The Artificial Doctor: Consumer perception on AI-driven preliminary medical diagnosis in critical and non-critical contexts

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ABSTRACT

Artificial Intelligence (AI) has emerged as a powerful tool capable of transforming industries. The healthcare industry hopes to leverage this technology to reduce costs, improve patient care, medical diagnosis and treatment recommendations, administrative work, and so forth. While there is optimism, skepticism about this technology still causes consumers to resist adopting it, which in turn can prevent the industry from harnessing its benefits. For a concept so critical for the successful implementation of a technology, very little is known about consumer acceptance, perceptions and intentions. This research aims to understand consumer intention to accept AI-driven medical diagnosis, and how context can influence intention, employing questionnaires to apply the Unified Theory of Acceptance and Use of Technology (UTAUT) in different medical contexts. This study concluded that while consumers lean towards a positive intention to accept AI-driven diagnosis, they do not demonstrate a particularly positive or negative perception of the matter yet. Behavioral intention is primarily shaped by three main factors: performance expectancy, effort expectancy, and social influence, and it can also vary in different medical contexts. As such, this research provides valuable insights into the current consumer perceptions and their possible impact on AI adoption.

KEYWORDS

Artificial Intelligence (AI); Preliminary diagnosis; Healthcare; Consumer; Consumer intention; UTAUT

TÍTULO: O Médico Artificial: A perceção dos consumidores na utilização de inteligência artificial para diagnósticos médicos preliminares em contextos de saúde críticos e não críticos

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RESUMO

A Inteligência Artificial (IA) surge como uma poderosa ferramenta capaz de transformar indústrias. O sector da saúde espera alavancar a IA para reduzir custos, melhorar o atendimento ao paciente, o diagnóstico médico e recomendações de tratamento, trabalho administrativo, entre outros. No entanto, apesar do otimismo evolvente, o ceticismo em relação a esta tecnologia faz com que os consumidores demonstrem resistência à sua adoção, o que, por sua vez, pode impedir a indústria de aproveitar os seus benefícios. Sendo um conceito crítico à implementação bem-sucedida de novas tecnologias, pouco se sabe sobre a aceitação do consumidor, as suas perceções e intenções. Através de questionários, esta pesquisa aplica a Teoria Unificada da Aceitação e Uso de Tecnologia (UTAUT), com o objetivo de perceber a intenção do consumir aceitar diagnósticos médicos preliminares gerados por IA, e como o contexto médico em que o consumidor se insere pode influenciar essa intenção. Este estudo concluiu que, embora os consumidores tendam a ter uma intenção positive para a aceitar diagnóstico médico preliminares impulsionados por IA, estes ainda não demonstram uma perceção particularmente negativa ou positiva em relação à matéria. A intenção do consumir é principalmente influenciada por três fatores preponderantes: expectativa de desempenho, expectativa de esforço e influência social. Assim, esta pesquisa contribui com insights valiosos sobre as atuais perceções dos consumidores e o seu potencial impacto na adoção de tecnologias de IA.

PALAVRAS-CHAVE

Inteligência Artificial (IA); Diagnóstico preliminar; Saúde; Consumidor; Intenção do consumidor; UTAUT

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TABLE OF CONTENTS

1. Introduction

1.1. Background

The volume of data produced by humans and machines in the modern era surpasses humans' capacity to absorb, interpret, and derive complex conclusions (Kissinger et al., 2023). According to Medtech Europe, 30% of the global data volume is generated by the healthcare industry; however, this data is not used to its full potential, as 97% of all data produced by hospitals remains unutilized (Medtech Europe, 2022). Because Big Data in healthcare encompasses health datasets of such vastness and intricacy – composed of a diversity of data types and demanding to be managed at such high speed – it poses a challenge to commonly used data management tools and methods (Raghupathi & Raghupathi, 2014).

This complex surge of data in healthcare means that technologies such as Artificial Intelligence (AI) have become increasingly prevalent and are poised to transform the practice of medicine (Helm et al., 2020). In this paper, the term AI will be employed to describe any technology utilizing algorithms or statistical models for executing cognitive, conversational, and perceptual tasks that mimic the human mind – these tasks can include problem-solving, visual and speech recognition as well as reasoning (Longoni et al., 2019).

The comprehensive term of Artificial Intelligence encompasses various forms of computer science that are already being applied to healthcare. Specifically, research has already highlighted the significance of Machine Learning (ML) in achievements such as improving accuracy of cardiovascular risk prediction (Weng et al., 2017), cancer prediction and prognosis (Cruz & Wishart, 2007), detecting skin cancer with a precision that can outperform experts (Haenssle et al., 2018), facilitating more precise risk stratification on early and pre-symptomatic Alzheimer disease (Gunter et al., 2024), and so forth.

Studies have highlighted how ChatGPT-4 demonstrated greater precision in adjusting treatment absent of bias - showcasing the potential to enhance decision-making in primary healthcare (Levkovich & Elyoseph, 2023). Furthermore, Computer Vision methods are being leveraged for data-driven decision-making in pulmonary medicine (Khemasuwan et al., 2020), improving the intraoperative phase of surgery at scale (Mascagni et al., 2022), and so forth.

As such, the healthcare industry is experiencing tremendous optimism in the use of Artificial Intelligence to provide efficacious and cost-effective care at scale (Bohr & Memarzadeh, 2020).

While attempts to utilize Artificial Intelligence for diagnosis and treatment recommendations have posed significant challenges such as the inability to embed AI-based diagnosis and treatment recommendations in clinical workflows and EHR systems (Davenport & Kalakota, 2019), complex data availability needed for ML and deep learning models to perform accurately (Johnson et al., 2018; Sun & Medaglia, 2019), ethical and social challenges including consumer distrust (Aung et al., 2021), and so forth, the speed of computational advancements is rapidly increasing, enabling what was once only possible in theory, to develop in practice (Susskind, R. & Susskind D., 2015) – resulting in a global race to harness the benefits of AI in industrial transformation (Ahmed et al., 2022).

According to experts, while the most powerful and flexible learning machine is still the human brain (P. Sajda, 2006), the combined diagnosis of a doctor and an algorithm can be more accurate than either alone (Richens et al, 2020). However, studies show that consumers are hesitant to utilize medical care provided by AI (Longoni et al., 2019). As AI technologies depend on the collection, analysis, and control of extensive sets of consumer data, privacy concerns have arisen as a significant barrier to the collection and sharing of data. Furthermore, a lack of trust in the technology's algorithms has also hindered the adoption of AI in healthcare (P. Kumar et al., 2023; Mazurek & Małagocka, 2019).

Moreover, consumer acceptance and confidence are crucial for the further development of any technology (Taherdoost, 2019) and there is still a significant opportunity for research on consumers' perspectives on AI in the healthcare domain (Davenport et al., 2020; Longoni et al., 2019).

1.2 **Research Questions**

This dissertation aims to provide valuable insights into consumer's willingness to accept receiving preliminary medical diagnosis delivered by medicine AI. Additionally, because AI acceptance depends on the context in which it is being utilized (Barkhuus & Dey, 2003; Luo et al., 2010; Sheng et al., 2008), this research also aims to understand how this willingness to accept might vary in different medical contexts. Understanding the primary determinants shaping consumer willingness to accept plays a vital role in successfully implementing and adopting Artificial Intelligence-based technology in healthcare. With it, the industry can better ensure that technological development is pursued in alignment with the patient's needs, preferences, and concerns. Thus leading to a more patient-centered healthcare system.

