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Exploring the Potential of Chatbots:
Insights into Consumer Preferences for Chatbots and
Chatbot Interaction Content

Chetna Johar

Supervisor: Dr Radu Dimitriu
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TRINITY BUSINESS SCHOOL
PhD in Business

DECLARATION

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ABSTRACT

The proliferation of chatbots has revolutionised customer service. By simulating human-human interaction and real-time information dissemination, chatbots enhance customer experiences while saving costs for businesses. However, despite their benefits, chatbot adoption remains limited due to user scepticism. Through a series of three studies, this PhD research aims to understand perceptions of chatbots and explores conversation styles that can mitigate negative perceptions and enhance customer experiences. Study 1 examines users' intentions to contact customer service through chatbots in comparison to alternative modes of contact. The findings reveal that consumers do not consistently exhibit positive intent for using chatbots throughout their customer journey, prompting an exploration of methods to enhance customer satisfaction in chatbot interactions. Thus, studies 2 and 3 demonstrate that chatbots utilising social interaction content (versus functional interaction content) are perceived as more empathetic by consumers, leading to increased customer satisfaction. However, two factors moderate this effect: 1) the disclosure (vs. non-disclosure) of the chatbot's identity, and 2) the successful (vs. non-successful) service outcome of the service provided by the chatbot. In cases where chatbots fail to provide the required service, chatbots utilising functional interaction content (versus social interaction content) are perceived as more competent, resulting in increased customer satisfaction. This research is the first to explore consumer perceptions of chatbots in comparison to other modes of contact across various customer

journey touchpoints. Additionally, it contributes to the existing knowledge on types of interaction content for enhancing customer experiences. This research also holds significant managerial implications as it enables companies to tailor chatbot strategies based on user intentions throughout the customer journey and implement suitable conversation styles to enhance customer experiences, thereby increasing chatbot adoption rates and improving overall customer satisfaction.

Keywords: Chatbots, Customer experience, Interaction content, Chatbot Identity Disclosure, Chatbot service failure, Interaction content, Perceived empathy, Perceived competence

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1 INTRODUCTION

Chatbots have gained widespread significance in recent years due to their potential to revolutionise customer service and enhance customer experiences. Chatbots can be referred to as social bots, conversational agents or virtual agents (Köhler, Rohm, De Ruyter, & Wetzels, 2011; Zhao, 2003). Their interaction style is designed to replicate human-human interactions and provide a human-like touch to online services (Edwards, Beattie, Edwards, & Spence, 2016; Sivaramakrishnan, Wan, & Tang, 2007). By simulating human conversations, chatbots enable consumers to obtain real-time information, answer basic inquiries, recommend products, and provide customer support (Sivaramakrishnan et al., 2007) either through natural language conversations or voice commands. These services are of enormous value, helping businesses save costs that would be traditionally spent on customer service agents.

Chatbots offer several advantages over traditional human-computer interfaces. One notable benefit is their 24x7 availability, allowing users to access information and services at any time, irrespective of time zones or geographical locations (Gelbrich, Hagel, & Orsingher, 2021; Thomaz, Salge, Karahanna, & Hulland, 2020). Chatbots possess the ability to handle large volumes of simultaneous conversations, ensuring scalability, efficiency and cost reduction (Sands, Ferraro, Campbell, & Tsao, 2021). This capability makes them particularly valuable in scenarios where a large number of users require immediate responses (Sands et al., 2021).

Furthermore, chatbots possess the ability to interact with customers in a friendly manner, unencumbered by the limitations of human emotions such as bad days, frustration, or fatigue (Luo, Tong, Fang, & Qu, 2019).

Chatbots are employed across various industries, including travel, retail, healthcare, banking, and education. For instance, in the banking sector, chatbots provide a cost-effective and efficient alternative to phone calls, assisting users with everyday banking tasks (Okuda & Shoda, 2018). Retail chatbots serve as personal shopping assistants, guiding consumers through their purchasing journey (Chung, Ko, Joung, & Kim, 2020). In the hospitality industry, chatbots are employed for various purposes, such as trip planning and virtual tour guiding (Buhalis et al., 2019; Tussyadiah, 2020).

Chatbots are expected to be the primary customer service channel for most organisations within the next few years (Gartner, 2022). Based on a survey conducted by Accenture (2018), about 57% of executives believe that chatbots can bring high ROI with minimal effort. The chatbot market which is currently (in 2023) estimated at ~5.8B USD, is projected to grow considerably at a compound annual growth rate of 29.28% to reach ~21B USD by 2032 (MordorIntelligence, 2023).

In spite of the various benefits that chatbots provide, businesses encounter substantial challenges due to scepticism from consumers (Mariani, Hashemi, & Wirtz, 2023; Van Pinxteren, Pluymaekers, & Lemmink, 2020). These challenges stem from a negative perception of chatbots, which can

be attributed to several factors encompassing design, user expectations, contextual considerations or environmental influences (Mariani et al., 2023). However, despite these obstacles, chatbots continue to hold significant commercial value. Consequently, it is imperative for businesses to address the negative perceptions surrounding chatbots and overcome the associated challenges. This necessitates designing chatbots in a way so that their customer interactions ensure positive customer experience and drives consumer adoption.

This research aims to provide a better understanding of consumer's perception towards text-based chatbots. It also explores ways (specifically conversation styles adopted by chatbots) to enhance the customer experience in order to fully leverage the benefits of chatbot technology.

1.1 Overview of studies

A series of three studies were conducted, with each study building upon the insights gained from the previous one.

