of the research findings for theory, practice, and policy in healthcare AI adoption.

2. Theoretical Background and Literature Review

Earlier studies delve the importance of AI in the healthcare sector, while exploring the related concepts and contributions made by the scientific community through projects developed over the years, mainly focusing on its applications in medical diagnosis, treatment innovation, and drug development. Artificial Intelligence (AI), a branch of science and technology, focuses on developing intelligent machines and computer programs that emulate human cognitive functions to perform tasks requiring human-like intelligence, including problem-solving, learning, and data analysis (S. H. Ting et al., 2021). Leveraging extensive datasets, often referred to as big data, AI enhances its performance and decision-making capabilities. Originally a concept associated with science fiction and theoretical debates, AI has become an integral part of your daily life. It plays a critical role across various sectors, significantly influencing industries such as manufacturing, healthcare, and supply chains. AI's distinct feature is its ability to execute tasks beyond human capabilities, resulting in a wide array of applications that improve performance and productivity (S. H. Ting et al., 2021).

Referred to as the intelligence demonstrated by machines, AI and its associated technologies are progressively pervasive in both business and society (Väänänen et al., 2021). They are increasingly finding applications in healthcare, with the goal of emulating hu-man cognitive functions (Väänänen et al., 2021). This transformative integration is significant-ly impacting the healthcare sector, propelled by the expanding availability of healthcare data and the rapid advancement of analytical techniques. Such integration has the potential to enhance productivity and the efficiency of care delivery, empowering healthcare

systems to offer improved care to a broader demographic. AI holds promise in transforming the healthcare landscape, alleviating burdens on healthcare practitioners and enabling them to prioritize direct patient care while minimizing burnout. This technology streamlines tasks typically handled by humans, enhancing the overall efficiency for patients, doctors, and hospital administrators, all achieved in a shorter timeframe and at a substantially reduced cost (Gómez-González & Gómez, 2020; Wisetsri, 2021).

2.1 Types of AI techniques used in AI based tools and devices

The integration of new digital technologies driven by health data and machine learning algorithms has profound implications in healthcare, enabling advancements in diagnostics, treatment innovation, and predictive healthcare (Jussupow et al., 2021). However, ensuring the success of AI-based recommendations requires not only their effectiveness but also their understandability and comprehensibility to users (Lyu et al., 2023).

In order to provide the best service possible, several AI based tools, applications and services have been developed over the years, incorporating techniques, such as Data Mining, Machine Learning (ML) and Deep Learning (DL).

The Data Mining process comprises methods of intuitive learning aimed at deriving general rules from a set of examples, obtained from past observations and diverse databases. Various learning methods exist to conduct Data Mining activities, such as classification trees or association rules. Techniques of this nature are commonly referred to as ML or Knowledge Discovery in Databases

(KDD). ML and KDD play a crucial role in analysing vast datasets in the healthcare domain, facilitating the identification of patterns and insights that can inform decision-making and optimize healthcare processes (Vercellis, 2009).

Machine Learning is a field of investigation and research that intersects the domains of statistics, AI, and computer science. It is also referred to as predictive analysis and statistical learning. ML encompasses a set of methods capable of automatically detecting patterns in data and utilizing them to uncover unknown patterns, thereby predicting future data or providing decision-making support in uncertain scenarios within the healthcare context (Müller & Guido, 2016).

Deep Learning represents a cutting-edge category of ML methodologies that has garnered substantial worldwide attention in recent years. DL leverages representation-learning techniques characterized by multiple layers of abstraction, enabling the processing of input data without relying on manual feature engineering. This inherent capability allows DL models to automatically discern complex structures in high-dimensional data by projecting it onto a lower-dimensional manifold. As a result, DL demonstrates significant potential for addressing intricate pattern recognition tasks, demonstrating its capacity to contribute to a wide range of applications across various domains (D. S. W. Ting et al., 2019).

Machine Learning and Deep Learning techniques have shown remarkable diagnostic capabilities in medical image analysis, enabling early disease detection and improved patient outcomes. Researchers are increasingly using AI to predict treatment outcomes and identify drug side effects, enhancing pharmaceutical research and development. Patient acceptance and trust in AI-driven tools emerge as crucial factors for successful implementation (Dlugatch et

al., 2023; Pasricha, 2022). Patients are more likely to embrace AI when they perceive it as accurate, reliable, and ethically designed (Longoni et al., 2019). Transparent communication and collaborative patient-provider relationships bolster acceptance. Overall, responsible integration of AI in healthcare holds great potential for transforming patient care and optimizing healthcare practices (Longoni et al., 2019).

2.2 AI Applications in Medical Diagnosis

The Data Mining, ML, and Deep Learning techniques have been widely used in healthcare and medicine, particularly in medical image analysis. ML and DL systems have demonstrated remarkable diagnostic capabilities in detecting various medical conditions (Lin et al., 2020). For instance, they have exhibited strong performance in identifying tuberculosis from chest X-rays, detecting malignant melanoma on skin photographs, and accurately identifying lymph node metastases secondary to breast cancer from tissue sections. These successful implementations of DL in medical imaging analysis highlighted its potential to revolutionize clinical practice by assisting medical professionals in early and precise disease detection, leading to improved patient outcomes and enhanced healthcare management. (Odhiambo et al., 2023; D. S. W. Ting et al., 2019).

Companies are increasingly utilizing machine learning techniques to predict future outcomes and assess the potential efficacy of treatments in the pharmaceutical domain (Qureshi et al., 2023). By applying machine learning to pharmaceutical research, drugs' researchers can identify and anticipate possible drug side effects and devise alternative components that mitigate undesirable

effects. Furthermore, AI technologies, including next-generation sequencing and precision medicine, play integral roles in the process of discovering and manufacturing medications (Qureshi et al., 2023). The integration of these advanced technologies in pharmaceutical research and development holds the promise of accelerating drug discovery, enhancing treatment effectiveness, and ultimately improving patient care and healthcare outcomes (Odhiambo et al., 2023).

2.3 Patient Acceptance, Trust, and Ethical Implications

The integration of AI in healthcare has prompted an examination of patient acceptance and trust in AI-based decision-support tools (Dlugatch et al., 2023). Patient acceptance of AI-driven tools in healthcare is contingent on several dimensions of trust. Notably, accuracy and reliability are pivotal factors, with patients being more inclined to adopt technology perceived as consistent with established medical knowledge (Sauerbrei et al., 2023). Transparent and explainable AI models enhance confidence. Additionally, the AI system's benevolence, prioritizing patients' well-being through ethical design principles and ensuring autonomy, safety, and privacy, fosters trust. Moreover, the competence and integrity of healthcare professionals involved influence acceptance (Sauerbrei et al., 2023). Effective communication and patient education, along with patient involvement in decision-making, bolster acceptance (Dlugatch et al., 2023). Lastly, a collaborative patient-provider relationship empowers patients to embrace AI-driven care through shared decision-making (Dlugatch et al., 2023).

