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Exploring the Impact of Branding and Anthropomorphism on User Perceptions and Interactions with Symptom Checker Chatbots

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Master in Marketing

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Department of Marketing, Operations and General Management, ISCTE Instituto Universitário de Lisboa

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BUSINESS
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Department of Marketing, Operations and General Management

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Abstract
This dissertation examines the impact of branding and anthropomorphism in shaping user perceptions and interactions with symptom checker chatbots. It addresses the gap in understanding how these design elements affect users' opinions regarding chatbot competence, warmth, and how these factors influence empathy and trust, as well as their intention to recommend and tolerance for errors. This is particularly important since symptom checker chatbots are being integrated into our lives. Four different chatbot interaction scenarios, each with varying levels of branding and anthropomorphism, were employed in the experimental design. These scenarios were assigned randomly to participants (n = 287), and validated measures were used to determine how they perceived the symptom checker chatbot. The study found that incorporating branding into chatbot presentations does not enhance users' perceptions of the chatbot, and giving the chatbot human-like traits—known as anthropomorphism—also had no impact. These results suggest that, even if branding and anthropomorphism are usually used as emotional connection strategies, their limited efficiency in this context challenges healthcare managers to explore new tools that are capable of building meaningful relationships with users.

Keywords: AI, Symptom Checker Chatbots, Branding, Anthropomorphism, Consumer Perceptions, Customer Engagement

JEL: M31: Marketing; L86: Information and Internet Services

Resumo

Esta dissertação tem como objeto de análise o impacto que a marca e o antropomorfismo assumem em utilizadores que interagem com chatbots na área da saúde. Do mesmo modo, pretende-se compreender, decorrente da marca e do antropomorfismo, a perceção que os utilizadores de chatbot têm em aspetos como a competência e a cordialidade, e como estas afetam a perceção da empatia, da confiança, da tolerância ao erro e sua intenção de recomendar o uso deste software. Trata-se de um tema relevante, dado que os chatbots que avaliam sintomas estão a ser cada vez mais utilizados como plataformas de diagnóstico. Assim, neste estudo, como ponto de partida, colocaram-se quatro cenários diferentes de interação com chatbots, cada um com diferentes níveis de branding e antropomorfismo. Estes cenários foram atribuídos aleatoriamente a 287 participantes (n = 287), e as medidas validadas foram usadas para determinar a reação ao chatbot verificador de sintomas. Depois de obtidas as respostas ao questionário aplicado, constatou-se o seguinte: a presença da marca nas apresentações do chatbot não melhora a perceção que os utilizadores têm sobre ele; a atribuição de características semelhantes às humanas — conhecidas como antropomorfismo — também não tem impacto naqueles que, hipoteticamente, se socorrem deste meio de diagnóstico. Estes resultados sugerem que, embora a marca e o antropomorfismo sejam tradicionalmente utilizados como estratégias de conexão emocional, neste contexto, a sua eficácia é limitada, desafiando, por esta razão, as organizações de saúde a explorarem novas ferramentas capazes de construir relações significativas com os utilizadores.

Palavras-chave: IA, Symptom Checker Chatbots, Marca, Anthropomorfismo, Perceção do Consumidor, Engajamento do Consumidor

JEL: M31: Marketing; L86: Informação e Serviços de Internet

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Index of Abbreviations

AI: Artificial Intelligence

NLP: Natural Language Processing

WOM: Word of mouth

S1: Scenario 1

S2: Scenario 2

S3: Scenario 3

S4: Scenario 4

1. Introduction

1.1. Relevance of the topic

Artificial intelligence (AI) is promoting major changes across diverse areas of people's lives, particularly in the healthcare sector (Libai et al., 2020). Nowadays, applications of AI in health, including health maintenance (Chun et al., 2020), predictive medicine (Abràmoff et al., 2018)and the discovery of medicines (Fleming, 2018) highlight how this emergent technology is revolutionising businesses.

Looking to the future, AI is ready to transform marketing approaches and how customers behave significantly (Davenport et al., 2020). Motivated by fast technological progresses and by the dissemination of numerous platforms, interactive marketing thrives on two-way communication and the involvement of an active consumer, allowing interaction with a brand in real-time (Wang, 2021). Notably, with the advancement in AI, chatbots have emerged as a fundamental innovation in interactive marketing, marking a new chapter in how brands connect with customers. This way, it is vital to comprehend the perceptions of users and the factors that influence human-AI interaction and how to improve them (Pentina, Xie, et al., 2023).

In recent years, the enthusiasm of marketing specialists and technology professionals turned to the consumers fed by AI increased significantly. That increased interest was caused by the quick advancements in deep learning and natural language processing (NLP) applications (Huang & Rust, 2018; Vlačić et al., 2021). In customer service, AI is being constantly integrated in various areas, including in software recommendation (Zhang et al., 2021), customer care and hospitality (Belanche et al., 2020b; Minton et al., 2022; Sands et al., 2022), assistance via personal voice (Ramadan, 2021), and social companions (Pentina et al., 2023).

In the last few years, the utilisation of AI in health services has expanded significantly, with the usage of AI-driven chatbots becoming more predominant in digital health services (Schachner et al., 2020). These types of chatbots use predefined rules and NLP techniques to combine user-entered symptoms and established medical knowledge, offering responses to users' worries (Bharti et al., 2020; Kurup & Shetty, 2022) .

Throughout the last century, researchers and designers have been trying to improve chatbots' users' perception and connection by incorporating the presence of brands and higher levels of anthropomorphism (Epley et al., 2007; Kull et al., 2021). Research shows that when people attribute human qualities to non-human entities, known as anthropomorphism, chatbots become more relatable and easier to connect (Epley et al., 2007). Apart from that, giving chatbots strong brand identities and human characteristics can improve users' perception of competence, warmth, empathy and trust, which are key elements in how we form social impressions (Fiske et al., 2007).

1.2. Contextualization

In recent years, the integration of digital tools in health systems has significantly increased (Quinn et al., 2021). Healthcare providers started to use chatbots because this technology enables patients to say what are their symptoms, get preliminary guidance on whether to seek hospital care, receive emotional support, and manage administrative duties (Amiri & Karahanna, 2022; Judson et al., 2020; Zhu et al., 2022) . Despite the advantages of AI, users still prefer to interact with human health specialists rather than relying on the support of these technological devices (Longoni & Cian, 2022). So, understanding how users perceive these applications and how to improve them can make a big impact on the future of health care.

1.3. Problem Statement, Research Questions, and Objectives

Symptom checker chatbots became popular tools in healthcare services, by providing users with accessible and immediate information about what they were feeling and guide them to the next steps (Qin et al., 2024). Although there is literature about these chatbots, it mostly focuses on the medical perspective, rather than the impact of design features—such as, anthropomorphism and branding—on user perception and emotional engagement.

Exploring how these dimensions work is crucial, particularly in the context of public health policy. Governments around the world seek to change how traditional health services work by promoting people's engagement with digital alternatives. Nevertheless, for this solution to be effective, people not only need to use them but also trust and feel comfortable using them, knowing that chatbot responses might not always be flawless.

Investigating which design mechanisms can boost user acceptance has implications beyond marketing—it is about improving the crossing point between citizens and healthcare systems. This thesis examines the impact of emotional and perceptual aspects on chatbot design on usage intention.

The research problem centres on the influence of branding and anthropomorphism in shaping user perceptions and interactions with symptom checker chatbots. Specifically, it addresses the gap in understanding how these design elements affect users' opinions regarding chatbot warmth, competence, and how these last perceptions influence empathy and trust, as well as users' engagement. This is very relevant as symptom checker chatbots are being more used in healthcare services (Montenegro et al., 2019), where user acceptance and satisfaction are crucial for effective utilisation.

The findings are expected to provide insights into enhancing chatbot design and encouraging more effective user experiences. Ultimately, the study aims to bridge the gap between technical capability and user-focused design, supporting the development of more effective and anthropomorphised digital health tools.

In light of this, the research aims to address the following questions:

RQ1: How does the presence of branding (branded vs. not branded) influence consumers' perceptions of warmth and competence towards symptom checker chatbots?

RQ2: Does the level of anthropomorphism (high vs. low) moderate the effect of branding on user perceptions of warmth and competence?

RQ3: How do perceptions of warmth and competence influence users' perceptions of empathy and trust towards the symptom checker chatbots?

RQ4: How does empathy towards a chatbot influence users' error tolerance and willingness to recommend the symptom checker?

RQ5: How does trust towards a symptom checker chatbot influence users' willingness to recommend the chatbot to others?

RQ6: How does the severity of the error committed by the symptom checker chatbot influence the users' error tolerance?

1.4. Dissertation's Structure

This dissertation adopts a structure approach to provide a full understanding of the research theme across six main chapters. It begins with the abstract in both English and Portuguese, followed by the table of contents and lists of figures, tables, and abbreviations. The first chapter highlights the importance of the theme for academics and professionals in marketing, offering a summary of the significance of AI-powered symptom checker chatbots in healthcare. The literature review examines key topics, such as chatbots in healthcare, human-computer interaction in healthcare, and the roles of branding and anthropomorphism in user perception. The subsequent chapter discusses the theoretical foundations and conceptual framework utilised to develop and justify the study's hypotheses.

The chapter on the methodology outlines the quantitative experimental approach adopted, including the measurement of constructs, survey design, data collection process, and a description of the participant profile. The Results and Discussion chapter presents the main findings of the study, examines the structural hypothesis, and provides a thorough interpretation of the data. The conclusion summarises the main insights, offers practical recommendations, and suggests directions for future research as well as theoretical and managerial implications. The document concludes with a list of references that were used and annexes containing additional material.

2. Literature Review

2.1. AI in Marketing

The digital revolution promoted by the growing use of Artificial Intelligence (AI) has influenced the disruption in enterprise businesses. Marketing is one of the businesses that has witnessed this transformation caused by AI (Chintalapati & Pandey, 2022). Marketing is defined as the action, group of organisations, and procedures to create, communicate, deliver, and exchange offers that are worth for customers, clients, partners, and society at large (American Marketing Association, 2017).

Marketing Science Institute (2022) highlights AI as a revolutionary skill that transforms the abilities and responsibilities of marketing management and increases the efficiency of marketing strategies and functions. As a consequence, incorporating AI in Marketing will drive innovation and increase efficiency in the upcoming years (Capatina et al., 2020).

According to different authors, artificial intelligence can be defined in various ways. Shieber (2004) describes it as "intelligence demonstrated by machines." This definition encompasses a comprehensive understanding of intelligence, which includes learning, planning, and problem resolution, but also includes understanding, self-awareness, emotional knowledge, reasoning, imagination, logic, and analytical thinking (Legg & Hutter, 2007). De Bruyn et al. (2020) defines it as "machines that mimic human intelligence in tasks such as learning, planning, and problem-solving through higher-level, autonomous knowledge creation." This definition emphasises three subtasks and avoids philosophical debates about whether machines can be intelligent. It also limits AI to procedures that freely generate new concepts and data structures (De Bruyn et al., 2020). Furthermore, De Bruyn et al. (2020) differentiate between "strong AI" and "weak AI." The first relates to machines that learn to perform a specific, well-defined task. In contrast, the second one involves machines that can learn and accomplish any task intellectually done by humans.

A few advantages of AI in marketing are the ability to improve predictive tasks by automating processes, uncover insights, preferences and trends of customers, automate various marketing tasks, such as customer segmentation, targeting, and campaign management, and, lastly, AI technologies, such as chatbots and virtual assistants, can enhance customer engagement by providing real-time feedback and personalised interactions (De Bruyn et al., 2020). All these advantages allow marketers to anticipate customer behaviour and preferences and tailor customer experiences while allocating resources more efficiently.

However, there are also numerous weaknesses related with the implementation of AI in marketing, starting with the difficulty in transferring knowledge between marketing experts and AI models, the difficulty for marketeers to articulate clear objectives to AI models and the danger of AI models being

trained in unrealistic or unsafe environments, which can lead to poor decision-making when applied in real-world marketing scenarios (De Bruyn et al., 2020).

As stated by Huang and Rust (2018) AI marketing services can be grouped into four categories: mechanical AI (such as self-service tools), analytics AI (for example, recommendation systems), intuitive AI (for instance, personalised adaptive services) and empathetic AI (including companion robots and chatbots). The majority of the researchers focused on mechanical, analytical and intuitive AI (Mehta et al., 2022). The rapid advancements in natural language processing (NLP), particularly models in generative pre-trained transformer (GPT) language, highlight the necessity to investigate how clients get involved with AI chatbots that demonstrate empathy and emotional intelligence (Huang & Rust, 2018; Pentina, Xie, et al., 2023).

Haleem et al., (2022) proposes that with the rapid advancement of technology, marketers should change their focus from only exploring the capability of AI in digital marketing to prioritising the client's involvement in real-time and assessing their needs through AI. From the viewpoint of the service worker, the chatbots can deal in an efficient form by dealing with multiple client consultations at the same time, opposite to human agents who can only respond to a consumer each one at a time (Cheng et al., 2022). Despite that, the chatbots do not feel the frustrations, boredom and exhaustion humans do, allowing them to interact consistently and amicably (Cheng et al., 2022; Luo et al., 2019). Lastly, chatbots can be programmed to reflect the personality and the corporate image of the brand, imitating interpersonal communication with customers (Ramerman, 2020).

2.2. Chatbots

2.2.1. Definition and Functionality

Chatbots are specific types of conversational agents that can participate in conversations mimicking humans using either pattern-matching techniques (non-AI chatbots), which occurs when chatbots use data from an already database and do not learn through the interactions they have with users, or machine learning approaches (AI-chatbots) when chatbots learn through the interactions they have by using natural language processing (Ramesh & Chawla, 2022). Regarding physical presence, chatbots can be embodied in a human-like form or face, or they can be disembodied and communicate through text (Araujo, 2018). Gao et al. (2021) describe three response methods for chatbots: rule-based models, which utilise predefined answers; generative models, which employ AI and machine learning to create new answers (for example, ChatGPT); and hybrid models, which combine both approaches (De Keyser & Kunz, 2022). Shevat (2017) distinguishes the dialogues as either task-led, which focuses on specific objectives, or topic-led, which revolves around in-depth discussions. Almurayh (2021) classified

chatbots into two functional types: information chatbots, which assist users in finding the desired answer, and transaction chatbots, which facilitate task organisation or decision-making.

Chatbots are predominantly used in customer service environments, allowing them to interact directly with users (Brandtzaeg & Følstad, 2018; Chung et al., 2020). The deployment of chatbots eases the use of human services in companies, decreasing labour costs and improving general operational efficiency in companies (Deloitte, 2020). Furthermore, it allows continued and monitored customer support, improving users' experience with 24/7 availability. As a result, many companies have adopted AI chatbot technologies to promote their business goals (Vora, 2018).

2.2.2. In health

There is no doubt that digital technology is revolutionising the traditional customer experience (Hoyer et al., 2020), becoming a relevant topic for professionals and academics. In the health sector, new digital technologies have sparked a significant transformation (O'Connor et al., 2021).

In recent past, the usage of AI in healthcare has expanded, and the use of technologies such as AI-driven chatbots has become increasingly important in digital health services (Schachner et al., 2020). AI-driven chatbots make use of predefined rules and NLP techniques to merge user-entered symptoms with established medical knowledge, giving responses to users' doubts (Bharti et al., 2020; Kurup & Shetty, 2022).

Due to the COVID-19 pandemic, there was an acceleration in the adoption of these chatbots (McGreevey et al., 2020), which have been used to streamline administrative tasks and appointments, offer emotional support, and even help in triage decisions (Amiri & Karahanna, 2022; Judson et al., 2020; Zhu et al., 2022).

Currently, AI applications in health, including the utilisation of AI for health maintenance (Chun et al., 2020), precision medicine (Abràmoff et al., 2018), the discovery of medication (Fleming, 2018), show the significant impact that this technology is having on the industry. Research says that AI can level or even surpass human health specialists, enhancing access to healthcare and treatments (Hoyer et al., 2020; Kleinberg et al., 2017; O'Connor et al., 2021). In spite of the benefits of AI when it comes to precision, velocity and rentability, consumers do not always favour its recommendations to the detriment of human health specialists (Longoni & Cian, 2022).

The appearance of ChatGPT, a chatbot capable of generating human-like text, sparked additional interest in AI-driven healthcare conversations (Javaid et al., 2023; Nazir & Wang, 2023; Pataranutaporn et al., 2023). Nonetheless, despite the increased interest, people tend to prefer human doctors over chatbots (Longoni et al., 2019). Many users have expressed reluctance or abandoned interactions with AI healthcare chatbots after trying them (Fan et al., 2021).