Study 1: Exploratory study

It is estimated that one third of all online customer service interactions are chatbot-consumer interaction. This number is expected to increase particularly in the post-COVID era (Hollebeek, Spratt, & Brady, 2021; Shumanov & Johnson, 2021). Notably, business leaders have expressed a belief in the future value of chatbots for their organisations within the next two years (Gartner, 2023a). Paradoxically, despite substantial investments

in chatbot technology, only a small fraction, about 8% of consumers, claim to have engaged with chatbots during recent customer service interactions (Gartner, 2023b; Statista, 2023). Moreover, recent research highlights a general preference for human agents over chatbot-based conversations (Adam, Wessel, & Benlian, 2021; Castelo, Boegershausen, Hildebrand, & Henkel, 2023; Sands et al., 2021; Sheehan, Jin, & Gottlieb, 2020).

These contrasting findings led to an exploratory study with the primary objective to understand consumers' intent to use chatbots, particularly when alternative customer service channels are available. Furthermore, the study seeks to examine how this usage intent varies across different touchpoints of the customer journey, thus providing insights into the customer experience of chatbots.

Study 2: Experimental Study

The findings of the first study reveal a consistent consumer preference for utilising alternative communication channels rather than chatbots when reaching out for customer service, regardless of the specific touchpoint in their customer journey. This discovery prompted to undertake the second study, which aimed to proactively enhance the customer experience provided by chatbots. Building upon existing research, it is evident that there is a gap in understanding how the messaging strategy and style used by chatbots can be optimised to improve the overall customer experience (Bleier, Harmeling, & Palmatier, 2019; Mariani et al., 2023). This study, specifically focused on the interaction content of chatbots, distinguishing

between two types: social and functional (Chattaraman, Kwon, Gilbert, & Ross, 2019; Köhler et al., 2011; Williams & Spiro, 1985). The social interaction content includes elements such as emojis, small talk, and a friendlier conversational style. Additionally, this research addresses the dilemma faced by companies as to whether to disclose that the customer is interacting with a chatbot (i.e., Identity disclosure of chatbots). This study finds that, especially in situations of disclosing a chatbot's identity in customer interactions, incorporating social interaction content in chatbots leads to greater customer satisfaction, which is mediated by the perceived empathy of the chatbot. Customer satisfaction is chosen as the dependent variable for this study, as it serves as a critical foundation for comprehending the customer experience as a whole (Lemon & Verhoef, 2016). Additionally, customer satisfaction represents a crucial outcome of the service encounter and reflects various consumer perceptions and attitudes throughout the journey (Meyer & Schwager, 2007; Szymanski & Hise, 2000). Moreover, customers who experience high levels of satisfaction with a service are more likely to exhibit a greater intent to use that given service (Bolton & Lemon, 1999).

Study 3: Experimental Study

Lastly, the third study focuses on investigating the boundary conditions for the proposed effect (from study 2), aiming to uncover the circumstances in which this effect may diminish or potentially exhibit a reverse pattern. In particular, the study examines the scenario of service failure (vs service success) by chatbots. By exploring this boundary condition, a deeper

understanding is gained regarding how different interaction content (social and functional) can influence the overall customer experience stemming from the service provided by chatbots. This investigation also sheds light on the factors that can either mitigate or exacerbate the impact of service failures, thereby offering valuable insights for improving customer satisfaction and optimising chatbot interactions.

1.2 Report structure

This doctoral thesis is divided into four distinct chapters, each serving a specific purpose and contributing to the overall research. This division allows for a systematic organisation of the content, providing a clear overview of the chapters and their respective contributions.

Chapter 1: Introduction

This current chapter provides a comprehensive overview of the contemporary significance of chatbots and their diverse applications. It emphasises the relevance of chatbots in various domains and outlines the overarching aim of this research. Furthermore, it presents a concise summary of the three studies undertaken for this thesis, outlining their specific objectives and the underlying motivations for conducting them.

Chapter 2: Literature Review

Chapter 2 examines the existing scholarly works on chatbots. This literature review encompasses an extensive review of pertinent studies that directly relate to the themes of this research. Additionally, this chapter identifies

gaps and limitations in the current body of knowledge and ends with the research questions addressed in this thesis.

Chapter 3: Research Design and Empirical Studies

Chapter 3 presents the underlying philosophical paradigm that underpins this research. This chapter is further subdivided into three sections, each focusing on a distinct study. Within each subchapter, the rationale and theoretical foundations for the specific study are discussed at length, followed by an exposition of the employed methodologies including research design, data collection techniques, and analysis methods. The results obtained from each study are also interpreted in relation to the research questions and theoretical frameworks.

Chapter 4: Conclusion

Chapter 4 offers a comprehensive discussion of the findings derived from the studies. Additionally, this chapter describes the contributions made by this thesis to the existing body of knowledge on chatbots, and explores potential managerial applications of the research findings. Furthermore, it delves into the future implications and potential future avenues for research. This chapter also addresses the limitations of this research.

2 LITERATURE REVIEW

2.1 Introduction

Between 1946 and 1966, the first chatbot ELIZA was developed (Weizenbaum, 1983). Using basic natural language processing techniques (NLP), the developers simulated a conversation between a computer and a human. Chatbots are natural language computer programs that replicate human language and involve interactions with customers through text-based conversations (Zumstein & Hundertmark, 2017). Unlike service robots, which are physical embodied, chatbots lack a physical presence and are solely perceptible to consumers through textual exchanges resembling SMS conversations (Söderlund & Oikarinen, 2021). They are specifically designed to facilitate human-computer interaction by emulating human-human interactions and infusing a human-like element into online interactions (Edwards et al., 2016; Sivaramakrishnan et al., 2007).

