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Exploring the Dynamics of Trust in Recommendation Chatbots: The Roles of Perceived Value, Parasocial Interaction, and Anthropomorphism

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Master in Marketing

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BUSINESS SCHOOL

Department of Marketing, Operations & General Management

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Resumo

A crescente integração dos chatbots no comércio eletrónico realça o seu potencial para transformar o serviço ao cliente, oferecendo um apoio contínuo e personalizado. Este estudo examina como o valor percebido, a interação parassocial e a confiança influenciam as intenções dos utilizadores de mudar de chatbots para agentes humanos, com o antropomorfismo a servir como fator moderador. Utilizando a Modelação de Equações Estruturais por Mínimos Quadrados Parciais (PLS-SEM) em dados de 326 participantes, os resultados revelam que tanto o valor percebido como a interação parassocial reduzem significativamente as intenções de mudança dos utilizadores. Verificou-se que a confiança influencia fortemente o valor percebido, tanto nos chatbots semelhantes a humanos como nos robóticos, sublinhando o seu papel vital na formação das perceções dos utilizadores sobre os serviços de chatbot. No entanto, a confiança não teve um impacto significativo na interação parassocial, nem reduziu eficazmente as intenções de mudança no cenário do chatbot semelhante ao humano. Embora se esperasse que as caraterísticas antropomórficas, como nomes e avatares semelhantes aos humanos, melhorassem a relação entre a confiança e o valor percebido e a interação parassocial, estes efeitos moderadores não foram estatisticamente significativos. Curiosamente, os utilizadores mostraram preferência por chatbots robóticos em vez de humanos, como evidenciado por uma menor tendência para mudar para agentes humanos quando interagem com chatbots robóticos. Estas conclusões sugerem que os chatbots com caraterísticas robóticas podem ser mais eficazes na retenção de utilizadores em determinados contextos de comércio eletrónico. As plataformas de comércio eletrónico devem concentrar-se em melhorar o valor percebido e o envolvimento emocional, equilibrando cuidadosamente as caraterísticas humanas e robóticas para maximizar a satisfação e a fidelidade do cliente.

Palavras-chave: Antropomorfismo, Chatbots, E-commerce, Valor Percecionado, Interação Parasocial, Confiança, Mudança de Intenções.

Abstract

The growing integration of chatbots in e-commerce highlights their potential to transform customer service by offering continuous, personalized support. This study examines how perceived value, parasocial interaction, and trust influence users' intentions to switch from chatbots to human agents, with anthropomorphism serving as a moderating factor. Using Partial Least Squares Structural Equation Modeling (PLS-SEM) on data from 326 participants, the findings reveal that both perceived value and parasocial interaction significantly reduce users' intentions to switch. Trust was found to strongly influence perceived value across both human-like and robotic chatbots, underscoring its vital role in shaping user perceptions of chatbot services. However, trust did not significantly impact parasocial interaction, nor did it effectively reduce switching intentions in the human-like chatbot scenario. Although anthropomorphic features, such as human-like names and avatars, were expected to enhance the relationship between trust and both perceived value and parasocial interaction, these moderating effects were not statistically significant. Interestingly, users showed a preference for robotic chatbots over human-like ones, as evidenced by a lower tendency to switch to human agents when interacting with robotic chatbots. These insights suggest that chatbots with robotic traits may be more effective in retaining users in certain e-commerce contexts. E-commerce platforms should focus on enhancing the perceived value and emotional engagement while carefully balancing human-like and robotic features to maximize customer satisfaction and loyalty.

Keywords: Anthropomorphism, Chatbots, E-commerce, Perceived Value, Parasocial Interaction, Trust, Switching Intentions.

Glossary

AA - Appearance Anthropomorphism

AI - Artificial Intelligence

AVE - Average Variance Extracted

CR - Composite Reliability

CRM - Customer Relationship Management

HTMT - Heterotrait-Monotrait Ratio

NLP - Natural Language Processing

PLS-SEM - Partial Least Squares Structural Equation Modeling

PSI - Parasocial Interaction

PV - Perceived Value

SRMR - Standardized Root Mean Square Residual

SWI - Switching Intentions

T - Trust in Chatbots

VIF - Variance Inflation Factor

FAQs - Frequently Asked Questions

RPA – Robotic Process Automation

ML – Machine Learning

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Chapter 1

Introduction

The introduction of digital technology has significantly transformed the way companies engage with consumers, starting in a new era of convenience and connectivity. E-commerce plays a central role in this revolution by merging customer preferences with technological advancements to create a market that transcends traditional limitations (Jain et al., 2021). Recognized for its multitude of benefits, e-commerce offers round-the-clock operation, convenience, time efficiency, and a diverse selection of products. It also provides substantial advantages to companies, such as diminished geographical constraints, financial savings, enhanced productivity, and more precise marketing (Taher, 2021).

Despite these advantages, challenges persist. The United States, a leading participant in the global e-commerce sector, is projected to have 500 million e-commerce users by 2028. However, inadequate customer service remains a significant issue, leading to the termination of around 40% of customer transactions (Statista, 2023; Statista, 2019). Chatbots, at the forefront of artificial intelligence for customer service, present potential solutions to these gaps. Adamopoulou and Moussiades (2020) emphasize that chatbots have evolved in various fields, including e-commerce, due to their ability to provide quick and convenient support, significantly reduce customer service costs, and handle multiple users simultaneously.

The integration of chatbots into customer support has generated different reactions. A survey in the United States revealed that 50.7% of customers prefer human interaction over chatbots, citing reasons such as being directed to FAQs and receiving irrelevant answers (Statista, 2019). Statista (2019) also found that some customers prefer direct human interaction, while others frequently express dissatisfaction with the functionality of chatbots. This situation raises a critical question: How can we enhance chatbots to increase customer satisfaction?

Although chatbots are becoming more widely used, there is a lack of research on variables that could contribute to customer satisfaction. Existing studies often focus on chatbot performance and technological improvements, but they do not sufficiently address key individual factors such as emotional engagement, personalization, and the perceived humanness of chatbots, which can impact customer satisfaction (Lee et al., 2023). Research also indicates that the social presence and anthropomorphic design of chatbots significantly influence user engagement and satisfaction. However, these aspects have not been thoroughly investigated in the existing literature (Tsai et al., 2021). Improving chatbot design and implementation, while addressing these gaps, is crucial for enhancing overall user satisfaction.

This study aims to consolidate diverse concepts from prior research into a comprehensive inquiry into the most robust connections that companies should embrace when incorporating chatbots into their online commerce strategies for product recommendations. The objective is to reduce the instances where users favor human agents over chatbots by identifying the most impactful connections among anthropomorphism, perceived value, parasocial interaction, and switching intentions. This research is guided by the following questions:

- Does the perceived value of chatbots influence users' propensity to engage with human customer service agents?
- Does the human-like appearance of chatbots affect users' inclination to switch to human agents, thereby impacting perceived value and parasocial interaction?
- Does overall confidence in chatbots influence users' perception of their value, parasocial interaction, and inclination to switch to human agents?

In the following chapters, this thesis will review the existing literature on e-commerce and chatbot interactions, focusing on aspects such as customer support, trust, perceived value, parasocial interaction, and anthropomorphism. The study will then present the methodology and data analysis of two surveys conducted to explore these relationships. Finally, the thesis will provide a comprehensive discussion of the findings, practical implications for e-commerce platforms, and recommendations for future research.

Chapter 2

1. Literature Review

In this chapter, the thesis will focus on the advancements in the field of customer support by chatbots, particularly within the e-commerce sector. Additionally, it will outline the hypotheses developed through the review of various concepts.

1.1 Customer Support in E-commerce

E-commerce has transformed the way businesses and consumers interact, enabling the buying and selling of goods and services over the Internet at any time from any location. As Grewal et al. (2017) highlight in "The Future of Retailing," this transformation has simplified price comparisons and broadened product accessibility, largely driven by the widespread use of smartphones and internet access (Grewal et al., 2017). However, as accessibility increases, so does the demand for more efficient customer service.

Effective customer support is important for addressing customer queries, resolving issues, and enhancing the overall shopping experience, as emphasized by Sheth et al. (2020). This not only ensures customer satisfaction but also fosters brand loyalty, thereby ensuring customer satisfaction and brand loyalty. Additionally, Luo et al. (2019) state that excellent customer service enhances the perceived value of products and services, while Becker and Jaakkola (2020) emphasize that customer experience is a critical element in achieving competitive advantage in e-commerce. They highlight that a positive customer experience can significantly influence customer satisfaction, loyalty, and advocacy, underscoring the importance of a smooth and effective customer support system in enhancing the overall e-commerce experience (Becker & Jaakkola, 2020; Sheth et al., 2020).

Customer service in e-commerce manifests in various forms, including live chat, email, telephone support, social networks, and community. For instance, live chat provides instant solutions, while email handles non-urgent issues. Despite technological advancements, telephone support remains crucial for urgent and complex problems. Furthermore, social networks and community forums also serve as valuable channels, particularly for customers who prefer self-service (Grewal et al., 2017; Sheth et al., 2020).

Nevertheless, several challenges persist in providing customer support. High volumes of orders can overwhelm support teams, leading to longer response times and customer dissatisfaction. The complexities of e-commerce transactions, such as order tracking, returns, product inquiries, and refunds, demand well-trained support teams. Moreover, integrating various support systems and tools to offer a seamless customer experience is both demanding and resource-intensive (Grewal et al., 2017; Sheth et al., 2020).

A solution to these challenges is the implementation of AI-powered chatbots. Bawack et al. (2022) suggest that improving customer support requires continuous efforts and the incorporation of customer feedback to maintain high service standards. Their study reveals that AI systems, such as chatbots using machine learning (ML) and natural language processing (NLP), can alleviate the workload of human agents by accurately understanding and responding to customer requests. This integration of AI enhances the personalization of customer support, as AI can analyze customer data to predict preferences and offer tailored recommendations. However, the preference for human interaction over automated systems remains a significant challenge (Bawack et al., 2022).

Building on the integration of technology in customer service, Lee and Lee (2020) introduced the concept of "untact" services, which enable customer interactions without face-to-face contact through advanced digital technologies. These services are becoming increasingly common in sectors such as food ordering, financial transactions, and online shopping. While “untact” services address the need for efficient service delivery and appeal to customers who prefer minimal human interaction, challenges such as the digital divide, cybersecurity concerns, and new types of customer complaints must be effectively managed (Lee & Lee, 2020).

Further expanding on the role of technology, Lu et al. (2020) provide insights into the impact of robotics and AI on customer service. Their systematic review of business literature highlights that service robots can improve customer experiences by offering efficient, reliable, and personalized services. However, the study also notes potential drawbacks, such as customer discomfort with robots and the need for employees to up-skill to work alongside these technologies. These findings underscore the importance of balancing technological advancements with human elements to maintain a positive customer service experience (Lu et al., 2020).

In conclusion, the significance of customer support in e-commerce is evident and essential for success. Excellent customer support can increase customer loyalty and enhance the perceived value of products and services (Luo et al., 2019; Becker & Jaakola, 2020). Therefore, to exceed customer expectations in the digital environment, it is crucial to develop strategies and allocate resources for implementing effective chatbot solutions. Despite the potential benefits of chatbots, addressing the ongoing preference for human interaction remains a critical challenge. In the next section, this study will explore the various uses of chatbots and examine their advantages and challenges in detail.

1.2 Chatbots in ecommerce

The rise of e-commerce has driven businesses to search for innovative ways to improve customer engagement and optimize operations. Among these innovations, chatbots, powered by artificial intelligence, have emerged as a significant tool. They enable brands to offer round-the-clock customer service, thereby reducing dependence on human staff and increasing operational efficiency (Li & Wang, 2023). This section reviews recent studies that examine the role and impact of chatbots in the e-commerce sector.

One application of chatbots can be found in the luxury fashion industry. Chung et al. (2020) explored how luxury fashion brands use chatbots to maintain the high level of personalized service their customers expect. Their study found that chatbots could effectively replicate aspects of the personalized customer service traditionally delivered in person, significantly enhancing customer satisfaction through interactive and engaging e-services. Building on this, Sanjaya et al. (2023) highlighted the growing accessibility of chatbots, noting that even small businesses can now leverage these tools due to the development of user-friendly platforms requiring minimal programming knowledge. Despite the benefits of reduced labor costs and increased customer engagement, challenges such as maintaining user interest and ensuring accurate responses persist (Chung et al., 2020; Sanjaya et al., 2023).

Consumer acceptance of chatbots is another area of study. Rese et al. (2020), using models like the Technology Acceptance Model (TAM) and Uses and Gratifications (U&G), investigated the chatbot "Emma" in the pre-purchase phase. Their research revealed that conversational authenticity, perceived utility, and enjoyment are critical factors influencing user acceptance. However, concerns about privacy and the technological limitations of chatbots can negatively impact their usage intentions. Similarly, Wang et al. (2023) examined the emotional experiences of consumers when interacting with chatbots versus human agents. They discovered that chatbots require more cognitive resources for emotion regulation and attract more subconscious attention than human interactions, indicating a lower level of trust in chatbots for subjective tasks (Rese et al., 2020; Wang et al., 2023).