It would also be expected that patients prefer to follow the advice of statistical models over human intuition, given its superior accuracy, however, that is not

the case, since in most cases consumers exhibit a marked reluctance to choose artificial AI-based providers, even when confronted with evidence of their superior performance relative to human providers (Longoni et al., 2019). This resistance to the adoption of AI in the medical domain is evident across various medical disciplines, encompassing preventive measures, diagnostic processes, and treatment interventions. This preference remains consistent in scenarios where AI providers perform at par with human providers, as well as in cases where the AI providers surpass human providers in delivering medical care (Longoni et al., 2019).

2.4 Theoretical models used in literature

In the realm of technology adoption and acceptance, some theoretical models have gained prominence in the academic discourse, namely the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT). The Technology Acceptance Model, developed by Davis (1989), posits that an individual's intention to use a technology is influenced by two primary factors: perceived ease of use and perceived usefulness. Perceived ease of use pertains to the extent to which a technology is perceived as effortless and user-friendly, while perceived usefulness relates to the degree to which individuals believe the technology can enhance their performance. TAM has been widely applied to understand the acceptance of various technologies, including information systems, mobile applications, and e-commerce platforms, serving as a foundational framework for examining user behaviour and adoption (Granić, 2023). Moreover, user behaviour extends beyond mere adoption. The notion of "intention to recommend" has gained significance in the realm of technology acceptance, with direct connection to the Unified Theory of Acceptance and Use of Technology (UTAUT) framework. Intention to

recommend, which was initially defined as a model for the organizational level, has been used lately by authors at an individual level, like in this study. It refers to an individual's willingness to recommend a technology or innovation to others based on their positive experience. It measures the extent to which users are inclined to advocate for the technology to potential users or customers. This concept is especially pertinent in assessing the social and communicative aspects of technology adoption, as it reflects the user's role as an influencer in the diffusion of innovations. Research has shown that a high intention to recommend is often indicative of user satisfaction and a positive user experience, making it a valuable dimension to consider in addition to adoption (Venkatesh et al., 2016). The UTAUT model has been used extensively throughout the last few years on numerous researches and carries the constructs of many other models. It is one of the most innovative research models, and has been used successfully in other health studies, being able to predict the decision to adopt new technologies (Cobelli et al., 2023), which is the focus point of this paper.

Other model used in AI literature is the Artificially Intelligent Device Use Acceptance Model (AIDUA), that extends TAM principles to address the specific context of AI-driven devices and acknowledges the unique challenges and considerations associated with AI technology, providing a tailored framework for investigating the acceptance and adoption of these devices (Chi et al., 2023). Many models, such as Theory of Reasoned Action (TRA) or theory of Planned Behaviour (TPB) have been suggested to explore human behavioural change over time and, although some of those theories have been developed to examine the human's behaviour change, scholars claim that the Health Belief Model (HBM) is the most suitable one, since its central focus is health motivation, addressing problem behaviours that raise health concerns. The four variables that define and influence people to adopt health-related behaviours are: Perceived Susceptibility,

Perceived Severity, Perceived Benefits and Perceived Barriers (Abdollahzadeh & Sharifzadeh, 2021).

Considering the body of literature examined in this comprehensive review, it is evident that a predominant proportion of the analysed articles adhere to a qualitative research methodology. These studies predominantly employ data collection techniques, such as interviews, focus groups, and case studies, which are inherently inclined toward smaller sample sizes. In contrast, the quantitative research methodology emphasizes the statistical, mathematical, or numerical analysis of data obtained through instruments like polls, questionnaires, and surveys (Mehrad & Zangeneh, 2019).

3. Research Model and Hypothesis

The integration of AI in healthcare has garnered significant attention for its potential to revolutionize medical practices, enhance patient care, and optimize healthcare operations (Sauerbrei et al., 2023). This research seeks to contribute to knowledge and to the evolving field of AI integration in healthcare. While healthcare professionals play a crucial role in the adoption and implementation of AI-driven tools in clinical settings, patient-centric research provides valuable insights into AI acceptance and trust from the end-users' perspective, turning the individual-level research into the best option for this investigation (Sauerbrei et al., 2023).

In our theoretical model we combine synergically Health Belief Model (HBM) with the Unified Theory of Acceptance and Use of Technology (UTAUT), and with an intention to recommend construct, to provide a better understanding of the AI adoption phenomenon in the healthcare sector. Consumers with a strong inclination to adopt new technology are more likely to become adopters and actively recommend the technology to others, contributing to its rapid dissemination (Oliveira et al., 2016). Despite extensive exploration in various contexts, the concept of consumers' intention to recommend technologies within adoption studies, without specifying the type of technology, remains relatively unexplored. This understanding is crucial for comprehending post-adoption dynamics and influencing broader adoption trends (Ferreira et al., 2023).

While mixing these two models and variable, several hypotheses were built, in order to test specific relationships between variables within the integrated framework.

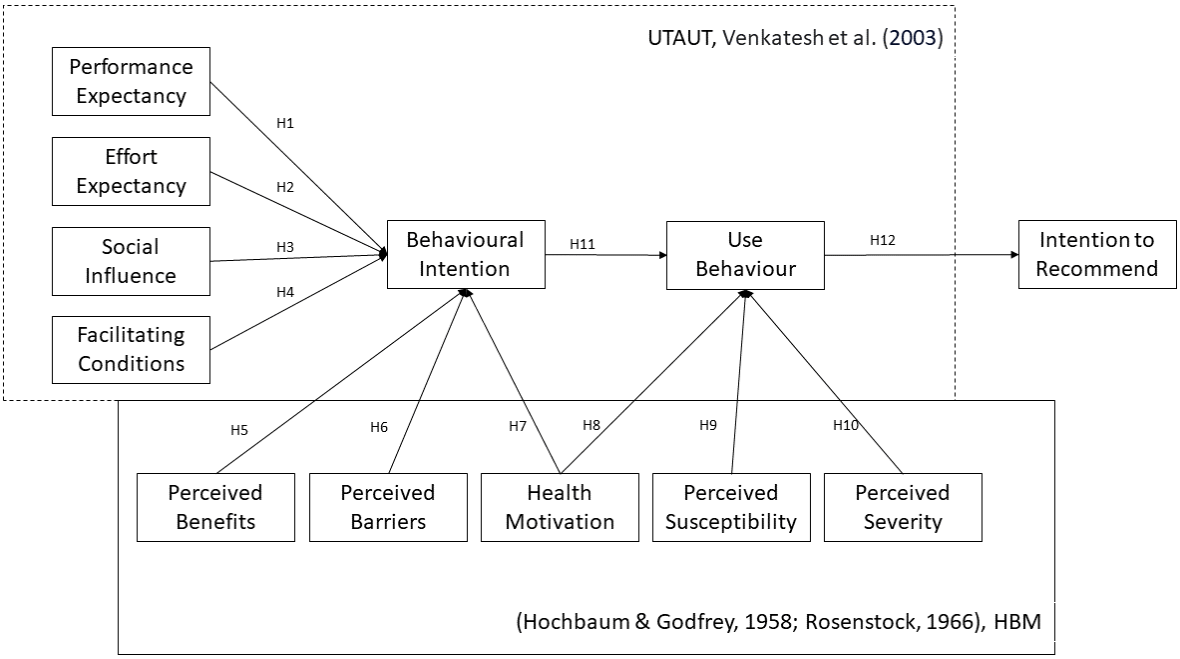


Figure 1: Research Model

Performance expectancy pertains to patients' beliefs regarding the benefits they perceive from using AI technology in healthcare contexts (Venkatesh et al., 2012). Patients' perceptions of how AI applications can improve their healthcare experience, such as facilitating access to medical information, enhancing the accuracy of diagnoses, or providing personalized treatment recommendations, play a crucial role in shaping their intention to adopt AI-based healthcare solutions.