Due to the increasing implementation of AI tools in various sectors, recent studies have tried to understand the psychological reasons behind the reluctance of users to accept AI in different areas, including health (Castelo et al., 2019; Dietvorst et al., 2018; Longoni & Cian, 2022) and comprehend the issues that impact the public adoption of these technologies, to maximise the positive impact AI has on healthcare (Qin et al., 2024).

2.2.3. **Symptom Checker Chatbots**

Recently, chatbot-based symptom checker apps have become more common in the market. These chatbots are computer programmes capable of talking with humans. The apps evaluate users' medical symptoms through conversations. Users enter their symptoms and receive a diagnosis through interactive processes. Most of these apps have emerged in recent years due to the advancements in AI algorithms applied to conversational chatbots (Montenegro et al., 2019).

Despite their growing popularity, symptom checker chatbots have received limited attention in the healthcare sector compared to other diagnostic technologies focused on supporting professionals in their clinical decisions (Fontil et al., 2019; Haynes & Kim, 2017). Although symptom checker app developers highlight the benefits of providing medication information and assistance in triage decisions, risks are implied. The users, especially those with high-risk conditions, can endanger their health by trusting solely in the diagnosis of these apps (Baker et al., 2020; Fraser et al., 2018; Palanica et al., 2019).

The symptom checker chatbots can result in inaccurate predictions and unwanted consequences in medical diagnosis (Laranjo et al., 2018). Therefore, users' perceptions of the efficiency of these apps are crucial, as they can significantly impact their future health decisions and intentions to use the chatbot again. Furthermore, Table 2.1 presents some studies on users' perceptions of chatbots in various service settings.

Table 2.1- Resume of articles about chatbots

Title	Reference	Objectives	Findings	Antecedents	Dependent Variables
Effect of anthropomorphism and perceived intelligence in chatbot avatars of visual design on user experience: accounting for perceived empathy and trust	(Ma et al., 2025)	How Anthropomorphism and Perceived Intelligence in Chatbot Design Affect Overall User Experience, Perceived Empathy, and Perceived Trust in the Chatbot.	Anthropomorphism and perceived intelligence do not significantly affect users' experience. Their combined influence was significantly mediated by perceived empathy and trust, which, as a consequence, improved users' experience.	Anthropomorphism level (High vs. Low). Perceived Intelligence (High vs. Low). Interaction effects (Anthropomorphism × Perceived Intelligence).	User Experience. Perceived empathy. Perceived trust.
How may I help you? Driving brand engagement through the warmth of an initial chatbot message	(Kull et al., 2021)	How the first message displayed by a chatbot can attract and engage consumers.	A warm initial message from a chatbot increases brand engagement by reducing brand-self distance—warmth makes consumers feel closer to the brand. The positive impact of a warm message is stronger when consumers are already connected to the brand. Chatbots using a warm tone elicit more authentic responses, making interactions feel more personal and engaging.	Message tone (Warm vs. Competent vs. Neutral). Brand Affiliation (Consumer vs. Non-consumer). Contextual Cues (Mobile vs. Desktop interface). Perceived warmth and competence. Chatbot message content.	Brand engagement. Brand-Self distance. Message response behaviour. Moderation and mediation effects.
What Makes People Feel Empathy for AI Chatbots? Assessing the Role of Competence and Warmth	(Kim & Hur, 2024)	To analyse how humanlike traits in AI chatbots—specifically competence and warmth—affect consumers' empathy and their willingness to use chatbot services.	AI chatbots' personalisation and anthropomorphism affect positively perceived competence and warmth, leading to empathy. This positively impacts consumers' willingness to use AI chatbots. Consumers' need for interaction moderates the relationship between anthropomorphism and competence.	Personalisation (perceived customisation of chatbot responses). Anthropomorphism. Need for Human Interaction (NHI).	Willingness to Use AI Chatbots.
Humanising chatbots: The effects of visual, identity and conversational cues on humanness perceptions	(Go & Sundar, 2019)	Examine how three types of design cues—visual, identity, and conversational style- shape users' perceptions of chatbot humanness, social presence, and attitudes toward websites.	A high level of message interactivity impacts the impersonal nature of a chatbot that is low on anthropomorphism. Identifying the agent as human raises user expectations for interactivity.	Visual Cues. Identity Cue. Message Interactivity. Interaction Effects.	Attitudes toward the Chatbot agent and the Website. behavioural intentions.
Chatbot e-service and customer satisfaction regarding luxury brands	(Chung et al., 2020)	Study whether luxury brands can maintain their core values and provide personalised care through e-services, particularly through Chatbots.	Chatbot e-service provides interactive and engaging brand/customer service encounters.	Chatbot marketing efforts (Interaction, Entertainment, Trendiness, Customisation, Problem-solving). Communication quality dimensions (Accuracy, Credibility, Competence).	Customer Satisfaction.

Title	Reference	Objectives	Findings	Antecedents	Dependent Variables
AI-based chatbots in customer service and their effects on user compliance	(Adam et al., 2021)	Examine how verbal anthropomorphic design cues and the foot-in-the-door technique affect user request compliance.	Anthropomorphism and the need to stay consistent increase the probability that users comply with a chatbot's request for service feedback.	Anthropomorphic Design Cues. Foot-in-the-Door Technique. Social Presence.	User Compliance.
The Chatbots Are Invading Us: A Map Point on the Evolution, Applications, Opportunities, and Emerging Problems in the Health Domain	(Giansanti, 2023)	Examine chatbots by mapping out their technological evolution, current usage, and potential applications, opportunities, and emerging problems within the health domain.	The findings highlighted the importance of launching initiatives that assess various areas in a coordinated and integrated way. Additionally, it's considered essential to track the interaction between the health sector and other fields, as well as to monitor the influence of chatbots that may contribute to psychological or behavioural issues affecting health.	Technological maturity. User expectations. Healthcare needs.	User satisfaction. Health behaviour change. Clinical effectiveness. Usability and acceptability. Patient safety and trust.
Determinants of customer satisfaction in chatbot use: evidence from a banking application in Turkey	(Eren, 2021)	Investigate customer satisfaction with chatbot use in banking and examine how perceived trust in chatbots and corporate reputation influence satisfaction.	Perceived performance, trust, and corporate reputation significantly boost customer satisfaction. Customer expectations and confirmation of expectations do *not* directly affect satisfaction. However, customer expectations positively influence perceived performance, which in turn affects satisfaction. Perceived performance also enhances confirmation of expectations, but confirmation itself doesn't significantly impact satisfaction.	Customer Expectations. Perceived Performance. Confirmation of Expectations. Perceived Trust. Corporate Reputation.	Customer satisfaction.
When chatbots make errors: Cognitive and affective pathways to understanding forgiveness of chatbot errors	(Cao et al., 2024)	This research seeks to explore the extent to which people are willing to pardon mistakes made by chatbots, in comparison to their forgiveness toward human errors.	The findings revealed that chatbots exhibiting higher levels of anthropomorphism were more likely to be forgiven for their mistakes than those with lower anthropomorphic traits	Chatbot Anthropomorphism (name, tone, empathy, informal language). Chatbot Type (Task-oriented and Relationship-oriented). Perceived Severity of Errors Aversion Toward Errors. Attribution to Self. User Expectations.	Forgiveness of Chatbot Errors. Perceived Severity of Errors. Aversion Toward Errors. Attribution to Self.
What drives continuance intention to use a food-ordering chatbot? An examination of trust and satisfaction	(Hsiao & Chen, 2022)	This study employs the constructs of service quality, trust, and user satisfaction to examine and predict individuals' intention to continue using a food-ordering chatbot.	The data indicates that anthropomorphic features and service quality—particularly in areas like problem resolution—serve as key predictors of user trust and satisfaction. Among these, satisfaction emerges as the strongest direct influence on users' continued intention to engage with the service.	Anthropomorphism. Service quality.	Users trust. User satisfaction. Continuance to use intention.

Source: Own elaboration

2.3. Branding

A brand consists of tangible elements, such as logos and colours, and intangible elements, such as associations, all intending to increase recognition and build a reputation for a product or organisation (Sammut-Bonnici, 2015). According to a study by Nordheim et al. (2019), customers' trust in a chatbot for customer service is greatly influenced by their perception of the brand. If customers trust the brand, they are more likely to trust the chatbot. It was also suggested that associating a customer service chatbot with a trustworthy brand can be an advantage. A brand can also improve the way customers perceive warmth, competence and empathy (Aaker et al., 2010). These findings are aligned with the categorisation theory from cognitive psychology (Aaker & Keller, 1900), which states that people transfer information between related entities. In this process, the effect of a brand is recovered from memory and matched with a new product by the brand. If this match is successful, the effect is likely to transfer; if not, the new object is evaluated based on its attributes. Even with the growing use of chatbots by brands, there is still limited research on their impact on users' perception and engagement.

For example, Kull et al. (2021) found that chatbots with strong brand messages increase users' involvement and fidelity to the brand since consumers tend to perceive branded chatbots as more informed and trustworthy. Branding helps humanise AI, allowing more personalised and emotional interactions (Chung et al., 2020). This is especially important for anthropomorphised chatbots, which reinforce the brand role of the chatbot as an empathic and trustworthy brand representative (Zheng et al., 2023).

Therefore, integrating a brand in a chatbot design is essential to combine chatbot function with the company's image but also to improve users' perceptions of warmth, competence, empathy, and trust in the chatbot. These factors are very important to build long-term relationships and promoting users' loyalty to the brand.

2.4. Anthropomorphism

Over the past 50 years, researchers and designers invested energy in making chatbots resemble humans more, a method known as anthropomorphism. A straightforward way to achieve this goal was by incorporating human characteristics or visual cues into these chat agents. These changes can influence the way people perceive and interact with them. Studies have shown that when anthropomorphism incorporates visual (as human figures) and linguistic cues, it can affect humans' perceptions and actions (Epley et al., 2007). For example, attributing human figures and names to chatbots has led to higher-quality interactions between the chatbots and users (Dianne et al., 2009). When machines present these signs, it can lead unconsciously to people treating the chatbots as a real person (Kim, 2010).

This "humanness" effect, fuelled by visual design, activates users' expectations that are typically reserved for humans (Sundar, 2008). As a result, people can interact with bots more naturally and socially, answering them as if they were their friends (Kim & Sundar, 2012). If users believe they are interacting with a machine, they will likely judge the interaction based on their preconceived notions of how machines typically perform. On the other hand, if the agent exhibits human-like behaviour, users will use their human expectations as a reference. The impression of who or what the agent is—human or machine—ultimately influences the standards people use to assess the quality of its communication. As Koh and Sundar (2010) noted that the actual content of the conversation may be less important than the identity the user attributes to the agent, which can lead to biased assessments.

When chatbots behave in a more human-like manner, they are more likely to be perceived as warm, intelligent, and competent. Additionally, anthropomorphic design increases credibility and trust, leading to a more favourable relationship between humans and machines (Natarajan & Gombolay, 2020). This perception of humanness is essential for the users' adoption, since users are more prone to engage with technologies that present traits similar to humans (Kiesler, et al., 2008; Nass & Moon, 2000).

From a psychological perspective, anthropomorphism can be linked to the Social Presence Theory. This theory suggests that when a system looks more human, users tend to create an emotional and cognitive connection (Lu et al., 2023). A heightened sense of social presence makes users feel more comfortable and connected during interactions, particularly when chatbots incorporate facial expressions and demonstrate empathy through their language (Meng et al., 2023). The Parasocial Interaction theory also offers insights, suggesting that people can form emotional relationships with anthropomorphised systems, similar to the bonds they feel with characters in media. These connections often lead to higher levels of trust, satisfaction, and loyalty (Gambino et al., 2024), which can encourage ongoing use and positive feedback. In addition, Attribution Theory explains how users tend to attribute human characteristics—such as empathy or trustworthiness—to these systems. This acknowledgement plays a crucial role in fields where trust is paramount, such as healthcare or customer service. For example, when a chatbot responds empathetically to a user's frustration, it can foster a sense of emotional understanding, thereby boosting perceived empathy and trust. Ultimately, these emotional dynamics not only enhance the overall user experience but also strengthen the bond between the user and the technology, promoting repeated and lasting engagement (Ma et al., 2025).

2.5. Social Perception: Warmth, Competence, Empathy and Trust

2.5.1. Warmth and Competence in Chatbot Perception

Studies about how customers assess services and their suppliers have been a focus of academic literature (Brady & Cronin, 2001). A recent perspective based on the investigation of human impressions highlights the principal aspects of social cognition, warmth and competence, which can be applied in a service context and positively influence the service results (Scott et al., 2013). The warmth dimension refers to evaluations of a service provider's social and moral qualities, whereas the competence dimension refers to the provider's abilities and skills. These dimensions have brought significant interest to researchers and professionals since they help to understand customers' evaluations of service providers (Bolton & Mattila, 2015; Kirmani et al., 2017), and technology-enhanced services like chatbots and service robots (van Doorn et al., 2017).

2.5.2. Customers perceived warmth

Warmth encloses the perceived intentions of others and comprises qualities that align with relationships and social interactions, such as friendliness, helpfulness and sincerity (Cuddy et al., 2008). Experience warmth during interactions can lead to customers to perceive chatbots as more human. This occurs because warmth indicates that chatbots have good intentions concerning customers' needs (Dwivedi et al., 2023). High levels of warmth can lead to positive results, such as increasing customers' satisfaction, loyalty and trust (Choi et al., 2016).

2.5.3. Customers perceived competence

Competence is a social construction that reflects an individual's capacity to fulfil their objectives. It encompasses capacity, intelligence and efficiency (Cuddy et al., 2008). Chatbot competence is evaluated in terms of their level of specialisation and their capacity to have the necessary expertise and intelligence. Consumers assume chatbots can solve their worries, identify with precision their problems and deliver the information they require. For users to understand chatbots positively in terms of comprehension and quality of content, the exchanges must be seamless, accurate and precise. When the data is delivered effectively, the chatbot will be perceived as competent and knowledgeable, and it is more probable that consumers trust the chatbot (Chung et al., 2020).

2.5.4. Competent vs. warm conversation style in healthcare Chatbots

Humans interact with chatbots the same way they interact with other humans (Reeves & Nass, 1996). Consequently, health chatbots can be evaluated using the same criteria as healthcare providers. So, it is important to highlight the balance between cure-oriented competence (medical knowledge and clinical thinking) and care-oriented warmth (treating patients as unique individuals and demonstrating

empathy), which are indispensable components of patient-centred care principles (De Valck et al., 2001; Howe et al., 2019). For that reason, health chatbots that demonstrate warmth and competence can be considered trustworthy (Huang & Ki, 2023).

2.5.5. Customers perceived empathy

When it comes to technology, empathy concerns to the ability of AI to recognise, recognise and answer other people's views, emotions and behaviours (Murray et al., 2019). In Information technology research, empathy is considered a central attribute of effective AI-individual interactions (Birnbaum et al., 2016). Furthermore, it was discovered that virtual agents' empathy towards individuals can make it seem like they are engaging with a human (Brave et al., 2005). Liu and Sundar (2018) researched empathic expression and individuals' perceptions of chatbots and concluded that users' pre-existing beliefs about automated intelligence shape their reactions towards chatbots' empathy. Portela and Granell-Canut (2017) discovered that during interactions with chatbots, when the chatbot remembers something mentioned before by users or asks them something personal, it triggers a feeling of empathy. In the same way, De Kervenoael et al. (2020) found that perceived empathy significantly influences the intention to use social robots. Therefore, it is recommended that chatbots display a basic level of empathy and respond appropriately and caringly (Zumstein & Hundertmark, 2017).

Researchers point out a criticism about health chatbots: their lack of empathy, mainly in recognising users' emotional states. This empathy deficiency can affect the way users interact with health chatbots (Nadarzynski et al., 2019).

2.5.6. Customers perceived trust

Trust has been examined in different areas, including human-automation relationships. In human automation relationships, trust is usually defined as the approach that an agent will aid to accomplish an individual's purpose in a condition characterised by doubt and susceptibility (Lee & See, 2004). Among various factors that influence individuals' adoption of technology, trust is seen as one of the critical elements in their interactions (Wang et al., 2018). This trust encompasses the objective performance of AI, like its precision and reliability, and an emotional, not rational aspect (Glikson & Woolley, 2020; Seitz et al., 2022). This dual perception of trust explains why some individuals can recognise that AI-driven chatbot knowledge can be compared to human knowledge, but still have resistance to using it (Zou et al., 2024).