Further expanding on the impact of chatbot communication, Li and Wang (2023) investigated how chatbot language style affects customer continuance usage intention and brand attitude. Their findings revealed that an informal language style in chatbot communication promotes a sense of parasocial interaction, leading to higher usage intentions and improved brand attitudes. However, this effect is moderated by brand affiliation and is less effective for non-customers. Additionally, Adam et al. (2020) explored the impact of verbal anthropomorphic design cues and the foot-in-the-door (FITD) technique on user compliance. They found that chatbots using human-like verbal cues significantly increased the likelihood of user compliance with requests, mediated by a heightened sense of social presence. This highlights the potential of well-designed chatbot interactions to positively influence customer behavior (Adam et al., 2020; Li & Wang, 2023).

Providing a comprehensive analysis of existing literature, Pentina et al. (2023) examined the relationships between consumers and machines in the era of artificial intelligence, revealing significant aspects such as trust, anthropomorphism, parasocial interaction, and switching intentions. They highlighted that trust, and the quality of AI-driven recommendations play a pivotal role in shaping consumer satisfaction and loyalty. Ebrahimi et al. (2022) expanded on this understanding by examining the differing impacts of trust and suggestion quality between interactive and non-interactive chatbots, concluding that suggestion quality strongly affects the perception of interactive chatbots, while trust remains essential for both types (Ebrahimi et al., 2022; Pentina et al., 2023).

In conclusion, recent studies have thoroughly explored the multifaceted use of chatbots in e-commerce. Key variables such as trust, perceived value, anthropomorphism, parasocial interaction, and switching intentions have emerged as critical factors. These insights collectively underscore the necessity for ongoing research to refine chatbot design and implementation, prioritizing trust, personalization, and effective recommendation systems.

1.3 Switching Intention

As previously discussed, various factors, such as dissatisfaction with chatbot performance, a need for more personalized assistance or trust issues, may cause customers to transition to human customer support. This section examines the motivations identified by previous studies that influence individuals' intentions to switch.

Li and Zhang (2023) explored the impact of several factors on customers' choices to transition from human agents to chatbots. Their study highlighted the limitations of human agents, such as a lack of empathy and adaptability, which can drive customers away from conventional customer service. On the other hand, chatbots offer the ability to connect with clients at any time and from any location, providing increased visibility, association, and personalization. These attributes make chatbots an appealing alternative to traditional services, significantly improving customer satisfaction and encouraging chatbot acceptance. Li and Zhang (2023) also identified service usage frequency as a moderating factor, with frequent users being more inclined to adopt chatbots due to their perceived convenience and efficiency. However, the negative attributes of human agents can diminish customer satisfaction and increase the likelihood of customers switching to chatbots (Li & Zhang, 2023).

Building on this idea, Lu et al. (2024) examined how anthropomorphic design influences consumers' intentions to switch from chatbots when service is unsatisfactory. Their study demonstrated that incorporating human-like traits in chatbots' appearance and communication style can increase users' expectations for service recovery by generating favorable social reactions. These human-like characteristics positively affect expectations for both emotional and functional service recovery. However, the way communication is conducted primarily influences emotional recovery expectations, with minimal impact on functional aspects. This finding highlights the importance of balancing anthropomorphic features to avoid excessively high customer expectations and reduce the potential for the uncanny valley effect, which refers to discomfort experienced when robots closely resemble humans (Lu et al., 2024).

Markovitch et al. (2024) investigated consumer reactions to chatbots versus human agents, focusing on the positive or negative result of an interaction and perceived empathy. They found that consumers report lower satisfaction and intentions to return or recommend after interacting with a chatbot compared to a human agent, regardless of the outcome. However, increasing a chatbot's perceived empathy through better communication can improve consumer satisfaction (Markovitch et al., 2024).

Collectively, these studies provide a detailed understanding of the factors that influence individuals' intentions to switch to chatbots. They emphasize the significance of managing service recovery expectations and cultivating trust, while also acknowledging that anthropomorphic design can enhance customer experience and reduce trust on human agents. Chatbots have the potential to boost user satisfaction and loyalty by building trust through reliable and personalized communication. Strategies such as anthropomorphic design, high social presence communication, and informal language patterns can enhance perceived value and trust in chatbot interactions (Li & Zhang, 2023; Lu et al., 2024; Markovitch et al., 2024).

In conclusion, these insights suggest that businesses should prioritize the development of chatbots that possess a balanced combination of human-like characteristics and robust service recovery capabilities to strengthen ongoing customer interaction, reduce dependence on human agents, optimize service efficiency, and improve customer satisfaction.

1.4 Appearance anthropomorphism

Building on the previously discussed research methods, this section delves into how incorporating anthropomorphic characteristics into chatbots can improve user satisfaction and trust, particularly in the e-commerce industry.

Anthropomorphism, the practice of attributing human-like qualities to non-human entities, has emerged as a crucial strategy for improving human interaction with technology. For instance, IKEA's chatbot "Anna" exemplifies how these characteristics can enhance trust and social impact. Tsai et al. (2021) discuss how anthropomorphic features such as names and gender make chatbots more relatable and trustworthy, resulting in greater acceptance and connection. This leads to the hypothesis that anthropomorphic features (names and avatars) in chatbots moderate the relationship between trust and switching intentions to human customer support (H1), as users inherent desire for social interaction is satisfied, fostering a sense of familiarity and trust.

Additionally highlighting the importance of design, Lu et al. (2024) found that anthropomorphic chatbots, characterized by a human-like appearance and communication style, influence customers' inclination to switch to human agents after experiencing service failures. Their study demonstrated that such designs could shape customers' expectations for service recovery, addressing both functional and emotional aspects. This supports the hypothesis that anthropomorphic features (names and avatars) in chatbots moderate the relationship between trust and perceived value of the chatbot service (H2), as anthropomorphic designs positively influence expectations and reduce the likelihood of customers switching to another service provider due to performance issues.

Zhang and Wang (2023) expanded this understanding by investigating the influence of anthropomorphic appearance on consumer behavior and brand evaluation under different AI product types. Their research showed that for hedonic AI products designed for enjoyment, a human-like appearance improves consumers' purchase intentions and brand perception by increasing the sense of entertainment. Conversely, for utilitarian AI products, anthropomorphic appearance enhances consumers' purchase intention and brand evaluation through perceived usefulness. This study underscores the importance of aligning anthropomorphic design with product type to optimize consumer response, suggesting that anthropomorphic features can increase perceived value and trust in chatbot services (H2).

In another study, Patrizi et al. (2024) explored the consequences of brand anthropomorphism in voice-based artificial intelligence contexts. They found that brand anthropomorphism positively affects brand trust and consumer-brand engagement across cognitive, affective, and behavioral dimensions. Moreover, they identified that perceived privacy risk moderates the relationship between brand anthropomorphism and brand trust. Specifically, higher levels of perceived privacy risk strengthen the positive impact of brand anthropomorphism on brand trust, highlighting the need to address privacy concerns in the design of anthropomorphic chatbots and foster greater trust and engagement. This reinforces the hypothesis that anthropomorphic features influence trust and switching intentions to human customer support (H1).

Recent advancements in AI technology have further emphasized the role of anthropomorphism in enhancing user trust and engagement. Pentina et al. (2023) highlight those anthropomorphic features, such as human-like appearance and behaviors, significantly impact the perceived trustworthiness and empathy of chatbots. Their review suggests that these features not only increase user satisfaction but also foster long-term engagement by creating a sense of social presence and emotional support, aligning with the hypothesis that anthropomorphic features improve user trust and perceived value (H2).

Yang et al. (2023) explored the dual pathways through which anthropomorphism influences service evaluations and customer purchase decisions. They found that anthropomorphic cues, such as warmth and competence, significantly enhance customer trust while reducing information overload. This balance of emotional and functional aspects is crucial in shaping positive service evaluations and increasing purchase intentions. Trust in chatbots positively influences service evaluations and purchase behaviors, whereas information overload negatively impacts these outcomes. The mediation effects of trust and overload suggest that well-designed anthropomorphic features can lead to better user experiences and higher customer satisfaction, further supporting the hypothesis that anthropomorphic features moderate the relationship between trust and switching intentions (H1) and perceived value (H2).

In summary, incorporating anthropomorphic designs such as names and avatars into chatbots can significantly increase trust, perceived value, and parasocial interactions. These designs make interactions more personal and relatable, fostering stronger emotional connections and reducing the tendency for users to switch to human agents.

1.5 Trust

As previously discussed, anthropomorphic design in chatbots can influence users by fostering a sense of trust, enhancing user engagement, and improving social cognition. Among these variables, trust emerges as a critical factor in determining the success of chatbot interactions. This section explores how various authors have investigated the impact of trust in chatbots and its implications for user interaction and satisfaction.

Choung et al. (2022) provide valuable insights into the role of trust in the acceptance of AI technologies. Their study highlights that trust significantly affects the intention to use AI technologies by operating through perceived usefulness and attitude towards these technologies. Trust is presented as multidimensional, comprising human-like trust and functionality trust, each significantly impacting the acceptance of AI technologies. These findings underscore the importance of building and maintaining trust in AI interactions, suggesting that similar dynamics could apply to chatbot interactions (Choung et al., 2022).

Expanding on this, Ameen et al. (2021) examined trust as a mediating factor in AI-enabled customer experiences. Their research, supported in trust-commitment theory, demonstrated that trust mediates the relationship between AI-enabled service quality, perceived convenience, personalization, and overall customer experience. They emphasize that trust, along with perceived sacrifice and relationship commitment, plays a crucial role in how customers perceive and engage with AI technologies. This underscores the importance of trust not only in enhancing customer satisfaction but also in strengthening customer-brand relationships (Ameen et al., 2021).

Huang et al. (2024) further analyze how trust influences the effectiveness of chatbots in customer service through a three-tiered model of trust, encompassing dispositional trust, learned trust, and situational trust. Dispositional trust affects initial perceptions, learned trust evolves from cumulative experiences, and situational trust is specific to service interactions. Their study reveals that these layers of trust significantly impact customer satisfaction, showing that chatbot services supplemented with minimal human oversight can achieve satisfaction levels comparable to human agents. This leads to the hypothesis that trust in chatbots influences users switching intentions to human customer support, as trust can affect users' preference to continue with chatbot assistance or switch to a human agent (H3).

Li et al. (2023) found that the degree of trust consumers has in chatbots is greatly impacted by the chatbot's ability to provide accurate and pertinent responses. Precision is especially vital in specialized domains like banking and healthcare, where the correctness of information is dominant. The promptness of a chatbot's responses is also crucial, as faster response times are associated with increased confidence. Interestingly, occasional delays might create the perception of human-like qualities in chatbots, potentially increasing customer satisfaction and trust. However, exaggerated human-like characteristics can lead to apprehension, known as the "uncanny valley," where users feel discomfort due to the chatbot's close resemblance to humans (Li et al., 2023).

The perception of value also plays a vital role in influencing customer trust in chatbots. Zhao and Wang (2021) found that service experience and customer knowledge significantly influence how chatbots are perceived in terms of value and confidence during service encounters. Enhancing the quality of service and increasing customer understanding can increase perceived value and build trust in chatbots. This leads to hypothesis that trust in chatbots positively influences users perceived value of the chatbot service, as trust directly impacts how users assess the value and effectiveness of chatbot services (H4).

In exploring emotional aspects of trust, Youn and Jin (2021) examined parasocial interaction, originally describing one-sided relationships, and applied it to human-chatbot interactions. They found that chatbots displaying relatable or calm behaviors can foster a sense of familiarity and trust, significantly influencing the level of trust users place in them. This leads to the hypothesis that trust in chatbots positively influences parasocial interaction between users and chatbots, as trust encourages users to feel a deeper emotional connection with chatbots (H5).

The study by Lukyanenko et al. (2022) offers a foundational trust framework to facilitate systematic research on trust in AI. This framework emphasizes trust as an interaction among systems and applies systems thinking to trust in AI. Key aspects include transparency, explainability, and the ability to manage and mitigate preferences. These principles are crucial for building and maintaining trust in AI interactions, which can be extended to chatbots. Understanding these dynamics helps in designing chatbot systems that are trustworthy, thereby improving user interaction and satisfaction (Lukyanenko et al., 2022).

Based on these studies, building trust in chatbots requires a comprehensive strategy that considers various factors, including expertise, responsiveness, user-friendliness, and a human-like interface. To increase trust and boost customer satisfaction in e-commerce environments, it is essential to understand the emotional dynamics, such as the parasocial interaction effect, as well as the perceived value that consumers attribute to chatbots.