H1: Performance Expectancy will positively influence Behavioural Intention.

Effort expectancy refers to the perceived ease with which patients can utilize AI technology in healthcare settings (Venkatesh et al., 2012). As highlighted by (Miltgen et al., 2013), effort expectancy significantly influences individuals' intention to adopt new technologies. When patients perceive AI applications in healthcare as user-friendly and requiring minimal effort to navigate or interact

with, they are more likely to have positive expectations regarding the performance of these technologies (Venkatesh et al., 2003).

H2: Effort Expectancy will positively influence Behavioural Intention.

Social influence refers to the degree to which patients perceive that significant people to them, such as family and friends, believe they should utilize AI technology in healthcare (Venkatesh et al., 2012). This construct captures the impact of environmental factors, including the opinions of individuals' social circle, on their behaviour (Venkatesh et al., 2003). Positive opinions from friends, relatives, and other influential figures may encourage patients to adopt AI-based healthcare services.

H3: Social Influence will positively influence Behavioural Intention.

Facilitating conditions pertain to patients' perceptions of the resources and support available to engage in a behaviour (Venkatesh et al., 2012). When patients perceive the presence of an operational infrastructure that supports the use of AI technology in healthcare settings, their behavioural intention to adopt AI-based healthcare services is likely to increase.

H4: Facilitating Conditions will positively influence Behavioural Intention.

As patients become aware of the benefits offered by AI-driven solutions, such as improved diagnostic accuracy and personalized treatment plans (Abdollahzadeh & Sharifzadeh, 2021), it is expected that their inclination to recommend these technologies to others will increase (Tajeri Moghadam et al., 2020). The perceived benefits are believed to play a significant role in motivating patients to advocate for the adoption of AI in healthcare settings, thereby establishing a positive correlation between perceived benefits and behavioural intention.

H5: Perceived Benefits will positively influence Behavioural Intention.

If patients' encounter obstacles such as concerns regarding data privacy or the complexity of integrating AI into existing healthcare systems, it is anticipated that their behaviour regarding the intention to use AI is cautiously or provide guidance on overcoming these barriers will strengthen (Tajeri Moghadam et al., 2020). Awareness of barriers could prompt patients to express a stronger intention to recommend AI (Guo et al., 2024), highlighting the positive relationship between perceived barriers and behavioural intention.

H6: Perceived Barriers will positively influence Behavioural Intention.

Health motivation refers to an individual's willingness and drive to take action towards maintaining or improving their health. It encompasses factors such as the importance an individual places on their health, their commitment to preventive behaviours, and their intrinsic motivation to adopt health-promoting actions (Abdollahzadeh & Sharifzadeh, 2021; Tajeri Moghadam et al., 2020). Driven by a strong desire to improve health outcomes, patients are expected to advocate for AI-driven solutions as a means of enhancing medical decision-making and patient care (Guo et al., 2024). Health motivation serves as a driving force behind patients' intention to use AI technologies in healthcare.

H7: Health Motivation will positively influence Behavioural Intention.

H8: Health Motivation will positively influence Use Behaviour.

Perceived Susceptibility is defined as an individual's belief regarding their likelihood of encountering a health problem or condition within healthcare settings (Abdollahzadeh & Sharifzadeh, 2021). When patients perceive themselves as susceptible to health issues and view AI applications in healthcare as effective tools for proactive monitoring and intervention, they are more

inclined to engage with these technologies (Guo et al., 2024). This belief in their vulnerability to health conditions prompts patients to actively utilize AI solutions, indicating a positive association between Perceived Susceptibility and Use Behaviour.

H9: Perceived Susceptibility will positively influence Use Behaviour.

Perceived Severity encompasses an individual's perception of the seriousness of a health problem, encompassing its potential consequences and impact on their life within healthcare settings (Tajeri Moghadam et al., 2020). When patients perceive health issues as severe threats to their well-being and recognize AI applications in healthcare as effective solutions for diagnosis and treatment, they are more inclined to engage with these technologies (Abdollahzadeh & Sharifzadeh, 2021). This understanding of the seriousness of health conditions motivates patients to actively utilize AI solutions.

H10: Perceived Severity will positively influence Use Behaviour.

Aligned with psychological theories underlying various models, which posit that individual behaviour is predictable and driven by personal intention (Yu, 2012), UTAUT underscores the significance of behavioural intention in shaping technology utilization (Venkatesh et al., 2003).

H11: Behavioural Intention will positively influence Use Behaviour.

In the realm of AI tools, devices, and services in healthcare, patients' intention to recommend such solutions has not been thoroughly investigated in adoption studies, to the best of our knowledge. Suppose patients intend to utilize AI-based healthcare technologies or have prior experience with them. In that case, they likely perceive their benefits, such as improved diagnostics, personalized treatment plans, or enhanced healthcare outcomes. Consequently, they are

inclined to recommend these AI-based solutions to others who may require similar medical assistance or seek innovative healthcare options (Ferreira et al., 2023).

H12: Use Behaviour will positively influence Intention to Recommend.

The questions used to test these hypotheses are in appendix 1.

4. Data collection and research methodology

The data collection was mainly conducted in Portuguese speaking countries, targeting people older than 18 years, Portuguese speaking persons, and users or potential users of healthcare services. Initially, a questionnaire based on the theoretical research model was created in English language and reviewed for content validity by an academic scholar. It contains three distinct sections: (i) UTAUT data constructs, (ii) HBM data and intention to recommend constructs, (iii) general information and demographic characteristics. The items and scales for the UTAUT constructs were adapted from Nordhoff et al. (2020), Chang et al. (2021) and Venkatesh et al. (2003, 2012), the HBM items were adapted from Abdollahzadeh & Sharifzadeh (2021) and Conner & Norman (2005) and the Intention to Recommend construct was adapted from Oliveira et al. (2016). Each item was measured with a seven-point Likert scale, ranging from "strongly disagree" (1) to "strongly agree" (7). The Use Behaviour was coded from 1 (never) to 7 (several times per day), according to use of AI in healthcare. In the end, the questionnaire was translated to Portuguese, submitted to a local Portuguese academic to review it, and then translated back to English to validate the consistency of the translation. Studies of technology acceptance have traditionally been conducted using survey research (Venkatesh et al., 2003), and therefore, an on-line survey instrument was designed with the Portuguese version of the questionnaire, hosted on a popular web service provider for collecting data. The survey was successively posted on several social media platforms, and it was also shared through word-of-mouth. After a period of 5 weeks, in the beginning of January 2024, a final number of 179 valid answers had been collected. From these, about 68% of respondents were women, 57% aged between 18 and 24 years old, and 54% with a Bachelor's degree. 92% of them live

in Portugal. Detailed descriptive statistics on the respondent's characteristics are shown in table 1.