Chatbots serve as consistently available personal assistants that play a crucial role in building customer relationships, optimising customer time usage, and enhancing insights into product performance (Mimoun, Poncin, & Garnier, 2017). Due to developments in natural language processing (NLP) and artificial intelligence (AI), users engage in intelligent social dialogues with conversational agents (Godey et al., 2016; Pizzi, Scarpi, & Pantano, 2021; Van Doorn et al., 2017). The ability of chatbots to engage with customers socially differentiates them from self-service technologies (Pizzi et al., 2021; Van Doorn et al., 2017). However, current customer

service chatbots are considered low-end AI applications that possess limited learning and adaptive capabilities and rely on mechanical methods of creating relations (Huang & Rust, 2018).

The practical use of chatbots in marketing and sales has significantly increased (Chui et al., 2018). The evolution of chatbots is transforming business practices and performance, offering prospects reduced costs, improved service quality, and increased user engagement (Bavaresco et al., 2020; Wirtz & Zeithaml, 2018). Consequently, chatbots are revolutionising traditional marketing and sales activities and processes. As a result, the considerable impact of chatbots on marketing has encouraged marketing scholars to delve into various aspects, including their characteristics, customers' perceptions, intentions to adopt chatbots (Moriuchi, 2021), their role as tools supporting purchase decisions (Roy & Naidoo, 2021; Sands et al., 2021), and their influence on customer satisfaction (Chung et al., 2020). The existing literature on chatbots and conversational agents spans multiple disciplines such as marketing and consumer behaviour, psychology and marketing, human-computer interactions.

In a recent literature review conducted by Mariani et al. (2023), the available scholarly works on chatbots were categorised into two main aspects: 1) factors influencing the adoption of chatbots by individuals and 2) the consequences and outcomes resulting from the adoption of chatbots (Figure 1). Various studies have aimed to elucidate the relationships between different factors within these two elements using various

mediators, including perceived empathy, warmth, and knowledge, to explicate the underlying mechanisms of these relationships. Numerous studies have also used existing models such as the Technology Acceptance Model (TAM), Social Presence Theory, Social Response Theory, and the Uncanny Valley to explain these relationships. However, there has been extensive application of these frameworks in the literature, due to which recent studies in the domain of chatbots are not based on a singular overarching theory. This pattern is visible in prominent publications such as the *Journal of Marketing* (Köhler et al., 2011), *Journal of Business Research* (Sheehan et al., 2020), *Journal of Consumer Research* (Castelo et al., 2023), and *Marketing Science* (Luo et al., 2019), wherein studies refrain from adhering exclusively to a specific grand theory, but instead include constructs of different theories.

Similarly, publications in other esteemed journals such as *Computers in Human Behaviour* (recognised as a principal repository of chatbot literature; Araujo, 2018; Go & Sundar, 2019), and *Journal of Service Management* (Sands et al., 2020), also do not have an overarching theoretical model in their research.

Therefore, in alignment with the prevailing pattern in extant literature on chatbots, this research is also not established over an overarching theory. Instead, it advances a theory-driven framework derived from diverse theoretical domains, including Customer Experience, Human-Computer Interaction, and Agent-Customer Interaction.

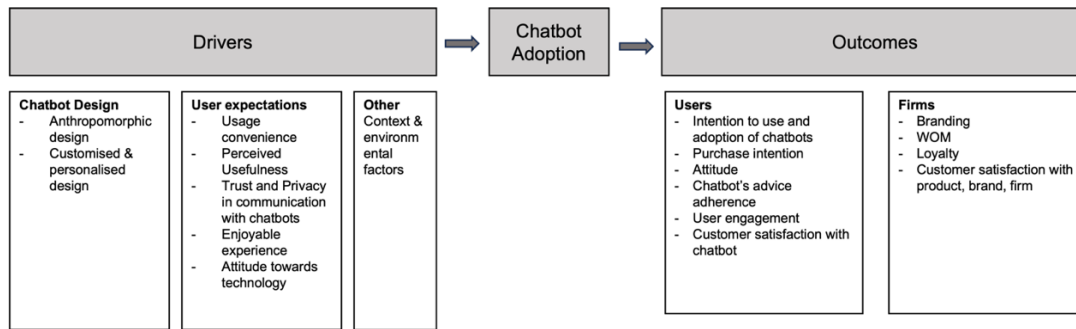


Figure 1: Drivers and outcomes of chatbot adoption (Mariani et al., 2023)

This chapter provides an extensive review of the literature relevant to this research. It initially explores diverse aspects of consumer perceptions and responses towards chatbots, subsequently focusing on the factors that influence customer satisfaction and interactions. Furthermore, the chapter examines the influence of social and visual cues, as well as interaction content, on the adoption of chatbots and their impact on consumer perceptions and satisfaction. Additionally, it investigates the perception of chatbots when they fail to fulfil consumer requests. Lastly, the chapter identifies gaps in the existing literature and formulates the research questions that are addressed in this research.

2.2 Consumer responses towards chatbots

Chatbots are programmed to handle consumer requests using predetermined procedures and algorithms (Broeck, Zarouali, & Poels, 2019). The literature on how customers respond to chatbots is nuanced. Longoni, Bonezzi, & Morewedge (2019) and Luo et al. (2019) find that as chatbots operate in a standardised manner, consumers perceive them as

lacking flexibility, innovation, uniqueness, and empathy. Consequently, it is plausible to assume that consumers would express higher satisfaction with services provided by human agents rather than chatbots. In fact, consumers generally hold a negative attitude towards chatbot-provided services, affecting their purchase intentions (Luo et al., 2019), satisfaction levels (Choi, Mattila, & Bolton, 2021; Crollic, Thomaz, Hadi, & Stephen, 2022; Yu, Xiong, & Shen, 2022), retention rates (Mozafari, Weiger, & Hammerschmidt, 2022), and usage intentions, contingent upon the service context (Longoni et al., 2019). Conversely, some studies find customers respond positively towards chatbots. Such research shows that chatbots offer functional rather than emotional responses to consumers due to their inability to experience emotions, which are preferred by customers (Araujo, 2018; Köhler et al., 2011). This functional response provided by chatbots enables consumers to develop higher perceptions of self-efficacy and feel greater acceptance towards the brand deploying the chatbot (Köhler et al., 2011).