1.6 Perceived Value

As Zhao and Wang (2021) highlighted, perceived value significantly influences consumer trust and plays a vital role in decision-making. This section delves into additional studies that examine the factors affecting value perception and their implications for e-commerce.

The study by Sharma and Klein (2020) on online group buying (OGB) provides valuable insights into how consumer perceived value (CPV), perceived trust (PT), and susceptibility to interpersonal influence (SIPI) affect consumer intentions to participate in OGB. Their findings show that CPV and PT are significant predictors of consumer involvement (CI) in OGB, which in turn strongly influences intention to participate (ITP). These results underscore the importance of CPV and PT in shaping consumer behavior and suggest that similar dynamics could apply to other e-commerce contexts, including chatbots (Sharma & Klein, 2020).

For instance, Sweeney and Soutar (2001) found that customers who perceive a high level of value in a product or service are more inclined to maintain their loyalty and are less likely to switch to alternative options. This relationship underscores the importance of perceived value in sustaining consumer and brand loyalty. This leads to the hypothesis that the perceived value of chatbot services influences users switching intentions to human customer support, as users who perceive higher value may still seek human interaction for more complex or personalized assistance (H6).

Expanding on this, Chiu et al. (2014) investigated how utilitarian and hedonic values impact the likelihood of customers making repeat purchases in e-commerce. Utilitarian value includes tangible benefits such as convenience and monetary savings, while hedonic value encompasses intangible benefits like excitement and satisfaction. Their study revealed that both utilitarian and hedonic values positively influence repeat purchases. These insights can be applied to chatbots by ensuring they provide both practical advantages (quick, clear replies) and affective engagement (personalized, friendly interactions) (Chiu et al., 2014). This further supports the hypothesis that perceived value in chatbot services encourages users to seek additional human interaction when necessary (H6).

Moreover, Akdim and Casaló (2023) explored the influence of AI-based recommendation services in voice assistants on perceived value. They focused on how these technologies impact perceived value by analyzing their social presence and personalized interactions. Their research emphasizes that voice assistants' ability to generate a sense of social interaction enhances perceived benefits like convenience, compatibility, and personalization. Similarly, chatbots can increase perceived value by offering customized suggestions and maintaining a strong social presence through natural, conversational interactions (Akdim & Casaló, 2023). This leads to the hypothesis that perceived value influences users switching intentions to human customer support, especially when personalized interactions are critical (H6).

Moreover, Zhao and Wang (2021) discussed the relationship between perceived value and trust, noting that service experience and customer knowledge significantly influence how chatbots are perceived in terms of value and confidence during service encounters. Enhancing the quality of service and deepening customer understanding can increase perceived value and build trust in chatbots, ultimately affecting customer satisfaction and loyalty (Zhao & Wang, 2021). This contributes to the hypothesis that perceived value plays a key role in influencing users’ intentions to switch from chatbots to human customer support (H6). Additionally, Zhao & Wang, 2021 highlight the crucial role of social relationship value in peer-to-peer (P2P) services. Their research indicates that consumers' perceptions of social interactions and connections with service providers significantly influence their intention to repurchase. This insight is particularly relevant for chatbot services, where cultivating a strong social presence and building relationships with users can greatly enhance perceived value and customer loyalty. By integrating features that promote personalized and empathetic interactions, chatbots can mimic the social engagement found in P2P services, thereby fostering a deeper connection with users and encouraging repeat usage (Zhao & Wang, 2021).

In summary, the literature suggests that consumer behavior is greatly influenced by the perception of value and trust. These factors, in turn, affect customer satisfaction, loyalty, and the perceived benefits of remaining loyal to a particular brand or service provider. The complex interaction among perceived value, emotional engagement, and trust is essential for organizations seeking to retain customers and achieve a competitive edge. A comprehensive understanding of these dynamics provides a robust foundation for future studies on customer behavior across different service and technological interfaces, including the enhancement and improvement of chatbots.

1.7 Parasocial Interaction

As highlighted in the Trust section, parasocial interaction (PSI) significantly impacts consumer trust. Other sections have emphasized the importance of emotional connections, such as social presence, in building trust and engagement. This section explores the factors influencing PSI and its impact on chatbot interactions, integrating various studies to create a comprehensive understanding.

Parasocial interaction describes the phenomenon where users feel they can establish a social connection with a mediated persona, such as a chatbot. This concept is crucial for understanding the psychological processes underlying user interactions with chatbots (Li & Wang, 2023; Tsai et al., 2021; Youn & Jin, 2021).

The study by Aw and Labrecque (2020) on celebrity promotions in social media contexts provides valuable insights into the mechanisms by which parasocial interactions (PSI) influence consumer behavior. They found that regular and personal interactions between celebrities and their followers on social media significantly enhance consumer attachment to the celebrity and positively influence brand perceptions and purchase intentions. These findings underscore the importance of PSI in fostering trust and loyalty, suggesting that similar dynamics could apply to chatbot interactions (Aw & Labrecque, 2020).

Furthermore, the study by Zheng et al. (2020) on social shopping websites (SSWs) explores how technology attraction, comprising social, task, and physical attraction, affects PSI and subsequently influences users' social commerce intentions. The results indicate that social and task attraction have a direct positive impact on users' parasocial interaction, while physical attraction indirectly influences users' PSI via social and task attraction. This framework can also be applied to chatbot interactions, emphasizing the need for well-designed, engaging interfaces that facilitate social and task-related interactions to enhance PSI (Zheng et al., 2020).

Youn and Jin (2021) started the exploration by reviewing how AI-enabled chatbots, perceived as either virtual assistants or virtual friends, affect customers' perceptions of brand personalities and customer relationship management (CRM) outcomes. Their study found that chatbots cultivating virtual friendships improved PSI, which in turn strengthened consumers' perceptions of a brand's competence and honesty. When users develop a stronger sense of trust and attachment to chatbots, their desire to switch to human customer support may decrease, particularly if the chatbot interaction consistently meets their needs. This leads to the hypothesis that parasocial interaction with chatbots influences users switching intentions to human customer support (H7), as enhanced PSI can create enough satisfaction to reduce the demand for human intervention.

Further supporting this idea, Li and Wang (2023) demonstrated that a chatbots casual and informal speaking style significantly increased PSI, improving users’ intentions to reuse the service and enhancing brand perception. This suggests that a more personable, relatable chatbot can build strong PSI, reinforcing the notion that users may prefer sticking with the chatbot rather than seeking human support.

In line with these findings, Tsai et al. (2021) explored the role of anthropomorphic features, such as human-like names and profile images, in increasing user engagement. They found that such features significantly boosted PSI, contributing to higher perceived dialogue quality and greater satisfaction. This suggests that adding human-like traits to chatbots enhances users’ emotional connections with them, increasing trust and engagement. This leads to the hypothesis that anthropomorphic features (names and avatars) in chatbots moderate the relationship between trust and parasocial interaction (H8), highlighting how carefully designed chatbots can amplify PSI and improve the overall user experience.

Recent advancements in AI technology have further highlighted the importance of PSI in chatbot interactions. Pentina et al. (2023) emphasized that AI chatbots capable of fostering parasocial interactions through empathetic and autonomous behaviors can significantly improve user retention and satisfaction. Their review underscores the role of anthropomorphism and social presence in creating strong PSI, which enhances consumer trust and loyalty (Pentina et al., 2023).

These studies collectively demonstrate that parasocial interaction is crucial in enhancing consumer trust and engagement with chatbots. Chatbots that simulate virtual friendships, use informal language, and feature anthropomorphic designs significantly impact PSI, leading to improved brand perceptions, better user retention, and increased satisfaction with interactions. Creating chatbot interactions that encourage strong PSI is essential for building trust and ensuring customer loyalty.

1.8 Conceptual Model and Hypothesis

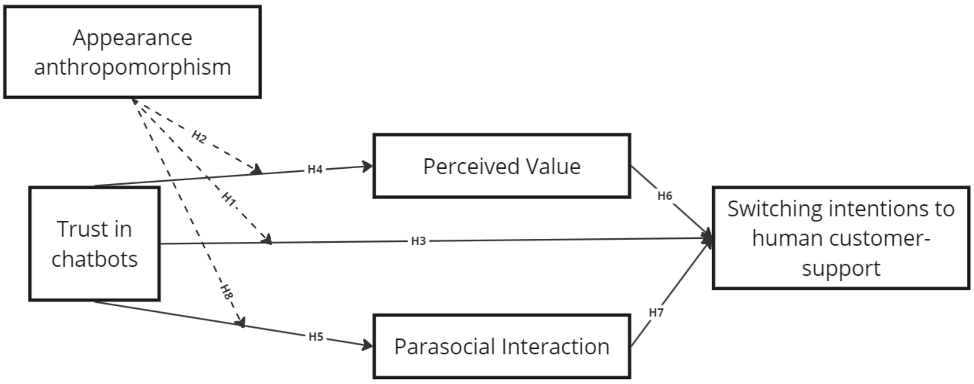

Figure 1 - Concept Model

	Hypotheses
H1	Anthropomorphic features (names and avatars) in chatbots moderate the relationship between trust and switching intentions to human customer support.
H2	Anthropomorphic features (names and avatars) in chatbots moderate the relationship between trust and perceived value of the chatbot service.
H3	Trust in chatbots influences users' switching intentions to human customer support.
H4	Trust in chatbots positively influences users' perceived value of the chatbot service.
H5	Trust in chatbots positively influences parasocial interaction between users and chatbots.
H6	Perceived value of chatbot services influences users' switching intentions to human customer support.
H7	Parasocial interaction with chatbots influences users' switching intentions to human customer support.
H8	Anthropomorphic features (names and avatars) in chatbots moderate the relationship between trust and parasocial interaction.

Table 1 - Summary of Hypotheses

Chapter 3

2. Research Methodology

The main objective of this study is to explore the factors that influence consumer's decisions to switch from interacting with chatbots to seeking assistance from human customer service representatives, specially within a product recommendation context. The research aims to examine the roles of perceived value, trust in chatbots, and parasocial interaction, with anthropomorphism serving as moderating variable, on consumers' switching intentions. This study will achieve this through the implementation of two distinct surveys.

2.1 The experiment

The primary data for this study was gathered through online surveys conducted using Prolific, a platform specifically developed for academic research participation. The sample was carefully selected from Prolific users who possess expertise in using chatbots in e-commerce environments, guaranteeing that the participants were knowledgeable about the topic at hand. Participants were able to access the surveys through a direct link that included a comprehensive introduction to the research goals. Before conducting the main survey, a screening question was employed to verify participants' familiarity with e-commerce chatbots. In contrast to volunteer participation models, the participants in this study were paid an average of 0.70€ per questionnaire.

The study has sample restrictions as it only included persons that possess fluency in the English language, have internet access, are capable of navigating and responding to surveys on Prolific, have provided consent to participate in the study and had previous experience with chatbots (screening question).

2.1.1Experimental design and measures

The study aimed to evaluate user reactions to simulated chatbot interactions centered around product recommendations in e-commerce. It involved a total of 326 participants divided into two separate groups. Both groups were shown similar screenshots of a chatbot interaction, but the chatbots had different visual appearances, for the purpose of studying the impact of Appearance Anthropomorphism variable as moderator of the relationships between Trust and Perceived Value, Switching intentions and Parasocial Interaction.

Regarding the characteristics, one chatbot had human-like elements, including a human name (João) and face, while the other had a robotic name (Ecobot) and face. The experiment analyzed the impact of chatbot design on trust, perceived value, and parasocial interaction. The study was divided into 2 sections (See Appendix A for more details):

- To start, they were asked for the demographic characteristics and for the existence of experience using chatbots through a screening question. The ones without previous experience would not proceed to complete the questionnaire and were not used for the study.
- Then before the simulated dialogue, individuals were asked for their overall trust in chatbots. Subsequently, people from both surveys were presented with various visual representations, simulating a conversation between the individual and the chatbot about a product recommendation. The only difference between the two surveys was the physical and name of the bot. This controlled arrangement meant that any variations in participant responses could be completely attributable to the chatbot's visual design. Following the screenshot observation, participants responded to a set of questions to assess their perceptions of the chatbot's appearance, perceived value, parasocial interaction feelings, and intention to switch from a chatbot to a human.

Questions	Type	Possible Answer
Age	Close	Under 18; 18-24; 25-34; 35-44; 45-54; 55 or older
Gender	Close	Male; Female; Non-binary/Third gender; Prefer not to say; Other.
Screening question	Close	Yes; No

Table 2 - Survey Segmentation Questions

In terms of the surveys applied, they were based on different constructs derived from existing research, which were modified to suit the setting of chatbot interactions. It consisted of 15 selected questions that covered many constructs, including perceived values, switching intentions, parasocial interaction, appearance anthropomorphism, and trust in chatbots.