The research questions framed for the purpose of this research are as follows:

Q1: What is the consumer's intention to accept preliminary healthcare diagnosis by Artificial Intelligence?

Q2: Does a consumer's intention to accept a preliminary medical diagnosis by Artificial Intelligence vary when different medical contexts are considered?

The term "preliminary" is used in this paper to signal that it is not a final medical diagnosis. Instead, it sets the foundation for a more inclusive and accurate final diagnosis through additional testing and in-depth analysis of the patient's condition (Abdul et al., 2024).

2. **LITERATURE REVIEW**

The following chapter presents the extant literature relevant to the research question and outlines its theoretical background. It starts with an overview of the definition of AI and its relevant branches. Secondly, it gives an overview of the status quo in the healthcare industry. Additionally, it considers the point where AI and Healthcare merge and deep dives specifically on Artificial Intelligence applied to preliminary medical diagnosis. Furthermore, it explores the concept of the consumer's behavioral intention and adoption. And finally, it provides an overview of the chosen model for this research.

2.1. Artificial Intelligence (AI)

When its scientific foundations were established nearly 70 years ago by John McCarthy, the term "Artificial intelligence" initially started as a simple theory of human intelligence exhibited by machines (McCarthy et al., 2006). In today's world, described as characterizing technology capable of interacting with the environment and aiming to simulate human intelligence (Glikson & Woolley, 2020), Artificial Intelligence represents the core of what has been defined as the "fourth industrial revolution" that "will transform the entire structure of the world economy, our communities, and our human identities" (Schwab, 2017).

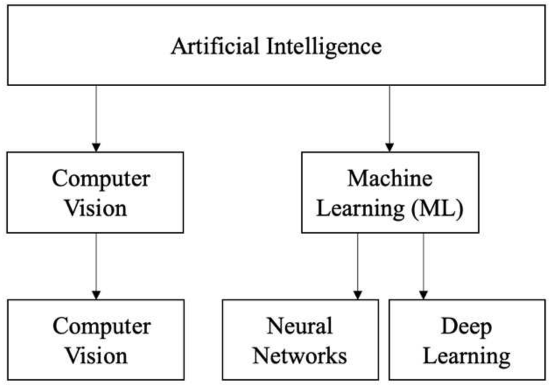
The research goals in the field of AI have changed over time and its progress has been described in generational shifts: rule-based systems and logical reasoning (1st generation) (Dreyfus, 1997; Shum et al., 2018); expert systems with extensive domain-specific knowledge (2nd generation) (Buchanan & Feigenbaum, 1981; Shortliffe, 1974); algorithms that improve performance through data exposure rather than explicit programming (3rd and current generation) (El Naqa & Murphy, 2015); and explainable and contextual AI (4th generation) (Saraswat et al., 2022); AI's generational shifts were driven by methods that broke through major challenges or anomalies that were significant at the time. Rule-based systems were costly to build and maintain, as they required explicit expressions of decision rules, human-authored updates, and complex limitations (Yu et al., 2018). As such, as more data became available, researchers created self-learning algorithms capable of autonomously generating rules or models directly from data. These algorithms use large sets of data to recognize patterns and effectively learn to train the machine to make autonomous recommendations or decisions (Helm et al., 2020). This continuous evolution has led us to where we are today, where the emergence of pre-trained models – such as GPT-3, the model that ChatGPT is trained on –turned the world's attention to AI.

While the comprehensive term of Artificial Intelligence encompasses various forms of computer science, in medicine one can mainly focus on: Imagine Processing; Computer Vision; Artificial Neural Network; Machine Learning; Deep Learning (Mintz & Brodie, 2019).

Image Processing is a mathematical process that enhances an image for the purpose of clarity, retrieval of specific information, or pattern measurements. The input is a picture, and the output is a more enhance picture for a specific applied purpose. Computer Vision the processing of the image to enable identification of the image input and to provide an appropriate output, i.e. interpretation of the image (Mintz & Brodie, 2019).

To better understand machine learning, deep learning, and neural networks, one can think of them as series of AI systems ranging from largest to smallest (Figure 1), each encompassing the next, and AI being overarching (IBM Data and AI Team, 2023). Machine Learning – a subset of AI - refers to the development of learning algorithms and statistical models that computer systems utilize to perform a specific task without being explicitly programmed to (Mahesh, 2020). While Machine Learning depends on human intervention for optimization, Deep Learning automates most of it (IBM Data and AI Team, 2023) Deep Learning – a subset of machine learning – is fueled by an increasing availability of large data sets and high computing capacity that can outperform other machine learning methods (Chassagnon et al., 2020). Artificial Neural Networks are a subset of machine learning and at the heart of deep learning - their name and structure are inspired by the human brain, mimicking how biological neurons signal to each other. Neural Networks take in data, train themselves to recognize patterns in it, and predict the output for a new set of similar data (IBM, 2024).

Figure 1 – Artificial Intelligence branches



2.2. Healthcare Sector – Current Challenges

The global healthcare sector underwent lasting transformation due to the COVID-19 pandemic – while it accelerated the adoption of new technology and care delivery models and heightened the focus on sustainability and resilience, it also highlighted pre-existing workforce challenges and global disparities in health equity (Allen, 2023). According to the World Economic Forum, the challenges faced by the global healthcare sector are expected to persist in the future. These challenges include worsening mental health, workforce shortages, supply-chain issues, an increasing funding gap, a lack of incentives for innovation and the widening disparities in overall health and wellness (Andreae et al., 2023).

Additionally, practitioners are also limited by human boundaries. According to experts, it is impossible for medical professionals to match the speed at which medical knowledge is published (Smith, 2010). To keep pace with new medical knowledge, doctors would need to dedicate a minimum of 160 hours per week to reading, without accounting for assessing relevance or applicability. Meaning it would take at least a decade to be up to date with their specialty and by that time, an estimate 82 000 new relevant papers would have been published (Steadman, 2013). Consequently, it has been theorized how the human tendency is to ignore or downplay events that are not adequately understood or anticipated (Orlik & Veldkamp, 2014) in medicine this theory can translate as rare diseases or uncommon symptoms that do not fit into the typical diagnostic patterns might not being promptly recognized or considered by doctors (Devarajan et al., 2023), especially as doctors tend to diagnose only common diseases and ignore outliers (Denecke et al., 2018). Moreover, patient data proliferation, time constraints, lack of skill and the inadequate integration of information into the appropriate workflows, leads to lower-quality information being utilized despite the existence of higher-quality alternatives, thus undermining evidence-based decision making in healthcare (Klerings et al., 2015). Thus, not only are practitioners overloaded by information and limited by human cognition (O'Sullivan & Schofield, 2018), but physicians are also limited to an average of 15 minutes of talking and examining their patients, with nearly half of that time allocated to tasks other than clinical diagnosis (Sinsky et al., 2016).

In addition to these challenges, the healthcare industry is expected to reach a shortage of 10 million healthcare workers worldwide by 2030 (Andreae et al., 2023)inevitably this unequitable distribution also contributes to the worsening of the current workforce's mental state. Consequently, physician burnout is linked to negative impacts on patient care, healthcare system costs and safety (West et al., 2018).