Several studies have also examined consumer responses to chatbots compared to human agents. When a chatbot makes an error, customer satisfaction tends to decline more significantly compared to errors made by humans, as human interaction is perceived as necessary to address communication mistakes (Sheehan et al., 2020). Another study explored the use of conversation scripts by service agents, revealing that consumers prefer frontline service employees over chatbots when seeking information for customer learning, such as product details. However, for entertainment

scripts that emphasise playfulness and fun, consumers do not exhibit a significant preference shift between the two (Sands et al., 2021). In contrast, Yu et al. (2022) discovered a reverse effect, indicating a preference for chatbots over humans when service agents fail to meet consumer needs and preferences. In such cases, consumers may attribute their request rejection to the constraints of the chatbot's response rather than the agent's unwillingness to assist. Consequently, consumers may be more accepting of unresolved service requests if handled by a chatbot rather than a human. However, the study also noted that satisfaction levels shift back in favour of human agents when the agent conveys emotions to apologise. While existing studies have compared chatbots to humans, there is a lack of research comparing preferences for chatbots against other contact service media, such as emails or customer service calls, which are also managed by humans.

In relation to information provided by websites versus chatbots, it is also important to note that a chatbot will have a stronger impact on helping consumers when the information on the website is limited and not when there is detailed information on the website (Sivaramakrishnan et al., 2007). This study also explained that when a consumer has a utilitarian motive, consumers prefer to have detailed information available on the website rather than to speak with a chatbot. However, for consumers with an experiential consumption motive, the medium through which they receive the required information (website or chatbot) is insignificant. At the same time, as different consumers have different needs regarding a chatbot

(Følstad & Brandtzaeg, 2020), an online virtual agent needs to deliver on both pragmatic and utilitarian values to increase the user experience and satisfaction of consumers (Følstad & Brandtzaeg, 2020; Mimoun & Poncin, 2015).

More recent research on chatbots have also examined how consumer perception towards chatbots can be improved by adding human-like elements. Studies have validated how different cues can aid in creating a more emotional relationship between chatbots and consumers (Araujo, 2018; Go & Sundar, 2019; Przegalinska, Ciechanowski, Stroz, Gloor, & Mazurek, 2019; Sands et al., 2021; Sivaramakrishnan et al., 2007). In the subsequent sections, the exploration delves into how consumer reactions are influenced when these cues are manipulated.

Effect of Identity Disclosure

In addition, research has identified that the disclosure of a chatbot (i.e., of its chatbot identity) affects consumer interaction and the purchase decision negatively (Luo et al., 2019). Identity disclosure of chatbots can be defined as disclosing whether users are interacting with a human or a chatbot that exhibits machine-like characteristics. While there is relatively little research on this topic, a small number of papers have examined the effects of disclosing the chatbot's identity on user perceptions and behaviours.

As chatbot technology advances and chatbots become more capable of mimicking human behaviour, it becomes increasingly important for firms to understand the implications of disclosing or not disclosing the chatbot's

identity (Skjuve, Haugstveit, Følstad, & Brandtzaeg, 2019). The discussion on this topic was initiated in 2018 with Google Duplex, an intelligent phone assistant that incorporated anthropomorphic cues typically found in human conversations, such as speech disfluencies, creating an uncannily realistic experience. In 2020, Meena, a chatbot with conversational quality ratings approaching those of human conversations, was introduced by Google (Adiwardana et al., 2020). Scholars argue that in such contexts, transparency about the identity of the conversational agent is crucial for consumers to evaluate the interaction and establish trust (Donath, 1999; W. Wang & Benbasat, 2008).

However, existing empirical research on the effects of chatbot disclosure has predominantly shown negative reactions to disclosed chatbots compared to undisclosed, even when their performance is identical. This suggests that transparency about identity comes at a cost. Ishowo-Oloko et al. (2019) conducted a behavioural experiment using the prisoner's dilemma and demonstrated that bots are more effective at generating cooperative behaviour, but this efficiency diminishes once the bot's identity is disclosed. Participants in the study also maintain their negative bias towards the bot even after disclosure. Studies have also demonstrated that on disclosing the identity of chatbots, chatbots received more negative user ratings (Murgia, Janssens, Demeyer, & Vasilescu, 2016) and are considered less persuasive (Shi et al., 2020), less socially present, and less human (Hendriks, Ou, Amiri, & Bockting, 2020). Luo et al. (2019) showed that chatbot disclosure significantly reduces interaction length and

subsequent purchase behaviour. Mozafari et al. (2022) explain that in cases of high service criticality, chatbot disclosure indirectly negatively affects retention, mediated by trust in the conversational partner. However, two studies paint a somewhat different picture. One of these studies suggests that disclosing the identity of bots may have a negative impact on user experience due to feelings of uncertainty, but it did not find significant evidence that a chatbot believed to be human is perceived as less pleasant than a chatbot with disclosed identity (Skjuve et al., 2019). The second study also explored whether the positive effect of chatbot disclosure is observed only when the chatbot is unable to resolve the issue. In such cases, disclosing the identity acts as an apology to the consumer as it creates a perception of trust, thereby enhancing retention (Mozafari et al., 2022). Previous research studies have mainly observed negative responses towards disclosed chatbots, and there is a lack in research of how or when disclosing the identity can yield positive effects.