The measuring items were initially chosen based on their proven reliability and validity in previous studies. Every individual item was subsequently and carefully altered to align with the unique context of engaging with two distinct chatbots, João and Ecobot, to embody human-like and robot-like attributes accordingly. The changes guarantee that the items are specifically pertinent to the subtle aspects of engagement with each form of chatbot.

The items were standardised to a 7-point Likert scale, which enables a consistent measure of response for all variables, improving the capacity to compare responses and facilitating a detailed study. The scale ranges from 1 (strongly disagree) to 7 (strongly agree).

The Table 3 below presents an overview of the modified measurement items, including their initial format, adapted format, references, and the exact names of the chatbots used in the adaptations:

Construct	Original Item	Adapted Item	Source	Code
Perceived Value	I believe that using the VA to obtain recommendations is valuable	I believe that using Chatbots to obtain recommendations is valuable	(Akdim & Casaló, 2023)	PV1
	I believe that using the VA to obtain recommendations is beneficial	I believe that using the Chatbots to obtain recommendations is beneficial		PV2
	Overall, using the VA to obtain recommendations delivers high value	Overall, using Chatbots to obtain recommendations delivers high value		PV3
Switching Intentions	In terms of frequency of usage, I use chatbot customer service.	In terms of frequency of usage, I will use more the [João or Ecobot] customer service.	(Li & Zhang, 2023)	SWI1
	I spend more time on chatbot customer service than on human customer service.	I intend to spend more time on [João or Ecobot] customer service than on human customer service.		SWI2
	I am considering decreasing time on human customer service and increasing time on using chatbot customer service.	I am considering decreasing time on human customer service and increasing time on using [João or Ecobot] customer service.		SWI3
Parasocial Interaction	I see this chatbot as a natural, down-to-earth person	I see [João or Ecobot] as a natural, down-to-earth person	(Li & Wang, 2023)	PSI1
	I feel the chatbot is like an old friend.	I feel that [João or Ecobot] is like an old friend.		PSI2
	The chatbot makes me feel comfortable, as if I am with a friend.	[João or Ecobot] makes me feel comfortable, as if I am with a friend.		PSI3
Appearance anthropomorphism	I feel that the chatbot behaves like a human.	I feel that the [João or Ecobot] behaves like a human.	(Lu et al., 2024)	AA1
	I feel like the chatbot can think like a human.	I feel like [João or Ecobot] can think like a human.		AA2
	I feel that the chatbot is similar to real human customer service.	I feel [João or Ecobot] is similar to real human customer service.		AA3
Trust in chatbots	The conversational agent is trustworthy	I believe Chatbots are trustworthy	(Lu et al., 2024)	T1

	I trust the conversational agent	I tend to trust the Chatbots	T2
	The conversational agent is adequate for my need	Overall, I trust Chatbots to meet my needs	T3

Table 3 - Questions and Loadings

2.1.2Pre-experiment

Prior to starting the primary research on human-chatbot interactions, a series of preliminary experiments were carried out to evaluate and improve the research methodology. According to Malhotra et al. (2017) recommendations, these initial studies play a vital role in adapting the data collection methods for the main study.

The pilot test included 40 responses from several participants. These participants were instructed to provide feedback on two versions of a questionnaire, one presented by a human and the other by a robot. Both versions contained identical text. This dual method aimed to assess the efficacy and uniformity of different constructs pertaining to chatbot interactions.

The constructs that were evaluated included perceived value, switching intentions, parasocial interaction, appearance anthropomorphism, and trust in chatbots. Participants' responses were recorded using a seven-point Likert scale, and the reliability of the measurements was assessed using Cronbach's alpha. The outcomes were predominantly positive, as all structures, except for one (AA1), exceeded the minimum criterion of 0.7.

The surveys were subject to iterative revisions in terms of both content and visual design, considering feedback from participants. The modifications included improving the clarity and accessibility of the language, as well as aligning the questionnaire's style with the research's logical framework.

This preliminary phase not only validated the research methodology but also underscored the significance of adaptability in activities that involve human interaction with chatbots. The knowledge gained was essential in developing a final experimental setup that was strong and capable of accurately detecting the intricacies of human-chatbot interaction.

2.1.3Data collection

As mentioned before, the main data for this study was gathered through online questionnaires conducted using Prolific, a platform designed exclusively for academic research. Experienced users of chatbots in e-commerce were chosen as participants. They were given a direct link that provided a detailed explanation of the study's goals. Prior to the survey, a screening question was used to evaluate participants' knowledge of e-commerce chatbots to confirm their expertise in the subject.

The study included individuals of diverse age groups, living in various geographical locations, and representing different genders. The surveys were intentionally designed to prevent participants from selecting which survey they would take, which guarantees unbiased group selection. The participants were compensated for their efforts, which served as motivation for their active participation, distinguishing it from traditional volunteer models.

The experiment involved a total of 326 participants, with 164 participants interacting with a human-like chatbot (Study 1) and 162 participants interacting with a non-human-like chatbot (Study 2), as indicated in Table 4.

N = 326s	**Frequency**
Human chatbot (Study 1)	164
Not human chatbot (Study 2)	162

Table 4 - Number of respondents by group

Chapter 4

3. Data analysis

This chapter provides a description and analysis of the data gathered for this research. The goal of this segment, which begins with a more comprehensive examination, is to first understand the essence of the gathered material. The acquired data was examined considering this study's conceptual model and the interrelationships between its constructs in both the inner and outer models, as well as the bootstrapping analysis.

3.1 Demographic description

The two studies examined a collective sample of 326 participants, 299 had prior experience interacting with chatbots for assistance or customer service. Most participants in Study 1 were female, accounting for 62.8% of the total, while in Study 2, females made up 71.6% of the participants. Both surveys revealed a significant concentration of individuals aged 25-44. Study 1 revealed that 29.3% of participants fell within the age range of 18-24, while 28% were aged 25-34. Additionally, 25.6% of respondents were between the ages of 35-44, 7.3% were aged 45-54, and 9.1% were 55 years or older. Furthermore, a mere 0.6% of participants were under the age of 18. Study 2 revealed that 34% of its participants were aged 25 to 34, 29.6% were aged 35 to 44, 14.2% were aged 45 to 54, 12.3% were aged 18 to 24, and 9.9% were aged 55 or above. The prevalence of younger age groups, especially those who are engaged on digital platforms, emphasizes the significance of user-friendly and easily available digital interfaces in customer service technologies.

Study	Total Responses	After the screening question	Age Distribution	Gender Distribution
1	164	152	18-24: 29.3% (48) 25-34: 28% (46) 35-44: 25.6% (42) 45-54: 7.3% (12) 55+: 9.1% (15) < 18: 0.6% (1)	Female: 62.8% (103) Male: 36% (59) Non-binary/Third gender: 1.2% (2)

2	162	147	18-24: 12.3% (20) 25-34: 34% (55) 35-44: 29.6% (48) 45-54: 14.2% (23) 55+: 9.9% (16)	Female: 71.6% (116) Male: 27.2% (44) Non-binary/Third gender: 1.2% (2)
total	326	299		

Table 5 - Demographic Report

3.2 PLS-SEM results

This study uses partial least squares structural equation modelling (PLS-SEM) to analyse and interpret the data. PLS-SEM has broad applicability in diverse fields such as strategic management, e-business, marketing, consumer behaviour, and management information systems (Henseler et al., 2009). The study finds the tool to be very suitable due to its adaptability and capacity to manage intricate interactions among variables (Hair et al., 2021).

PLS-SEM has an advantage over CB-SEM in that it is more appropriate for smaller sample numbers. As per Hair et al. (2021), the necessary sample size for PLS-SEM is defined by the maximum number of arrows directed towards a latent variable, specifically, perceived usefulness. Given that the model has four independent variables, it requires a minimum of 40 responses for each questionnaire to ensure adequate sample size. This research comfortably exceeds that requirement, with 326 respondents. In addition, Cohen (1988) guidelines suggest that a substantial sample size should be used, with a 5% likelihood of error and a minimum R2 value of 0.25 for the latent variable with the highest number of arrows. This further confirms that the sample size is appropriate.

The investigation proceeds to examine the PLS-SEM conceptual model, which is comprised of the outer and inner models. The outer model, referred to as the measurement model, clarifies the connections between constructs and associated indicator variables. Conversely, the inner model, often known as the structural model, examines the immediate relationships between constructs (Hair et al., 2021). The sections that follow go into more detail about the outer and inner models of PLS-SEM using the PLS algorithm and bootstrapping methods for calculations.

3.3 Outer model

The outer model of this thesis investigates four main aspects of the conceptual model: internal consistency reliability, convergent validity, discriminant validity, and multicollinearity (Hair et al., 2021). The findings are thoroughly documented in subsequent tables (Table 6; Table 7; Table 8; Table 10).

3.3.1Indicator Reliability

The initial step in assessing the outer model is to verify the indicator's reliability. This involves confirming how much of the indicator variance is explained by the constructs. Although all indicators have been validated in previous research, it is essential to confirm their appropriateness for this study specifically. Indicator loadings above 0.7 are considered adequate, indicating strong reliability, and those below 0.4 should be eliminated (Hair et al., 2021). If an indicator's loading is between 0.4 and 0.7, it may mean that it is less reliable. It could be removed if doing so improves the construct's composite reliability (CR) or average variance extracted (AVE).

Construct (Latent Variable)	Indicator	Outer Loading
Appearance anthropomorphism	AA1	0.839
	AA2	0.84
	AA3	0.871
Parasocial Interaction	PSI1	0.891
	PSI2	0.906
	PSI3	0.912
Perceived Value	PV1	0.948
	PV2	0.96
	PV3	0.951
Switching Intentions	SWI1	0.863
	SWI2	0.883
	SWI3	0.906
Trust in chatbots	T1	0.899
	T2	0.932

	T3	0.847

Table 6 - Indicator Reliability

3.3.2 Internal Consistency Reliability

Internal consistency reliability is assessed using Cronbach’s Alpha and Composite Reliability (CR) (Henseler et al., 2009). The results are satisfactory for all constructs:

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AA	0.808	0.810	0.887	0.723
PSI	0.887	0.889	0.930	0.816
PV	0.950	0.951	0.968	0.908
SWI	0.862	0.873	0.915	0.782
T	0.873	0.876	0.922	0.798

Table 7 - Internal Consistency Reliability

3.3.3 Convergent Validity

Convergent validity is assessed by analyzing the Average Variance Extracted (AVE) for each construct in Table 7. All constructs demonstrate AVE values significantly higher than the minimum threshold of 0.5, thereby confirming robust convergent validity (Hair et al., 2021).

3.3.4 Discriminant Validity

To establish discriminant validity, cross-loadings are examined, and the Fornell-Larcker criterion is applied. The indicators in Table 8 have a much stronger relationship with their assigned constructs than with other constructs. This proves that it is possible to tell the difference between different constructs (Fornell & Larcker, 1981). In addition, the square root of the average variance extracted (AVE) for each construct is greater than its highest correlation with any other construct, therefore meeting the Fornell-Larcker criterion.

	AA	PSI	PV	SWI	T	AA x T
AA1	0.839	0.616	0.481	0.489	0.387	-0.046
AA2	0.840	0.659	0.519	0.565	0.421	0.108
AA3	0.871	0.590	0.579	0.596	0.397	-0.027
PSI1	0.708	0.891	0.538	0.624	0.403	0.054
PSI2	0.609	0.906	0.444	0.599	0.300	0.091
PSI3	0.658	0.912	0.568	0.665	0.423	0.045

PV1	0.568	0.525	0.948	0.674	0.534	-0.002
PV2	0.590	0.538	0.960	0.703	0.564	-0.054
PV3	0.616	0.579	0.951	0.724	0.560	-0.059
SWI1	0.657	0.663	0.765	0.863	0.582	-0.053
SWI2	0.501	0.574	0.564	0.883	0.419	-0.057
SWI3	0.539	0.599	0.589	0.906	0.387	-0.008
T1	0.382	0.337	0.483	0.414	0.899	-0.147
T2	0.417	0.369	0.521	0.471	0.932	-0.116
T3	0.459	0.407	0.542	0.533	0.847	-0.063
AA x T	0.016	0.069	-0.041	-0.045	-0.119	1.000

Table 8 - Discriminant Validity

3.3.5Discriminant Validity Using HTMT Ratio

To make sure the model is discriminant, the HTMT (Heterotrait-monotrait ratio) ratio is also checked. All the values in Table 9 are well below the 0.90 threshold, like PSI->AA at 0.861 and T->SWI at 0.596. This shows that each construct is unique and well separated from the others, supporting the model's discriminant validity.