Trust is essential in human interactions and behaviours since it is described as a mechanism that reduces social complexity. Trust is essential in various fields, including medicine (Goles et al., 2009). In this field, AI growth offers significant advantages in comparison to human clinicians (Shin, 2021). Nevertheless, building trust in a medical AI device is challenging. In health, trust has an even greater

importance (Seitz et al., 2022). Trust in health chatbots refers to confidence in the reliability and security of healthcare services and the outcomes they deliver (Shin, 2021). In the health sector, people tend to hesitate to trust AI in medical services (Longoni et al., 2019), as a result, people tend to prefer to go to the hospital rather than use an AI medical system, even if the latter is more convenient and has been improved (Hsiao & Chen, 2022). The increased use of AI in healthcare presents a valuable opportunity for research to deepen our understanding of the emotional and psychological facets of trust, which are often neglected. It is crucial to investigate these areas to understand how trust is created and influences the adoption of AI.

2.6. Users' engagement

2.6.1. Intention to Recommend

The concept known as intention to recommend involves the informal sharing of positive or negative experiences about consumers' experiences. Essentially, intention to recommend refers to the transmission of information from person to person during talkss. Customer loyalty is the preference for a specific product or service, resulting from a customer's acknowledgement of the value and benefits they expect from it. When customer satisfaction is continually met and products or services are consistently provided, it encourages customers to return and recommend them to others (Lee, 2001). Individuals who tend to adopt new technologies are more likely to become users and recommend them to others (Leong et al., 2013; Miltgen et al., 2013). Nowadays, consumers are highly influenced by word-of-mouth (WOM) when evaluating innovation quality (Venkatesh et al., 2001). Consequently, they also express their own opinions on social networks, which work as electronic WOM platforms since users can freely share information related to the brand (Vollmer & Precourt, 2008).

2.6.2. Tolerance to error and perceived error severity

Chatbots with AI technology are becoming an essential part of our daily lives. These interactions cover various fields, including customer service, healthcare, counselling, tutoring and specialised training (Crolic et al., 2022; Hwang & Chang, 2023; Xu et al., 2021). Despite the significant advancements in chatbot technology over the last ten-year period, it is important to acknowledge that errors continue to occur and are a natural part of continuous technological development (Mirnig et al., 2017). Negative or erroneous experiences can negatively affect how people understand, acknowledge and trust a chatbot (Toader et al., 2020). Even with minor errors in the service, when it comes to healthcare, the consequences can be significant and limit the adoption of AI in healthcare (Chen et al., 2022).

Although chatbots are being used increasingly, little knowledge and research exist about how consumers react to and understand them after their service fails. In serious situations, significant

mistakes committed by chatbots, including erroneous claims, can cause considerable damage to companies' reputations, and at the same time amplify ethical concerns related to chatbots and AI technologies (Neff & Nagy, 2016; Olson, 2023; Zemčík, 2021). Forgiving errors also depends on their severity, how they are perceived, and users' sensitivity to them. When users encounter an error, their reactions can vary significantly depending on the type of error. The perceived severity describes how prejudicial, offensive or damaging the mistake is considered, and how people respond to them (Mccullough et al., 1998). Studies show that the more severe the mistake is perceived, the less likely people are to forgive the one who made it (Miao et al., 2022; Srinivasan & Sarial-Abi, 2021). Research done by Cao et al. (2024) also reveals that, depending on the context in which a chatbot is used, the forgiveness responses to mistakes can vary.

Given that errors are expected as chatbots evolve, recognise how the users recognise and excuse these errors is necessary to increasing approval from society and enhance users' experience. Furthermore, studying users' perceptions of chatbot errors can reveal their responses during failed exchanges, offering beneficial visions for AI chatbot developers to solve these problems (Mahmood et al., 2022).

3. Conceptual Model and Research Hypotheses

This chapter presents the hypothesis for this study, which examines how branding and anthropomorphism impact users' perceptions of chatbots. The study investigates how these factors influence key aspects such as warmth, competence, empathy, trust, error tolerance, and ultimately, the intention to recommend. The research draws on theories of social cognition and human-computer interaction.

Branding and anthropomorphism can significantly influence users' perceptions of a chatbot's competence and warmth. These perceptions, in turn, influence users' empathy and trust concerning the chatbots. The main concepts of competence and warmth from social cognition theory explain how consumers assess AI-driven entities, like chatbots, in the same way as they evaluate humans. These factors are crucial for evaluate user trust and overall satisfaction.

Furthermore, empathy and trust will improve the emotional connection between users and the chatbot, impacting their intention to recommend the chatbot to others. Empathy also influences error tolerance, which is how forgiving users are towards any mistakes made by the chatbot.

This study has as its goal to provide insights into how health companies can design chatbots that improve user involvement and create brand loyalty by exploring these relationships.

The effect of branding on perceived Warmth and Competence

The idea of the perception of brand is rooted in the stereotype content model (Aaker et al., 2012), that explains that people form social impressions about individuals or groups of people based on two fundamental characteristics (Fiske et al., 2002), warmth, which encompasses qualities like sincerity, friendliness, helpfulness, and enthusiasm, and competence, which reflects attitudes such as capability, efficiency, skilfulness, and confidence (Aaker et al., 2010).

Research about branding shows consistently that consumers' perceptions of a brand's warmth and competence effectively reflect stereotypes that influence key outcomes. These stereotypes include attitudes towards the brand, intention to purchase, customer satisfaction, willingness to endorse the brand, perceived value, and the extent to which consumers identify with the brand (Meyer et al., 2024).

When consumers perceive a brand as highly competent, they tend to evaluate the quality and performance of their products as more favourable, which, in turn, boosts their willingness to use them. In the same way, if a brand is seen as warmer, appearing to be sincere, friendly, and thoughtful, it improves consumers' perception of the products. If consumers feel genuinely valued and understood by a brand, their psychological needs for respect and belonging are fulfilled. This emotional connection strengthens their positive attitude toward the brand and significantly increases their intention to use the product (Xue et al., 2020).

Brands influence a lot of consumers' perceptions, signalling quality and competence. The brand of a technologically qualified company is perceived as highly competent (Erdem & Swait, 2004), this occurs because most consumers depend on the brand to evaluate the capacity of an entity, which can also evoke positive emotional responses, characterised by warmth (Fiske et al., 2007). In this context, a brand can improve its identification capacity and emotional involvement (Aaker et al., 2010). So, if a chatbot incorporates a brand, it will be perceived as competent as well as warm. Therefore, it is expected that:

H (1): Branded chatbot has significant effects on perceived competence compared to a non-branded chatbot.

H (2): Branded chatbot has significant effects on perceived warmth compared to a non-branded chatbot.

Anthropomorphism as a moderator of branding on perceived Warmth and Competence

Through brand anthropomorphism, marketers use elements such as mascots, packaging styles, and storytelling to give brands human-like traits (Zhang et al., 2020). These anthropomorphised brands play an active role in consumers´ experience. By adopting a human complex personality, full of emotions and intentions, these brands are seen as fundamentally different from the ones perceived as inanimate objects (Yang et al., 2020).

When a brand assumes human qualities, it can start to resemble a personal relationship in the way it interacts with consumers (Nass & Isbister, 2000). Research done by Zhou and Sha (2017) show that attributing human characteristics to a brand improves the perception of warmth and competence, incentivising people to relate to it much like they would to other people. In contrast, removing those traits tends to lower perceptions of both warmth and competence, suggesting that humanising a brand can enhance both qualities.

By interacting with brands that feel human, consumers naturally look for clues about their intentions and capacities. These two aspects, warmth and competence, shape how people perceive the brand. Warmth creates a feeling of friendliness and likability, helping to promote trust and emotional proximity (Aaker et al., 2012), while competence signals intelligence, reliability, and service quality. Improving a brand's perceived competence also boosts consumer trust (Zhou & Sha, 2017).

For brands that have a positioning of being socially popular, anthropomorphism can deepen their consumers' emotional connection. By looking more personal and likeable, brands increase the feeling of warmth and competence, which, in turn, improves customer confidence towards themselves (Zhou & Sha, 2017).

When chatbots behave in a more human-like manner, it is more probable that they are perceived as warm, intelligent and competent. This perception of humanness is essential for the users' adoption

since users are more prone to engage with technologies that present traits similar to humans (Kiesler, et al., 2008; Nass & Moon, 2000). Branding, when combined with anthropomorphism, potentially enhances both the perceived warmth and competence of a highly branded anthropomorphised chatbot more than a non-branded or low-anthropomorphised one. It is expected that a highly anthropomorphised, branded chatbot will be viewed as both warm and competent. So, it is hypothesised that:

H (3): The effect of branding on competence is moderated by the level of anthropomorphism.

H (4): The effect of branding on warmth is moderated by the level of anthropomorphism.

The effect of warmth and competence on empathy

Previous research suggests that empathy plays a crucial role in enhancing quality and satisfaction among collaborators and consumers. Similarly, when services based on AI are perceived as empathetic, they can enhance the human-machine connection. Due to the advancements in AI, computers are now able to express empathy, interpreting and responding to users' emotions and information (Adam et al., 2021). For example, users can feel that AI chatbots are empathic when systems carefully process their answers and react accordingly (Bove, 2019).

Supporting this, Bove (2019) argued that technology in the service environment can detect the needs and emotional states of customers, leading to empathic answers. Pelau et al. (2021) investigate how perceived empathy and interaction quality mediate the relation between the human-like traits of AI and users' willingness to accept the technology.

Belanche et al. (2021) introduce the theoretical model- humanness (reflected in robot appearance, competence, and warmth) linked to value creation (functional, emotional, monetary, and social) and loyalty. These discoveries reveal that perceived competence and warmth significantly increase the emotional value. Taken together, these studies recognise that perceived competence and warmth are key dimensions for evaluating AI chatbots and propose that these dimensions positively influence empathy. Furthermore, the following hypotheses are proposed:

H (5): Perceived competence positively impacts empathy.

H (6): Perceived warmth positively impacts empathy.

The effect of warmth and competence on trust

Consumers' experiences with chatbots are shaped significantly by the way they perceive two key human-like traits: warmth and competence. In the service context, human warmth is crucial because it has a significant impact on consumers' brand perceptions (Shuqair et al., 2021). Perceived warmth can promote social proximity between humans and chatbots during service interactions, which is vital to building trust. Warmth can be a significant factor in increasing chatbot trust (Xue et al., 2020) as well

as competence (Liew & Tan, 2018; Yen & Chiang, 2021). This emotional connection is closely tied to the chatbot's style of communication, particularly when it adopts a socially oriented approach that mimics human interaction (Giansanti, 2023). When chatbots interact with users using empathetic language, it fosters a sense of presence and builds a connection, they can evoke feelings of warmth that enhance customer satisfaction and trust (Silva et al., 2023).

On the other hand, the perception of competence is related to how capable, knowledgeable, and effective a chatbot is seen when handling tasks and providing information (Estevan & Barnett, 2018). Chatbots that deliver precise, high-quality responses are perceived as more competent, leading to higher user satisfaction and more positive service experiences. In addition, in interactions in which chatbots adopt anthropomorphic traits, competence can influence how the communication style affects the feelings of users toward the chatbot (Xu et al., 2023).

Together, warmth and competence form the core of human social judgment, playing a vital role in shaping chatbot interactions. A chatbot perceived as warm and competent strengthens emotional bonds and trust, and the ability to serve and inform. Chatbots which can capably deal with both simple and complex tasks, delivering good results, will be seen by consumers as more trustworthy. Thus, we hypothesise the following:

H (7): Perceived competence of chatbots has a positive impact on perceived trust in chatbots.

H (8): Perceived warmth of chatbots has a positive impact on perceived trust in chatbots.

The effect of empathy and trust on intention to recommend a chatbot

WOM refers to the act of consumers sharing their personal experiences about specific products or services (Bowman & Narayandas, 2001). This behaviour creates a highly competitive advantage in shaping the way others perceive these offers (Dagger et al., 2007). Research done by Nguyen and Romaniuk (2014) verify that WOM frequently influences people more effectively than traditional advertising. Similarly, Akinci and Aksoy (2019) highlight that consumers' satisfaction is an important factor that drives WOM behaviour. Supporting this idea, Verkijika and De Wet (2019) observed that satisfied users are keener to speak positively about their initial experience (Kassim & Asiah Abdullah, 2010; Kitapci et al., 2014; Meilatinova, 2021).

Apart from that, several studies demonstrate that satisfaction not only has an impact on WOM but also plays a fundamental role in incentivising the continuous use in various sectors. Empathy plays a crucial role in reaching customer satisfaction with a service, a factor that is essential for users to recommend a service. When a chatbot is perceived as empathic, it is more likely to generate a positive WOM (Yun & Park, 2022). Kumar et al. (2019) proposed that building trust can increase the efficiency of AI tools, like chatbots, which promotes higher user engagement. Hsiao and Chen (2022) verify that trust plays a fundamental role in increasing user satisfaction by using chatbots. Likewise, Eren (2021)

highlights the crucial role of trust, pointing out its strong influence on users' overall satisfaction with chatbot interactions. Research indicates that individuals are more inclined to recommend these technologies if they are highly efficient in performing their tasks and if they are satisfied with them (Talukder et al., 2019). Because of this, we propose:

H (9): Empathy significantly impacts the intention to recommend the chatbot.

H (10): Trust in chatbots is positively related to recommending a chatbot.

The effects of empathy on error tolerance

Empathy plays a crucial role in the forgiveness process. When somebody feels empathy for another person, it is more likely that they will let go of the resemblance and search for reconciliation instead of revenge (Mccullough et al., 1998). In a services context, empathy can reduce the consumers' dissatisfaction with loyalty, since empathic consumers tend to blame situational factors rather than personal shortcomings for service issues (Wieseke et al., 2012).

Empathy can also influence how users respond to service failure. Users who are guided by empathy, rather than a self-serving mindset, are more likely to take responsibility (van Laer et al., 2013). Even a simple empathic response to a negative review can positively change how customers view the interaction (Min et al., 2015). In essence, empathy on the part of service providers helps promote forgiveness after a service failure, thereby reducing guilt and fostering trust.

Emphatic answers from AI chatbots involve advanced interaction and communication skills that are crucial to improving service quality between humans and computers (Huang & Rust, 2018). According to Lv et al. (2022) when an AI application answers with empathy during a service failure, customers tend to adhere to social norms and engage in interpersonal interactions, temporarily reducing their dissatisfaction. This friendly and collaborative communication helps solve problems, improves the quality of interaction, and incentivises the users to continue using the service.

H (11): The higher the level of empathy, the higher the error tolerance.

Severity of the error as a moderator of error tolerance

Forgiveness of chatbot errors depends on two factors: the severity perceived by the users and the level of discomfort it causes them. When users encounter a particularly severe error, they are less likely to forgive it, often reacting frequently with negative emotions like anger, frustration, annoyance, or even disgust. These reactions can be directed toward the chatbot or the error committed (Dietvorst et al., 2018; Mccullough et al., 1998; Miao et al., 2022).

The more intense the perceived severity of the error, the stronger the aversion becomes, making it harder for users to overlook the mistake and extend forgiveness. However, chatbots that have

human-like traits (anthropomorphism) tend to induce kinder judgments from users. These bots are seen as more relatable and emotionally communicative, which can soften users' perceptions of the error's severity. As a result, users experience lower levels of aversion and are more likely to forgive the chatbot compared to those interacting with less human-like systems (Cao et al., 2024).

The perceived severity of an error affects how people respond to it. Studies have demonstrated that the greater the perceived severity of the mistake is, the less likely people are to excuse the one who made it (Miao et al., 2022; Srinivasan & Sarial-Abi, 2021).

H (12): The greater the perceived severity of a mistake, the less likely individuals are to forgive the person who made the error.

3.1. Proposed Model

Twelve hypotheses were developed after empirical and theoretical analysis of various research papers within the study field, as demonstrated throughout the third chapter. Therefore, Figure 2.1 visually represents the anticipated relationships and formulated hypotheses based on academic findings.