In summary, the existing body of literature primarily focuses on the negative consumer perceptions towards chatbots (Araujo, 2018; Bavaresco et al., 2020; Ciechanowski, Przegalinska, Magnuski, & Gloor, 2019; Følstad & Brandtzaeg, 2020; Go & Sundar, 2019; Luo et al., 2019). However, despite these negative perceptions, chatbots possess significant potential to engage in human-like interactions and establish social connections with humans. Consequently, chatbots are increasingly being integrated into customer service, thereby transforming the way firms cultivate relationships with consumers (Grewal, Hulland, Kopalle, & Karahanna, 2020; Mende,

Scott, van Doorn, Grewal, & Shanks, 2019). Previous research demonstrates that customers' perceptions of service technology and the outcomes it delivers, play a crucial role in their evaluation and satisfaction with the service.

2.3 Customer satisfaction from interaction with chatbots

Customer satisfaction is an important determinant of positive service encounters and represents the culmination of various customer experiences throughout the customer journey (Parcell, 2007; Szymanski & Hise, 2000). The success of a service encounter contributes to the increased perception of effectiveness and ease of use of a company's product (Jones & Sasser, 1995), influences customer choices regardless of whether the service is delivered offline or online (Shankar, Smith, & Rangaswamy, 2003), and is associated with desired outcomes such as positive word-of-mouth, customer loyalty, and intention to repurchase a product (Bitner, Brown, & Meuter, 2000). Therefore, customer satisfaction resulting from service encounters serves as a critical indicator of successful customer service for organisations (Jones & Sasser, 1995).

Several factors influence service encounter satisfaction with chatbots. These include the level of customisation and flexibility in the service encounter, effective service recovery strategies following failures, and the occurrence of spontaneous delights (i.e., pleasing experiences customers do not expect) (Bitner et al., 2000). Research studies also indicate that customer satisfaction occurs when customers perceive that products or

services meet or surpass their positive expectations (Chiou & Droge, 2006; Santini, Ladeira, Sampaio, & Pinto, 2018). In the context of this research, customer satisfaction is operationalised as the overall evaluation of the service provided by the online chat (Van Dolen, Dabholkar, & De Ruyter, 2007).

The theme of customer satisfaction regarding chatbots has received relatively limited attention within the existing literature on chatbots and conversational agents. Marikyan et al. (2022) suggest that customer satisfaction with digital assistants is influenced by various factors such as performance expectations, perceived enjoyment, intelligence, social presence, and trust. Youn and Jin (2021) explore the impact of relationship type on parasocial interaction and brand personality, with satisfaction. Their findings reveal that the brand personality (competence and sincerity) mediates the relationship between relationship type (assistant vs. friend) and satisfaction. Drawing on functionalist emotion theory and appraisal theory, Crollic et al. (2022) showed that anthropomorphism has a negative effect on the satisfaction of angry customers (compared to happy customers) during interactions with a chatbot service. Another study investigated users' affective relationships with smart voice assistants and compared user satisfaction between a chatbot system and a menu-based interface system (Nguyen, Sidorova, & Torres, 2022). This study revealed that chatbot systems result in lower perceived autonomy and higher cognitive load compared to menu-based interface systems, leading to decreased user satisfaction. Customer satisfaction with chatbot interactions

has also been studied in the luxury industry, Chung et al. (2020) proposed that chatbots provide interactive and engaging brand service encounters, which further increases customer satisfaction with chatbots.

Lee, Pan & Hsieh (2022) conducted a study based on the theory of social support to examine the factors that precede and follow customer satisfaction with communication in the context of chatbot promotion. The study aimed to identify strategies to enhance consumer purchase intention through chatbot interactions. The findings indicate that social attraction and emotional credibility play significant roles in influencing purchase intention and fostering affective attachment in consumers. A number of authors have further contributed to explain that customer satisfaction further leads to high purchase intention and chatbot usage continuation (Crolic et al., 2022; Sands et al., 2021).

In the context of text-based chatbot service interactions, research examined various factors that influence customer satisfaction. These factors include communication cues, level of expertise, and visual cues. According to previous research, communication cues such as politeness, responsiveness, and mutual understanding have been found to influence customer satisfaction (Verhagen, Van Nes, Feldberg, & Van Dolen, 2014). The study also showed the level of expertise (a core attribute of service employees) and visual cues, (such as the presence of an avatar), impact customer satisfaction. Jones, Hancock, Kazandjian & Voorhees (2022) focused on how authenticity signals are affected during chat-based service recoveries. Their research showed that female virtual assistants have

higher levels of avatar authenticity, and this impact increases when the virtual assistant is dressed professionally or comes from a different racial background than the consumers. Customer satisfaction with the chat-based service interactions was found to be favourably impacted by the improved authenticity. Roy and Naidoo (2021) conducted a study examining the preferences of users based on their present or future orientation. They found that present-oriented users tend to prefer warm and friendly chatbot conversations, while future-oriented consumers prefer conversations that exhibit competence and expertise. Another study by Sands et al. (2021) explores the impact of service scripts in chatbot conversations on customer experience satisfaction. Their findings indicate that when an education script is used, human service (compared to chatbot service) has a more positive effect on customer satisfaction. Collectively, these studies contribute to our understanding of the factors influencing customer satisfaction in chat-based service interactions, including communication cues, expertise, visual cues, authenticity signals, and script usage. Of particular interest for this research, the following sub-chapter looks at the research dealing with the usage of social and visual cues in chatbot interactions.