Table 1: Descriptive statistics of respondents' characteristics

Measure	Value	Frequency	%
Gender	Male	57	32%
	Female	121	68%
Age	18 - 24	93	52%
	25 - 34	25	14%
	35 - 44	15	9%
	45 - 54	21	12%
	55 - 64	15	8%
	Over 64	9	5%
Highest level of education achieved	High school	29	16%
	Bachelor's (BSc)	96	54%
	Master's (MSc)	48	27%
	Doctorate (PhD)	5	3%
Country	Brazil	11	6%
	Poland	2	1%
	Portugal	158	92%
	Switzerland	1	1%

The CMB was tested using two different methods: (i) Harman's single factor test, which is a widely employed method for identifying common method bias, utilized either in exploratory or confirmatory factor analysis, and (ii) random dependent variable. Specifically, in the exploratory factor analysis, if the unrotated solution, inclusive of all measured items, reveals a single factor explaining more than 50% of the variance, it indicates the presence of common method bias (F. Kock et al., 2021). Harman's single factor was tested using IBM SPSS, obtaining a total variance of about 26%, therefore, lower than the threshold of 50% (Podsakoff et al., 2003). Concerning the random dependent variable

method, the final Variance Inflation Factor (VIF) values were analysed, being all below the threshold of 5 (Hair et al., 2017; N. Kock & Lynn, 2012). These observations confirmed that no significant common method bias was present in the data.

5. Data Analysis and Results

Structural equation modelling (SEM) encompasses various statistical models aimed at assessing the validity of theoretical frameworks using empirical data. There are two principal techniques: covariance-based and variance-based. Our study employed a variance-based method, specifically the partial least squares (PLS), and it was conducted using Smart PLS 4 software (Ringle et al., 2022). This statistical method is valued for its versatility and effectiveness across various research scenarios. It is particularly suited for analysing complex models with multiple variables (Henseler et al., 2009). The large size of the sample relative to the number of paths to each construct ensures the reliability of the estimation, making PLS one of the most suitable choices to use. PLS imposes fewer constraints on residual distributions and sample sizes compared to other structural equation modelling (SEM) techniques (Chin, 1998). This analysis comprises two sequential steps: assessing the reliability and validity of the measurement model, followed by testing hypotheses through structural model analysis. These steps are elaborated upon in the subsequent sections.

5.1 Measurement model

The measurement model' step underwent the assessment of the items' reliability, internal consistency, convergent validity, and discriminant validity analysis. Item's reliability was assessed by comparing the factor loadings against the established criteria that the loadings must be greater than 0.7 and every loading under that threshold would have to be eliminated (Henseler et al., 2009). That resulted in the removal of EE2, FC4, HM2, HM4, PB3, PBa3, PS1, PS2 and PS4, due to low loading, keeping the remaining items as seen in Table 2. Composite reliability and most of Cronbach's alpha values, were above 0.7,

indicating their reliability (Straub, 1989). HM was the only one with a value below the threshold, however, Taan & Hajjar (2018) defends that the Cronbach's alpha values that fall between 0.6 and 0.8 are still acceptable, and therefore we maintained it. Convergent validity was confirmed by the average variance extracted (AVE) criterion, revealed that all constructs met the threshold of 0.5, indicating adequate explanation of variance (Fornell & Larcker, 1981; Henseler et al., 2009). These results can be confirmed in Table 2.

Table 2: Quality criteria and factor loadings

Construct	Item	AVE	Composite Reliability	Cronbach's Alpha	Loadings	t-value
Behavioural Intention	BI1	0.744	0.920	0.883	0.722	15.321
	BI2				0.882	36.576
	BI3				0.911	56.930
	BI4				0.920	64.278
Effort Expectancy	EE1	0.854	0.946	0.914	0.926	67.922
	EE3				0.945	82.960
	EE4				0.900	33.565
Facilitating Conditions	FC1	0.790	0.918	0.867	0.884	40.282
	FC2				0.902	51.535
	FC3				0.880	40.155
Health Motivation	HM1	0.715	0.834	0.604	0.872	18.239
	HM3				0.818	14.590
Perceived Benefits	PB1	0.823	0.933	0.892	0.917	10.490
	PB2				0.943	10.944
	PB4				0.859	10.140
Perceived Barriers	PBa1	0.638	0.841	0.724	0.797	14.153
	PBa2				0.751	10.486
	PBa4				0.846	21.584
	PE1				0.808	17.767

Construct	Item	AVE	Composite Reliability	Cronbach's Alpha	Loadings	t-value
Performance Expectancy	PE2	0.643	0.878	0.815	0.850	33.394
	PE3				0.774	21.390
	PE4				0.772	15.985
Perceived Susceptibility	PS3	-	-	-	1.000	n/a
Perceived Severity	PV1	0.622	0.868	0.800	0.772	4.543
	PV2				0.849	5.368
	PV3				0.789	4.605
	PV4				0.741	4.218
Intention to recommend	REC1	0.804	0.891	0.762	0.932	47.842
	REC2				0.860	22.202
Social Influence	SI1	0.679	0.894	0.845	0.804	28.839
	SI2				0.839	43.287
	SI3				0.840	28.931
	SI4				0.813	23.903
Use Behaviour	UB1	0.760	0.950	0.936	0.886	46.937
	UB2				0.889	47.144
	UB3				0.856	35.401
	UB4				0.772	21.456
	UB5				0.907	52.365
	UB6				0.914	57.453

Discriminant validity was assessed through three established methods: (i) the Fornell-Larcker criterion, (ii) cross-loadings analysis, and HTMT – heterotrait-monotrait ratio of correlations. In accordance with Fornell & Larcker (1981), the square root of the Average Variance Extracted (AVE), in bold on diagonal in Table 3, should exceed the inter-construct correlations, which was verified. Regarding the cross-loadings method, that indicate that the loading of each factor

should be higher than all cross-loadings (Götz et al., 2009), was met, as seen in appendix 3. The HTMT was analysed against the threshold of 0.9, according to (Henseler et al., 2015) best practices, as seem in appendix 4 - All criteria were met, thus affirming the discriminant validity of the measurement scales.