2.3. Artificial Intelligence applied to the healthcare sector

Artificial Intelligence has been a standard part of the industrial repertoire since at least the 70s, including the healthcare industry. Clinical Decision Support Systems have been elaborated and proposed by researchers since the mid-twentieth century (Miller, R.A., Geissbuhler, A., 2007). Rule-based approaches achieved significant successes in the 1970s (Shortliffe, 1976), as well as have shown the ability to interpret ECGs (Kundu et al., 2000), diagnose diseases (de Dombal, F T et al, 1972), choose appropriate treatments (Shortlife, E. H. et al, 1975), and assist physicians in generating diagnostic hypotheses in complex patient cases (Miller, R A et al., 1986).

Today, it is predicted that the global AI market in healthcare will reach $188 billion by 2030 (Wong et al., 2024) and that it will generate savings of over $150 billion for the industry by 2025 (Fernandez, 2018). Expected benefits from AI-enabled solutions applied to healthcare include advancements in precision medicine, an emerging approach for disease treatment and prevention that takes into account individual variability in genes, environment and lifestyle for each person (Mesko, 2017), clinical decision support that draws upon clinical data and knowledge to reduce medical errors and support healthcare professionals' decisions (Reddy et al., 2019), real-time supply chain management that will enable practitioners to augment their competitive advantage and lessen supply chain fallouts and market failures (A. Kumar et al., 2023), disease prediction

(Ghaffar Nia et al., 2023) and lessening the administrative burden on healthcare workers (Al Kuwaiti et al., 2023).

Different AI technologies are being applied to the various medical fields within healthcare – in ophthalmology, deep learning is revolutionizing the diagnosis and treatment of retinal diseases. With its algorithms capable of analyzing complex retinal data, enhancing diagnostic accuracy and efficiency (Parmar et al., 2024). In surgery, AI is enabling image-guided surgeries (Kenngott et al., 2015) and expected to improve the quality of global surgical care (Hashimoto et al., 2018). In oncology, deep learning is being used for detection, diagnosis and prognosis of several cancer subtypes. Despite existing challenges, AI for digital pathology is considered promising and key for the analysis and interpretation of high-volume data, aiding pathologists and oncologists (Bera et al., 2019). Psychology places its expectations on redefining diagnosis with AI, facilitating earlier detection of mental illness, continuous learning systems that assess patients based on context, built-in computational models that make mental health safer, more efficient, personalized, and so forth (E. E. Lee et al., 2021).

However, although Artificial Intelligence promises to benefit the industry in many ways, there are also diverse challenges to the successful implementation of AI technology. Considering that effectiveness of AI algorithms depends solely on the quality of the data and assumptions they are trained on (Kolla & Parikh, 2024), the first obstacle for an AI-driven healthcare sector the availability of data. Because machine learning and deep learning models require large datasets to accurately classify or predict different tasks (Johnson et al., 2018), it is the sectors with large datasets available that are capable of enabling more complex and precise algorithms that see the most progress (Aung et al., 2021). However, in the healthcare industry, data availability is a complex matter. Not only is data expensive, but ingrained organizational beliefs and resistance also hinder data sharing and availability for the continuous improvement and training of machine learning-based systems (Aung et al., 2021; Sun & Medaglia, 2019). Furthermore, the quality of data used to train these systems is also difficult to ascertain as healthcare data is often disorganized, inconsistent, inaccurate and lacking a standardized storage and formatting (Sun & Medaglia, 2019).

2.4. Artificial Intelligence applied to medical diagnosis

Presently there is a growing interest in leveraging Artificial Intelligence to complement, enrich, or potentially replace general practitioner (GP) diagnostic capabilities. AI advocates suggest that these technologies could enhance diagnostic precision – with fewer instances of underdiagnoses and overdiagnoses – as well as diagnostic efficiency. Reports estimate that every year 40,000 to 80,000 lives are lost – in American hospitals – due to preventable diagnostic errors (D. Lee & Yoon, 2021). Others argue that it might introduce an additional information load amidst an already hectic clinical environment with minimal improvement in patient outcomes, healthcare finances, and practitioners stress levels (Academy of Medical Royal Colleges, 2019). Additionally, practitioners are reluctant to modify existing workflow processes, expressing concerns about the threat to their professional autonomy and apprehension of the potential biases and clinical risks of adopting a technology that is not completely understood (Zorc et al., 2019).

Despite the challenges, the offering, availability and relevance of Artificial Intelligence applied to medical diagnosis continues to evolve. These technologies include advances decision-making systems, robotic systems, machine learning, deep learning, natural language processing, visual test interpretation of electrocardiograms (ECGs), mammography, computer tomography (CT) scans, as well as aiding clinical reasoning (Zorc et al., 2019). Moreover, according to experts, pre-trained language models (PLMs) or large language models (LLMs) (Zhang et al., 2021) such as GPT-3 and GPT-4 (OpenAI, 2024) have demonstrated great promise in NLP tasks such as natural language generation (NLG) and question answering.

Medical diagnosis is a complex and sensitive process that demands a deep understanding of medical knowledge and expertise (Abdul et al., 2024). Although language models are able to generate responses based on patterns learned from large datasets, they may lack the specialized medical knowledge needed to make an accurate clinical diagnosis (Zeng et al., 2020). Nevertheless, a specifically pre-trained LLM capable of accurately providing a preliminary medical diagnosis based on the patient's description of symptoms can contribute to improving healthcare (Balogh et al., 2015).

2.5. Consumers' behavior intention and adoption

All technological innovation largely depends on users' motivation and resistances, which can either serve as facilitate or serve as an obstacle to their diffusion and adoption (Huang et al., 2021; Yadav et al., 2022). However, even if consumers initially exhibit reluctancy to a technology-driven breakthrough, users often come to appreciate and accept these advancements over time (Yadav et al., 2022). As such, technological innovations must overcome these adoption challenges and become desirable to gain consumer acceptance (Chakraborty & Paul, 2023).

Research has supported that behavioral intention influences significantly consumers' actual use of a technology (Ain et al., 2016). Additionally, individual behavioral intentions are also crucial in the broader adoption of technology (Davis, 1989). Limited consumer acceptance could lead to reduced adoption of Artificial Intelligence-driven tools – resulting in wasted resources, an oversupply of AI devices and the possible slowdown in technological advancements, ultimately impacting consumers negatively (Kirlidog & Kaynak, 2011; J. D. Lee & See, 2004; Parasuraman & Riley, 1997) Thus, assessing users' acceptance is essential for stakeholders to understand the variables required to maximizing technology adoption in diverse situations (Kelly et al., 2023).

The Theory of Planned behavior (TBP) defined behavioral intention as one's willingness to perform a specific behavior and proposed it to be the main predictor of actual behavior. The TBP states there are three main factors which influence an individual's behavior intention: the individual's attitudes toward the behavior, subjective norms and perceived behavioral control (Ajzen, 1991).

2.6. Unified Theory of Acceptance and Use of Technology

Continuously ensuring user acceptance of technology is an on-going challenge in management (Schwarz & Chin, 2007) that has captured the attention of researchers to the extent where technology adoption and diffusion is regarded as one of the more mature areas of exploration (Venkatesh et al., 2003). Consequently, various exploratory techniques have been employed across different systems and contexts, resulting in an extensive body of literature with multiple stakeholder perspectives, technologies, theories and research methods. Such diversity aggravated researchers' confusion, who often navigate competing models and theories (Williams et al., 2009). To address this challenge, the Unified Theory of Acceptance and Use of Technology (UTAUT) was proposed to harmonize this literature and integrate alternative views on user acceptance of technology (Williams et al., 2015).