Heterotrait-monotrait ratio (HTMT)						
	AA	**PSI**	**PV**	**SWI**	**T**	**AA X T**
AA						
PSI	0.861					
PV	0.706	0.623				
SWI	0.762	0.790	0.797			
T	0.558	0.469	0.633	0.596		
AA X T	0.079	0.075	0.041	0.048	0.131	

Table 9 - Discriminant Validity Using HTMT Ratio

3.3.6Multicollinearity

The Variance Inflation Factor (VIF) is used to assess the presence of multicollinearity in Table 10. The VIF values are all within acceptable thresholds, indicating the absence of significant multicollinearity problems in the model. Specifically, VIF values below 5 are generally considered acceptable, and values between 5 and 10 may indicate moderate multicollinearity but are still withing a tolerable range. In this model, the VIF values that exceed 5 are acknowledged but do not surpass the critical threshold of 10, suggesting that multicollinearity is not a severe issue. (Yoo W et al., 2014).

	VIF

AA1	1.776
AA2	1.652
AA3	1.912
PSI1	2.260
PSI2	2.811
PSI3	2.771
PV1	4.804
PV2	5.742
PV3	4.698
SWI1	1.732
SWI2	2.889
SWI3	3.171
T1	3.953
T2	4.530
T3	1.727

Table 10 - Multicollinearity

To summarise, the outer model analysis provides evidence for the reliability and validity of the measurement model, as well as the statistical independence of the constructs. This establishes a strong foundation for the subsequent structural analysis in the thesis.

3.4 Inner model

The inner model of this thesis investigates the relationships between latent variables, focusing on model fitness, multicollinearity, predictive capability, and the effect sizes of each construct. This section begins with an examination of the model's fitness using various statistical indices and continues with an assessment of multicollinearity among the latent variables.

3.4.1Model Fitness

Model fitness is critically evaluated using several statistical indices presented in Table 11 to ensure that the model adequately fits the observed data:

- **Standardized Root Mean Square Residual (SRMR):** This index is crucial for assessing the goodness of fit of the model. A SRMR value less than 0.08 generally indicates a good fit. For the estimated model, the SRMR value is 0.073, which falls within the acceptable range, suggesting a satisfactory fit (Hu & Bentler, 1999).
- **Chi-square:** This statistic tests the model's fit against a perfect model. A lower chi-square value relative to the degrees of freedom suggests a better fit. The chi-square value for the estimated model is 595.192, indicating a reasonable fit given the model's complexity.

- **Normed Fit Index (NFI):** The NFI compares the fit of the estimated model to a baseline model, typically a null model with no relationships among variables. An NFI value closer to 1 indicates a better fit. In this case, the NFI is 0.843, approaching the commonly accepted threshold of 0.90, which supports the model's adequacy.

	Saturated model	Estimated model
SRMR	0.070	0.073
d_ULS	0.594	0.642
d_G	0.328	0.328
Chi-square	610.642	595.192
NFI	0.838	0.843

Table 11 - Model Fitness

3.4.2Multicollinearity among Latent Variables

Assessing multicollinearity is essential to ensure that the latent variables in the model do not exhibit high intercorrelations, which could inflate the variance of the estimated coefficients:

The Variance Inflation Factor (VIF) is used to measure how much the variance of an estimated regression coefficient is increased due to multicollinearity. VIF values greater than 5 generally indicate problematic levels of multicollinearity. In this model, the VIF values presented in Table 11 for the paths between constructs are all well below 5, with the highest being 2.506 for the path from appearance anthropomorphism (AA) to switching intentions (SWI). This suggests that multicollinearity is not a concern within this model, allowing for reliable interpretation of the path coefficients (Hair et al., 2021).

	VIF
AA -> PSI	1.297
AA -> PV	1.297
AA -> SWI	2.506
PSI -> SWI	2.292
PV -> SWI	2.044
T -> PSI	1.315
T -> PV	1.315
T -> SWI	1.585
AA x T -> PSI	1.021
AA x T -> PV	1.021
AA x T -> SWI	1.033

Table 12 - Multicollinearity among Latent Variables

3.4.3Model Predictive Accuracy

The predictive capability of the model is assessed through the coefficient of determination, known as R-squared (R^2), for each dependent construct. This measure indicates how much of the variance in the dependent variables is explained by the independent variables:

- **Parasocial Interaction (PSI):** The R^2 value of 0.546 suggests that approximately 54.6% of the variance in PSI is explained by its predictors, demonstrating strong explanatory power.
- **Perceived Value (PV):** An R^2 value of 0.491 indicates that about 49.1% of the variance in PV is accounted for by the predictors, showing substantial explanatory power.
- **Switching Intentions (SWI):** The highest R^2 value of 0.667 indicates that the predictors explain about 66.7% of the variance in SWI, indicating a very strong predictive capability.

	R-square	R-square adjusted
PSI	0.546	0.542
PV	0.491	0.486
SWI	0.667	0.661

Table 13 - Predictive Capability

3.4.4Effect Sizes (f-squared)

The impact of each independent variable on the dependent variables is quantified using Cohen's f-squared (f^2), which assesses the effect sizes:

- **AA -> PSI**: $f^2 = 0.785$, indicating a large effect size, suggesting that changes in AA have a substantial impact on PSI.
- **AA -> PV:** $f^2 = 0.302$, indicating a medium effect size.
- **AA -> SWI:** $f^2 = 0.007$, indicating a negligible effect size, showing minimal practical significance.
- **PSI -> SWI:** $f^2 = 0.171$, indicating a medium effect size, suggesting a notable impact.
- **PV -> SWI:** $f^2 = 0.261$, indicating a medium effect size, showing a significant practical impact.
- **T -> PSI, PV, SWI:** Smaller f^2 values (0.019, 0.203, 0.018) range from negligible to medium, indicating varying levels of influence.

	f-square
AA -> PSI	0.785
AA -> PV	0.302

AA -> SWI	0.007
PSI -> SWI	0.171
PV -> SWI	0.261
T -> PSI	0.019
T -> PV	0.203
T -> SWI	0.018
AA x T -> PSI	0.011
AA x T -> PV	0.000
AA x T -> SWI	0.005

Table 14 - Effect Sizes (f-squared)

To sum up, the inner model analysis shows that the model is robust, with strong model fitness, no multicollinearity, and good predictive abilities. The effect sizes reveal varying degrees of impact by different predictors, with some paths showing significant influence while others are minimal. This analysis supports the theoretical framework and hypotheses posited in this study, indicating a well-specified model that effectively captures the dynamics among the constructs.

3.5 Bootstrapping for the Comparison

Bootstrapping is a nonparametric method used to assess the statistical significance of different results obtained from PLS-SEM, including path coefficients, Cronbach's alpha, HTMT, and R^2 values. This method does not make any assumptions about the distribution of the data being analysed. Instead, it uses a nonparametric bootstrap method (Davison & Hinkley, 1997; Efron & Tibshirani, 1998) to create many subsamples by picking observations at random from the original dataset and replacing them. The subsamples are used to estimate the PLS path model multiple times, typically up to 10,000 iterations. This enables the calculation of 95% confidence intervals and standard errors for conducting significance tests.

This approach is critical for comparative analysis of Study 1 and Study 2. It plays a critical role in producing solid and reliable outcomes by improving the accuracy of parameter estimates and guaranteeing the consistency and reproducibility of our discoveries (Becker et al., 2022; Hair et al., 2021). Researchers should ensure that the sample size per bootstrap subsample matches the number of observations in the original dataset, and more subsamples generally lead to better approximations of parameter distributions (Becker et al., 2022). The use of bootstrapping in PLS-SEM not only facilitates inference testing of model parameters but also supports a range of other evaluation criteria, such as the heterotrait-monotrait ratio of correlations criterion (Henseler et al., 2015).

In PLS-SEM analysis, it is also important to choose an appropriate significance level. While many researchers commonly use a 5% error level probability, a p-value of 0.1 can also be considered acceptable, particularly when aiming to achieve higher statistical power and reducing the risk of Type II errors (Becker et al., 2022).

3.5.1Study 1 Structural Model Analysis (Human)

The structural model analysis for Study 1 (human name and look) examines the relationships between Appearance Anthropomorphism (AA), Parasocial Interaction (PSI), Perceived Value (PV), Switching Intentions (SWI), and Trust in Chatbots (T). The following Table 15 presents the path coefficients, T-statistics, P-values, and interpretations for each hypothesised path in the model.

Path	Coefficient	T-statistic	P-value	Interpretation
AA -> PSI	0.673	11.997	0.000	Strong positive relationship, statistically significant
AA -> PV	0.478	6.654	0.000	Moderate positive relationship, statistically significant
AA -> SWI	-0.026	0.337	0.736	Negligible negative relationship, not statistically significant
PSI -> SWI	0.336	4.556	0.000	Moderate positive relationship, statistically significant
PV -> SWI	0.580	8.853	0.000	Strong positive relationship, statistically significant
T -> PSI	0.118	1.818	0.069	Weak positive relationship, statistically not significant
T -> PV	0.374	4.797	0.000	Moderate positive relationship, statistically significant
T -> SWI	0.033	0.594	0.552	Weak positive relationship, statistically not significant
AA x T -> PSI	0.063	1.280	0.201	Weak positive relationship, statistically not significant
AA x T -> PV	0.028	0.514	0.607	Weak positive relationship, statistically not significant
AA x T -> SWI	-0.022	0.635	0.525	Negligible negative relationship, not

				statistically significant

Table 15 - Study 1 Structural Model Analysis (Human)

To sum up, Study 1, which involved a chatbot with a human name and design during a product recommendation experience, demonstrates strong connections between Appearance Anthropomorphism (AA) and Parasocial Interaction (PSI), as week as AA and Perceived Value (PV), and PV and Switching Intentions (SWI). These findings indicate that human-like features in chatbots improve user's parasocial interactions and perceived value, which in turn positively influence their intention to increase the use of chatbot support over human support.

Trust (T) had a moderate effect on Perceived Value (PV), supporting Hypothesis 4, but did not significantly affect Switching Intentions (SWI), so Hypothesis 3 was not supported. Trust also had no significant effect on Parasocial Interaction (PSI), meaning Hypothesis 5 was not supported. Additionally, Perceived Value (PV) had a significant on switching intentions (SWI), supporting Hypothesis 6, and Parasocial Interaction (PSI) also significantly influenced Switching Intentions (SWI), supporting Hypothesis 7. However, the proposed moderating effects of AA on the relationships between Trust and Switching Intentions (SWI), Perceived Value (PV), and Parasocial Interaction (PSI), as mentioned in Hypothesis 1, 2 and 8, were not statistically significant.

3.5.2Study 2 - Structural Model Analysis (Robot)

The structural model analysis for Study 2 explores the relationships between Appearance Anthropomorphism (AA), Parasocial Interaction (PSI), Perceived Value (PV), Switching Intentions (SWI), and Trust in Chatbots (T). The following Table 16 summarises the path coefficients, T-statistics, P-values, and interpretations for each hypothesised path in the model.

Path	Coefficient	T-statistic	P-value	Interpretation
AA -> PSI	0.647	10.653	0.000	Strong positive relationship, statistically significant
AA -> PV	0.412	6.198	0.000	Moderate positive relationship, statistically significant
AA -> SWI	0.142	1.820	0.069	Weak positive relationship, nearly significant (close to 0.05)
PSI -> SWI	0.395	5.681	0.000	Moderate positive relationship, statistically significant
PV -> SWI	0.290	3.961	0.000	Moderate positive relationship,

				statistically significant
T -> PSI	0.105	1.541	0.123	Weak positive relationship, not statistically significant
T -> PV	0.363	4.749	0.000	Moderate positive relationship, statistically significant
T -> SWI	0.149	2.148	0.032	Weak positive relationship, statistically significant
AA x T -> PSI	0.057	0.966	0.334	Weak positive relationship, not statistically significant
AA x T -> PV	-0.026	0.544	0.586	Negligible negative relationship, not statistically significant
AA x T -> SWI	-0.066	1.762	0.078	Weak negative relationship, nearly significant

Table 16 - Study 2 Structural Model Analysis

To sum up, Study 2, which involved a chatbot with robotic features during a product recommendation experience, demonstrates strong connections between Appearance Anthropomorphism (AA) and Parasocial Interaction (PSI), AA and Perceived Value (PV), and PSI and Switching Intentions (SWI). These findings suggest that robotic features in chatbots significantly enhance users' perceived value and parasocial interactions, which in turn increase their preference for chatbot support over human support.

Trust (T) had a moderate effect on Perceived Value (PV), supporting Hypothesis 4, and a weak but significant effect on Switching Intentions (SWI), partially supporting Hypothesis 3. Trust had no significant effect on Parasocial interaction (PSI), so Hypothesis 5 was not supported. Additionally, Perceived Value (PV) significantly influenced Switching Intentions (SWI), supporting Hypothesis 6, and Parasocial Interaction (PSI) also significantly impacted Switching Intentions (SWI), supporting Hypothesis 7. However, the moderating effects of AA proposed in Hypothesis 1, 2 and 8, were not statistically significant.