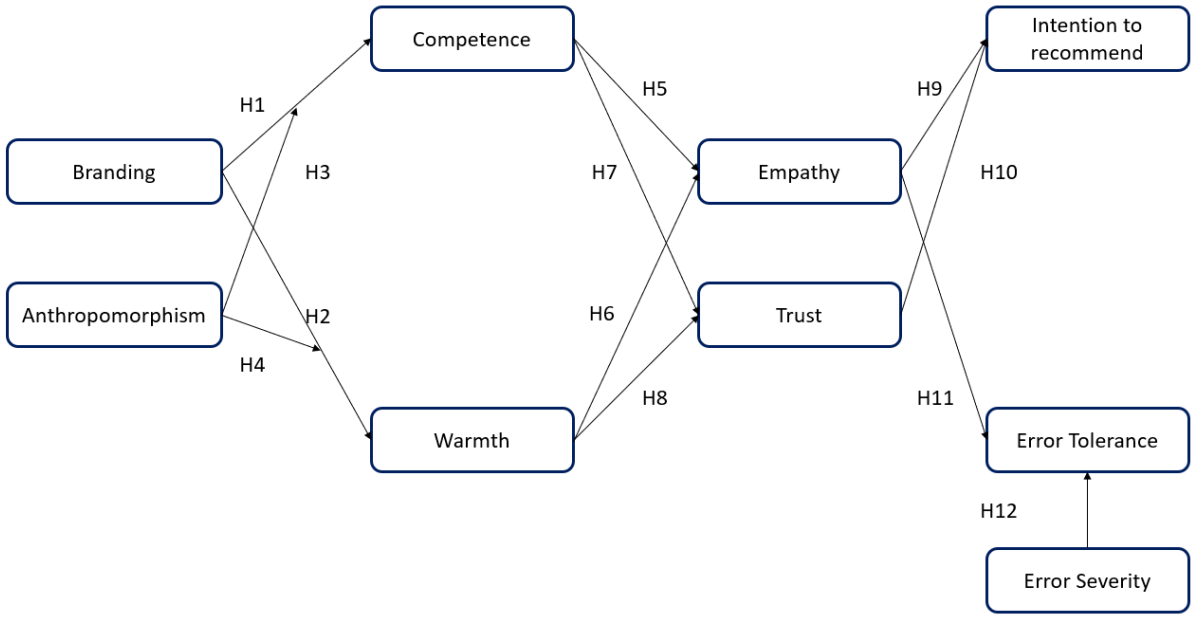


Figure 3.1- Proposed Conceptual Model Framework

Source: Own elaboration

4. Methodology

This research employed experimental structures with four different chatbot interaction scenarios that varied in terms of branding and anthropomorphism levels. The aim is to evaluate how these two elements impact users' opinions about warmth, competence, and subsequently, empathy and trust, besides their overall engagement. To adjust the levels of branding and anthropomorphism, the research sought to test hypotheses about the effects of branding (H1, H2) and the role of anthropomorphism (H3, H4) as a moderator, along with the mediating effects of competence (H5, H7), warmth (H6, H8) on empathy (H9, H11) and trust (H10), and the impact of the last two, in intention to recommend and error tolerance. It also examined how the severity of an error (H12) affects users' tolerance to it.

The participants were randomly assigned to one of the four different scenarios.

Scenario 1: High anthropomorphised, branded chatbot

In this case, participants engaged with a symptom checker chatbot that was personalised to mimic the behaviour of a healthcare assistant. The chatbot displayed the brand SNS 24, including its logos and design visual elements, to make the connection with the brand unmistakable.



Figure 4.1- Scenario 1

Source: Own elaboration

Scenario 2: Low anthropomorphised, branded chatbot

In this scenario, participants engaged with a symptom checker chatbot with a robotic appearance and few details resembling a human. The brand SNS 24 was present with its logos and visual elements.

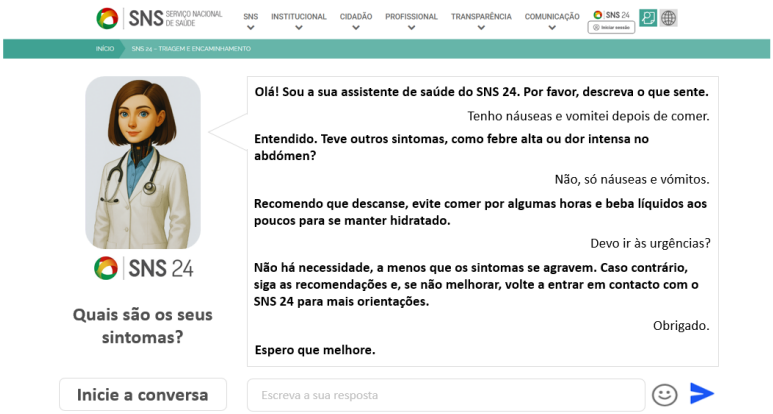


Figure 4.2- Scenario 2

Source: Own elaboration

Scenario 3: High anthropomorphised, branded chatbot

In this next scenario, participants interact with a personified chatbot as in the previous one, but there is no visible brand this time. By removing the brand SNS 24, it became possible to evaluate only the impact of anthropomorphism present in the symptom checker chatbot.



Figure 4.3- Scenario 3

Source: Own elaboration

Scenario 4: Low anthropomorphised, not branded chatbot

In the final scenario, participants interacted with a symptom checker chatbot designed with a robotic aesthetic, without any logos or visual elements associated with the SNS 24 brand.



Figure 4.4- Scenario 4

Source: Own elaboration

This study was projected to explore how a brand and human characteristics impact human perceptions about chatbots. Each scenario played a role in testing critical hypotheses about the direct effects of branding, as well as the potential influence of anthropomorphism on factors such as warmth, competence, empathy, trust, error tolerance and error severity.

The brand SNS 24 was the one selected since it represents the Portuguese public health service system to which the majority of the population resorts when ill, making it a brand with a widespread presence in the life of all population in Portugal.

Before conducting the main experiment, the symptom checker chatbot scenarios were pre-tested with 10 people, guaranteeing that the manipulations were clear and efficient. The participants were asked to interact with the four different chatbot scenarios and were able to distinguish the presence and absence of the brand and the different levels of anthropomorphism. After being in contact with the scenarios, it was suggested to increase the SNS 24 logo and its presence in scenarios 1 and 2, as well as to decrease the level of anthropomorphism of the robot in scenarios 3 and 4.

4.1. Construct Measures

The participants discover four scenarios in a controlled experimental setting. After the interaction, they complete a questionnaire that evaluates key variables, including perceived warmth, competence, empathy, and trust. Additionally, the respondents are asked about the likelihood of recommending and forgiving the chatbot because of its mistakes.

The questionnaire items were based on validated research by well-known authors in the fields of chatbot perceptions and user engagement (Table 4.1). All variables in this survey were measured using a 7-point Likert scale.

Table 4.1- Constructs

Construct	Source	Original Items	Adapted Items
Perceived Competence	(Kirmani et al., 2017)	"I think the service provider is competent." "I think the service provider is knowledgeable" "I think the service provider is skilled."	"The chatbot is competent."- Competence 1 "The chatbot is knowledgeable"- Competence 2 "The chatbot is skilled."- Competence 3
Perceived Warmth	(Fiske et al., 2002)	"The [target] is warm." "The [target] is friendly." "The [target] is sincere."	"The chatbot is warm."- Warmth 1 "The chatbot is friendly."- Warmth 2 "The chatbot is sincere."- Warmth 3
Perceived Empathy	(Croes & Antheunis, 2021; Stiff et al., 1988)	"Mitsuku said the right thing to make me feel better." "Mitsuku responded appropriately to my feelings and Emotions." "Mitsuku came across as empathic."	"The chatbot said the right thing to make me feel better."- Empathy 1 "The chatbot responded appropriately to my feelings and emotions."- Empathy 2 "The chatbot came across as empathic."- Empathy 3
Perceived Trust	(Corritore et al., 2003)	"I experience this website as trustworthy." "I believe this website will not act in a way that harms me." "I trust this website."	"The chatbot is trustworthy."- Trust 1 "I believe the chatbot will not act in a way that harms me."- Trust 2 "I trust this chatbot."- Trust 3
Intention to Recommend	(Reichheld, 2003)	"I would recommend this company/ product to others." "I am likely to use this company/ product again." "I would speak positively about this company/ product." "I am satisfied with this company/ product."	"I would recommend this chatbot to others."- Recommend 1 "I am likely to use this chatbot again." – Recommend 2 "I would speak positively about this chatbot."- Recommend 3 "I am satisfied with this chatbot."- Recommend 4

Error Tolerance	(Cao et al., 2024)	Imagine the chatbot making errors, how forgivable would you feel towards the following error: "The chatbot disseminates incorrect information" "The chatbot answers are unprofessional". "The chatbot fails to understand queries."	Imagine the symptom checker chatbot making errors, how forgivable would you feel towards the following error: "The chatbot disseminates incorrect information."- Tolerance 1 "The chatbot answers are unprofessional."- Tolerance 2 "The chatbot fails to understand queries."- Tolerance 3
Perceived Error Severity	(Cao et al., 2024)	Imagine the above chatbot making errors, how severe would you feel towards the following error: "The chatbot disseminates incorrect information" "The chatbot answers are unprofessional". "The chatbot fails to understand queries."	Imagine the chatbot making errors, how severe would you feel towards the following error: "The chatbot disseminates incorrect information."- Severity 1 "The chatbot answers are unprofessional". - Severity 2 "The chatbot fails to understand queries."- Severity 3

Source: Own elaboration

4.2. Questionnaire Design and Data Collection

The questionnaire (Annexe A) was developed using the Qualtrics program before being presented to the Ethics Committee of ISCTE Business School (Project IBS_EC 022/2025) and distributed on social media platforms and Prolific, an online platform used to recruit participants for academic research. The study's target audience was Portuguese individuals over eighteen (18) years old, as they were more aware of the brand SNS 24 than individuals from other countries.

At the start of the survey, participants were presented with an informed consent form, emphasising that participation was voluntary and anonymous and would take ten (10) minutes to answer. After this initial section, the participants were asked if they were Portuguese and if they accepted the use of chatbots. If they responded negatively to the first question, they were informed that they were not eligible to continue the study.

After answering the control question, the Qualtrics platform would automatically assign participants to one of the survey versions. Participants only complete one version of the study and do

not see the others. In each version, the first section displays a video of a symptom checker chatbot, and, after analysing the chatbot's content, respondents are required to answer every item in the presented table.

The questionnaire ended with questions regarding participants' relationships with SNS 24, their opinions on the brand, and some demographic questions. For Prolific, each submission was verified between Qualtrics and Prolific, and only valid, completed responses were included. This verification was based on participants' Prolific ID, which they provided at the start of the questionnaire. A thorough review was conducted because some answers in the Qualtrics database were incomplete, having been submitted by participants who did not complete the survey and did not return it on Prolific. After removing all ineligible answers, all qualifying participants received approximately 0.84 pounds as compensation for their participation in the study.

4.3. Programmes used for data analysis

The results will be analysed using IBM SPSS Statistics 29 and SmartPLS 4, interpreted within the framework established in the Literature review. Descriptive statistics for each variable were generated with SPSS 29, while SmartPLS 4 was used to assess the reliability and validity of the conceptual model. Additionally, it supported the execution of bootstrapping procedures, mediation analysis, and multigroup comparisons.

5. Results and Discussion

5.1. Sample Profile

In this study, 315 responses were collected, with 252 obtained through the Prolific platform and 63 via social media. However, after a rigorous cleaning and data validation process, only 287 responses were considered suitable for analysis. This refinement was essential to guarantee the accuracy and reliability of the results, as 28 responses were excluded due to missing information, since respondents did not complete the questionnaire. Consequently, the following analysis will be based exclusively on 287 valid answers (n=287).

As previously referred, part of these answers was collected through Prolific, where the target population was selected using a non-probability convenience sampling method. To ensure that a representative sample, two screening criteria were applied: participants had to be Portuguese and aged between 18 and 100 years. Since this was a control question at the beginning of the survey, and Prolific only displayed the study to individuals who met these criteria, all 252 Prolific participants were confirmed to be born in Portugal.

Acceptance of chatbot-based services over human interaction was an important factor, but it was not used as an exclusion criterion. Gathering information about the ones that have been reluctant to use chatbots was equally valuable. Thus, 82.9% would not mind using chatbots over human service provision, while 17.1 % would not substitute a human with a machine.

Socio-demographic characteristics (Table 4.2) of the participants were evaluated through four simple questions. By integrating the data of the Qualtrics database, compiled from Prolific and social media, with IBM SPSS Statistics 29, precise results were obtained about four main variables: gender, education level, occupation and age group.

The gender with the highest representation is male, which makes up 59.9% of the sample, while female participants make up 39%. A small percentage of participants identified as non-binary (0.7%), and others preferred not to disclose what gender they identified with (0.3%). The majority of participants (50.5%) have a bachelor's degree, followed by those with a master's degree (31%). Around seventeen per cent hold a high school diploma or its equivalent. Those with doctorates (0.4%) and those who chose Other (1%) comprise smaller groups. A sizable percentage of participants are students (26.8%), after which the majority of participants (55.7%) are employed. The percentage of self-employed people (5.9%) is lower than that of unemployed people (9.1%). Furthermore, 1.0% of participants are retired, and 1.4% of participants belong to another category. The age distribution of the participants shows that 45.6% of the sample, the largest group, is between the ages of 25 and 34. Ages 18 to 24 make up the second-largest group, making up 31.4%. Of the total sample, 12.5% of participants are 35–44 years old, while smaller percentages are 45-54 (5.9%) and over 55 (4.5%). This

distribution indicates that there are fewer participants from older age groups and that the sample is primarily made up of younger people, especially those in their 20s and early 30s (77%).

Table 5.1- Sociodemographic characteristics

	N	%
Gender		
Female	112	39
Male	172	59.9
Prefer not to say	1	0.3
Non-binary	2	0.7
Education		
High school or equivalent	49	17.1
Bachelor's degree	145	50.5
Master's degree	89	31
Doctorate	1	0.4
Other	3	1
Occupation		
Student	77	26.8
Employed	160	55.7
Self-employed	17	5.9
Unemployed	26	9.1
Retired	3	1.0
Other	4	1.4
Age		
18-24	90	31.4
25-34	131	45.6
35-44	36	12.5
45-54	17	5.9
>55	13	4.5

Source: Own elaboration based on SPSS outputs

After completing the survey, participants were asked whether they would prefer to use an AI chatbot instead of calling SNS24. Fifty-three point three per cent expressed willingness to use this tool, while 46.7 per cent preferred the traditional method of contacting the Portuguese health system. Of the 287 participants, 204 (71.1%) had previously used the SNS24 calling service before going to urgent care, and 83 (28.9%) had never called the service before. Based on the respondents' experiences, 43.9 per cent agreed they had a good experience with SNS24, whereas 7.5 per cent disagreed, and 15 had no opinion about the service offered by SNS24; the mean of the answers for this question about users' opinion of SNS24 was 5.01. For a better understanding of participants' perceptions of the SNS24 brand, please refer to the following table.

Table 5.2- Perception of SNS24

Would you consider using an artificial intelligence (AI)-powered chatbot instead of calling SNS 24?		
	N	**%**
Yes	153	53.3
No	134	46.7

Have you ever called SNS 24 before going to the emergency room?		
	N	**%**
Yes	204	71.1
No	83	28.9

I have a positive impression of the service provided by SNS 24.		
	N	**%**
Strongly disagree	1	0.3
Disagree	13	4.5
Partially disagree	34	11.8
Neutral	43	15.0
Partially agree	70	24.4
Agree	95	33.1
Strongly agree	31	10.8

Source: Own elaboration based on SPSS outputs

5.2. Data analysis

5.2.1. Descriptive statistics

The initial phase of data analysis involved creating statistical summaries that describe each variable in terms of frequency. For better understanding and comparability, the results of each survey version were presented separately, allowing a clear comprehension of the main differences across study conditions.

To begin, it is important to note that all versions of the survey had roughly the same number of respondents, which contributes to a balanced statistical comparison. This balance is detailed in Table 5.3, which describes the distribution of answers per version. Specifically, scenario 1 (High anthropomorphised, branded chatbot), scenario 2 (Low anthropomorphised, not branded chatbot), and scenario 4 (Low anthropomorphised, not branded chatbot) each received 72 responses, while scenario 3 (High anthropomorphised, not branded chatbot) received 71 responses.

Table 5.3- Nº of participants per scenario

Scenario	N
1	72
2	72
3	71
4	72

Source: Own elaboration based on SPSS outputs

Based on Table 5.4, all variables have a p-value greater than 0.05, indicating that the groups have comparable characteristics in the analysed dimensions, except for age, which is not entirely comparable across all aspects.