2.4 Social and visual cues in chatbot conversations

Numerous brands have created chatbots with human-like personas, such as Coca-Cola's "Hank" and IKEA's "Anna," both of which have human profile pictures. Scholars and designers are interested in enhancing the

human qualities of chatbots (Roy & Naidoo, 2021; Schuetzler, Grimes, & Scott Giboney, 2020) and have discovered that incorporating human attributes into chatbots can improve user experiences, foster social and emotional connections (Adam et al., 2021; Araujo, 2018). Drawing from the CASA (computers are social actors) paradigm (Nass & Moon, 2000), research also indicates that using human-like characters effectively leads users to perceive computers as possessing human characteristics, making them more susceptible to the social influence exerted by computers (Nowak & Rauh, 2005).

In the context of online shopping, consumers perceive retail websites featuring images of human representatives as more interactive and socially supportive. This leads to increased trust and stronger intentions to patronise the site (Chattaraman, Kwon, Gilbert, & Li, 2014). Studies based on physical robots also highlight the importance of anthropomorphic cues, such as gender portrayals (e.g., healthcare robots resembling female nurses or security robots resembling male guards), in enhancing perceived task suitability and competence, thereby improving user acceptance and evaluation. Previous research has also examined how visual cues (e.g., human figures) and identity cues (e.g., human names or identities), collectively known as socialisation cues, shape customer attitudes and behaviours (Araujo, 2018; Broeck et al., 2019; Go & Sundar, 2019; Köhler et al., 2011). For instance, a chatbot with a human-like name fosters a more emotional connection with the human, as compared to a chatbot with no name (Araujo, 2018; Go & Sundar, 2019). Similarly, a simple text based

chatbot creates a more human touch and lesser uncanny effects than an animated chatbot or an avatar with sound. This is a consequences of less intense psychophysiological reactions (Ciechanowski et al., 2019). If a chatbot is low on anthropomorphic visual and identity cues, the chatbot should have higher message interactivity to create a similar human touch to the chatbot (Go & Sundar, 2019). The effects of anthropomorphism on attributes of Technology acceptance Model (TAM) have also been studied, showing that anthropomorphism strongly affects the perceived usefulness of chatbots (Rietz, Benke, & Maedche, 2019).

The emerging area of research exploring the use of online agents in marketing has revealed that basic social signals can impact customer satisfaction, enjoyment, and intention to make a purchase. Several studies draw on the Social Response Theory to explain these effects. According to this theory, humans apply social norms when interacting with machines and computers (Moon, 2000; Nass, Moon, & Carney, 1999). Specifically, when humans encounter machines and computers that exhibit human-like characteristics (e.g., anthropomorphism) or social cues (e.g., interactivity), they adhere to social rules and adopt social behaviours (Reeves & Nass, 1996). These behaviours include reciprocity (Moon, 2000), politeness (Nass et al., 1999), contact between individuals with similar personalities (Nass, Moon, Fogg, Reeves, & Dryer, 1995), and interdependence among group members (Nass, Fogg, & Moon, 1996). For example, Huang and Lee (2022) applied the social response theory to investigate the underlying mechanisms behind the continued use of fintech chatbots. By examining

the interaction between social capital (social signals) and attitudes towards fintech chatbots, the study explores how consumers' continuance usage intention can be influenced. Another study by Holzwarth, Janiszewski, and Neumann (2006) explores the impact of the online agents' presence on websites and the type of online agent (e.g., attractive, expert) on customer satisfaction, attitudes, and purchase intention. Their manipulation of online agent attributes (such as attractiveness and expertise) is solely based on visual and text cues. Overall, the outcome of the study showed that higher levels of retailer satisfaction, more positive product attitude and higher purchase intentions are attained by the mere presence of an online agent. Furthermore, it finds that physically attractive online agents are more effective at moderate levels of product involvement, while expert online agents are more effective at higher levels of product involvement. In a similar study drawing on social response theory, Wang, Baker, Wagner and Wakefield (2007) utilise social cues, including written text, spoken language, an animated character with a computerized voice, and a website with limited interactivity, to demonstrate that these cues result in enhanced perceptions of flow, hedonic and utilitarian value, and increased intentions to patronize. Additionally, Adam et al. (2021) draw on the principles of social response and commitment-consistency theories. They explore how verbal anthropomorphic design cues and the foot-in-the-door technique impacts user compliance with requests from a chatbot. The study reveals that the need for consistency, combined with anthropomorphism, positively

and significantly influences the likelihood of users complying with a chatbot's request for service feedback.

Recently, scholars have also started focusing on design of discourse and communication styles to enhance the human qualities of chatbots (Go & Sundar, 2019; Roy & Naidoo, 2021). Emerging research suggests that anthropomorphic cues can enable chatbots to better fulfil the social desires of consumers seeking human interaction (Sheehan et al., 2020), which is closely related to the effects of social presence. Different authors propose that human-like language, interactive messaging, conversational skills, emotional support, and conversational styles all contribute to this goal (Gelbrich et al., 2021; Go & Sundar, 2019; Roy & Naidoo, 2021; Schuetzler et al., 2020; Sheehan et al., 2020; Shumanov & Johnson, 2021).

The development of chatbots places significant importance on their communication style (Thomas, Czerwinski, McDuff, Craswell, & Mark, 2018; Thomaz et al., 2020) as it is a controllable factor that can greatly impact consumer responses. Previous research has examined different dimensions of communication styles, considering aspects such as relationship building, social presence, and conversation structure (Araujo, 2018; Følstad & Brandtzaeg, 2020; Hill, Ford, & Farreras, 2015; Przegalinska et al., 2019). Additionally, Hill et al. (2015) note that conversations with chatbots tend to have shorter messages and use basic vocabulary compared to conversations with humans. In a study involving older individuals, it was found that less technologically proficient consumers prefer functional conversations with chatbots (Chattaraman et al., 2019).