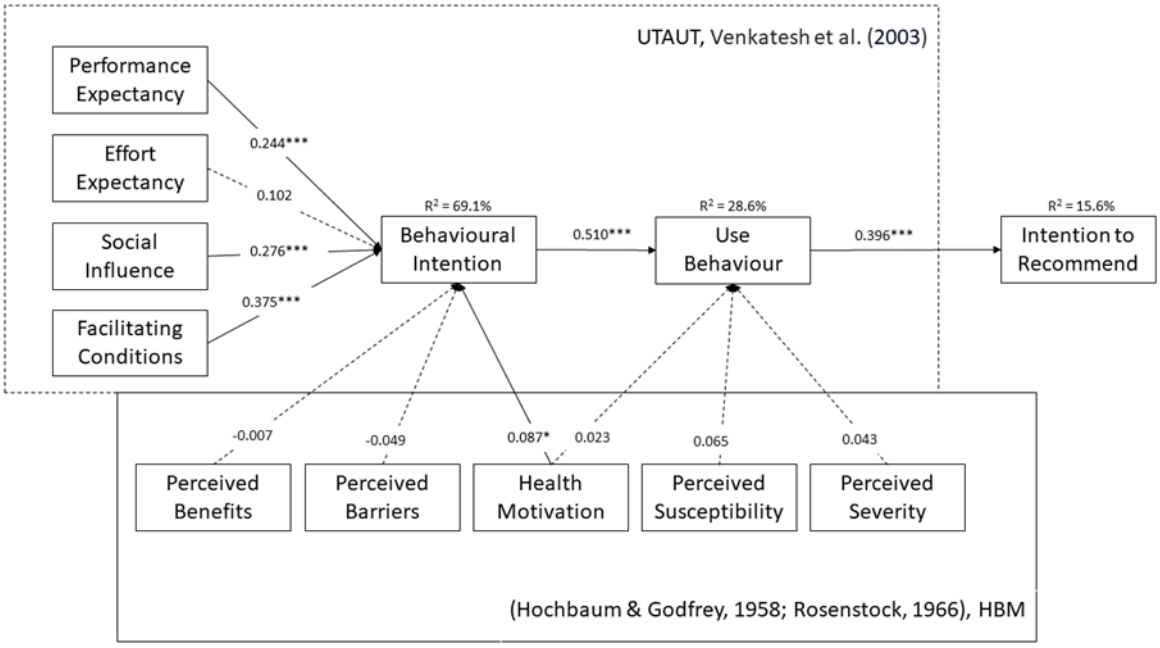
Table 3: Correlation matrix with mean and standard deviation values

	BI	**EE**	**FC**	**HM**	**PB**	**PBa**	**PE**	**PS**	**PV**	**REC**	**SI**
BI	**0.862**										
EE	0.568	**0.924**									
FC	0.681	0.677	**0.889**								
HM	0.338	0.160	0.218	**0.846**							
PB	0.174	0.073	0.059	0.273	**0.907**						
PBa	-0.413	-0.304	-0.299	-0.087	-0.103	**0.799**					
PE	0.600	0.340	0.344	0.233	0.252	-0.378	**0.802**				
PS	0.023	-0.063	-0.064	0.194	0.238	0.033	0.061	**1.000**			
PV	0.120	-0.024	0.061	0.183	0.257	-0.046	0.130	0.496	**0.789**		
REC	0.531	0.331	0.362	0.350	0.342	-0.346	0.499	0.161	0.123	**0.896**	
SI	0.662	0.362	0.434	0.338	0.218	-0.440	0.559	0.094	0.183	0.620	**0.824**

The results from the measurement model demonstrate a good levels of construct reliability, indicator reliability, convergence validity, and discriminant validity. These results confirm the statistical distinctiveness of the constructs under investigation, thereby substantiating their suitability for examining the structural model.

5.2 Structural model

To further test for multicollinearity, we analysed all the items Variance Inflation Factor (VIF) against the maximum value of 5 (Hair et al., 2017; Kock & Lynn, 2012), revealing no multicollinearity problems (appendix 2). The examination of hypotheses and associations between constructs was conducted by assessing standardized paths. Path significance was ascertained through the bootstrap resampling technique (Henseler et al., 2009) which involved 5,000 iterations of resampling. The results are shown in figure 2.



Note: (*p<0.10; **p<0.05; ***p<0.01)

Figure 2: Structural model results

The model explains 69.1% of the variance in behavioural intention, 28.6% of use behaviour, and 15.6% of the intention to recommend. Performance expectancy, social influence and facilitating conditions emerge as statistically significant predictors of behavioural intention, at a significance level of $p < 0.01$,

thus confirming hypotheses H1, H3 and H4. Contrarily, effort expectancy does not demonstrate statistical significance, failing to support hypotheses H2. Notably, the influence of behavioural intention on use behaviour, and the influence of use behaviour on intention to recommend are both statistically significant, confirming hypothesis H11 and H12, at a significance level of $p < 0.01$. Moreover, health motivation is the only HBM variable statistically significant on behavioural intention, at a significance level of $p < 0.10$, meaning perceived benefits and perceived barriers, which represent hypothesis H5 and H6, are not supported by this model. Lastly, health motivation, perceived susceptibility and perceived severity fail to be statistically significant in explaining use behaviour, opposing hypothesis H8, H9 and H10. The list of all hypotheses results is presented in Table 4.

Table 4: Hypothesis testing

Relationship	Hypothesis	Original Sample	p-values	Statistically significant?
BI -> UB	H11	0.510	0.000	Yes
EE -> BI	H2	0.102	0.161	No
FC -> BI	H4	0.375	0.000	Yes
HM -> BI	H7	0.087	0.087	Yes
HM -> UB	H8	0.023	0.743	No
PB -> BI	H5	-0.007	0.884	No
PBa -> BI	H6	-0.049	0.237	No
PE -> BI	H1	0.244	0.001	Yes
PS -> UB	H9	0.065	0.380	No
PV -> UB	H10	0.043	0.560	No
SI -> BI	H3	0.276	0.000	Yes
UB -> REC	H12	0.396	0.000	Yes

In summary, among the twelve hypotheses formulated, six are supported by the collected data. The next step in the analysis was to examine the total effects, as presented in Table 5. Based on the analysis of determinants influencing technology adoption and recommendation intention in the healthcare sector, several conclusions emerge.

Table 5: Total effect analysis

Relationship	$\hat{\beta}$	**p-value**	**Statistically significant?**
BI -> REC	0.202	0.000	Yes
BI -> UB	0.510	0.000	Yes
EE -> BI	0.102	0.161	No
EE -> REC	0.021	0.207	No
EE -> UB	0.052	0.174	No
FC -> BI	0.375	0.000	Yes
FC -> REC	0.076	0.001	Yes
FC -> UB	0.191	0.000	Yes
HM -> BI	0.087	0.087	Yes
HM -> REC	0.027	0.352	No
HM -> UB	0.068	0.330	No
PB -> BI	-0.007	0.884	No
PB -> REC	-0.001	0.888	No
PB -> UB	-0.003	0.884	No
PBa -> BI	-0.049	0.237	No
PBa -> REC	-0.010	0.274	No
PBa -> UB	-0.025	0.246	No
PE -> BI	0.244	0.001	Yes
PE -> REC	0.049	0.005	Yes
PE -> UB	0.125	0.001	Yes
PS -> REC	0.026	0.397	No
PS -> UB	0.065	0.380	No
PV -> REC	0.017	0.567	No