Table 5.4- ANOVA for comparison among the scenarios

Anova						
		Sum of Squares	df	Mean Square	F	p-value
Would you use an artificial intelligence (AI)-powered chatbot instead of calling SNS 24?	Between Groups	0.524	3	0.175	0.696	0.555
Have you ever called SNS 24 before going to the emergency room?	Between Groups	0.589	3	0.196	0.951	0.416

Considering your experience with the SNS 24 service, please select the option that best reflects your agreement with the following statement: I have a positive impression of the service provided by SNS 24.	Between Groups	2.066	3	0.689	0.368	0.776
Age	Between Groups	10.120	3	3.373	3.186	0.024
Gender	Between Groups	1.076	3	0.359	1.268	0.286
Education	Between Groups	1.073	3	0.358	0.637	0.592
Occupation	Between Groups	2.481	3	0.827	0.820	0.484

Source: Own elaboration based on SPSS outputs

The results in Table 5.5 show the overall mean scores across all scenarios. Scenario 2 achieved a higher overall result in all constructs except perceived warmth, which scored highest in scenario 4. Specifically, all scenarios had the highest mean score for perceived competence and the lowest for perceived error severity in scenarios 1, 3, and 4, as well as error tolerance in scenario 3.

Table 5.5- Summary of descriptive statistics (Mean scores of All Scenarios)

	Scenario 1		**Scenario 2**		**Scenario 3**		**Scenario 4**	
Construct	**Mean**	**STDEV**	**Mean**	**STDEV**	**Mean**	**STDV**	**Mean**	**STDEV**
Perceived Competence	4.61	1.12	4.67	1.25	4.56	1.25	4.60	1.22
Perceived Empathy	4.43	1.16	4.54	1.34	4.46	1.22	4.37	1.26
Perceived Trust	4.43	1.16	4.54	1.34	4.46	1.22	4.37	1.26
Perceived Warmth	4.14	1.49	4.30	1.34	4.51	1.29	4.54	1.51
Intention to Recommend	4.27	1.38	4.42	1.63	4.38	1.30	4.20	1.46
Perceived Error Severity	1.99	1.03	2.60	1.24	2.50	1.40	2.32	1.21
Error tolerance	2.18	1.05	2.52	1.15	2.50	1.15	2.33	1.06

Source: Own elaboration based on SPSS outputs

5.2.2. Assessment of the measurement model

To ensure the reliability and validity of the collected data of the chosen variables and overall research model, a verification process was necessary. Each one of the four versions of the study was entered into SmartPLS software to evaluate both the measurement and structural models. Since the participants answered questions about health chatbots related to the presence/ absence of a brand and with different levels of anthropomorphism, four distinct PLS-SEM models were created—each scenario being split and analysed separately to avoid cross-contamination of results.

It is essential to highlight that perceived empathy, perceived trust, intention to recommend, and error tolerance are classified as endogenous constructs, which means they are influenced by other variables of the model (Hair et al., 2022). In opposition, the constructs perceived competence, perceived warmth and perceived severity are exogenous, as they exert influence but are not affected in return. Furthermore, all the constructs of this study are reflective lower-order constructs. To confirm the model's reliability and validity, the study assessed the lower-order constructs using the PLS-SEM algorithm (Becker et al., 2012).

5.2.3. Reliability and Validity

According to the guidelines from Hair et al. (2022), the first step in validating the reflective lower-order constructs was to evaluate the reliability of each indicator. Smart PLS was used to access the measurement model. For that, Alpha Cronbach and CR were inspected as well as AVF. Constructs achieved good results in most cases, except for warmth, intention to recommend, error tolerance and severity level. Thus, items were redefined as detailed in Table 5.6.

Table 5.6- Items removed from the model

Constructs	**Nº of items excluded**	**Items excluded**
Warmth	1	"The chatbot is sincere."
Intention to recommend	2	"I am likely to use this chatbot again." "I would speak positively about this chatbot."
Error tolerance	1	"The chatbot answers are unprofessional".
Severity level	1	"The chatbot answers are unprofessional".

Source: Own elaboration

After refinement, composite reliability was assessed using three measures provided by the PLS-SEM outputs seen in Table 5.7: Cronbach's alpha, composite reliability (rhoC), and reliability coefficient (rhoA). Cronbach's alpha ranged from 0.605 to 0.918, and rhoC from 0.609 to 0.918. Convergent validity was also established for all constructs in each model. All constructs met the Average Variance Extracted (AVE) criterion, which means all the constructs had an AVE equal to or above the standard threshold of 0.5, confirming that over 50% of the variance in each case was explained by the associated indicators (Hair et al., 2022).

Table 5.7- Reliability and Validity Measures

Constructs	**Cronbach's alpha**	**Composite reliability (rho_a)**	**Composite reliability (rho_c)**	**Average variance extracted (AVE)**
Perceived Competence	0.895	0.895	0.935	0.827
Perceived Empathy	0.850	0.852	0.909	0.770
Perceived Warmth	0.897	0.897	0.951	0.906
Perceived Trust	0.894	0.912	0.934	0.826
Intention to recommend	0.918	0.918	0.961	0.924
Perceived Error Severity	0.712	0.712	0.874	0.776
Error Tolerance	0.605	0.609	0.835	0.716

Source: Own elaboration based on SMART PLS outputs

Discriminant validity was also verified using the Fornell and Larcker criterion (Table 5.8). When the square root of AVE for each construct exceeds its correlation with any other construct, discriminant validity is confirmed.

Table 5.8- Discriminant Validity- Fornell-Larcker criterion

	Perceived Competence	**Perceived Empathy**	**Perceived Error Severity**	**Error Tolerance**	**Intention to Recommend**	**Perceived Trust**	**Perceived Warmth**
Perceived Competence	**0.909**						
Perceived Empathy	0.681	**0.877**					
Perceived Error Severity	0.063	0.072	**0.881**				
Error Tolerance	0.114	0.168	0.579	**0.846**			

Intention to Recommend	0.814	0.785	0.119	0.181	**0.961**		
Perceived Trust	0.814	0.688	0.109	0.136	0.871	**0.909**	
Perceived Warmth	0.498	0.802	0.042	0.102	0.601	0.511	**0.952**

Source: Own elaboration based on SMART PLS outputs

To begin, collinearity among dimensions was examined using the Variance Inflation Factor (VIF). In the model, all VIF values (Table 5.9) were below 5, indicating no issues with collinearity (Hair et al., 2022). This was followed by a bootstrapping analysis to evaluate the outer weights and loadings of each dimension. When outer weights were not statistically significant, outer loadings were used to determine whether beta coefficients exceeded 0.5 and were statistically significant. Results showed that the outer loadings of the observed variables measured in the survey are statistically significant ($p < 0.001$), demonstrating strong indicator reliability. These findings suggest that all items are reliable measures of the underlying latent constructs of perceived competence, perceived warmth, perceived empathy, perceived trust, intention to recommend, error tolerance, and perceived error severity.

Table 5.9- Collinearity statistics- VIF

	VIF
Competence 1	2.686
Competence 2	2.753
Competence 3	2.660
Empathy 1	2.250
Empathy 2	2.431
Empathy 3	1.811
Tolerance 1	1.000
Recommend 4	3.565
Recommend 1	3.565
Severity 1	1.000
Trust 1	3.544
Trust 2	2.099
Trust 3	4.271
Warmth 1	2.947
Warmth 2	2.947

Source: Own elaboration based on SMART PLS outputs

5.2.4. Assessment of Structural Model

After confirmation of the reliability and validity of the measurement model, the structural model was examined using non-parametric bootstrapping with 5000 samples. This approach was applied to assess the significance and strength of the path coefficients, as well as to test the mediation effect of the

hypothesis (Hair et al., 2022). After analysing the results, it was concluded that the relationships between constructs are statistically significant. Table 5.10 summarises the outcomes of these analyses. These results were used to validate hypotheses 5 to 12.

Table 5.10- Bootstrapping results

	β	Mean	STDEV	T statistics	P values
Competence -> Empathy	0.374	0.376	0.038	9.882	0.000
Competence -> Trust	0.744	0.745	0.030	24.561	0.000
Empathy -> Error tolerance	0.127	0.126	0.049	2.593	0.010
Empathy -> Intention to recommend	0.352	0.351	0.040	8.780	0.000
Severity -> Error tolerance	0.570	0.574	0.050	11.440	0.000
Trust -> Intention to recommend	0.629	0.630	0.037	16.866	0.000
Warmth -> Empathy	0.616	0.614	0.037	16.827	0.000
Warmth -> Trust	0.140	0.140	0.040	3.518	0.000

Source: Own elaboration based on SmartPLS outputs

Apart from the model-based relationships, SmartPLS4 provides the indirect effects between constructs, which are therefore important for the overall research. Below, Table 5.11 illustrates the significant relationships found in this model. Regarding the significant interrelations found among the model, it can be concluded that competence and warmth have a significant impact on most indirect relationships, as they significantly influence error tolerance (p-value = 0.013, p-value = 0.010, respectively), the intention to recommend (p-value > 0.05), and three complex paths.

Table 5.11- Specific and indirect effects

Significant relationships- Specific Indirect Effects				
	β	**STDEV**	**T statistics**	**P values**
Competence -> Empathy -> Error tolerance	0.048	0.019	2.475	0.013
Competence -> Empathy -> Intention to recommend	0.132	0.020	6.579	0.000
Warmth -> Trust -> Intention to recommend	0.088	0.025	3.540	0.000
Warmth -> Empathy -> Error tolerance	0.078	0.031	2.560	0.010
Warmth -> Empathy -> Intention to recommend	0.216	0.028	7.702	0.000
Competence -> Trust -> Intention to recommend	0.468	0.036	12.968	0.000
Significant relationships- Total Indirect Effects				

	β	STDEV	T statistics	P values
Competence -> Error tolerance	0.048	0.019	2.475	0.013
Competence -> Intention to recommend	0.600	0.032	18.933	0.000
Warmth -> Error tolerance	0.078	0.031	2.560	0.010
Warmth -> Intention to recommend	0.305	0.037	8.325	0.000

Source: Own elaboration based on SmartPLS outputs

5.2.5. Overall Model Prediction and Fit

To complete the evaluation of the structural model, the analysis focused on the R^2, Q^2, and f^2 statistics, along with the model fit indicators. The R^2 value reflects the proportion of variance in an endogenous construct that is explained by its predictors, representing its in-sample explanatory strength. In contrast, Q^2 assesses the model's predictive accuracy for new data from different samples (Hair et al., 2022).

Among all constructs, Error tolerance exhibited the lowest R^2 and Q^2 scores (R^2 = 0.365 and Q^2 = 0.344). In comparison, Intention to recommend demonstrated the highest explanatory power (R^2 = 0.824 and Q^2 = 0.704). Furthermore, all endogenous constructs showed Q^2 values greater than zero, confirming that the model possesses acceptable predictive relevance (Hair et al., 2013).

The f^2 statistic measures the extent to which each exogenous variable contributes to the variance explained in an endogenous construct. The analysis revealed alignment between the f^2 effect sizes and the respective path coefficients. For instance, empathy exhibited only a minimal effect on error tolerance. Perceived Competence had a strong effect on perceived trust (f^2 = 1.293). These results provide further support for the robustness of the relationships identified through bootstrapping (Cohen, 1988).

Finally, the model's overall fit was evaluated using the Standardised Root Mean Square Residual (SRMR) and the Normed Fit Index (NFI). The SRMR value is below the recommended upper threshold of 0.10 (Hair et al., 2013), so the model can be considered well-fitting. That said, the NFI scores in all models suggest room for improvement, as they fall short of the ideal value of 1 (Bentler & Bonett, 1980). Additional details are available in the Annexe D.

5.2.6. Multigroup Analysis

To verify whether the different scenarios of the chatbots had different results among them, a multigroup analysis (MGA) was performed. In this sense, high-anthropomorphised chatbots were compared to low-anthropomorphised chatbots, and branded chatbots were compared with non-branded chatbots. Therefore, to proceed with the analysis, measurement invariance must be established, which involves three main steps (Henseler et al., 2016). The initial phase—configural

invariance—was automatically confirmed by SmartPLS. Subsequently, compositional invariance was also validated, as the original correlation coefficients matched the mean values derived from the permutation procedure. Finally, the third phase, consisting of an assessment of mean differences (3a) and variance differences (3b), was likewise successfully established (Ringle et al., 2024). These results disclose full measurement invariance and, subsequently, are adequate for the MGA (Henseler et al., 2016).

To advance with the present analysis, it is essential to review the bootstrapped results of the full PLS-SEM models, as they contain critical insights necessary for accurately interpreting the MGA outcomes (Matthews, 2017).

Table 5.12- Multigroup analysis (Scenario 1 vs Scenario 2; Scenario 1 vs Scenario 3; Scenario 2 vs Scenario 4; Scenario 3 vs Scenario 4)

	S1 – S2		S1 – S3		S2 – S4		S3 – S4	
	β difference	**p value**	**β difference**	**p value**	**β difference**	**p value**	**β difference**	**p value**
Competence -> Empathy	-0.034	0.750	-0.046	0.690	0.046	0.674	0.058	0.618
Competence -> Trust	-0.049	0.600	0.003	0.982	0.105	0.282	0.054	0.560
Empathy -> Error tolerance	-0.146	0.287	-0.118	0.322	-0.168	0.260	-0.196	0.140
Empathy -> Intention to recommend	0.070	0.540	-0.261	0.017	-0.154	0.163	0.177	0.087
Severity -> Error tolerance	0.099	0.378	0.037	0.809	-0.004	0.975	0.058	0.681
Trust -> Intention to recommend	-0.054	0.585	0.291	0.005	0.105	0.301	-0.239	0.021
Warmth -> Empathy	0.033	0.757	-0.032	0.783	-0.069	0.496	-0.004	0.952
Warmth -> Trust	-0.004	0.975	-0.109	0.308	-0.095	0.468	0.010	0.941

Source: Own elaboration based on SmartPLS outputs

When comparing all the construct relationships across the scenarios, it can be concluded that the presence of a brand and the level of anthropomorphism within symptom checker chatbots only affect the relationships between Empathy and Intention to recommend, and Trust and Intention to recommend. This suggests that in symptom checker chatbots, users may prioritise useful information and simplicity over aesthetic cues.

5.2.7. Validation of the hypothesis

For inspecting hypotheses, Table 5.12 will be used to validate H1 through H4, and Table 5.10 will be used to validate H5 through H12. Hypothesis 1 proposes that branded chatbots (S1 vs. S3 and S2 vs. S4) have a significant effect on perceived competence compared to non-branded chatbots. However, the MGAs presented in Table 5.12 indicated that there is no impact of the presence of a brand on perceived competence (S1 vs. S3, β diff. = -0.032, p-value = 0.783; S2 vs. S4, β diff. = -0.069, p-value = 0.496), thus failing to support H1.

As stated in H2, a branded chatbot has significant effects on perceived warmth compared to a non-branded chatbot (S1 vs. S3 and S2 vs. S4). However, according to the results shown in Table 5.12, it can be inferred that the presence of a brand did not have a significant influence on perceived warmth (S1 vs. S3, β diff. = -0.046, p-value = 0.690; S2 vs. S4, β diff. = 0.046, p-value = 0.674). Therefore, the hypothesis is rejected.

Additionally, H3 proposed that the level of anthropomorphism moderates the effect of branding on perceived competence (S1 vs S2). However, the data presented in Table 5.12 indicate that anthropomorphism does not significantly influence this relationship (S1vs S2, β diff. = -0.034, p-value = 0.750). Therefore, the hypothesis is rejected.

As mentioned in H4, the effect of branding on perceived warmth is moderated by the level of anthropomorphism (S1 vs S2). However, as demonstrated by the findings in Table 5.12, the null hypothesis is not rejected, suggesting that anthropomorphism does not significantly impact the effect of branding on perceived warmth (S1vs S2, β diff. = 0.033, p-value = 0.757).

Table 5.10 indicated that perceived competence had a significant positive effect on perceived empathy (H5: $\beta = 0.374$; $p < 0.001$), thus validating H5. However, it is clear from the results presented in Table 5.12 that the relationship between perceived competence and perceived empathy did not vary across the different scenarios, indicating that the presence of a brand and the level of anthropomorphism do not affect this relationship.

Aligned with the initial expectations outlined in H6, perceived warmth also significantly influenced the dependent variable, exhibiting positive and meaningful effects on perceived empathy (H6: $\beta = 0.616$, $p < 0.001$). Consequently, the relationship between these variables is statistically significant, confirming H6. However, the association between perceived warmth and perceived empathy remains consistent across the scenarios, as the p-values in all MGAs exceed 0.05, indicating that the results are not statistically significant and that the presence of a brand and the level of anthropomorphism do not notably affect this relationship.