3.5.3Results:

a) Study 1 – Human

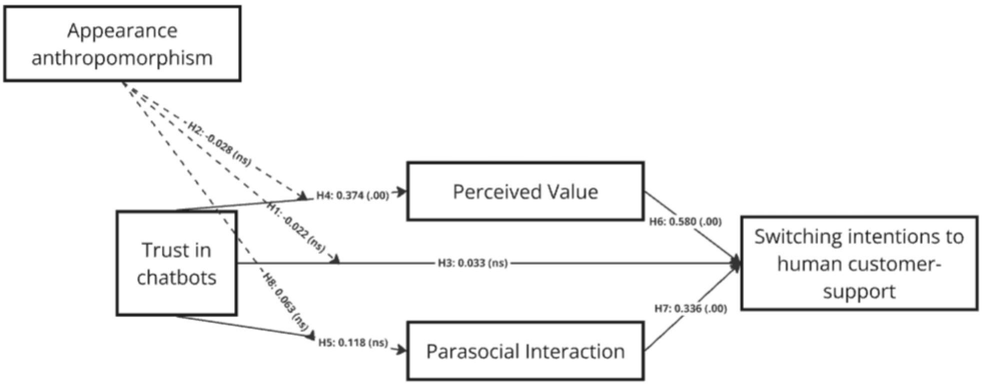

Figure 2- Results - Study 1 (Human)

b) Study 2 – Robot

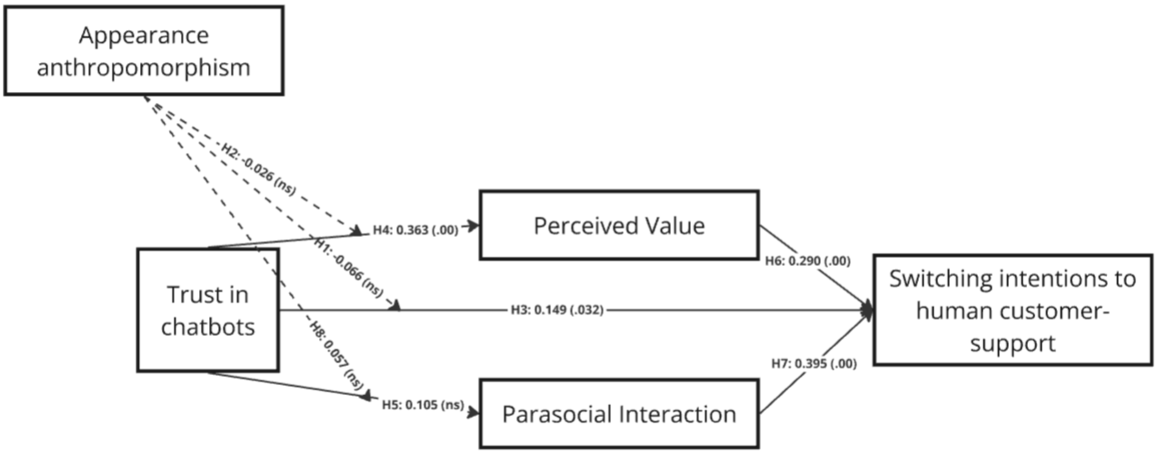

Figure 3 - Results - Study 2 (Robot)

Chapter 5

4. Discussion

Both studies consistently show strong and significant relationships between Appearance Anthropomorphism (AA) and Parasocial Interaction (PSI), as well as between AA and Perceived Value (PV). Moreover, the paths from PSI to Switching Intentions (SWI) and from PV to SWI show moderate to strong effects in both studies, indicating a mutual influence among these concepts. A clear difference between the studies is observed in the pathway from AA to SWI. In Study 2, which involved a chatbot with robot features (Ecobot), this path shows a weak but nearly significant positive relationship. In contrast, in Study 1, involving a human-like chatbot (João), this path was not significant. This suggests a slight preference for robotic features over human-like features in chatbot services, as users are more inclined to prefer the chatbot when it has robotic characteristics.

The impact of Trust (T) also varies between the studies. T significantly influences Perceived Value (PV) in both, emphasizing the role of trust in enhancing perceived value. However, the path from T to SWI is significant only in Study 2, indicating that Trust has a stronger effect on Switching Intentions when the chatbot has robotic features. The path from T to PSI is not significant in either study. These findings suggest that in a product recommendation context, users may prefer the robotic looking chatbot, as shown by the stronger relationships between AA and SWI, and T and SWI in Study 2.

4.1 The Moderating Role of Anthropomorphic Features in Trust-Based Relationships

H1: Anthropomorphic features (names and avatars) in chatbots moderate the relationship between trust and switching intentions to human customer support.

The moderating effect of Appearance Anthropomorphism (AA) on the relationship between Trust (T) and Switching Intentions (SWI) was not statistically significant in either study (Study 1: coefficient = -0.022, $p = 0.525$; Study 2: coefficient = -0.066, $p = 0.078$). Although anthropomorphic features were expected to enhance the relationship between trust and switching intentions, the results indicate otherwise. These findings contrast with those of Tsai et al. (2021), who highlighted that human-like elements, such as names and avatars, can foster stronger relationships through familiarity and perceived trust. Additionally, Pentina et al. (2023) suggested that while anthropomorphic cues may increase user engagement, they do not always improve switching intentions.

H2: Anthropomorphic features (names and avatars) in chatbots moderate the relationship between trust and perceived value of the chatbot service.

Similar to H1, the moderating effect of anthropomorphic features on the relationship between Trust (T) and Perceived Value (PV) was not significant (Study 1: coefficient = 0.028, p = 0.607; Study 2: coefficient = -0.026, p = 0.586). While anthropomorphism directly influences perceived value, it does not amplify the trust-perceived relationship. Previous research by Adam et al. (2020) emphasized that anthropomorphic design cues, such as human-like communication, increase compliance and social presence. However, this study shows that those features do not strengthen the trust-value relationship, challenging earlier suggestions by Li and Wang (2023), who proposed that anthropomorphism may improve perceived service value through a stronger trust framework.

H8: Anthropomorphic features (names and avatars) in chatbots moderate the relationship between trust and parasocial interaction.

The moderating effect of Appearance Anthropomorphism (AA) on the relationship between Trust (T) and Parasocial Interaction (PSI) was not significant in either study (Study 1: coefficient = 0.063, p = 0.201; Study 2: coefficient = 0.057, p = 0.334), rejecting H8. This result suggests that while anthropomorphic features directly foster parasocial interaction, they do not significantly enhance the role of trust in shaping these emotional bonds. This aligns with the research by Li and Wang (2023), who suggested that parasocial interaction relies more on relational dynamics such as perceived social presence and friendliness rather than trust. Additionally, Adam et al. (2020) pointed out that verbal anthropomorphic cues can increase compliance and perceived presence but may not necessarily affect trust-based emotional interactions.

4.2 The Influence of Trust on Switching Intentions, Perceived Value, and Parasocial Interaction

H3: Trust in chatbots influences users' switching intentions to human customer support.

Trust (T) did not significantly affect Switching Intentions (SWI) in Study 1 (coefficient = 0.033, p = 0.552), but a weak yet significant effect was observed in Study 2 (coefficient = 0.149, p = 0.032). This indicates that trust plays a more pronounced role in users' decisions to remain with robotic chatbots rather than switch to human-like ones. This aligns with Choung et al. (2022), who found that trust in AI technologies is crucial in driving continued user engagement with automated services. However, the lack of a strong predictive effect in Study 1 reflects the findings of Wang et al. (2023), who noted that trust in chatbots may not always reduce switching rates, especially when users prefer human support for more complex tasks.

H4: Trust in chatbots positively influences users' perceived value of the chatbot service.

Trust (T) significantly influenced Perceived Value (PV) in both studies (Study 1: coefficient = 0.374, p = 0.000; Study 2: coefficient = 0.363, p = 0.000), supporting H4. Trust was shown to enhance users' perceptions of the value provided by chatbot services. This finding is consistent with Zhao and Wang (2021), who demonstrated that trust in AI technologies positively shapes perceived value. Moreover, Ebrahimi et al. (2022) emphasized that trust is critical in both interactive and non-interactive chatbot systems, significantly impacting how users perceive the quality of the recommendations they receive. This result underscores the idea that trust is essential in establishing perceived value, particularly when users rely on chatbots for efficient and accurate service.

H5: Trust in chatbots positively influences parasocial interaction between users and chatbots.

The relationship between Trust (T) and Parasocial Interaction (PSI) was not statistically significant in either study (Study 1: coefficient = 0.118, p = 0.069; Study 2: coefficient = 0.105, p = 0.123), rejecting H5. This result suggests that trust alone does not enhance parasocial interaction, consistent with Youn and Jin (2021), who argued that emotional bonds between users and chatbots are more dependent on relational aspects, such as personality or social presence, rather than functional trust. Parasocial interaction appears to rely more on users perceiving the chatbot as emotionally supportive rather than just competent, supporting the earlier work by Zheng et al. (2020), who emphasized the importance of social attraction in fostering these emotional connections.

4.3 The Influence of Perceived Value and Parasocial Interaction on Switching Intentions

H6: Perceived value of chatbot services influences users' switching intentions to human customer support.

Perceived Value (PV) was a strong predictor of Switching Intentions (SWI) in both studies (Study 1: coefficient = 0.580, p = 0.000; Study 2: coefficient = 0.290, p = 0.000), supporting H6.

These findings align with the research by Sweeney and Soutar (2001), who found that high perceived value reduces switching behavior. Luo et al. (2019) similarly emphasized that customer satisfaction, driven by perceived value, can enhance loyalty and reduce the reliance on human support. Users who perceive chatbot services as valuable are more likely to rely on them, reducing their need to switch to human agents. This highlights the importance of delivering efficient and valuable chatbot interactions to minimize the likelihood of users seeking human customer support.

H7: Parasocial interaction with chatbots influences users' switching intentions to human customer support.

Parasocial Interaction (PSI) had a significant positive effect on Switching Intentions (SWI) in both studies (Study 1: coefficient = 0.336, p = 0.000; Study 2: coefficient = 0.395, p = 0.000), supporting H7. These results underscore the importance of emotional connections in chatbot-user relationships. Aw and Labrecque (2020) noted that parasocial bonds can significantly enhance customer loyalty, and these findings align with their conclusions. Users who develop emotional attachments with chatbots are less inclined to switch to human support. This also reinforces the work by Pentina et al. (2023), who highlighted that parasocial interaction leads to higher engagement and retention in AI-driven services, making these emotional connections crucial in maintaining user loyalty.

Chapter 6

5. Conclusion

5.1 Research aims and goal

The primary objective of this study is to examine and understand the dynamics of trust in chatbots in the e-commerce sector through a product recommendation simulation. It investigates how trust, perceived value, parasocial interaction, and anthropomorphism impact customers' inclination to switch to human customer service representatives. By analyzing these relationships, the study seeks to provide a comprehensive understanding of the factors that either improve or negatively affect chatbots' capacity to improve customer satisfaction and loyalty with chatbots services.

In terms of specific goals, one main objective is to determine how users' perceptions of the value of chatbot conversations affect their trust and reduce switching intentions. Another goal is to analyze if trust facilitates parasocial interaction and influences switching intentions. Additionally, the study investigates how anthropomorphic traits in chatbots affect parasocial interaction and perceived value relationship with trust. By exploring these aspects in a product recommendation simulation, the research aims to provide practical implications for e-commerce platforms in designing and implementing chatbots, offering insights to boost customer satisfaction, loyalty, and chatbot efficacy. To conclude, the study seeks to contribute to theoretical understanding by advancing knowledge of chatbot interactions in e-commerce, incorporating concepts like anthropomorphism, perceived value, and parasocial interaction to better understand the factors influencing trust and loyalty in chatbot-mediated customer support.

5.2 Theoretical and practical contributions

This study, conducted within a product recommendation simulation, has made significant theoretical advancements in understanding chatbot interactions in e-commerce. It provides an analysis of how trust impacts perceived value, parasocial interaction, and anthropomorphism in chatbot interactions. The relationship between trust and perceived value underscores the crucial role of trust in enhancing users' perception of chatbots, as suggested by Li and Wang (2023), who emphasized that trust and perceived value are key factors in influencing consumer behavior and brand attitudes. By integrating the notion of parasocial interaction into chatbot-mediated suggestions, the study expands the theoretical framework of parasocial interactions, extending its application beyond traditional and social media to AI-driven customer service, supporting the findings of Youn and Jin (2021) on the impact of parasocial interactions in enhancing brand loyalty and consumer trust. The meaningful connections between anthropomorphism and parasocial interaction highlight the importance of this theoretical expansion, following Tsai et al. (2021), who found that anthropomorphic design significantly increases parasocial interaction and engagement. Additionally, the research confirms the relationship between perceived value and switching intentions, emphasizing the need to offer valuable experiences to establish trust and reduce the potential of switching to human customer service. This finding aligns with studies by Zhao and Wang (2021), who highlighted that perceived value enhances customer satisfaction and loyalty in service interactions. This contributes to the existing knowledge on customer loyalty and retention tactics, noting that the different levels of significance of trust in different contexts may affect user behavior, as explored by Pentina et al. (2023), who found that trust plays a critical role in consumer satisfaction with AI technologies.