Relationship	$\hat{\beta}$	p-value	Statistically significant?
PV -> UB	0.043	0.560	No
SI -> BI	0.276	0.000	Yes
SI -> REC	0.056	0.001	Yes
SI -> UB	0.141	0.000	Yes
UB -> REC	0.396	0.000	Yes

Notably, significant positive effects were observed for behavioural intention (BI) on recommendation intention (REC) ($\hat{\beta}$ = 0.202; $p < 0.01$), suggesting a robust influence of BI on these outcomes. Additionally, performance expectancy (PE) demonstrated a notable positive effect on REC ($\hat{\beta}$ = 0.049; $p < 0.01$), indicating its significance in shaping individuals' intentions towards recommending technology adoption, and social influence (SI) emerged as a significant predictor of REC ($\hat{\beta}$ = 0.056; $p < 0.01$), underscoring the role of social factors in influencing individuals' recommendation decisions. Conversely, variables such as perceived barrier (PB) and perceived severities (PV) showed no statistically significant effects on REC, implying their limited impact in this context. Overall, these findings contribute to a better understanding of the factors driving technology adoption and recommendation intention within the healthcare domain, offering valuable insights for practitioners and policymakers in enhancing technology implementation strategies.

6. Discussion

The theoretical model presented is unique, combining the extended unified theory of acceptance and use of technology (UTAUT), of Venkatesh et al. (2012) with the health belief model (HBM) from (Hochbaum & Godfrey, 1958; Rosenstock, 1966), to explain AI acceptance in the healthcare sector. The factors that positively influence acceptance are performance expectancy, social influence, facilitating conditions, and health motivation, all explaining BI. The effect of behaviour intention on use behaviour was also found to be significant, confirming earlier research, indicating that individuals who have a strong intention to use a technology are more likely to actually use it (Venkatesh et al., 2003, 2012).

The research model validated three relationships of behavioural intention, namely performance expectancy (H1), social influence (H3) and facilitating conditions (H4), which means that the degree to which AI devices, applications, and services offer advantages in facilitating tasks within the healthcare sector significantly influence the use of AI technology. These findings are consistent with previous research (Baptista et al., 2015), however, effort expectancy's (H2) relationship with behavioural intention was not validated by the model, which Is confirmed by Oliveira et al. (2016), but contradicts the findings of Rouidi et al. (2022) and Wang et al. (2020), meaning that people might not find AI in healthcare easy to use, or important for their needs, in order to make the effort to learn and use it frequently.

As for the relationship of the HBM constructs with behavioural intention, only health motivation (H7) was validated. Contrary to (Guo et al., 2024) discovery, the influence of perceived benefits (H5) and perceived barriers (H6)

was not confirmed by the model. This suggests that the perceived advantages and obstacles associated with AI devices in healthcare, as proposed by H5 and H6, may not play significant roles in influencing individuals' adoption decisions. The other constructs, such as health motivation (H8), perceived susceptibility (H9), and perceived severity (H10), were all found to have no significant relationship with use behaviour, contradicting the findings of Tajeri Moghadam et al. (2020). This implies that factors like motivation to maintain health, perception of susceptibility to health risks, and the severity of potential health issues may not strongly influence individuals' actual use of AI devices, applications, and services in the healthcare sector, as suggested by Tajeri Moghadam et al. (2020).

The research model explains 15.6% of variation in Intention to Recommend, 69.1% of the variance in behavioural intention, 28.6% of use behaviour of AI devices, applications, and services in healthcare. While the R-squared value for intention to recommend may appear relatively low compared to other variables, such as behavioural intention, it nonetheless signifies a substantial portion of the variance explained within the context of technology recommendation, which can be attributed to the unique challenges and considerations inherent in healthcare technology adoption. However, the findings do not indicate a tendency to endorse AI-based devices, presenting a lower percentage compared to previous studies, such as Oliveira et al. (2016). This difference may stem from limited research in this specific area and the conservative nature of the healthcare industry, which tends to adopt new technologies more slowly (Anderson, 2022). Regarding behavioural intention, there were some similarities with other studies, such as Wang et al. (2020) with 68% and Ferreira et al. (2023) with 70%. However, in contrast, use behaviour presented an R-squared much lower than Ferreira et al. (2023), at 58%.

The integration of UTAUT and HBM in our model is facilitated, offering a comprehensive framework for understanding AI adoption in the healthcare sector. By elucidating the interplay between various factors such as performance expectancy, social influence, and health motivation, a nuanced understanding of individuals' intentions to recommend AI technologies is provided by our model. Moreover, the importance of addressing factors that influence individuals' willingness to embrace AI solutions in healthcare settings is underscored by the significant effect of behavioural intention on actual use behaviour, thereby paving the way for tailored interventions aimed at promoting technology adoption.

Furthermore, the need for further exploration into the perceived ease of use of AI technologies in healthcare is highlighted by the divergent findings regarding the relationship between effort expectancy and behavioural intention. Understanding why AI may not be perceived as easy to use or essential for individuals' needs is deemed crucial for the design of user-friendly solutions that align with the unique requirements of healthcare professionals and patients. Additionally, the lack of significant relationships between certain HBM constructs and use behaviour suggests that the complexities of AI adoption in healthcare may not be fully captured by traditional health belief factors, emphasizing the importance of context-specific variables in future research and intervention strategies.

6.1 Theoretical Implications

This study serves as a fundamental step in clarifying acceptance models, paving the way for future investigations, by shedding light on the nuanced interplay of various factors influencing the adoption of AI-based technologies in healthcare, thereby offering a robust framework for further exploration and

refinement in this critical area of research. The research explored both direct and indirect factors influencing the acceptance of AI-based devices, applications, and services, highlighting significant elements like performance expectancy, social influence, and facilitating conditions.

6.2 Practical Implications

The quantitative research yields three crucial practical implications concerning the integration of AI-based devices within the healthcare sector. Firstly, the study emphasizes the influential roles of performance expectancy and social influence. It demonstrates that individuals' perceptions of the performance benefits of AI technologies and the influence of social networks significantly impact their acceptance and adoption. Secondly, the research highlights the significance of facilitating conditions in providing the necessary technical infrastructure and support, crucial for the effective implementation of AI technologies in the healthcare sector. A supportive infrastructure not only enhances confidence in using these technologies, but also mitigates potential technical challenges, thereby positively influencing individuals' intentions to adopt AI solutions in their healthcare practices. Moreover, the study highlights the role of health motivation in shaping behavioural intentions. Health motivation reflects an individual's recognition of the importance of health and wellness, driving their willingness to engage with technologies that promise better health outcomes. In the context of AI devices in healthcare, individuals with high health motivation are more likely to perceive these technologies as valuable tools for managing their health.

Companies developing applications or providing services for the healthcare should pay closer attention to these factors to ensure better acceptance and adoption ratios in their solutions. Marketers need to consider strategies that take into account the influence of social networks on the perception and adoption of

AI-based health technologies. Physicians and healthcare professionals need to be aware of the impact of health motivation on patients' willingness to adopt and use these technologies, effectively integrating them into their clinical practices to provide better outcomes for patients.