The UTAUT was formulated by redefining foundational technology acceptance theories, such as the Theory of Reasoned Action (TRA), the Theory of Acceptance Model (TAM) and the Theory of Planned Behavior (TPB) (Venkatesh et al., 2003). The UTAUT suggests that its four constructs – performance expectancy, effort expectancy, social influence, and facilitation conditions – are direct determinants of behavioral intention and ultimately, behavior. These constructs are in turn moderated by gender, age, experience, and voluntariness of use (Venkatesh et al., 2003). It is suggested that by evaluating the existence of these constructs in a "real word" setting, one can assess an individual's intention to use a specific system, hence facilitating the identification of the primary factors shaping acceptance in a given context (Williams et al., 2015). The main constructs proposed by the UTAU are outlined as follows:

Performance expectancy *(PE)* is defined as "*the degree to which an individual believes that using the system will help him or her to attain gains in job performance*" and is considered the strongest predictor of intention and remains significant in both voluntary and mandatory settings. The relationship between Performance Expectancy and Behavioral Intention (BI) is moderated by Age and Gender. (Venkatesh et al., 2003).

Effort expectancy *(EE)* is defined as "*the degree of ease associated with the use of the system"* and it is derived from the perceived ease of use and complexity, drawing for TAM, the Model of PC Utilization (MPCU), and Innovation Diffusion Theory (IDT). The relationship between Efforte Expectancy and BI is moderated by gender, age and experience (Venkatesh et al., 2003). The effect of it becomes nonsignificant after a prolonged usage of the technology (Chauhan & Jaiswal, 2016; Gupta et al., 2008).

Social Influence *(SI)* is defined as "*the degree to which an individual perceives that important others believe he or she should use the new system*" and it refers to the notion that an individual's behavior is shaped by their perception of how others view them because of having user technology. Additionally, the relationship between Social Influence and BI is moderated by gender, age, experience and voluntariness of use (Venkatesh et al., 2003).

Faciltating Conditions *(FC)* are defined as *"the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system"*. The relationship between Facilitating Conditions and BI is moderated by age and experience (Venkatesh et al., 2003).

Since its introduction, the UTAUT has seen extensive utilization in technology adoption and diffusion research, serving as a theoretical framework for researchers conducting empirical studies on user intention and behavior – specifically it has become dominant in the healthcare service adoption literature (Fan et al., 2020). Some examples include the acceptance of intelligent healthcare systems (Fan et al., 2020), electronic medical records (Wills et al., 2008), healthcare wearable devices (Wang et al., 2020), telemedicine (Kohnke et al., 2014; Shiferaw et al., 2021), artificial intelligence-based diagnosis support systems (Tran et al., 2021), and so forth.

3. Research Model

Figure 2 illustrates the research model with hypothesized relationship between the dimensions of UTAUT. The UTAUT model proposes four main hypotheses:

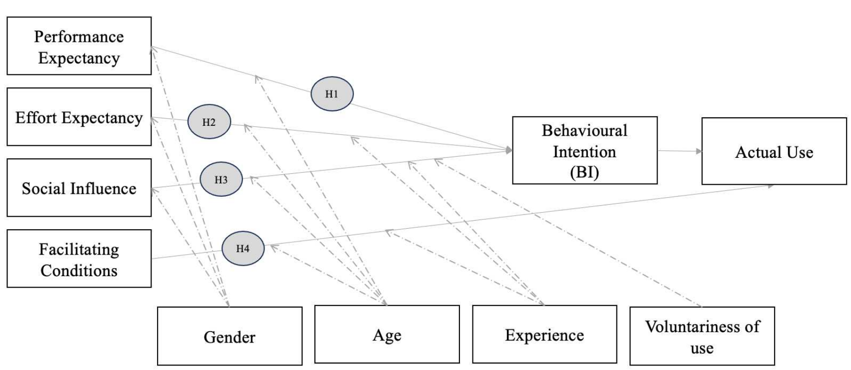
H1: Performance Expectancy positively influences Behavioral Intention.

H2: Effort Expectancy positively influences Behavioral Intention.

H3: Social Influence positively influences Behavioral Intention.

H4: Facilitating Conditions positively influence actual use.

Figure 2 – Research Model



4. Methodology

4.1. Measurement

The data was collected using two questionnaires hosted on the Qualtrics platform, created from previously validated scales found in related literature (Appendix A and Appendix B). These scales represent a synthesis of contributions from various sources, lacking a single origin. Instead, they are the culmination of research efforts driven by the specific needs and context of this paper.

The surveys' items were split into two independent surveys: one survey with a set of questions in the context of a non-critical medical situation and a second survey with the same set of questions but in the context of critical medical situations. There are different reasons sustaining this decision. Firstly, with having two surveys, it would be easier for consumers to maintain a clear focus on the specific context being studied. Secondly, it facilitated the comparative analysis between the responses obtained in each questionnaire. Thirdly, separating the questionnaires may enhance participant engagement and reduce the likelihood of survey abandonment.

In the questionnaires, responding to all items was mandatory, and most were measured using a seven-point Likert scale (1 = "Strongly disagree" and 7 = "Strongly agree"), except for the demographic data of gender and age. The surveys were developed primarily in English, translated to Portuguese, and back-translated to ensure accuracy (Brislin, 1970). For each question of the surveys, a small example was placed underneath to facilitate user comprehension and ensure scientific accuracy.

In the first part of each questionnaire, the purpose of the survey was presented to the respondents, confidentiality was assured, and the definition of the focus topic, including the relevant medical context and preliminary medical diagnosis, was included to ensure that the respondents would have clarity on the information needed to participate and accurately place their choices. The second part of the surveys contained questions related to the constructs studied. There were four items for the performance expectancy construct, three items for facilitating conditions, three items for facilitating conditions, two items for social influence, three items for behavioral intention and two items for voluntariness of use. The third part of the questionnaires consisted of the respondent's demographic information and level of familiarity with the technology relevant to this research. The survey was initially tested with ten respondents to ensure face validity and respondent comprehension. Thereafter, minor revisions to the items' spelling were made before publishing the questionnaires.

5. Data Analysis and Results

The statistical analysis was performed using SPSS software, version 29. For statistical inference, a significance level α of 0.05 (95% confidence level) was used, with the null hypothesis of the tests being rejected whenever the associated p-value was less than α.

5.1. Data

The data collection was conducted between the March 25th and April 2nd, 2024. The two questionnaires were distributed through WhatsApp groups and posted on relevant Reddit forums. A total of three hundred twenty-five valid answers were collected – from which one hundred seventy-six were collected on the non-critical medical context survey and one hundred forty-nine on the critical medical context. As seen in Table 1, 71.6% of the respondents were Female (176 respondents) and 27.8% were Men (149 respondents). The most represented age group is between 45 to 54 years-old and senior citizens were the less represented age group (5.5%). Both groups present a similar gender and age group distribution (p>>0.05), allowing us to perform a direct comparison of the two contexts without bias. The collected samples are independent, via non-probability sampling by convenience.