However, as previously mentioned, many chatbots aim to build relationships with customers through informal and relational dialogues that incorporate social interactions such as greetings, addressing emotional concerns, offering social praise, and expressing well-wishes (Wilson-Nash, Goode, & Currie, 2020). These social-oriented aspects are particularly relevant but have not been thoroughly examined in the consumer behaviour and marketing literature. Additionally, there is limited understanding of how consumers respond to chatbots that are designed to establish and maintain relationships (Huang & Rust, 2021). Hence, the focus of this research revolves around two types of communication styles adopted by chatbots: social and functional interaction content, which is characterised as the way chatbots communicate.

2.5 Chatbot interaction content

The literature on agent-customer interaction has progressed since Sheth's (1976) framework, which proposed that buyer-seller interaction is driven by two key functions: interaction content and style. In the study of communication and buyer-seller interaction, interaction content has been classified as social and functional and Interaction style is classified as proactive and reactive (Williams, Spiro, & Fine, 1990). Previous research has examined these aspects in various human-human interactions, including sales interactions, online group interactions, and social media interactions. To contribute to this extensive body of literature, this research investigates the interaction content or the communication style of chatbots

and its impact on consumer responses. Similar categorisations to interaction content (as social and functional) has been applied in the field of chatbots. Köhler et al. (2011) define social interaction with a virtual agent as a conversation that does not revolve around the company's offerings, but rather focuses on other social matters. This study operationalises interaction content based on the definition provided by Go & Sundar (2019) and Van Dolen et al (2007). In this context, social interaction content is operationalised as “a conversational cue that highlights friendliness and emotions and delivers the message on a social level”. Functional content refers to “a simple back-and-forth conversational message which involves only task-related dialogue and achieves functional goals”.

A chatbot utilising social interaction content takes a more personalised approach putting more of an emphasis on addressing customers' emotional needs and building relationships while providing support. It frequently engages in relational and informal dialogues that include customary greetings, small talk, resolving emotional issues, providing social praises, and well-wishing. A chatbot with functional interaction content, in contrast, prioritises task efficiency and is goal-oriented and purposeful. The conversation is more formal and solely focused on task-related dialogues (Chattaraman et al., 2019; Keeling, McGoldrick, & Beatty, 2010; Van Dolen et al., 2007; Williams & Spiro, 1985). These social interactions can enhance the sense of closeness, extending beyond mere expressions of warmth. Both forms of communication can satisfy a customer's utilitarian demands by addressing inquiries and disseminating information about the product or

service. However, a social communication style may also address certain social needs of the customer, albeit potentially consuming unnecessary time.

Avatars are visual representations of an entity, and related research has looked at how they communicate (Holzwarth et al., 2006; Keeling et al., 2010). In their study of sales avatars and online agents, Köhler et al. (2011) discovered that using both social and functional interaction content influence customer trust, purchasing intentions, and newcomer adjustment. Foster, McLelland and Wallace (2022) examined brand avatars and revealed that social interactions facilitated by brand avatars positively impact consumer-brand relationships. Additionally, studies have shown that incorporating social cues in chatbot communication leads to more positive outcomes for users with high internet competency because they perceive the chatbot to be trustworthy (Chattaraman et al., 2019). Bleier et al. (2019) focused on web design and found that chatbots using a conversational tone, as opposed to a journalistic tone, play a crucial role in establishing social presence. Roy and Naidoo (2021) investigate warmth in chatbot conversational styles, highlighting traits such as friendliness, helpfulness, and competence. They demonstrate how these factors positively influence consumer attitudes toward the brand and purchase intentions.

These findings collectively emphasise the significant role of communication styles in shaping customers' responses. However, it remains unclear which specific communication style adopted by chatbots leads to more positive consumer reactions, warranting further exploration in future research.

2.6 Service failure in chatbots

Service failure presents significant risks for companies as it can evoke strong negative emotions and trigger vindictive coping strategies among customers (Gelbrich, 2010). Moreover, customers also expect effective measures for recovery following a service failure. However, there is a possibility of double deviation occurring if the company fails to resolve the situation adequately, leading to a secondary failure with severe negative consequences, including anger and frustration (Gelbrich, 2010). Bitner et al. (2000) propose that service failures may exhibit unique characteristics in encounters involving technology. Given the complexities and profound impact on service organizations, the research conducted by various service scholars has focused on investigating service failures specifically in the context of chatbots (Fan, Wu, & Mattila, 2016; Ho, Tojib, & Tsarenko, 2020; Lu et al., 2020; Su & Teng, 2018).

The recent literature on chatbots explores the factors that contribute to negative consumer responses when a chatbot service failure occurs. Choi et al. (2021) found that consumers tend to hold negative perceptions of chatbots due to lack of warmth following an error caused by a robot. However, they discovered that humanoid robots could compensate for a service error by offering a sincere apology, thereby restoring perceptions of warmth. Another study by Yu, Xiong, and Shen (2022) investigates how consumers react to a service failure by a chatbot compared to a human. The results indicate that consumers experience lower dissatisfaction with chatbots (compared to humans) because they have lower expectations

regarding the chatbot's ability to provide flexible services. The study also suggests that this is the case only when the chatbot does not convey emotions in its apology for rejecting requests or when consumers have had prior experience with the service of the chatbot.

However, it is important to note that existing research on service failure by chatbots has revealed that consumers do not always blame the chatbot for the failed service and their resulting frustration. Instead, consumers tend to attribute blame to the company, leading to higher levels of dissatisfaction (Belanche, Casaló, Flavián, & Schepers, 2020; Pavone, Meyer-Waarden, & Munzel, 2023). This is because chatbots are perceived as lacking intentions to fail and therefore not considered responsible (Pavone et al., 2023). Different researchers suggest that anthropomorphic visual cues may help mitigate negative attributions, promoting both problem-focused coping and emotion-focused coping strategies.