6.3 Limitations and Further Research

Like any other, the study has several limitations and must be interpreted considering these constraints. Firstly, the current research adopted just a quantitative methodology, using mix method, combining quantitative and qualitative method in the future, could provide additional insights into individuals' attitudes, perceptions, and experiences related to the adoption of AI-based devices in the healthcare sector. Secondly, 92% of the respondents from this sample are from a European country, which may limit the generalizability of the findings. Future research could also consider exploring the factors influencing the usage of AI in different contexts and in different cultural settings. Another venue to pursue in future studies could be to include some factors that some authors consider important for the technology adoption, such as trust (Liébana-Cabanillas et al., 2013) and risk (Slade et al., 2015). Also, an experience moderator and habit construct from the UTAUT2 should be included in the research model, to gain insights into users' prior experience and habitual behaviours, enhancing the understanding of technology acceptance and usage within the healthcare sector (Venkatesh et al., 2016). Measuring the effects of these constructs and comparing results would be a fruitful path forward.

Additionally, future research could explore: (1) the level of mistrust people have on AI technology, such as assessing its significance in various healthcare activities; (2) the potential productivity gains for healthcare providers and patients resulting from AI adoption; (3) outcome measures like usage patterns,

volume of usage, time saved, and comparisons with traditional methods, offering a more comprehensive understanding of AI adoption and utilization in healthcare settings. By examining factors like usability, productivity gains, and outcome measures at firm level, a more comprehensive understanding of how AI adoption influences healthcare practitioners and patient acceptance could be reached.

7. Conclusions

Combining the Unified Theory of Acceptance and Use of Technology (UTAUT) with the Health Belief Model (HBM) we created an innovative and integrated model that is able to identify the variables influencing people's acceptance and recommendation intentions regarding AI-based devices, applications, and services in a healthcare setting. This study methodology offers insightful information about the factors that influence the acceptance and recommendation of technology in the healthcare sector. The results show how important performance expectation, social influence, and supportive environments are in influencing people's behavioural intentions about the use of AI in healthcare. Furthermore, the study emphasizes how people's motivation to use AI technologies is influenced by their health, underscoring the need of appreciating health and wellness while making technological adoption decisions.

All things considered, this study significantly advances our understanding of the complex dynamics surrounding AI adoption and recommendation intentions within the medical field, contributing valuable insights to both theoretical frameworks and practical applications. By elucidating the nuanced interactions among various factors influencing technology acceptance, this research lays the groundwork for developing tailored strategies to effectively integrate AI technologies into healthcare systems, thereby optimizing patient outcomes and enhancing overall healthcare delivery.

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Appendices

Appendix 1 – Survey' questions

Constructs	Items	Item	Source
Performance Expectancy (PE)	- I believe that AI in healthcare would enhance the effectiveness of my medical treatments. - Using AI in healthcare would contribute to the safety and accuracy of healthcare procedures. - Healthcare AI applications are helpful in managing my healthcare needs. - Using healthcare AI applications can improve my efficiency in monitoring health conditions.	PE1 PE2 PE3 PE4	(Nordhoff et al., 2020) (Chang et al., 2021)
Effort Expectancy (EE)	- Learning how to use AI applications in healthcare would be straightforward for me. - I expect that using AI in healthcare would be user-friendly and easy to navigate. - Learning how to use healthcare AI applications is easy for me. - My interaction with healthcare AI applications is clear and understandable.	EE1 EE2 EE3 EE4	(Nordhoff et al., 2020) (Venkatesh et al., 2003)
Social Influence (SI):	- I assume that healthcare professionals whose opinions I value would recommend the use of AI in healthcare. - I would recommend using AI applications in healthcare to fellow patients and friends. - People who are important to me think that I should use healthcare AI applications. - People who influence my behaviour think that I should use healthcare AI applications.	SI1 SI2 SI3 SI4	(Nordhoff et al., 2020) (Venkatesh et al., 2003)
Facilitating Conditions (FC)	- I have the resources necessary to use healthcare AI applications. - I have the knowledge necessary to use healthcare AI applications - Healthcare AI applications is compatible with other technologies I use. - I can get help from others when I have difficulties using healthcare AI applications.	FC1 FC2 FC3 FC4	 (Venkatesh et al., 2003)
Behavioural Intention (BI)	- I plan to use healthcare AI applications in healthcare even in challenging health conditions or critical situations. - I would incorporate healthcare AI applications into my routine health-related activities. - I intend to continue using healthcare AI applications in the future. - I plan to continue to use healthcare AI applications frequently.	BI1 BI2 BI3 BI4	(Nordhoff et al., 2020) (Venkatesh et al., 2003)
Perceived Susceptibility (PS)	- My present physical state inclines towards potential health issues. - I perceive a reasonable probability of facing health concerns in the future. - I have significant concerns about experiencing health-related issues. - Within the following year, I might face certain health problems.	PS1 PS2 PS3 PS4	 (Conner & Norman, 2005)
Perceived Severity (PV)	- The thought of dealing with health issues worries me. - If I had health issues, my career would be endangered. - Health issues could impact my significant relationships. - Health problems might threaten my financial stability.	PV1 PV2 PV3 PV4	 (Conner & Norman, 2005)
Perceived Benefits (PB)	- Engaging in regular health check-ups helps in preventing potential future health issues. - Health check-ups assist in identifying potential health concerns early. - My anxiety regarding health issues might reduce if I were consistent with regular health check-ups. - Consistent health check-ups may aid in detecting abnormalities before routine medical exams.	PB1 PB2 PB3 PB4	 (Conner & Norman, 2005)
Perceived Barriers (Pba)	- Incorporating healthcare-related AI technologies might lead to discomfort. - Using healthcare-related AI technologies might demand considerable time and effort. - Engaging with healthcare-related technologies might disrupt my daily routine or activities. - I might lack confidence in effectively using AI healthcare-related technologies.	PBa1 PBa2 PBa3 PBa4	 (Conner & Norman, 2005)
Health Motivation (HM)	- I actively seek information to safeguard my health against potential illnesses. - I prioritize regular health check-ups even when not experiencing any symptoms. - Maintaining good health holds significant importance to me. - I consider it important to engage in activities that enhance my overall health and well-being.	HM1 HM2 HM3 HM4	(Abdollahzadeh & Sharifzadeh, 2021)
Use Behaviour	Please choose your usage frequency for each of the following: a) AI healthcare applications b) medical AI applications c) AI healthcare devices d) AI healthcare wearables e) AI healthcare websites	 UB1 UB2 UB3 UB4 UB5	 (Venkatesh et al., 2012)

Constructs	Items	Item	Source
	f) Mobile AI healthcare applications or services	UB6	
Intention to recommend	- I will recommend to my friends to subscribe to healthcare AI applications, if they are available. - If I have a good experience with healthcare AI applications, I will recommend friends to subscribe to the service.	REC1 REC2	(Oliveira et al., 2016)

Appendix 2 - Collinearity statistics (VIF)