Table 1 – Sample characteristic

Variable	Non-Critical		Critical		Total		p-value (χ^2 test)
	n	**%**	***n***	**%**	***n***	**%**	
Sample Size	176	54.2	149	45.8	325	100	
Gender							
Male	49	27.8	47	31.5	96	29.5	
Female	126	71.6	101	67.8	227	69.8	0.462 (*ns*)
Prefer not to say	1	0.6	1	0.7	2	0.6	
Age Group							

<18	1	0.6	1	0.7	2	0.6	
18-24	14	8.0	24	16.1	38	11.7	
25-34	40	22.7	36	24.2	76	23.4	
35-44	38	21.6	28	18.8	66	20.3	0.434 (*ns*)
45-54	55	31.3	39	26.2	94	28.9	
55-64	18	10.2	13	8.7	31	9.5	
>=65	10	5.7	8	5.4	18	5.5	

5.2. Likert Scales

The scales associated with each construct revert 7-point Likert scale items – except for experience, which is associated with a single 5-point Likert scale item. Making an analysis by context and age group, consumers are overall optimistic about AI for preliminary medical diagnosis. On a non-critical context, the biggest difference between the age groups is exhibited in effort expectance, facilitating conditions, behavioral intention and voluntariness of use. Specifically, younger consumers tend to be more optimistic on their capacity to easily use and learn to use an AI diagnostic tool in a non-critical context, moreover they also show greater confidence on having the necessary resources to use these tools. Lastly, younger consumers demonstrate greater willingness on using AI diagnostic tools and are more confident that receiving preliminary diagnosis by AI would be a voluntary act when compared to older consumers.

On a critical context, the biggest difference between age groups is exhibited in performance expectancy, facilitating conditions, social influence and voluntariness of use. In line with the results on non-critical contexts, younger consumers are more optimistic regarding performance expectancy, however, not as confident as exhibited in non-critical contexts. Additionally, older consumers are more trusting that medical organizations would have the necessary preconditions for the effective use of AI diagnostic tools in a critical medical context. On the contrary, younger consumers are not only much less trusting than older consumers but significantly less when compared to non-critical context. Furthermore, older consumers are much more optimistic on their doctors and people important to them advising them utilize AI for preliminary diagnosis in critical situations. Finally, older consumers are more inclined to believe that they would be obligated to receive preliminary medical diagnosis by AI.

Table 2 – Mean of each questionnaire question per context

Question	Non-Critical Mean		Critical Mean	
	Age < 35	**Age >= 35**	**Age < 35**	**Age >= 35**
PE1	5.36	4.76	5.02	4.58
PE2	4.40	4.47	3.95	4.16
PE3	4.49	4.46	4.31	4.39
PE4	4.87	4.36	4.08	4.27
EE1	5.44	4.74	4.16	4.19
EE2	5.20	4.61	4.18	4.09
EE3	5.49	4.61	4.43	4.24
FC1	5.04	4.79	4.57	4.65
FC2	4.51	4.57	3.84	4.47
FC3	5.16	4.55	4.25	4.24
SI1	4.13	4.29	3.26	3.92
SI2	4.09	4.17	3.31	3.90
BI1	5.27	4.65	4.20	4.24
BI2	5.38	4.66	4.36	4.36
BI3	5.05	4.50	3.89	4.15
VU1	5.69	5.03	5.26	4.88
VU2	3.49	3.64	2.75	3.56

5.3. Correlation Analysis

Pearson's correlations for each construct are reported on table 3. Considering that experience (EXP) is a 5-point Likert scale single item, Spearman's correlation was used. All correlations are significant with a trust-level of 99% ($p<0.01$). Additionally, all correlations are moderate or strong

– the positive correlation's coefficients mean that an increase in one variable is associated with an increase in the other variables. BI correlates positively and strongly (PE, EE, FC, SI) and moderately with a strong tendency (VU) with the remaining scales. In EXP, the correlation coefficients are significant, equally positive, but weak or moderate – meaning that familiarity with AI contributes positively to BI, although in a more modest manner and non-comparable to the remaining constructs.

Table 3 – Pearson and Spearman's correlations

Pearson's r / Spearman's ρ	PE score	EE score	FC score	SI score	VU score	BI score	EXP score
PE score (r)	1						
EE score (r)	.722**	1					
FC score (r)	.658**	.724**	1				
SI score (r)	.620**	.615**	.658**	1			
VU score (r)	.555**	.554**	.600**	.669**	1		
BI score (r)	.760**	.776**	.699**	.742**	.650**	1	
EXP score (r)	.292**	.313**	.228**	.116*	.162**	.262**	1

** p<0.05; ** p < 0.01*

5.4. Statistical Inference

The UTAUT model establishes a relationship between the intention to use a designated technology and a group of predictive constructs. However, it does not explicitly include the effect of context in a way that could affect the consumer's behavioral intention. In this research, context was not added to the UTAU model as a predictive construct, and therefore, its impact on BI cannot be measured. This decision was motivated by the paper's objective to understand how the established constructs vary according to context. If context had been added as a construct, we would lose this information.

For this reason, as we cannot directly measure context's impact directly, an ANOVA analysis was employed to understand if BI varies with context when the relevant variables are controlled.

To measure the impact of context, a 2-way ANOVA model was built under the following conditions:

- Answer (dependent variable): behavior intention (BI)
- Factors (independent variables): context (NC;C) and age (<35;>=35 years old)

It is important to note that age is a continuous variable that was collected in the form of age groups in this paper. In this case, to enhance the test's statistical power and to limit the number of interactions, this variable was dichotomized into two age groups of: people younger than 35 and people older than 35. This cutoff age was sustained by the relevant technology's development over time and previous data findings.

As reported in Table 4, our 2-way ANOVA results support that the average BI differs between contexts, and this difference is highly significant ($p<0.001$). Additionally, while age on its own is not statistically significant ($p=0.12$) in the average value of BI, the interaction of context*age is statistically significant ($p=0.031$), meaning that the effect of context in BI varies with age. This variable is, then, considered a moderator.

Table 4 – ANOVA table

Source	Type III Sum of Squares	df	Mean Square	F	p-value
Corrected Model	43.91	3	14.64	6.87	<.001
Intercept	6136.07	1	6136.07	2878.00	<.001
Context	38.369	1	38.369	17.996	<.001
Age_binary	5.194	1	5.194	2.436	0.12
Context*age_binary	9.981	1	9.981	4.681	0.031
Error	684.39	321	2.13		
Total	7395.33	325			
Corrected Total	728.31	324			

We have observed that context is significant in the average BI. Table 5 quantifies the observed difference. Once controlled for age, the average intention to use the relevant technology changes from 4.20 in a critical context to 4.92 in a non-critical context (a difference of 0.72).

Table 5 – Impact of context in the average BI quantified

			95% Confidence Interval			
Context	Mean	Std. Error	Lower Bound	Upper Bound	Difference	p-value
Non-Critical	4.92	0.119	4.69	5.15	0.72	< 0.001
Critical	4.20	0.122	3.96	4.44		

The impact of the interaction between context and age on BI is shown in Table 6. If the individual is younger than 35 years old, their behavioral intention increases on average by 1.09 when the context changes from critical to non-critical – and this difference is highly significative ($p<0.001$).