Practically, the research provides valuable insights for e-commerce platforms to enhance chatbot effectiveness. By analyzing the impact of perceived value, parasocial interaction, anthropomorphism, trust on consumer switching intentions, the study suggests improvements for chatbot interfaces to meet customer needs better. For example, the preference for the robot-like appearance (Ecobot) over the human-like appearance (João) suggests that robotic characteristics may be more effective in certain contexts, particularly in industries where efficiency and functionality are prioritized, such as digital marketing automation or customer data analysis. Companies in these sectors could design chatbots with more mechanical voices, task-oriented communication, avoiding attempts to humanize the chatbot too much, which could cause discomfort due to the "uncanny valley" effect, as noted by Li et al. (2023). For example, a digital marketing agency could implement a robot-like chatbot to assist clients with scheduling meeting, obtaining campaign reports, or offering automated market reports. The chatbot could deliver quick, data-driven responses, conducting routine interactions without the need for human-like traits.

Additionally, marketers should focus on chatbot features that improve perceived value and trust through personalization. For example, a fashion retailer could employ a chatbot that recommends outfits based on the user’s browsing history and previous purchases, providing personalized and relevant suggestions that increase perceived value. This aligns with Akdim and Casaló's (2023) findings on personalized interactions positively influencing perceived value. Finding a balance between human-like and robotic features is also crucial; for example, a B2B retailer chatbot could maintain a neutral, professional tone to provide clear, concise answers, avoiding overly human-like features in emotionally sensitive situations. Furthermore, the differing influence of trust on switching intentions suggests that e-commerce platforms should adapt their communication strategies to build trust in different contexts. For instance, an online retailer could use a chatbot that transparently explains its limitations (e.g., "I'm here to assist with basic questions, but for more detailed, consult… "), which builds trust by setting realistic expectations, as suggested by Markovitch et al. (2024).

5.3 Limitations and recommendations for future research

This study has several limitations that are important to acknowledge. First, it focused on specific aspects of chatbots, such as perceived value, anthropomorphism, and parasocial interactions, excluding other potentially important characteristics like voice interaction and sophisticated problem-solving capabilities. Consequently, the results may not be as comprehensive due to this narrow focus. Second, the study was limited to the e-commerce industry, potentially missing the dynamics of chatbot interactions in other sectors like finance, healthcare, and education. Thus, the conclusions may not be generalizable beyond e-commerce. Additionally, the data were collected at a single point in time using a cross-sectional design, which limits the ability to draw conclusions about long-term effects and trends, and not accounting for changes in user perceptions and behaviors over time. Finally, the research used screenshots of simulated chatbot conversations rather than live, real-time encounters, which may affect the study's validity by not capturing the details and complexities of real-world user experiences.

To overcome these limitations and improve our understanding of chatbot interactions, future studies should consider the following recommendations. First, future research should explore additional chatbot features, such as voice interaction, emotional intelligence, contextual awareness, and sophisticated problem-solving capabilities. Investigating these features could provide a more comprehensive understanding of the factors that influence user satisfaction and chatbot effectiveness. Second, future research should be conducted across various sectors beyond e-commerce, including healthcare, banking, and education. Understanding the unique dynamics in different contexts can help tailor chatbot designs to meet specific industry needs and user expectations. Third, more research should focus on the cognitive and emotional aspects of chatbot interactions. This includes understanding how cognitive load affects user satisfaction and trust and how chatbots can more effectively identify and respond to user emotions. Additionally, future studies should investigate how internal employees perceive and use chatbots. Insights into employee interactions with chatbots can help improve internal processes, increase employee satisfaction, and enhance overall organizational efficiency. Finally, future research should examine chatbot interactions in real-time situations rather than relying on simulations. Capturing the details and complexities of live interactions would provide a deeper understanding of user experiences and chatbot effectiveness in dynamic, real-world environments

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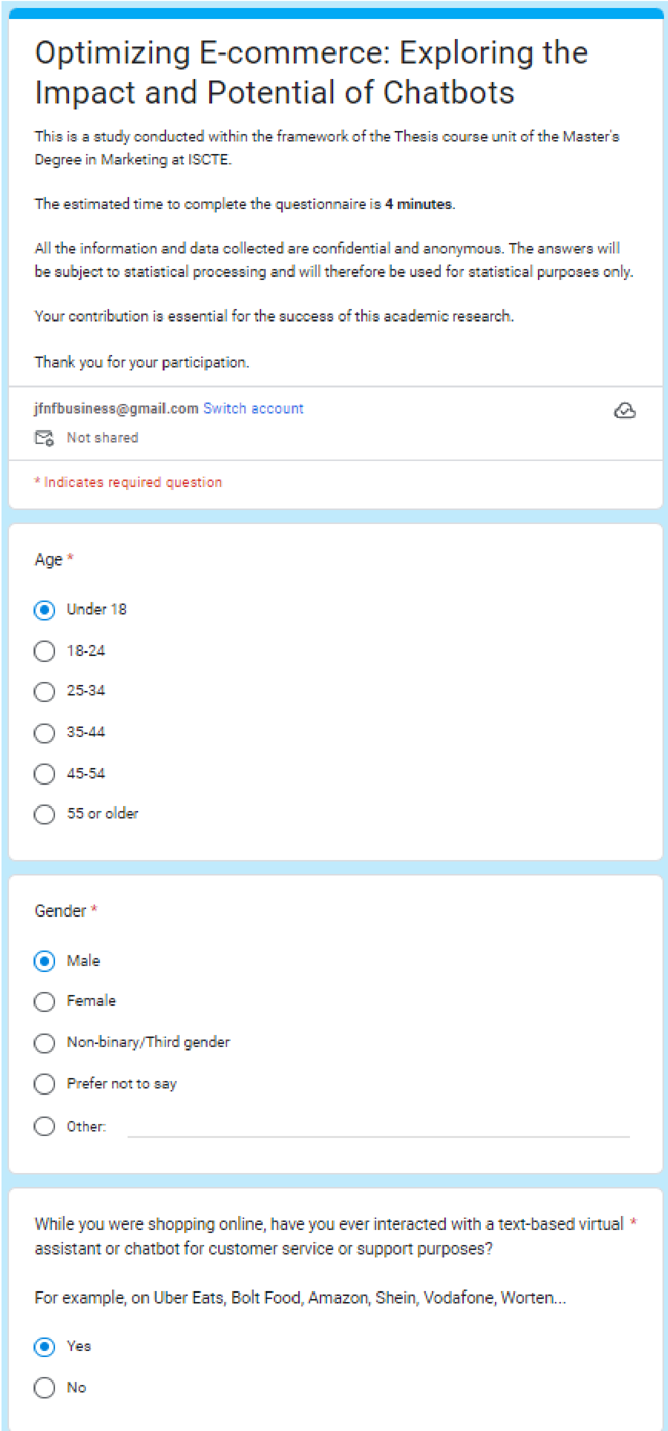
Annexes

A - Questionnaire



Optimizing E-commerce: Exploring the Impact and Potential of Chatbots

This is a study conducted within the framework of the Thesis course unit of the Master's Degree in Marketing at ISCTE.

The estimated time to complete the questionnaire is **4 minutes**.

All the information and data collected are confidential and anonymous. The answers will be subject to statistical processing and will therefore be used for statistical purposes only.

Your contribution is essential for the success of this academic research.

Thank you for your participation.

jfnfbusiness@gmail.com Switch account

Not shared

* Indicates required question

Age *

- Under 18
- 18-24
- 25-34
- 35-44
- 45-54
- 55 or older

Gender *

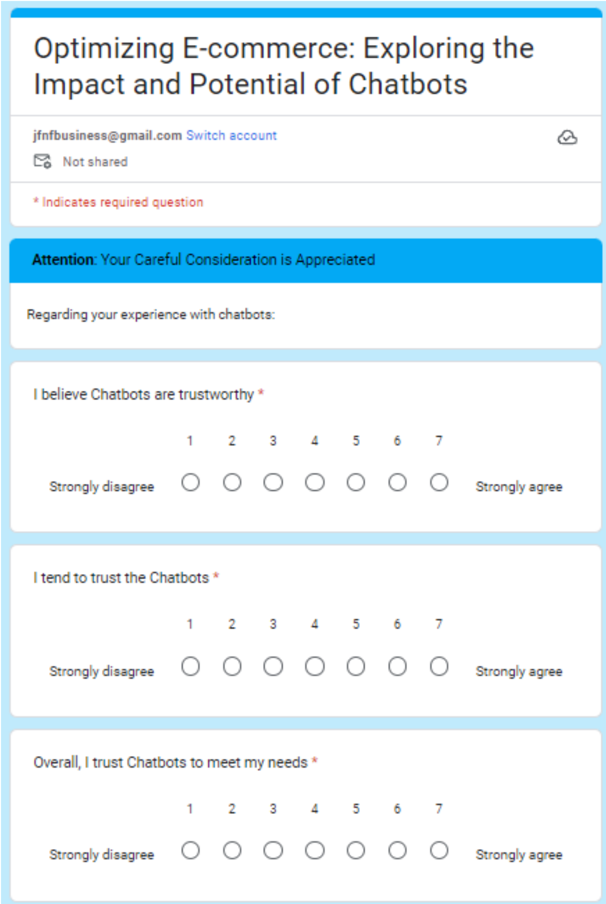
- Male
- Female
- Non-binary/Third gender
- Prefer not to say
- Other:

While you were shopping online, have you ever interacted with a text-based virtual assistant or chatbot for customer service or support purposes? *

For example, on Uber Eats, Bolt Food, Amazon, Shein, Vodafone, Worten...

- Yes
- No

Figure 4 - Section 1 of both questionnaires



Optimizing E-commerce: Exploring the Impact and Potential of Chatbots

jfnfbusiness@gmail.com Switch account

Not shared

* Indicates required question

Attention: Your Careful Consideration is Appreciated

Regarding your experience with chatbots:

I believe Chatbots are trustworthy *

	1	2	3	4	5	6	7	
Strongly disagree	○	○	○	○	○	○	○	Strongly agree

I tend to trust the Chatbots *

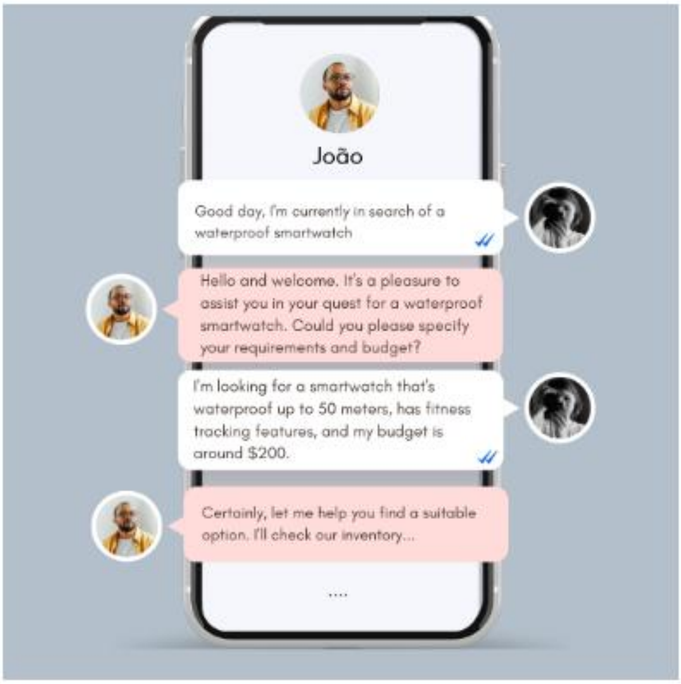
	1	2	3	4	5	6	7	
Strongly disagree	○	○	○	○	○	○	○	Strongly agree

Overall, I trust Chatbots to meet my needs *

	1	2	3	4	5	6	7	
Strongly disagree	○	○	○	○	○	○	○	Strongly agree

Figure 5 - Section 2 - Before simulation (Study 1 and 2)

Picture yourself browsing online for a waterproof smartwatch or another cutting-edge gadget and seeking assistance from João, our customer support chatbot.