Item	VIF
BI1	1.525
BI2	2.616
BI3	3.520
BI4	3.780
EE1	3.433
EE3	4.112
EE4	2.693
FC1	2.285
FC2	2.521
FC3	2.082
HM1	1.230
HM2	1.230
PB1	3.440
PB2	3.754
PB4	2.052
PBa1	1.503
PBa2	1.433
PBa4	1.363

Item	VIF
PE1	2.129
PE2	2.371
PE3	1.705
PE4	1.766
PS3	1.000
PV1	1.462
PV2	1.783
PV3	1.808
PV4	1.506
REC1	1.610
REC2	1.610
SI1	1.769
SI2	1.844
SI3	3.253
SI4	2.988
UB1	3.705
UB2	4.082
UB3	3.003
UB4	2.324
UB5	4.886
UB6	4.705

Appendix 3 – Cross Loadings

	BI	EE	FC	HM	PB	PBA	PE	PS	PV	REC	SI	UB
BI1	0.722	0.281	0.338	0.286	0.026	-0.377	0.429	0.127	0.197	0.356	0.573	0.365
BI2	0.882	0.515	0.578	0.284	0.245	-0.428	0.548	0.045	0.133	0.541	0.627	0.384
BI3	0.911	0.567	0.700	0.316	0.171	-0.289	0.578	-0.022	0.047	0.481	0.553	0.529
BI4	0.920	0.550	0.677	0.284	0.134	-0.354	0.503	-0.038	0.070	0.445	0.552	0.512
EE1	0.529	0.926	0.624	0.154	0.090	-0.302	0.309	-0.036	-0.009	0.319	0.321	0.270
EE3	0.544	0.945	0.652	0.146	0.058	-0.274	0.280	-0.061	-0.026	0.315	0.300	0.341
EE4	0.499	0.900	0.600	0.143	0.054	-0.267	0.359	-0.080	-0.033	0.283	0.387	0.399
FC1	0.589	0.560	0.884	0.169	0.005	-0.218	0.247	-0.094	0.032	0.289	0.365	0.373
FC2	0.601	0.620	0.902	0.195	-0.017	-0.304	0.303	-0.079	0.089	0.287	0.402	0.409
FC3	0.625	0.624	0.880	0.215	0.165	-0.274	0.362	0.000	0.041	0.386	0.390	0.358
HM1	0.316	0.142	0.243	0.872	0.224	-0.085	0.243	0.221	0.171	0.324	0.287	0.183
HM2	0.251	0.128	0.116	0.818	0.240	-0.060	0.143	0.097	0.137	0.264	0.286	0.183
PB1	0.144	0.098	0.062	0.244	0.917	-0.094	0.220	0.226	0.207	0.333	0.137	0.062
PB2	0.181	0.079	0.076	0.310	0.943	-0.037	0.235	0.211	0.217	0.295	0.224	0.122
PB4	0.143	0.018	0.019	0.174	0.859	-0.164	0.230	0.213	0.281	0.309	0.227	0.138
PBA1	-0.296	-0.162	-0.148	-0.037	0.014	0.797	-0.346	0.061	-0.013	-0.259	-0.406	-0.213
PBA2	-0.258	-0.140	-0.209	-0.083	-0.013	0.751	-0.189	-0.046	-0.100	-0.172	-0.278	-0.204
PBA4	-0.406	-0.372	-0.329	-0.085	-0.198	0.846	-0.347	0.048	-0.014	-0.360	-0.365	-0.316
PE1	0.500	0.287	0.262	0.142	0.173	-0.262	0.808	-0.040	0.055	0.357	0.428	0.218
PE2	0.502	0.229	0.247	0.175	0.200	-0.310	0.850	0.026	0.086	0.373	0.481	0.345
PE3	0.488	0.262	0.277	0.241	0.191	-0.344	0.774	0.122	0.110	0.472	0.434	0.302
PE4	0.428	0.322	0.324	0.191	0.253	-0.299	0.772	0.096	0.177	0.402	0.454	0.284
PS3	0.023	-0.063	-0.064	0.194	0.238	0.033	0.061	1.000	0.496	0.161	0.094	0.103
PV1	0.118	-0.046	0.088	0.202	0.313	-0.031	0.043	0.497	0.772	0.173	0.180	0.119
PV2	0.103	0.007	0.038	0.115	0.123	-0.051	0.145	0.323	0.849	0.091	0.142	0.136
PV3	-0.013	-0.127	-0.067	0.096	0.131	0.033	0.025	0.447	0.789	0.049	0.121	0.082
PV4	0.150	0.069	0.113	0.160	0.245	-0.082	0.186	0.317	0.741	0.053	0.126	0.095
REC1	0.566	0.340	0.378	0.365	0.267	-0.373	0.456	0.170	0.124	0.932	0.657	0.405
REC2	0.356	0.240	0.255	0.245	0.368	-0.226	0.442	0.111	0.091	0.860	0.421	0.288
SI1	0.558	0.285	0.312	0.337	0.121	-0.378	0.468	0.064	0.135	0.475	0.804	0.319
SI2	0.647	0.459	0.501	0.277	0.232	-0.451	0.595	0.048	0.155	0.633	0.839	0.392
SI3	0.443	0.175	0.263	0.258	0.161	-0.313	0.358	0.098	0.166	0.415	0.840	0.355
SI4	0.492	0.213	0.308	0.233	0.193	-0.273	0.370	0.113	0.150	0.477	0.813	0.384
UB1	0.506	0.324	0.440	0.294	0.125	-0.273	0.296	0.090	0.112	0.352	0.419	0.886
UB2	0.451	0.276	0.343	0.262	0.080	-0.252	0.284	0.128	0.144	0.387	0.464	0.889
UB3	0.420	0.255	0.295	0.198	0.009	-0.206	0.294	0.135	0.147	0.345	0.376	0.856
UB4	0.455	0.380	0.394	0.054	0.108	-0.331	0.389	0.049	0.113	0.318	0.279	0.772
UB5	0.464	0.314	0.354	0.084	0.177	-0.290	0.330	0.067	0.151	0.334	0.369	0.907
UB6	0.443	0.350	0.405	0.222	0.121	-0.299	0.283	0.066	0.070	0.328	0.386	0.914

Appendix 4 - Heterotrait-monotrait ratio (HTMT)

	BI	**EE**	**FC**	**HM**	**PB**	**PBa**	**PE**	**PS**	**PV**	**REC**	**SI**	**UB**
BI												
EE	0.619											
FC	0.762	0.760										
HM	0.463	0.215	0.293									
PB	0.187	0.079	0.095	0.366								
PBa	0.510	0.344	0.359	0.137	0.172							
PE	0.704	0.399	0.410	0.330	0.299	0.477						
PS	0.072	0.067	0.070	0.242	0.253	0.076	0.098					
PV	0.180	0.092	0.123	0.259	0.307	0.113	0.183	0.561				
REC	0.624	0.386	0.431	0.496	0.431	0.426	0.635	0.179	0.145			
SI	0.760	0.392	0.489	0.469	0.244	0.543	0.654	0.106	0.220	0.729		
UB	0.572	0.395	0.474	0.284	0.136	0.370	0.411	0.106	0.158	0.456	0.491	