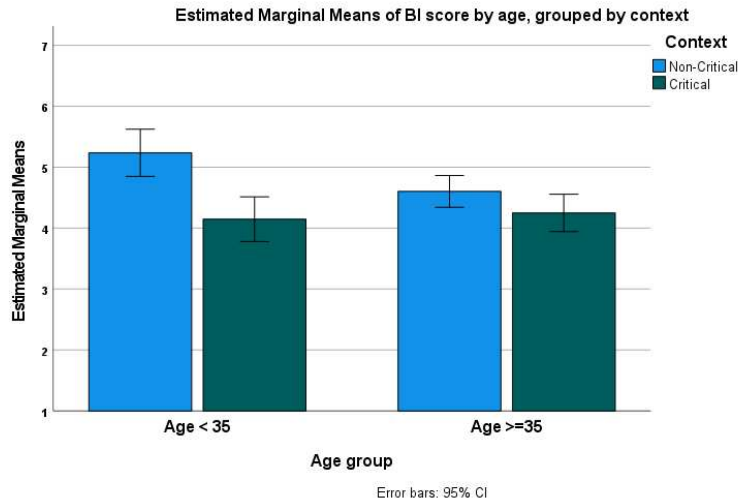
However, when an individual is older than 35 years, BI increases by only 0.35 – and this difference is not significant ($p=0.085$), although it would be marginally significant if this research had considered a level of $p<0.1$. Furthermore, despite being more acceptant of AI technology in non-critical contexts, younger consumers are more cautious to use AI technology in critical medical contexts.

Table 6 – Impact of the interaction context*age on the average BI quantified

Age	Context	Mean	Std. Error	Lower Bound	Upper Bound	Difference	p-value
<35	Non-Critical	5.24	0.197	4.85	5.62	1.09	<0.001
	Critical	4.15	0.187	3.78	4.52		
>35	Non-Critical	4.60	0.133	4.34	4.86	0.35	0.085
	Critical	4.24	0.156	3.94	4.56		

Figure 3 aims to illustrate the moderator effect of age. While non-critical contexts are significantly more favorable to the use of artificial intelligence technology than critical contexts, this difference is primarily associated to younger age groups (<35 years old).

Figure 3 – Estimated marginal means of BI scope by age, grouped by context



5.5. Measurement model

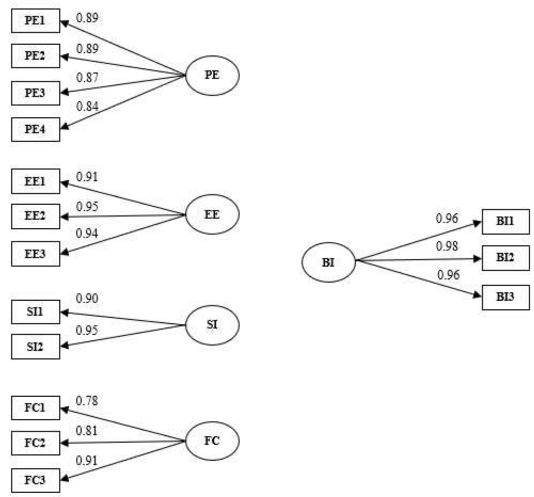
In this chapter, we will evaluate two UTAUT models – one model for each context – and evaluate if there are differences on the constructs that explain behavior intention.

To measure the model's constructs, a 7-point Likert was utilized. As such, its validity and reliability were examined. As observed in Table 7, regarding reliability, the consistency measure by Cronbach's α is – in all scales – largely superior to the minimum desirable value of 0.7. Additionally, regarding validity, all individual factorial loadings are higher than 0.5, thus validating each item individually (Figure 4). The Average Variance Extracted (AVE) (Table 7) is, in all scales, equal or higher than 0.7, thus being able to verify the model's convergent validity. With the model having confirmed discriminant validity, convergent validity, and internal consistency, the model is validated.

Table 7 – Reliability and validity measures (Cronbach's α and AVE)

Construct	Cronbach's α	AVE
BI score	0.96	0.94
PE score	0.91	0.77
EE score	0.94	0.87
FC score	0.85	0.70
SI score	0.90	0.86

Figure 4 – Factor loadings



5.6. Structural Model

To consider both medical contexts (critical and non-critical) simultaneously, a multi-group path analysis was performed. In this analysis, the significant path coefficients β ($p<0.05$) and the marginally significant (p-value between 0.05 and 0.10) were maintained at least in one of the models. Regarding moderation, the classic definition was used. This definition considers that, if for instances, BI is the answer, SI a predictor and age a moderator, then the moderation is composed of two components: the direct effect of age in BI (main effect) and the moderator effect that age has in the relation between SI and BI (interaction term).

Both models have a high explanatory power of BI as a function of predictors with an R^2 of 79.6% in the non-critical context and 78.1% in the critical context. Table 8 presents the results of both models. The predictor's importance to BI is measured by the path coefficient β – a standardized coefficient – allowing us to compare the remaining β within the same model.

In the non-critical context's model, EE is the main positive predictor ($\beta = 0.418$) – while in the critical context's model PE is the main positive predictor ($\beta = 0.390$).

In both models, the H1, H2 and H3 of the UTAUT model were confirmed. The constructs of PE, EE and SI have a positive and significant effect ($p<0.05$) in both contexts – while FC does not ($p>0.05$). However, the UTAU model does not theorize that FC has a direct effect on BI.

Performance Expectancy (β = 0.134; p=0.015; β = 0.390; p=<.001) is statistically significant in explaining behavioral intention, therefore supporting hypothesis 1 in both models. Effort Expectancy is statistically significant in explaining BI (β = 0.418; p=<.001; β = 0.139; p=0.025), therefore supporting hypothesis 2 in both models. Additionally, Social Influence is statistically significant (β = 0.253; p=<.001; β = 0.337; =<.001), therefore supporting hypothesis 3 in both models.

While gender did not demonstrate a direct main effect on BI in neither context, a positive interaction between the female gender and SI on the critical context's model was verified – which partially supports its theorized moderating effect by the UTAUT model. Gender demonstrated to be a statistically significant moderator (β = 0.086; p=<0.049), which might indicate that in a critical context, the influence of SI on BI can be exacerbated in the case of a female, although with a low β.

Furthermore, of all theorized moderating effects related to age, only its interaction with SI was confirmed to be significant – and specifically in the non-critical model only. Age>=35 demonstrates to be a statistically significant moderator (β = 0.088; p=<0.026) – meaning that in a non-critical context, despite older consumers being more reluctant to use AI than younger consumers, this effect can be offset in the presence of social influence and thus partially supporting its theorized moderating effect in the critical model.

Interestingly, and not hypothesized by the UTAUT model, in this research age demonstrated to have statistically significant negative main effect on BI (β = -0.087; p=<0.023), but only in the non-critical model - meaning that in a non-critical context, older consumers are more negative in their intention to use artificial intelligence technology.

Moreover, of all theorized moderating effect related to VU – only the interaction between VU and SI was confirmed. VU demonstrated be a statistically significant moderator in a critical context (β =-0.107; p=0.013) and approaching significance in a non-critical context (β =-0.069; p=0.053) thus partially supporting its theorized moderating effect. Although interestingly, and not hypothesized by the UTAUT model, VU demonstrated to have a statistically significant main effect on BI (β = 0.115; p=<0.017), but only on in the non-critical model. Meaning that in non-critical contexts, the perception of voluntariness by itself is enough to positively influence BI.

Finally, none of the theorized moderating effects related to EXP were confirmed by the models. However, and not hypothesized by the UTAU model, experience demonstrated to have a positive but weak main effect (β = 0.068) and only marginally significant (p= 0.082) on BI – meaning that being familiar with the technology might facilitate the consumer's intention to use, but only in a non-critical context.