As shown in Table 5.10, perceived competence has a positive influence on perceived trust (H7: $\beta = 0.744$; $p < 0.001$), confirming that competence enhances trust in chatbots. When comparing the different scenarios, it is evident that the presence or absence of a brand and the varying levels of

anthropomorphism are not significant, as all the p-values in the MGAs are above 0.05, indicating no statistical difference among them.

Similar to the previous hypothesis, perceived warmth also had positive and significant effects on perceived trust (H8: $\beta = 0.140$; $p < 0.001$), reinforcing the role of warmth in shaping feelings of trust towards a chatbot. Based on the MGAS presented in Table 5.12, there is no difference in the relationship between these two constructs across the scenarios, indicating that the presence of a brand and the level of anthropomorphism have no impact on this relationship.

Furthermore, the analysis of perceived empathy further corroborated H9, as it was both positive and statistically significant ($\beta = 0.352$, $p < 0.001$), thereby validating the hypothesis. However, unlike what happened in the previous relationships, the MGAs comparing scenario 1 versus scenario 3 indicated that in S1 versus S3, the relationship between empathy and the intention to recommend ($\beta = -0.261$; p-value = 0.017) in symptom checker chatbots is influenced by the presence of a brand effect, since both scenarios shared the same level of anthropomorphism.

In line with this, the analysis confirmed H10, as perceived trust produced a significant positive effect on the intention to recommend the health chatbot ($\beta = 0.629$; $p < 0.001$), suggesting that trust may influence others' WOM. Additionally, according to some MGAs (scenario 1 versus scenario 3 and scenario 3 versus scenario 4), it can also be concluded that the presence of a brand in chatbots with a high level of anthropomorphism and the level of anthropomorphism in non-branded chatbots influence the relationship between perceived trust and the intention to recommend, since in both cases the p-value was below 0.05.

Additionally, perceived empathy also significantly influenced error tolerance, as initially hypothesised in H11 ($\beta = 0.127$; p 0.010). Thus, this hypothesis is confirmed. However, the relationship between perceived empathy and error tolerance remains consistent across the scenarios, as the p-values for all MGAs are above 0.05, indicating that neither the presence of a brand nor the level of anthropomorphism significantly affects this relationship.

Finally, H12 was also supported, with perceived severity having a significant positive effect on error tolerance ($\beta = 0.570$; $p < 0.001$). MGAS results indicate that the relationship between perceived error severity and error tolerance is not significantly influenced by the presence of a brand or the level of anthropomorphism, as all p-values exceed 0.05.

The table below summarises the hypotheses and their validation status:

Table 5.13- Summary of Hypothesis

Hypothesis	Validated
H1: Branded chatbot has significant effects on perceived competence compared to a non-branded chatbot.	No
H2: Branded chatbot has significant effects on perceived warmth compared to a non-branded chatbot.	No
H3: The effect of branding on competence is moderated by the level of anthropomorphism.	No
H4: The effect of branding on warmth is moderated by the level of anthropomorphism.	No
H5: Perceived competence has a positive impact on empathy.	Yes
H6: Perceived warmth has a positive impact on empathy.	Yes
H7: Perceived competence of chatbots has a positive impact on perceived trust in chatbots.	Yes
H8: Perceived warmth of chatbots has a positive impact on perceived trust in chatbots.	Yes
H9: Empathy significantly impacts the intention to recommend the chatbot.	Yes
H10: Trust in chatbots is positively related to recommending a chatbot.	Yes
H11: The higher the level of empathy, the higher the error tolerance.	Yes
H12: The greater the perceived severity of a mistake, the less likely individuals are to forgive the person who made the error.	Yes

Source: Own elaboration

5.2.8. Additional analyses- ANOVA for comparing constructs

After inspecting the H proposed, which focused on validating effects among constructs, we further examined whether there were differences among the constructs between groups. For this purpose, an ANOVA analysis was conducted to determine whether there are statistically significant differences in the means of a dependent variable across multiple groups and if the constructs are comparable across the scenarios. Based on Table 5.14, the variables perceived competence, perceived warmth, perceived empathy, perceived trust, intention to recommend, and error tolerance all have p-values greater than 0.05, indicating insufficient evidence to assert that the groups differ significantly in these aspects. Hence, the groups demonstrate statistically comparable characteristics in the dimensions analysed, with no significant differences between them. However, the perceived error severity has a p-value lower than 0.05, indicating that the groups differ in their perception.

Table 5.14- ANOVA of the constructs among all Scenarios

ANOVA						
		Sum of Squares	df	Mean Square	F	p-value
Perceived Competence	Between Groups	0.470	3	0.157	0.107	0.956
Perceived Warmth	Between Groups	5.170	3	1.723	1.191	0.313
Perceived Empathy	Between Groups	1.103	3	0.368	0.237	0.871
Perceived Trust	Between Groups	1.103	3	0.368	0.237	0.871
Intention to Recommend	Between Groups	2.874	3	0.958	0.439	0.725
Perceived Error Severity	Between Groups	14.861	3	4.954	3.873	0.010
Error Tolerance	Between Groups	2.880	3	0.960	0.844	0.471

Source: Own elaboration based on SPSS output

The analysis of variance (ANOVA) indicated that the perceived error severity variable presented significant differences across the four scenarios analysed, demonstrating that perceptions of severity are not homogeneous. A post-hoc test (Tukey, Duncan, and Scheffé) was performed to identify which groups differed. The results (Table 5.15) reinforce the importance of considering the specific scenario when assessing the perceived severity of a situation.

Table 5.155- Post-Hoc test for variable Perceived Error Severity

Multiple Comparisons						
Dependent Variable: Perceived Error Severity						
(I) Scenario	**Mean Difference (I-J)**			**Sig.**	**95% Confidence Interval**	
					Lower Bound	**Upper Bound**
Tukey HSD	1	2	-.59259*	0.010	-1.0797	-0.1055
		3	-.49504*	0.046	-0.9839	-0.0062
		4	-0.28241	0.440	-0.7695	0.2047
	2	1	.59259*	0.010	0.1055	1.0797
		3	0.09755	0.955	-0.3913	0.5864
		4	0.31019	0.355	-0.1769	0.7973
	3	1	.49504*	0.046	0.0062	0.9839
		2	-0.09755	0.955	-0.5864	0.3913
		4	0.21264	0.675	-0.2762	0.7015
	4	1	0.28241	0.440	-0.2047	0.7695
		2	-0.31019	0.355	-0.7973	0.1769
		3	-0.21264	0.675	-0.7015	0.2762
Scheffe	1	2	-.59259*	0.021	-1.1227	-0.0625
		3	-0.49504	0.079	-1.0270	0.0369
		4	-0.28241	0.524	-0.8125	0.2477
	2	1	.59259*	0.021	0.0625	1.1227

		3	0.09755	0.966	-0.4344	0.6295
		4	0.31019	0.440	-0.2199	0.8403
	3	1	0.49504	0.079	-0.0369	1.0270
		2	-0.09755	0.966	-0.6295	0.4344
		4	0.21264	0.738	-0.3193	0.7446
	4	1	0.28241	0.524	-0.2477	0.8125
		2	-0.31019	0.440	-0.8403	0.2199
		3	-0.21264	0.738	-0.7446	0.3193
Bonferroni	1	2	-.59259*	0.011	-1.0934	-0.0918
		3	-0.49504	0.056	-0.9976	0.0075
		4	-0.28241	0.811	-0.7832	0.2184
	2	1	.59259*	0.011	0.0918	1.0934
		3	0.09755	1.000	-0.4050	0.6001
		4	0.31019	0.606	-0.1906	0.8110
	3	1	0.49504	0.056	-0.0075	0.9976
		2	-0.09755	1.000	-0.6001	0.4050
		4	0.21264	1.000	-0.2899	0.7152
	4	1	0.28241	0.811	-0.2184	0.7832
		2	-0.31019	0.606	-0.8110	0.1906
		3	-0.21264	1.000	-0.7152	0.2899
***.The mean difference is significant at the 0.05 level.**						

Source: Own elaboration based on SPSS output

Post-hoc tests indicate that Scenario 1 differs significantly from Scenarios 2 and 3 in perceived severity, since they have a p-value lower than 0.05. No significant differences were found between Scenarios 2, 3 and 4. This suggests that Scenario 1 (Human + Brand) is perceived as having a distinct severity, while the other three scenarios share more similar perceptions.

In the Turkey HSD test, when comparing Scenario 1 with Scenario 2 (branded chatbots), the observed mean difference was -0.59259, with a p-value of 0.010. This result, with a p-value of less than 0.05, demonstrates a significant difference in the perception of error severity between these two scenarios. In Scenario 1 vs. Scenario 3 (high-anthropomorphised chatbots), the mean difference was -0.49504, with a p-value of 0.046. The difference, although smaller than the previous comparison, is also statistically significant.

Based on Scheffe's Test, in Scenario 1 vs. Scenario 2, the mean difference of -0.59259 was confirmed as significant, with a p-value of 0.021. Unlike the Tukey test, when comparing Scenario 1 vs Scenario 3, the mean difference of -0.49504 did not reach the significance threshold (p-value = 0.079), highlighting the more rigorous nature of the Scheffe test.

According to the Bonferroni Test, when comparing Scenario 1 vs. Scenario 2, the mean difference of -0.59259 was validated as statistically significant (p-value = 0.011). As with the Scheffé test, in Scenario 1 vs Scenario 3, the mean difference was not considered significant, with a p-value of 0.056.

To conclude, the comparative analysis of the three multiple comparison tests provides strong evidence that the perceived error severity differs significantly between Scenario 1 and Scenario 2. This is the only mean difference that proved robust and consistent across all tests, regardless of their level of conservatism. The difference between Scenario 1 and Scenario 3, although significant for the Tukey test, was not confirmed by the Scheffé and Bonferroni tests. Thus, although a trend toward a difference may exist, it is not as statistically reliable as that observed between Scenario 1 and Scenario 2. The other comparisons between the scenarios revealed no statistically significant differences.

5.3. Discussion of the findings

This research aimed to examine the influence of branding and anthropomorphism on users' perceptions of symptom checker chatbots, particularly regarding competence, warmth, and how these two factors affect empathy, trust, willingness to recommend, perceived error severity, and error tolerance. To achieve this, four distinct chatbot interaction scenarios were developed to isolate the effects of these two elements, making the study's design essential for identifying their individual and combined impacts. Accordingly, this section aims to verify the relationships outlined in the conceptual framework by referencing both existing literature and the results of the current study. It also seeks to provide a plausible explanation for any discrepancies observed between the actual findings and initial expectations. To do this effectively, it is first crucial to review the primary outcomes from the descriptive statistics to gain clearer insights into the performance of each hypothesis.

Descriptive statistics offered initial insights into participants' perceptions under different branding and anthropomorphism conditions. Scenarios combining brand presence with a lower level of anthropomorphism tended to produce higher average ratings for perceived competence, empathy, trust, warmth, willingness to recommend, perceived error severity, and error tolerance, indicating more positive evaluations. Moreover, the high standard deviation values observed in this condition suggest considerable variability in participant responses, reflecting different personal preferences or interpretations of the chatbot's design. Conversely, scenarios without both branding and anthropomorphic cues generally resulted in lower mean scores, with higher standard deviations, indicating less favourable and more diverse perceptions among participants. With a glimpse into what users perceive when it comes to symptom checker chatbots, we can further discuss the results in relation to our hypothesis.

Regarding the discussion of the hypothesis, in line with the existing literature, previous research suggests that brands with higher levels of anthropomorphism are perceived as more competent, warm,

empathetic, and trustworthy, and generate greater engagement. Based on this, it was expected that the chatbot in scenario 1 would have a greater impact on users' perceptions. However, contrary to this expectation, no significant relationship was found between the presence of a brand and the level of anthropomorphism on the perceptions of competence and warmth. According to Erdem and Swait (2004) and Fiske et al. (2007), a brand influences the perceptions of many consumers, evoking positive emotions such as competence and warmth. Nevertheless, the results obtained in this study contrast with what was expected, with H1 and H2 being unexpectedly not supported. One explanation for these results is that previous studies have not focused on any particular brand or product. In contrast, the current research focused on the use of a brand in the health area. It is plausible to assume that a user who interacts with a symptom checker chatbot does not feel particularly concerned about its appearance, but rather the level of expertise and accuracy it presents.

While authors have highlighted that when chatbots have human-like features, they are more likely to be perceived as competent and warmer (Kiesler et al., 2008; Nass & Moon, 2000), this was not perceived after analysing the data, leading to the rejection of H3 and H4. However, this can be explained by the fact that most participants did not perceive they were chatting with a person but with a robot, which is supported by the results of a survey conducted after analysing the data from the main study (Annexe B). In this survey, 140 participants answered a question about who they thought they were talking to, and only one person in scenario 2 (a low-anthropomorphised branded chatbot) and two in scenario 3 (a non-branded high-anthropomorphised chatbot) reported that they believed they were speaking with a human instead of a robot (Annexe C).

Scholars have found evidence about the importance of key dimensions such as competence and warmth, and how they positively influence empathy and trust (Belanche et al., 2020a; Liew & Tan, 2018; Xue et al., 2020; Yen & Chiang, 2021), and this was verified in the study supporting H5, H6, H7 and H8. In healthcare, understanding how competence and warmth influence empathy and trust is crucial for designing digital tools that people actually want to use. In healthcare, if users do not feel understood or safe, they may ignore advice, delay treatment, or abandon the chatbot altogether.

Empathy plays a crucial role in users´ satisfaction with a service and influences how tolerant chatbot users are to errors. When a chatbot is perceived as empathic, it is more likely to generate a positive WOM (Yun & Park, 2022) and enhance the quality of the interaction, which leads to the encouragement of users to continue to use the chatbot following a service failure (Lv et al.,2022). Following data analysis, the relationship between H9 and H11 variables proved to be significant, demonstrating that when symptom checker chatbots understand, care about, or respond to users' needs, they are more likely to develop a favourable impression of the interaction, which translates into a greater willingness to recommend the service to others (Dwivedi et al., 2023; Yun & Park, 2022) and continuous use.

The acceptance of H10 reinforces that higher levels of trust positively influence users' intention to recommend and the central role of trust in shaping advocacy behaviours. When users perceive a chatbot or service as trustworthy, they are more likely to endorse it to others, reflecting both satisfaction with the experience and confidence in its reliability (Talukder et al., 2019). This finding aligns with prior research suggesting that trust is a key antecedent of positive word-of-mouth and recommendation intentions (Venkatesh et al., 2001). In the context of AI-mediated interactions, this underscores the importance of designing systems that not only function effectively but also foster a sense of integrity and transparency.

As hypothesised and validated in H12, greater perceived error severity reduces user tolerance to them, underscoring the importance of perceived consequences in shaping user reactions to chatbot performance. When users interpret an error as serious—such as misinformation in a health context or a failure to complete a critical task—they are less likely to overlook or forgive the mistake. (Chen et al., 2022; Mccullough et al., 1998). These results highlight the need for chatbot designers to not only minimise high-severity errors but also manage user perceptions through rapid recovery mechanisms.

Lastly, when comparing the relationships among the constructs across the scenarios through MGAs, it can be concluded that the impact of the presence of a brand and the level of anthropomorphism within symptom checkers' chatbots is validated exclusively in two relationships: Empathy → Intention to recommend and Trust → Intention to recommend. The results indicate that branding and anthropomorphism do not directly influence intention to recommend, but selectively affect the relationships between emotional and behavioural variables. This occurs only in specific scenarios—such as branded chatbots with high anthropomorphism versus unbranded chatbots with high anthropomorphism, or even between unbranded chatbots with different levels of anthropomorphism—suggesting that these elements trigger emotions. Thus, branding and anthropomorphism do not generate recommendations by themselves, but rather intensify affective bonds that, when activated, increase the likelihood of recommendation behaviour. These findings reinforce the idea that the effectiveness of design strategies depends on their ability to foster empathy and trust, challenging managers to invest in approaches that build meaningful relationships with users.

6. Conclusions and Recommendations

Healthcare organisations are increasingly turning to AI-powered chatbots, such as symptom checkers, to enhance patient engagement, improve access to medical information, and streamline digital health services. This dissertation set out to explore how design factors—specifically the presence of branding and the degree of anthropomorphism—influence users' perceptions of competence, warmth, empathy and trust, as well as users' engagement in these digital tools. Through a quantitative experimental methodology, the study was able to examine the effects of these design elements on users' perceptions about health-related chatbots, offering insights into how branding and human-like features can either support or hinder the user experience in sensitive, high-stakes environments like healthcare.