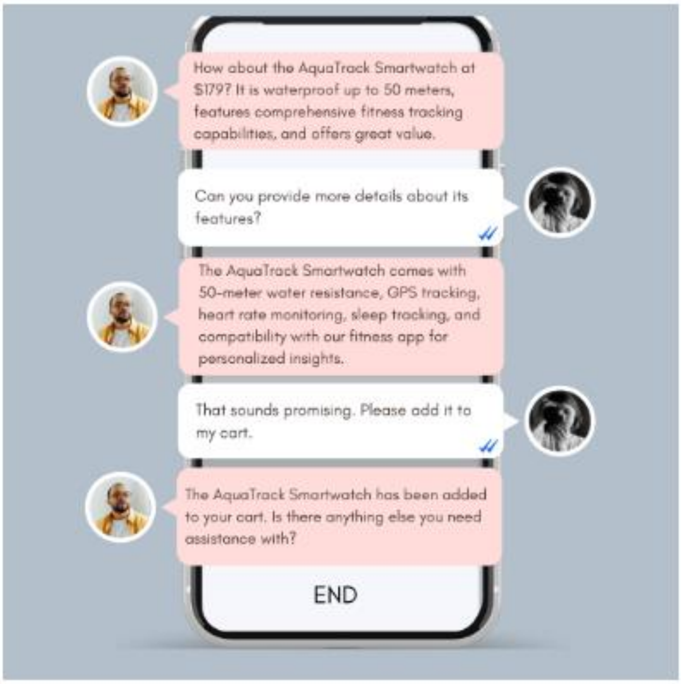
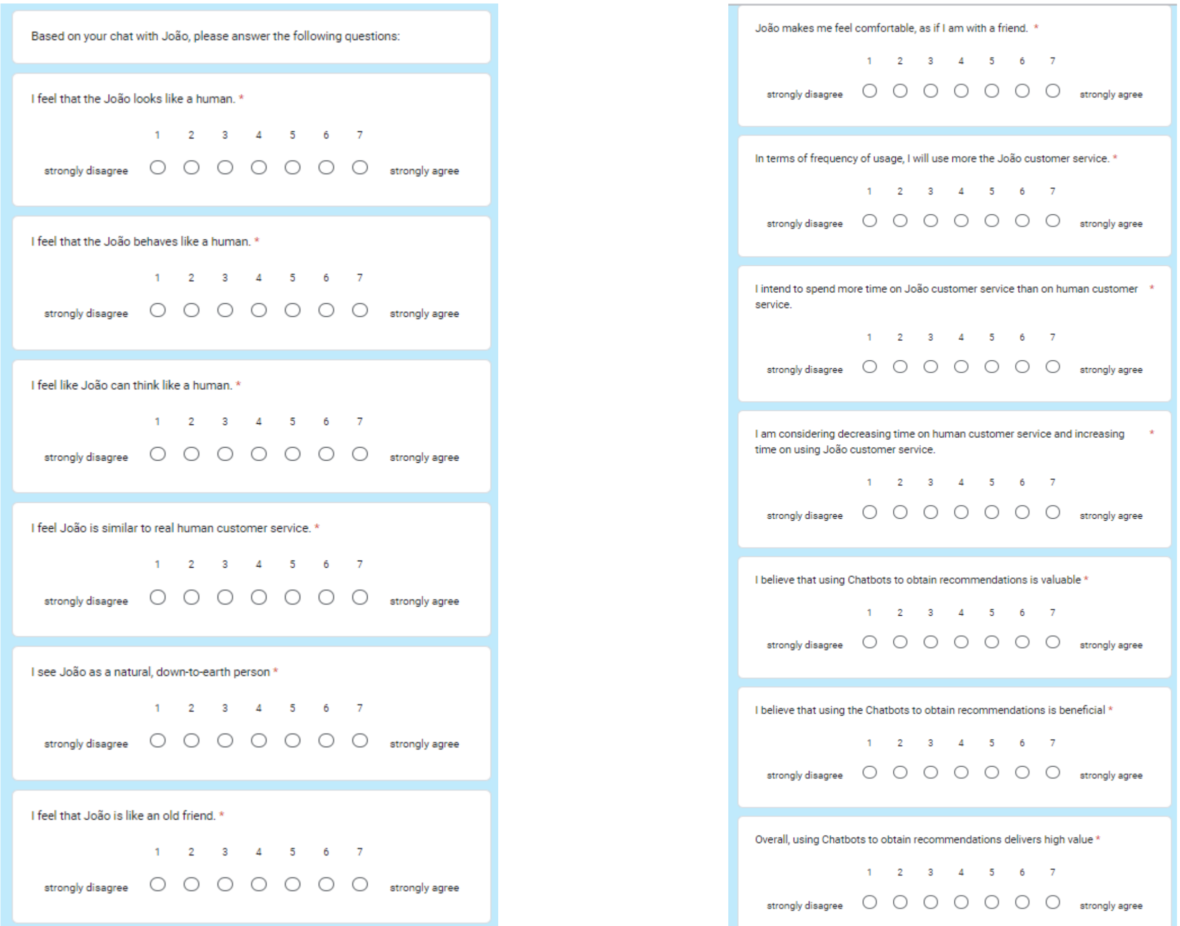


Figure 6 - Section 2 - Product recommendation simulation (Study 1)



Based on your chat with João, please answer the following questions:

I feel that the João looks like a human. *

strongly disagree 1 2 3 4 5 6 7 strongly agree

I feel that the João behaves like a human. *

strongly disagree 1 2 3 4 5 6 7 strongly agree

I feel like João can think like a human. *

strongly disagree 1 2 3 4 5 6 7 strongly agree

I feel João is similar to real human customer service. *

strongly disagree 1 2 3 4 5 6 7 strongly agree

I see João as a natural, down-to-earth person *

strongly disagree 1 2 3 4 5 6 7 strongly agree

I feel that João is like an old friend. *

strongly disagree 1 2 3 4 5 6 7 strongly agree

João makes me feel comfortable, as if I am with a friend. *

strongly disagree 1 2 3 4 5 6 7 strongly agree

In terms of frequency of usage, I will use more the João customer service. *

strongly disagree 1 2 3 4 5 6 7 strongly agree

I intend to spend more time on João customer service than on human customer service. *

strongly disagree 1 2 3 4 5 6 7 strongly agree

I am considering decreasing time on human customer service and increasing time on using João customer service. *

strongly disagree 1 2 3 4 5 6 7 strongly agree

I believe that using Chatbots to obtain recommendations is valuable *

strongly disagree 1 2 3 4 5 6 7 strongly agree

I believe that using the Chatbots to obtain recommendations is beneficial *

strongly disagree 1 2 3 4 5 6 7 strongly agree

Overall, using Chatbots to obtain recommendations delivers high value *

strongly disagree 1 2 3 4 5 6 7 strongly agree

Figure 7 - After Simulation evaluation (Study 1)

B - Product recommendation simulation

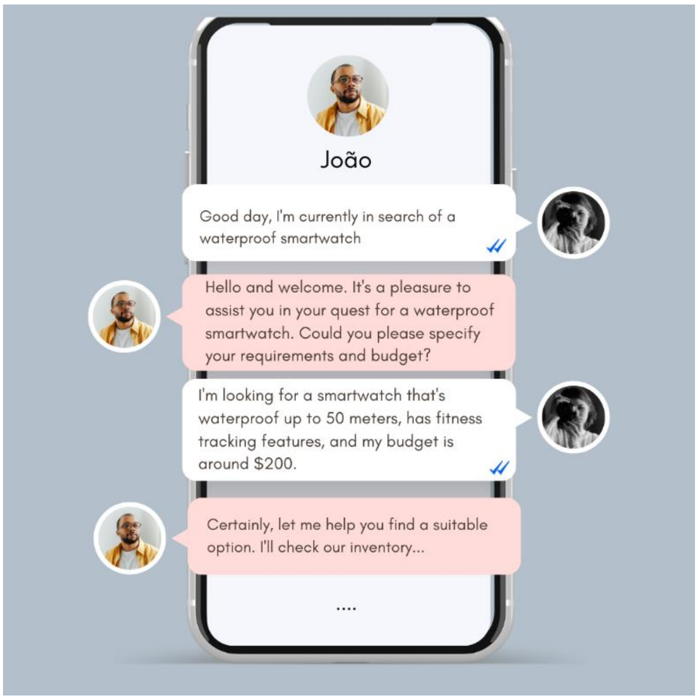


Figure 8 - Dialogue Simulation Study 1

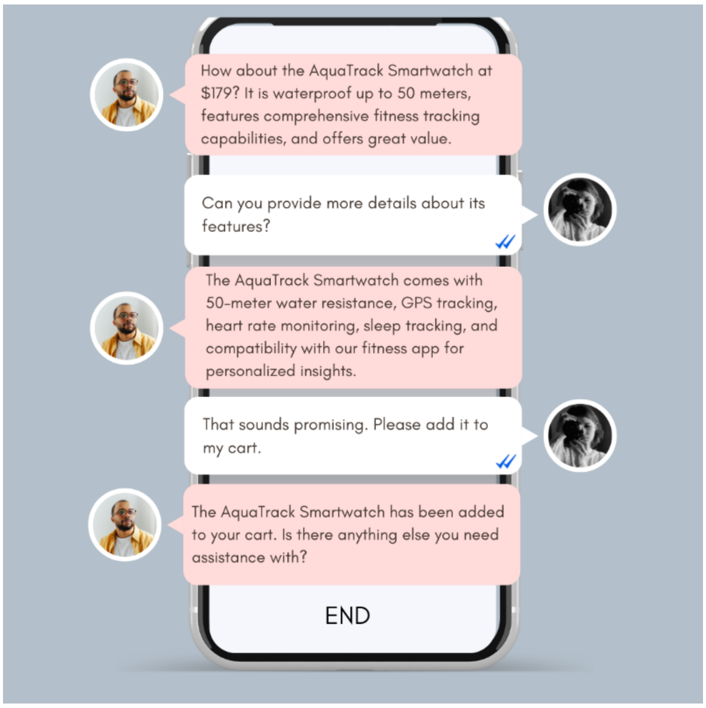


Figure 9 - Dialogue Simulation Study 1

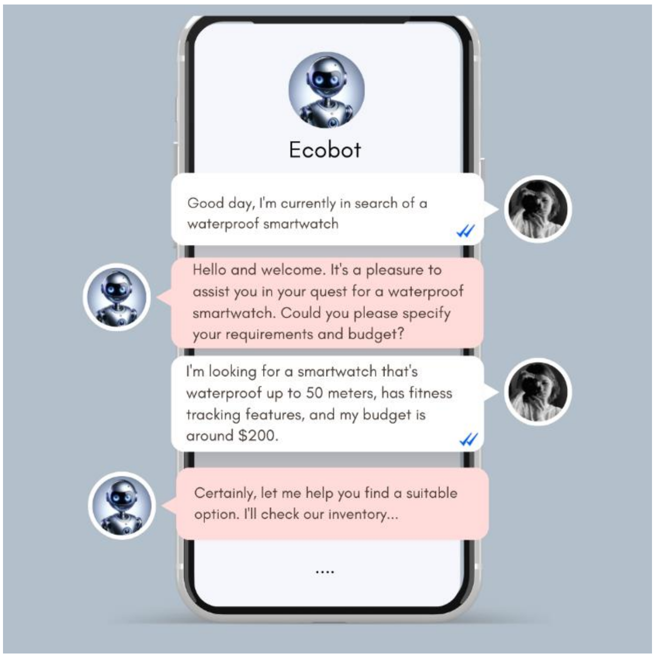


Figure 10 - Dialogue Simulation Study 2

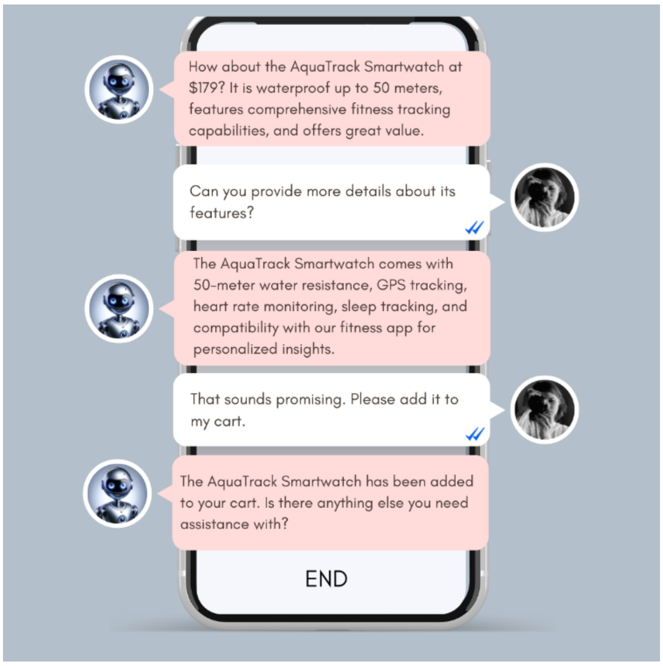


Figure 11 - Dialogue Simulation Study 2