Table 8 – Model's results for both non-critical and critical context

Context	Variable	Role	β	z	p
Non-Critical	PE	Main effect	0.134	2.43	0.015
	EE	Main effect	0.418	6.45	<.001
	FC	Main effect	0.050	0.83	0.409
	SI	Main effect	0.253	4.52	<.001
	VU	Main effect	0.115	2.39	0.017
	SI*VU	Interaction	-0.069	-1.94	0.053
	Gender_female	Main effect	0.024	0.64	0.521
	SI*Gender_female	Interaction	-0.060	-1.49	0.137
	Age>=35	Main effect	-0.087	-2.27	0.023
	SI*Age>=35	Interaction	0.088	2.23	0.026
	EXP_AI	Main effect	0.068	1.74	0.082
Critical	PE	Main effect	0.390	6.14	<.001
	EE	Main effect	0.139	2.24	0.025
	FC	Main effect	0.069	1.15	0.251
	SI	Main effect	0.337	5.18	<.001
	VU	Main effect	0.058	0.97	0.33
	SI*VU	Interaction	-0.107	-2.47	0.013
	Gender_Female	Main effect	-0.040	-0.97	0.335
	SI*Gender_female	Interaction	0.086	1.97	0.049
	Age>=35	Main effect	-0.045	-1.03	0.305

SI*Age>=35	Interaction	-0.032	-0.69	0.488
EXP_AI	Main effect	-0.012	-0.27	0.789

Figure 5 – Non-critical model diagram

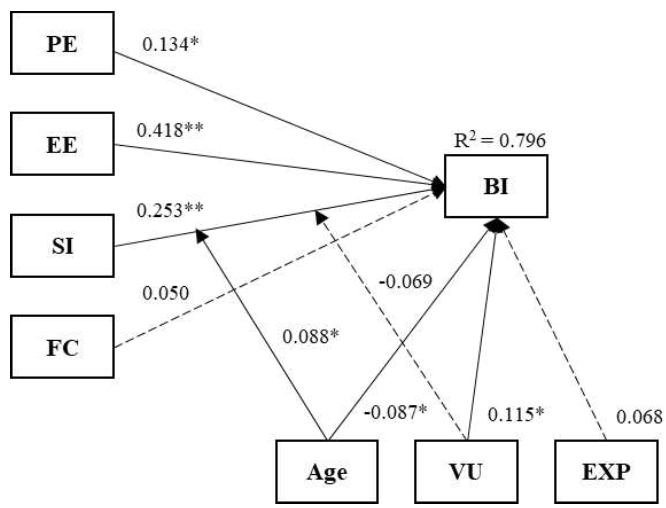
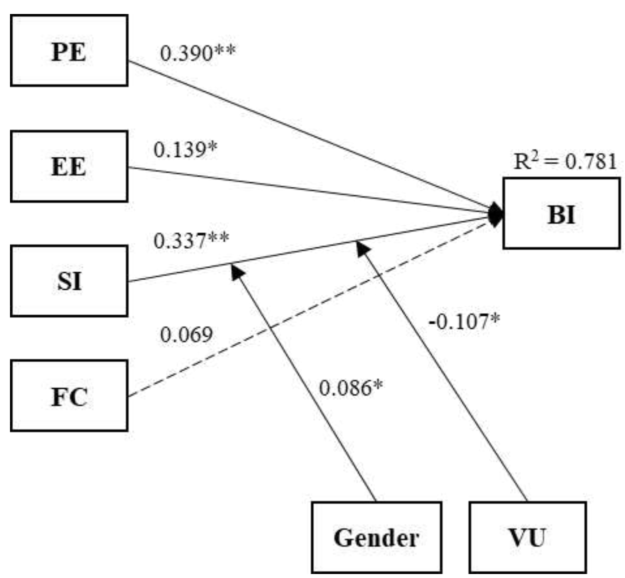


Figure 6 – Critical model diagram



6. CONLUSIONS AND LIMITATIONS

The focus of this research is to better understand consumers' intention of using artificial intelligence technology for preliminary medical diagnosis and how it varies depending on the medical context's criticality. To understand this subject, three main hypotheses derived from the UTAUT model were chosen. All three hypotheses of **H1**: PE positively influences BI; **H2**: EE positively influences BI and **H3**: SI positively influences BI were supported by the results in both contexts.

The critical model explains 78.1% of behavioral intention variation to use AI technology and the non-critical model explains 79.6%. Both results are considered good, as more than half the dependent variable is explained by the models. The UTAUT has been found to have the potential to explain between 70% to 90% of behavioral intention (Venkatesh et al., 2003), therefore it is encouraging that our models can explain close to 80%.

Additionally, the measurement model was tested for discriminant validity, convergent validity, and internal consistency and was verified to exhibit all.

6.1. Managerial / Academic Implications

In both contexts, performance expectancy, effort expectancy, social influence and facilitating conditions (although the latter is only approaching significance and not theorized to have such influence in the UTAUT) demonstrated to significantly influence consumers' intention to use AI – with EE being the main predictor in a non-critical context and PE in a critical context. These findings sustain the importance that future technology should be developed and marketed accordingly – emphasizing the ease of use of products and services in non-critical contexts and highlighting performance superiority in critical contexts. Additionally, consumers exhibited that they did not strongly believe that doctors or people important to them would advise them to use AI technology for preliminary medical diagnosis – especially, but not only – in critical contexts. With social influence demonstrating power to influence BI in both contexts, the industry should consider leveraging endorsement or social proof to boost consumers' intention to use – and consequently actually use – AI technology. Interestingly, and not theorized by UTAUT model, this research demonstrated that facilitating conditions have the potential of influencing behavioral intention – therefore, future adoption and marketing strategies should highlight how the needed infrastructure conditions and support systems have been put in place to facilitate consumers' adoption of AI products and services available to them.

Furthermore, in this research VU demonstrated to have a negative effect on social influence in both contexts, meaning that consumers demonstrate being less influenced by the opinions of others when they perceive that they have the autonomy to choose whether to use AI for medical preliminary diagnosis or not. Furthermore, and not theorized by the UTAUT, VU demonstrated to have a significant main effect on BI in non-critical contexts. Therefore, depending on the business decision regarding voluntariness, where applicable, it should be highlighted that it is the individual's choice, or clearly sustained if not the case in an attempt to redirect consumer perception towards a more positive feeling.

Overall, while consumers' behavioral intention demonstrated to vary in accordance with context – with consumers favoring the usage of AI in non-critical contexts – this intention is not strongly positive nor negative, and consumers are still hesitant on their perceptions towards AI for preliminary medical diagnosis. Therefore, there is still an opportunity for the industry to use these insights to shape consumers' perceptions.

6.2. **Limitations and Potential for Further Research**

The key limitations of this study provide a basis for future research. Firstly, the generalizability is limited. The samples are not considered to generalize to the general population, as female respondents are overly represented and the respondents are predominantly younger, therefore the results might not reflect the behaviors of the broader population. Secondly, this survey does not specify an AI technology, it refers only to the general definition of AI – because consumers may have different perceptions of different AI technologies, by not differentiating between them, this research may lack the depth gained by narrowing the focus to specific types of AI. Therefore, future research could consider focusing on a specify AI technology applicable to preliminary medical diagnosis. Thirdly, this research only differentiates between critical and non-critical medical contexts, this lack of specificity may oversimplify the complexity of medical contexts. Additionally, it does not consider specific medical conditions nor clearly communicates the potential consequences of misdiagnosis. As such, future research could consider further limiting the context being studied by referring to specific medical conditions or different medical contexts (e.g., contexts where stigmatized information is revealed, specific conditions). Lastly, this research did not compare consumers' perceptions of AI versus a human practitioner – future researchers could contribute with additional insights on consumer attitudes by establishing a baseline for comparison of traditional human-driven diagnostic versus AI-driven approaches. These insights could provide the industry with more contrasting strengths and weakness for each approach, further contributing to the development of efficient adoptions strategies.