The study reveals that user perceptions of symptom checker chatbots are not significantly influenced by the presence of branding and the level of anthropomorphism. These design elements did not play a nuanced role in shaping how users evaluate the chatbot's reliability and professionalism, particularly within the delicate context of healthcare. The research highlights that users are not concerned about how the chatbot looks when engaging with medical technologies. Overall, the findings reinforce that effective design in health communication tools must go beyond aesthetic appeal, prioritising competence, empathy, warmth and trust to foster meaningful and sustained user engagement.

Based on these findings, this study offers diverse implications for designers of digital health tools and marketing professionals in the healthcare area. Since the presence of a brand and the level of anthropomorphism do not significantly impact the perception of the users, health organisations should reconsider their investment in design features when developing symptom checker chatbots. Instead, they should prioritize cure-oriented competence, that is showed through demonstrable medical knowledge and clinical thinking, and care-oriented warmth, which involves treating users as unique individuals and conveying empathy throughout the interaction. These dimensions align closely with the values of patient-centred care, which highlights both technical skills and emotional compensation (De Valck et al., 2001; Howe et al., 2019). Rather than trusting on superficial design prompts, the chatbot creators should incorporate these functional qualities into the interaction logic and language, ensuring that the user experience demonstrates genuine support and trustworthy guidance. Also, smaller health care brands should feel encouraged by the finding that a strong brand identity is not a requirement to gaining people's engagement, instead they should focus on fostering perceived competence and warmth, since they positively impact perceived empathy and trust (Belanche et al., 2021; Liew & Tan, 2018; Xue et al., 2020; Yen & Chiang, 2021), which leads to users' behavioural intentions, such as willingness to recommend the symptom checker chatbot (Eren, 2021; Yun & Park, 2022) and tolerate errors (Lv et al., 2022) made by it. Additionally, the study confirmed that error tolerance is moderated by error severity, suggesting that users are more forgiving of minor mistakes than of critical ones. To

foster meaningful engagement, developers should prioritise interaction strategies that strengthen users' perceptions, guaranteeing that chatbot experiences are both reliable and responsive to users' emotional needs.

Last, this investigation contributes to the literature about health marketing, highlighting that, in medical environments, limiting emotional display and informational transparency may be more impactful than aesthetic or anthropomorphic enhancements in shaping user engagement and credibility perception.

6.1. Theoretical Contributions

This study makes a significant contribution to the growing body of scholarship in various ways. Firstly, this study is grounded in the healthcare context and makes a meaningful contribution to the literature on human–AI interaction by exploring its application within symptom checker chatbot services. The second explores how anthropomorphism and branding shape psychological perceptions—specifically competence, warmth—during interactions with AI systems (Kiesler, Powers, Fussell, et al., 2008; Nass & Moon, 2000), particularly symptom checker chatbots. Thirdly, it examines how these perceptions influence empathy, trust, and ultimately, customer engagement.

While previous research emphasised the effect of branding and the level of anthropomorphism on perceived competence and warmth (Erdem & Swait, 2004; Fiske et al., 2007; Zhou & Sha, 2017), this study found that the influence of these variables on users' perceptions may not differ and did not produce the expected effects, suggesting that perceived competence and warmth in chatbot interactions might be driven more by functional performance and informational clarity than by surface-level design cues. It also highlights the need for a more detailed understanding of anthropomorphism, noting its conditional effectiveness, which depends on the task type and user motivation. By revealing these limitations, the study opens avenues for future research into alternative design strategies that better meet user needs in digital health environments.

The study also reinforces established theoretical pathways by confirming that perceived competence and warmth positively impact perceived empathy and trust (Belanche et al., 2021; Liew & Tan, 2018; Xue et al., 2020; Yen & Chiang, 2021), which in turn shape users' behavioural intentions, including their willingness to recommend the chatbot (Eren, 2021; Yun & Park, 2022) and tolerate errors (Lv et al., 2022). Finally, the research introduces a new construct—perceived error severity—as a key factor influencing error tolerance. By empirically examining how the severity of an error affects user forgiveness, this study opens new theoretical ground in understanding user responses to AI mistakes, particularly in sensitive domains such as healthcare. Together, these insights refine existing frameworks and suggest new directions for theory development in chatbot design and user experience.

6.2. Managerial Implications

This study provides valuable guidance for health companies and marketing professionals seeking to refine their chatbot-driven customer engagement strategies through practical application. First, the results challenge common assumptions about the effectiveness of brand presence and anthropomorphic design features in shaping user perceptions of competence and warmth. Contrary to expectations, the limited impact of branding and anthropomorphism in this context suggests that design strategies successful in other sectors (e.g., retail, entertainment) may not easily transfer to healthcare applications. This suggests that in health-related settings—where users likely prioritise accuracy, clarity, and reliability—superficial design cues may have a minimal persuasive effect. Managers and designers should therefore reconsider how they allocate resources towards branding and anthropomorphic enhancements and instead focus on features that directly support functional performance and build user trust. Managers should adopt a user-centred approach that considers the cognitive and emotional demands of health-related decision-making, ensuring that chatbot features align with the expectations and priorities of users seeking medical advice.

Secondly, the study reaffirms the importance of perceived competence and warmth in shaping users' emotional and behavioural responses. Consistent with theoretical expectations, these perceptions were found to influence perceived empathy and trust significantly (Belanche et al., 2021; Liew & Tan, 2018; Xue et al., 2020; Yen & Chiang, 2021), which in turn affected users' intention to recommend the chatbot and their tolerance of errors (Eren, 2021; Lv et al., 2022; Yun & Park, 2022). These findings underline the need for chatbot interfaces that effectively communicate both technical proficiency and interpersonal sensitivity. Managers should invest in conversational design strategies that enhance clarity, responsiveness, and emotional connection, as these qualities help to foster user engagement (Kumar et al., 2019).

Thirdly, this research introduces the concept of perceived error severity as a factor influencing error tolerance. This aspect has not been previously examined in the context of symptom checker chatbots. The results suggest that users' willingness to forgive errors depends on their evaluation of the error's seriousness. This insight is practically important for designing error-handling protocols and user feedback mechanisms. Specifically, chatbot systems should be able to recognise and respond to errors based on their perceived severity, including features such as transparent explanations, corrective suggestions, and empathetic messaging to reduce adverse user reactions.

6.3. Limitations and Further Research

Despite its valuable contributions, this study has several limitations that should be acknowledged. First, the research focused solely on a single brand (SNS24) and a specific sector (health), which restricts the applicability of the findings to other industries. To improve external validity, future research could

explore a broader range of brands and product categories to assess the generalizability of anthropomorphism and branding effects.

Second, the relatively small sample size may have diminished the statistical power of the analysis. Using larger and more diverse samples in future studies would enhance the robustness and generalisability of the results. Thirdly, the data collected was solely from Portugal, and differences in cultural backgrounds could influence how individuals perceive and interact with AI-powered chatbots, potentially restricting the broader applicability of our findings across different cultural or geographic contexts. Future research should aim to address these issues.

Fourthly, since most participants did not perceive they were interacting with a human but a robot, future research should present the stimulus more transparently and include a control question to assess whether participants correctly understood it. Additionally, the chatbot interactions used in the study may not fully reflect the dynamic and changing nature of real-world chatbot conversations, which could limit their validity and understanding of how users respond to chatbots in emotionally intense or urgent health situations, where perceptions can change significantly. In this way, future research could examine chatbot performance and user perception in emotionally charged contexts.

To summarise, future research should build on the limitations and suggested paths suggested in this study to enhance both theoretical and practical understanding of user perception in healthcare chatbot interactions. By investigating these areas further, scholars can deepen their knowledge of how design choices, such as anthropomorphic elements and brand presence, influence competence, warmth, empathy, trust, and user engagement within digital health environments, thereby expanding the insights presented in this dissertation.

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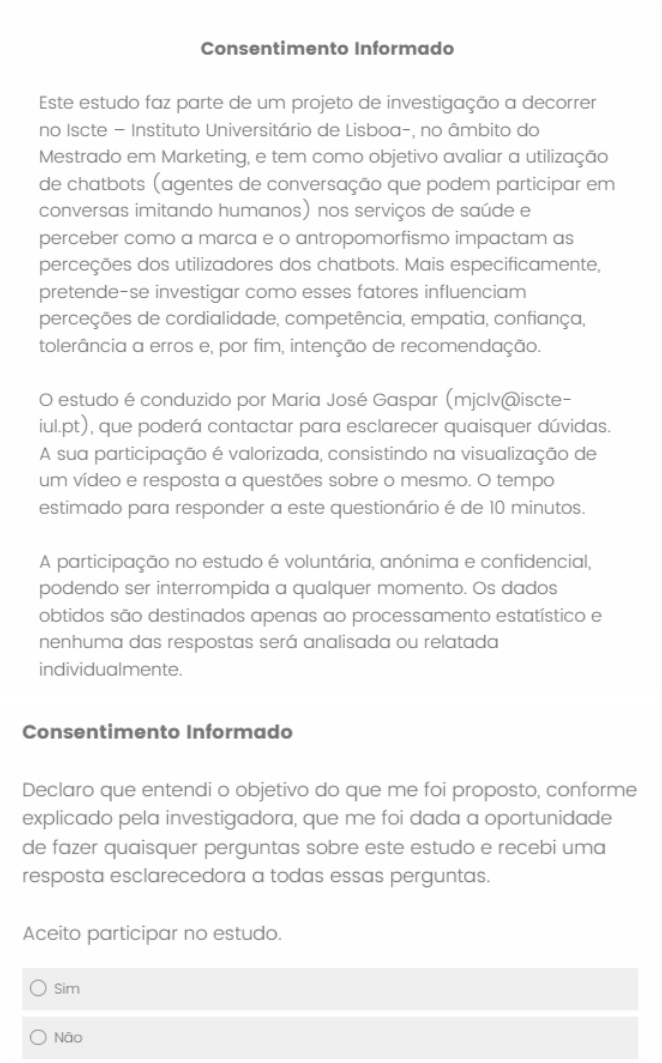
8. Annexes

All included annexes were prepared by the author. The stimuli were designed using Canva. The descriptive statistical data were derived from analyses conducted with IBM SPSS Statistics 29 and SmartPLS 4. The other tables were compiled from the output generated by SmartPLS 4.

Annexe A- First Questionnaire

The questionnaire version demonstrated below is related to Scenario 4. The remaining versions had the same questions, in the same order, with the sole difference being the stimuli.

In Portuguese:



Consentimento Informado

Este estudo faz parte de um projeto de investigação a decorrer no Iscte – Instituto Universitário de Lisboa-, no âmbito do Mestrado em Marketing, e tem como objetivo avaliar a utilização de chatbots (agentes de conversação que podem participar em conversas imitando humanos) nos serviços de saúde e perceber como a marca e o antropomorfismo impactam as perceções dos utilizadores dos chatbots. Mais especificamente, pretende-se investigar como esses fatores influenciam perceções de cordialidade, competência, empatia, confiança, tolerância a erros e, por fim, intenção de recomendação.

O estudo é conduzido por Maria José Gaspar (mjclv@iscte-iul.pt), que poderá contactar para esclarecer quaisquer dúvidas. A sua participação é valorizada, consistindo na visualização de um vídeo e resposta a questões sobre o mesmo. O tempo estimado para responder a este questionário é de 10 minutos.

A participação no estudo é voluntária, anónima e confidencial, podendo ser interrompida a qualquer momento. Os dados obtidos são destinados apenas ao processamento estatístico e nenhuma das respostas será analisada ou relatada individualmente.

Consentimento Informado

Declaro que entendi o objetivo do que me foi proposto, conforme explicado pela investigadora, que me foi dada a oportunidade de fazer quaisquer perguntas sobre este estudo e recebi uma resposta esclarecedora a todas essas perguntas.

Aceito participar no estudo.

◯ Sim

◯ Não

Tem nacionalidade portuguesa?

- ○ Sim
- ○ Não

← →

Aceitaria o uso de chatbots para a prestação de serviços em vez de atendimento humano?
Chatbot- agentes de conversação que podem participar em conversas imitando humanos.

- ○ Sim
- ○ Não

← →

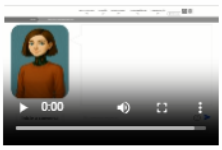
Visualize o vídeo, que se encontra a seguir (coloque em modo "ecrã completo"), uma vez que todo o questionário se centra nele.

Imagine que se sente nauseado, já vomitou e necessita de ajuda para saber se deve ir às urgências. Decide usar um chatbot para ajudá-lo a tomar esta decisão. O chatbot faz-lhe algumas questões sobre os seus sintomas, posteriormente analisa a informação e responde-lhe de forma personalizada.

Assistente de saúde de um chatbot que encontrou na internet com quem vai conversar:



Vídeo:



Por favor, considere as seguintes afirmações sobre o chatbot e selecione a que melhor reflete a sua opinião (de "discordo totalmente" a "concordo totalmente").

	Discordo totalmente	Discordo	Discordo parcialmente	Nem concordo nem discordo	Concordo parcialmente	Concordo	Concordo totalmente
O chatbot é competente no diagnóstico.	○	○	○	○	○	○	○
O chatbot é bem informado.	○	○	○	○	○	○	○
O chatbot é habilitado.	○	○	○	○	○	○	○
O chatbot é caloroso.	○	○	○	○	○	○	○
O chatbot é amigável.	○	○	○	○	○	○	○
O chatbot é sincero.	○	○	○	○	○	○	○
A resposta do chatbot fez-me sentir melhor.	○	○	○	○	○	○	○
O chatbot respondeu apropriadamente aos meus sentimentos e emoções.	○	○	○	○	○	○	○
O chatbot pareceu empático.	○	○	○	○	○	○	○
O chatbot é confiável.	○	○	○	○	○	○	○
Acredito que o chatbot não agirá de uma forma que me prejudique.	○	○	○	○	○	○	○
Eu confio neste chatbot.	○	○	○	○	○	○	○
Recomendaria este chatbot a outras pessoas.	○	○	○	○	○	○	○
É provável que eu use este chatbot novamente.	○	○	○	○	○	○	○
Eu falaria positivamente sobre este chatbot.	○	○	○	○	○	○	○
Estou satisfeito com este chatbot.	○	○	○	○	○	○	○

Por favor, considere as seguintes afirmações sobre o chatbot e selecione a que melhor reflete a sua opinião, (de "nada severo" a "extremamente severo").

Imagine que o chatbot cometeu um erro, qual o nível de gravidade com que avalia os seguintes erros:

	Extremamente severo	Muito severo	Severo	Neutro	Moderamente severo	Pouco severo	Nada severo
O chatbot divulga informação incorreta.	○	○	○	○	○	○	○
O chatbot responde de forma pouco profissional.	○	○	○	○	○	○	○
O chatbot não compreende as questões.	○	○	○	○	○	○	○

Por favor, considere as seguintes afirmações sobre o chatbot e selecione a que melhor reflete a sua opinião, (de "nada perdoável" a "totalmente perdoável").

Imagine que o chatbot cometeu um erro, qual a sua predisposição para perdoar os seguintes erros:

	Nada perdoável	Pouco perdoável	Moderadamente perdoável	Neutro	Perdoável	Muito perdoável	Totalment perdoáve
O chatbot divulga informação incorreta.	○	○	○	○	○	○	○
O chatbot de forma pouco profissional.	○	○	○	○	○	○	○
O chatbot não compreende as questões.	○	○	○	○	○	○	○

← →

Pondera usar um chatbot com tecnologia de inteligência artificial (IA) em vez de fazer uma chamada para o SNS 24?

- ○ Sim
- ○ Não

Alguma vez ligou para o SNS 24, antes de se deslocar às urgências?

- ○ Sim
- ○ Não

Tendo em conta a sua experiência com o serviço do SNS 24, por favor, selecione a opção que melhor reflete a sua concordância com a seguinte afirmação.

Eu tenho uma impressão positiva sobre o serviço prestado pelo SNS 24.

- ◯ Discordo totalmente
- ◯ Discordo
- ◯ Discordo parcialmente
- ◯ Nem concordo nem discordo
- ◯ Concordo parcialmente
- ◯ Concordo
- ◯ Concordo totalmente

← →

Idade:

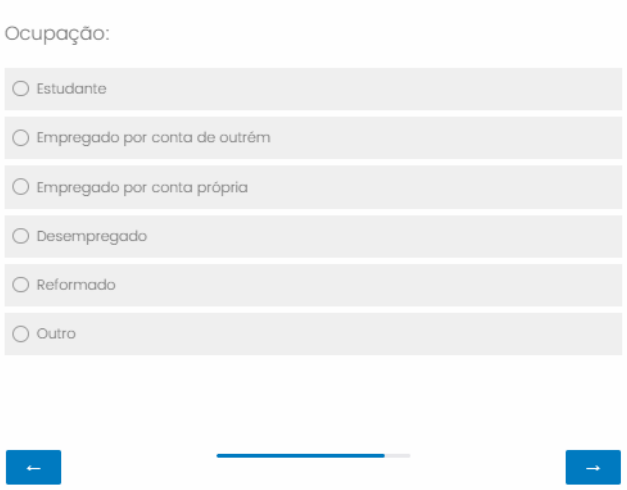
- ◯ Menos de 18
- ◯ 18 - 24
- ◯ 25 - 34
- ◯ 35 - 44
- ◯ 45 - 54
- ◯ Mais de 55

Género:

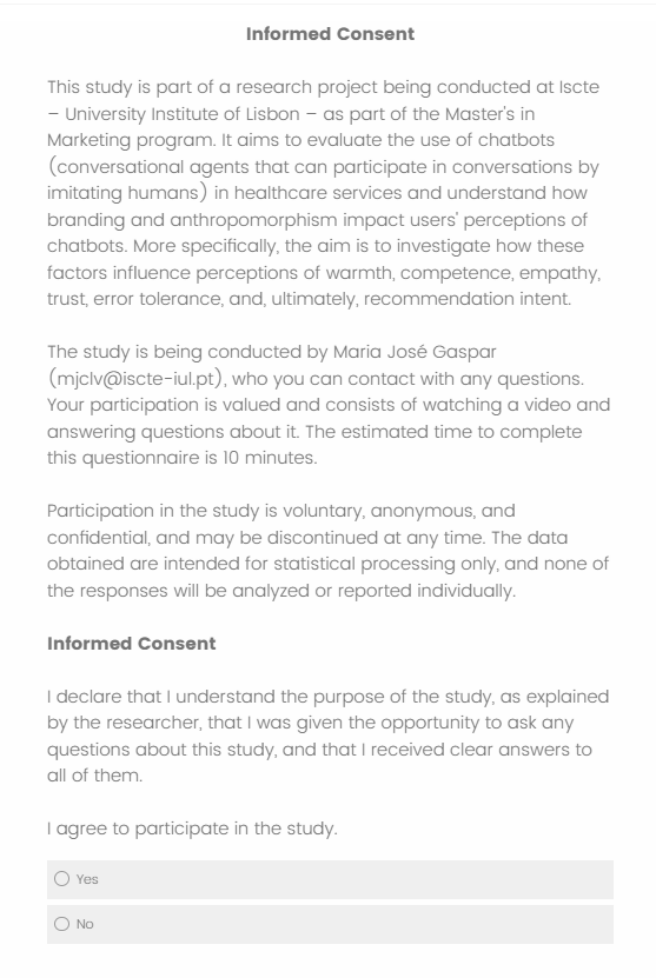
- ◯ Feminino
- ◯ Masculino
- ◯ Prefiro não dizer
- ◯ Não binário

Habilitações literárias:

- ◯ Secundário ou equivalente
- ◯ Licenciatura ou bacharelato
- ◯ Mestrado
- ◯ Doutoramento
- ◯ Outro


Ocupação:
Estudante
Empregado por conta de outrém
Empregado por conta própria
Desempregado
Reformado
Outro
←
→

In English :


Informed Consent
This study is part of a research project being conducted at Iscte – University Institute of Lisbon – as part of the Master's in Marketing program. It aims to evaluate the use of chatbots (conversational agents that can participate in conversations by imitating humans) in healthcare services and understand how branding and anthropomorphism impact users' perceptions of chatbots. More specifically, the aim is to investigate how these factors influence perceptions of warmth, competence, empathy, trust, error tolerance, and, ultimately, recommendation intent.
The study is being conducted by Maria José Gaspar (mjclv@iscte-iul.pt), who you can contact with any questions. Your participation is valued and consists of watching a video and answering questions about it. The estimated time to complete this questionnaire is 10 minutes.
Participation in the study is voluntary, anonymous, and confidential, and may be discontinued at any time. The data obtained are intended for statistical processing only, and none of the responses will be analyzed or reported individually.
Informed Consent
I declare that I understand the purpose of the study, as explained by the researcher, that I was given the opportunity to ask any questions about this study, and that I received clear answers to all of them.
I agree to participate in the study.
Yes
No

Do you have Portuguese nationality?

- ○ Yes
- ○ No

Would you accept the use of chatbots to provide services instead of human assistance?
Chatbot – conversational agents that can participate in conversations by imitating humans.

- ○ Yes
- ○ No

→

Watch the video below (set to full screen), as the entire questionnaire focuses on it.

Imagine you feel nauseous, have already vomited, and need help deciding whether to go to the emergency room. You decide to use a chatbot to help you make this decision. The chatbot asks you a few questions about your symptoms, then analyzes the information and responds to you in a personalized way.

SNS 24 health assistant you will chat with:



Video:



Please consider the following statements about the chatbot and select the one that best reflects your opinion (from "strongly disagree" to "strongly agree").

	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
The chatbots is competent in the diagnostic.	○	○	○	○	○	○	○
The chatbot is knowledgeable	○	○	○	○	○	○	○
The chatbot is skilled.	○	○	○	○	○	○	○
The chatbot is warm.	○	○	○	○	○	○	○
The chatbot is friendly.	○	○	○	○	○	○	○
The chatbot is sincere.	○	○	○	○	○	○	○
The chatbot said the right thing to make me feel better.	○	○	○	○	○	○	○
The chatbot responded appropriately to my feelings and emotions..	○	○	○	○	○	○	○
The chatbot came across as empathic.	○	○	○	○	○	○	○
The chatbot is trustworthy.	○	○	○	○	○	○	○
The chatbot will not act in a way that harms me.	○	○	○	○	○	○	○
I trust this chatbot.	○	○	○	○	○	○	○
I would recommend this chatbot to others.	○	○	○	○	○	○	○
I am likely to use this chatbot again.	○	○	○	○	○	○	○
I would speak positively about this chatbot.	○	○	○	○	○	○	○
I am satisfied with this chatbot.	○	○	○	○	○	○	○

Please consider the following statements about the chatbot and select the one that best reflects your opinion (from "not at all severe" to "extremely severe").

Imagine the chatbot made an error. How severe would it rate the following errors?

	Extremely severe	Midly severe	Severe	Neutral	Moderately severe	Slightly severe	Not severe at all
The chatbot disseminates incorrect information.	○	○	○	○	○	○	○
The chatbot answers are unprofessional.	○	○	○	○	○	○	○
The chatbot fails to understand queries.	○	○	○	○	○	○	○

Please consider the following statements about the chatbot and select the one that best reflects your opinion (from "not at all forgivable" to "completely forgivable").

Imagine the chatbot made a mistake. How likely are you to forgive the following errors?

	Not forgivable at all	Unforgivable	Slightly unforgivable	Neutral	Forgivable	Very forgivable	Totally forgivable
The chatbot disseminates incorrect information.	○	○	○	○	○	○	○
The chatbot answers are unprofessional.	○	○	○	○	○	○	○
The chatbot fails to understand queries.	○	○	○	○	○	○	○

Would you consider using an artificial intelligence (AI)-powered chatbot instead of calling SNS 24?

- ◯ Yes
- ◯ No

Have you ever called SNS 24 before going to the emergency room?

- ◯ Yes
- ◯ No

Considering your experience with the SNS 24 service, please select the option that best reflects your agreement with the following statement:

I have a positive impression of the service provided by SNS 24.

- ◯ Strongly disagree
- ◯ Disagree
- ◯ Somewhat disagree
- ◯ Neutral
- ◯ Somewhat agree
- ◯ Agree
- ◯ Totally agree

Age:

- ◯ Less than 18
- ◯ 18-24
- ◯ 25-34
- ◯ 35-44
- ◯ 45-54
- ◯ More than 55

Gender:

- ◯ Feminine
- ◯ Masculine
- ◯ Prefer not to tell
- ◯ Non-binary

Education:

- ◯ High school or equivalent
- ◯ Bachelor
- ◯ Master
- ◯ Doctorate
- ◯ Other

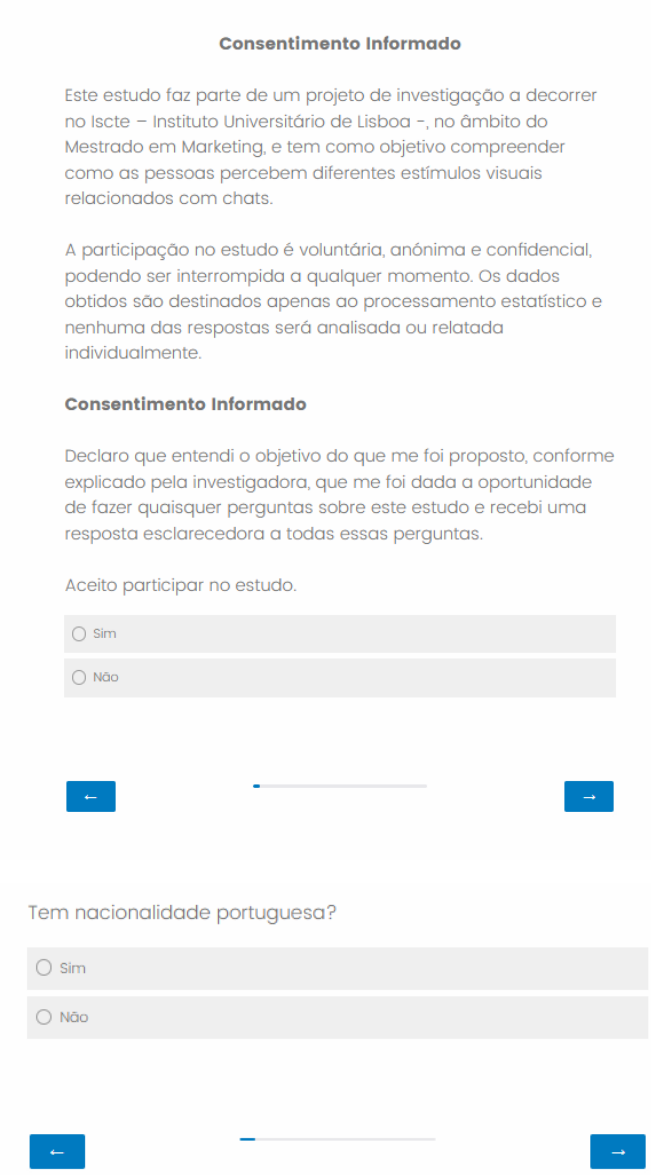
Occupation:

- ◯ Student
- ◯ Employed
- ◯ Self-employed
- ◯ Unemployed
- ◯ Retired

Annexe B- Second Questionnaire

The questionnaire version demonstrated below is related to Scenario 1. The remaining versions had the same questions, in the same order, with the sole difference being the stimuli.

In Portuguese:

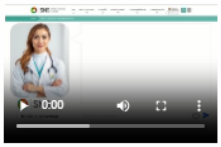


Visualize o vídeo, que se encontra a seguir (coloque em modo "ecrã completo"), uma vez que todo o questionário se centra nele.

Assistente de saúde do SNS 24 com quem vai conversar:



Vídeo:



Neste chat está a conversar com um humano ou um robot?

- ○ Humano
- ○ Robot

Reconhece alguma marca neste chat?

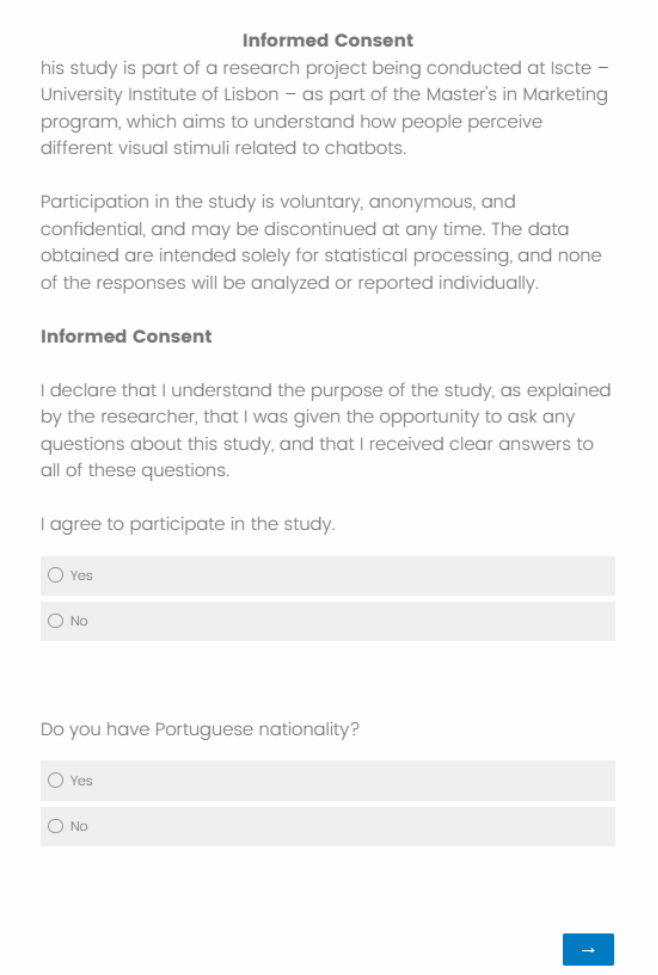
- ○ Sim
- ○ Não

Se sim, qual?

←

→

In English:



Informed Consent

his study is part of a research project being conducted at Iscte – University Institute of Lisbon – as part of the Master's in Marketing program, which aims to understand how people perceive different visual stimuli related to chatbots.

Participation in the study is voluntary, anonymous, and confidential, and may be discontinued at any time. The data obtained are intended solely for statistical processing, and none of the responses will be analyzed or reported individually.

Informed Consent

I declare that I understand the purpose of the study, as explained by the researcher, that I was given the opportunity to ask any questions about this study, and that I received clear answers to all of these questions.

I agree to participate in the study.

- ○ Yes
- ○ No

Do you have Portuguese nationality?

- ○ Yes
- ○ No

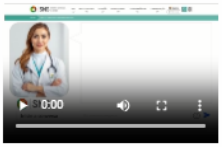
→

Watch the video below (set to "full screen"), as the entire questionnaire focuses on it.

SNS 24 health assistant you will speak with:



Video:



In this chat, are you talking to a human or a robot?

- ○ Human
- ○ Robot

Do you recognize any brands in this chat?

- ○ Yes
- ○ No

If so, which one?

→

Annexe C- Descriptive statistics of Second Questionnaire

Nº of participants per scenario

	N
Scenario 1	33
Scenario 2	35
Scenario 3	36
Scenario 4	36

Awareness of the stimuli

Version 1

In this chat are you talking to a Human or a Robot?	**N**	**%**
Robot	33	100
Human	0	0

Do you recognise any brands?	**N**	**%**
Yes	22	66.7
No	11	33.3

If so, which one?	**N**	**%**
SNS 24	22	66.7
Any	11	33.3

Version 2

In this chat are you talking to a Human or a Robot?	**N**	**%**
Robot	34	97.1
Human	1	2.9

Do you recognise any brands?	**N**	**%**
Yes	25	71.4
No	10	28.6

If so, which one?	**N**	**%**
SNS 24	25	71.4
Any	10	28.6

Version 3

In this chat are you talking to a Human or a Robot?	**N**	**%**
Robot	34	94.4
Human	2	5.6

Do you recognise any brands?	**N**	**%**
Yes	0	0
No	36	100

If so, which one?	**N**	**%**
No answer	36	100

Version 4

In this chat are you talking to a Human or a Robot?	**N**	**%**
Robot	36	100
Human	0	0

Do you recognise any brands?	**N**	**%**
Yes	1	2.8
No	35	97.2

If so, which one?	**N**	**%**
No answer	35	97.2
Other answer	1	2.8

Annexe D- Model Validity

R^2, Q^2 and Model Fit

	R^2	Q^2
Empathy	0.749	0.745
Error tolerance	0.365	0.344
Intention to recommend	0.824	0.704
Trust	0.678	0.673

	Saturated model	Estimated model
SRMR	0.056	0.060
NFI	0.840	0.847

	f-square
Competence -> Empathy	0.419
Competence -> Trust	1.293
Empathy -> Error tolerance	0.019
Empathy -> Intention to recommend	0.370
Severity -> Error tolerance	0.548
Trust -> Intention to recommend	1.188
Warmth -> Empathy	1.135
Warmth -> Trust	0.046