6.3. **Conclusions**

The goal of this study was to examine consumer's willingness to accept being provided with medical preliminary medical diagnosis by AI technology and how this behavioral intention would vary according to medical context – in the case of this research two specific contexts were considered: critical and non-critical medical contexts. For this purpose, an UTAUT model was constructed, and two surveys were published and distributed among consumers. These questionnaires gathered a total of 325 answers and the results provided valuable results as it explained up to 79.6% of the behavior intention to receive preliminary medical diagnosis by AI.

The findings align with the theoretical framework proposed by the UTAUT model. It was observed that the three main constructs of PE, EE and SI are significant in explaining BI in different contexts. These conclusions reveal that it is important for consumers to clearly understand that AI for preliminary medical diagnosis is useful, recommended by the relevant stakeholders and easy to operate, thus establishing positive associations with the adoption of this AI-driven technology for medical purposes becomes imperative for fostering consumer acceptance.

Regarding performance expectancy, overall consumers demonstrated to be most optimistic of AI serving as an accelerator to them receiving their preliminary medical diagnosis while simultaneously leaned more towards reluctancy that it would provide them with an accurate preliminary diagnosis.

As for effort expectancy, in both contexts, consumers were less confident that they could skillfully operate an AI diagnostic tool – nonetheless, in non-critical contexts consumers leaned most towards optimism in their ability to utilize an AI diagnostic tool; and in critical contexts consumers leaned most towards optimism in their ability to learn to use an AI diagnostic tool.

Regarding social influence, consumers are a lot more optimistic that their doctors or people important to them would advise them to use AI for preliminary medical diagnosis in non-critical contexts than in critical contexts.

Furthermore, this research also confirmed that while younger consumers are much more accepting of AI technology in non-critical contexts, they exhibit a significantly higher degree of caution compared to older consumers when it comes to critical and potentially high-stakes contexts. This heightened wariness among younger users highlights their awareness of the potential implications associated with AI, demonstrating a nuanced understanding that contrasts with the relatively more trusting attitude observed in the older demographic.

Overall, while consumers generally leaned towards optimism, they showed neither a particularly negative nor positive perception of AI on the evaluated dimensions of PE, EE, SI, FC, as well as on their current willingness to use such technology. As such, this research is proposed to serve as a support for the development and implementation of AI technology for preliminary medical diagnosis specifically designed to enhance and direct the current consumer perceptions. Additionally, these findings are also of interest for researchers who intend to undertake studies regarding consumer perception of AI technologies for preliminary diagnosis.

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APPENDIX

Appendix A – Non-Critical Items

Constructs		Item	Adapted from
Performance Expectancy	PE1	In a non-critical healthcare context, AI would enable me to accelerate my preliminary diagnosis.	(Tran et al., 2021)
	PE2	In a non-critical healthcare context, AI would provide me with an accurate preliminary diagnosis.	(Hameed et al., 2023)
	PE3	In a non-critical healthcare context, AI would improve my preliminary diagnosis.	(Arfi et al., 2021)
	PE4	In a non-critical healthcare context, receiving a preliminary diagnosis by AI would be more convenient for me.	(Ly & Ly, 2022)
Effort Expectancy	EE1	In a non-critical healthcare context, using an AI preliminary diagnostic tool would be easy for me.	(Tran et al., 2021)
	EE2	In a non-critical healthcare context, I think I could skillfully operate an AI preliminary diagnostic tool.	(Tran et al., 2021)
	EE3	In a non-critical healthcare context, learning to operate an AI preliminary diagnostic tool would be easy for me.	(Ly & Ly, 2022)
Facilitating Conditions	FC1	In a non-critical healthcare context, someone would be available for assistance if there were difficulties using an AI preliminary diagnostic tool.	(Venkatesh et al., 2003)
	FC2	In a non-critical healthcare context, medical organizations would have the necessary preconditions for the effective use of AI preliminary diagnostic tools.	(Cornelissen et al., 2022)
	FC3	In a non-critical healthcare context, I would have the necessary resources for the use of AI preliminary diagnostic tools.	(Wang et al., 2020)

Social Influence	SI1	In a non-critical healthcare context, my doctors would advise me to use AI preliminary diagnostic tools.	(Gohil, 2023)
	SI2	In a non-critical healthcare context, people who are important to me would advise me to use AI preliminary diagnostic tools.	(Gohil, 2023)
Behavioral Intention	BI1	In a non-critical healthcare context, I would use AI preliminary diagnostic tools.	(Tran et al., 2021)
	BI2	In a non-critical healthcare context, I am willing to use AI preliminary diagnostic tools.	(Cheng et al., 2022)
	BI3	In a non-critical healthcare context, I will use AI preliminary diagnostic tools.	(Gohil, 2023)
Voluntariness of Use	VU1	In a non-critical healthcare context, receiving preliminary diagnosis by AI would be voluntary.	(Marques et al., 2011)
	VU2	In a non-critical healthcare context, I would be obligated to receive preliminary diagnosis by AI.	(Marques et al., 2011)

Appendix B – Critical Items

Constructs		Item	Adapted from
Performance Expectancy	PE1	In a critical healthcare context, AI would enable me to accelerate my preliminary diagnosis.	(Tran et al., 2021)
	PE2	In a critical healthcare context, AI would provide me with an accurate preliminary diagnosis.	(Hameed et al., 2023)
	PE3	In a critical healthcare context, AI would improve my preliminary diagnosis.	(Arfi et al., 2021)
	PE4	In a critical healthcare context, receiving a preliminary diagnosis by AI would be more convenient for me.	(Ly & Ly, 2022
Effort Expectancy	EE1	In a critical healthcare context, using an AI preliminary diagnostic tool would be easy for me.	(Tran et al., 2021)
	EE2	In a critical healthcare context, I think I could skillfully operate an AI preliminary diagnostic tool.	(Tran et al., 2021)

	EE3	In a critical healthcare context, learning to operate an AI preliminary diagnostic tool would be easy for me.	(Ly & Ly, 2022)
Facilitating Conditions	FC1	In a critical healthcare context, someone would be available for assistance if there were difficulties using an AI preliminary diagnostic tool.	(Venkatesh et al., 2003)
	FC2	In a critical healthcare context, medical organizations would have the necessary preconditions for the effective use of AI preliminary diagnostic tools.	(Cornelissen et al., 2022)
	FC3	In a critical healthcare context, I would have the necessary resources for the use of AI preliminary diagnostic tools.	(Wang et al., 2020)
Social Influence	SI1	In a critical healthcare context, my doctors would advise me to use AI preliminary diagnostic tools.	(Gohil, 2023)
	SI2	In a critical healthcare context, people who are important to me would advise me to use AI preliminary diagnostic tools.	(Gohil, 2023)
Behavioral Intention	BI1	In a non-critical healthcare context, I would use AI preliminary diagnostic tools.	(Tran et al., 2021)
	BI2	In a critical healthcare context, I am willing to use AI preliminary diagnostic tools.	(Cheng et al., 2022)
	BI3	In a critical healthcare context, I will use AI preliminary diagnostic tools.	(Gohil, 2023)
Voluntariness of Use	VU1	In a critical healthcare context, receiving preliminary diagnosis by AI would be voluntary.	(Marques et al., 2011)
	VU2	In a critical healthcare context, I would be obligated to receive preliminary diagnosis by AI.	(Marques et al., 2011)