Research in this area has consistently emphasised the importance of providing service recovery efforts by service providers in order to alleviate customers' anger and frustration following a service failure (Fan et al., 2016; Mattila & Ro, 2008). Customer satisfaction with service recovery is particularly influenced by how customers are treated during the recovery process (Min, Lim, & Magnini, 2015). Chatbots are programmed to use empathic remediation strategies, such as offering apologies and explanations, to enhance customer satisfaction and trust (Sun & Guan, 2022). Additionally, the authors also found that the mediating factors of social presence and trust can influence the impact of empathic remediation

on customer satisfaction. The use of emojis in apologising has also demonstrated a positive effect on customer forgiveness (Wang, Chih, & Honora, 2023), with perceived firm sincerity and empathy mediating this effect. Based on the communication accommodation theory, Jones et al. (2022) looked at the effects of authenticity signals during chatbot service recovery. Their research suggests that an avatar is perceived as more authentic when it is portrayed as a female and dressed professionally. Higher authenticity levels drive engagement towards chatbot interactions. Drawing on inoculation theory and the elaboration likelihood model, Weiler, Matt and Hess (2022) examined the use of inoculation messages, which aim to prepare users for potential response failures. The findings indicate that inoculation messages alleviate the negative effects of chatbot response failures on users' tendency to discontinue usage.

In a study comparing service recovery provided by chatbots versus humans, the authors find that consumers perceive service recovery by a human as more sincere than that provided by a service robot, resulting in higher levels of satisfaction. Moreover, this effect is stronger among individuals with a greater need for human interaction (Hu, Min, & Su, 2021).

Considerable attention has been devoted to examining the emotions of anger and frustration experienced by consumers following a service failure involving a chatbot. In response, various service recovery strategies, including offering apologies or anthropomorphising the chatbot, have been proposed to alleviate these negative emotions. However, a previous study also found that chatbot anthropomorphising may elicit unfavourable

assessments of customer satisfaction and purchase intentions, particularly when consumers are in a state of anger (Crollic et al., 2022). Despite the extensive research on design elements in chatbots, there is a paucity of studies investigating the efficacy of using the appropriate content scripts by chatbots as a means to reduce dissatisfaction resulting from service failures.

2.7 Literature gap and research questions

The literature on chatbots has made significant strides in understanding consumer responses, customer satisfaction, social and visual cues, and service failures. However, several important gaps remain that warrant further investigation.

While the existing literature has examined consumer responses towards chatbots, there is a need to further investigate how chatbot evaluations compare to evaluations of other means of customer contact. Understanding the preference and usage intent compared to traditional customer contact channels can provide valuable insights in determining the optimal use of chatbot technology and ways to enhance customer experience.

Secondly, while studies have examined the effectiveness of different chatbot scripts and linguistic styles, little attention has been given to their potential to mitigate in mitigating negative perceptions and enhance customer satisfaction, especially when the law requires companies to disclose the identity of chatbots. At the same time, there is a gap in the literature regarding how negative consumer perceptions towards disclosed

chatbots can be mitigated using interaction content to increase customer satisfaction.

Furthermore, the above review underscores the increasing focus in the literature on service failures stemming from chatbots. Despite technological advancements, several chatbots used for customer service still fail to solve consumers' issues. Hence, it is crucial to examine whether the interaction content strategies for enhancing satisfaction with disclosed chatbots differ in the context of service failures. Investigating the impact of conversation scripts during service failures can provide insights into effective service recovery mechanisms and the restoration of customer satisfaction.

To summarise, the literature currently lacks research on comparing chatbot evaluations against other customer contact channels and understanding the communication strategies that can increase satisfaction when chatbot identities are disclosed, particularly in the context of service failures. Addressing these gaps through empirical investigations will contribute to a deeper understanding of chatbot effectiveness, design considerations, and service recovery strategies, enabling organisations to optimise the customer experiences from chatbots they are offering, and to improve customer satisfaction levels.

Given the identified gaps in the existing literature, the following research questions have been formulated for this doctoral investigation:

RQ1: How do customers' usage intent for chatbots, as a mode of contact for customer service, compare to alternative modes of contact across different stages in the customer journey?

RQ2: What types of interaction content can organisations employ to enhance customer satisfaction when the identity of the chatbot is disclosed? Does this differ in the case of a service failure (vs. a service success) by the chatbot?

To address these research questions, three distinct studies were conducted. The aim and the methodology for each study, corresponding to the formulated research questions are outlined in Table 1.

Research Question	Study and Aim	Methodology
RQ1: How do customers' usage intent for chatbots, as a mode of contact for customer service, compare to alternative modes of contact across different stages in the customer journey?	<i>Study 1:</i> To explore consumers' intent of using chatbots as compared to other modes of contact, and to ascertain whether usage intent for chatbots varies across distinct touchpoints within the whole customer experience.	1. Conjoint Analysis 2. Experiment
RQ2: What types of interaction content can organisations employ to enhance customer satisfaction when the identity of the chatbot is disclosed? Does this differ in the case of a service failure (vs. a service success) by the chatbot?	<i>Study 2:</i> By investigating interaction content (social vs functional), the study aims to identify strategies that can improve the chatbot experience and mitigate the unfavourable perception associated with this mode of contact.	Experiment
	<i>Study 3:</i> To examine whether the utilisation of social interaction content (versus functional interaction content) in chatbots amplifies customer satisfaction or if this effect is reversed, in the event of a chatbot service failure.	Experiment

Table 1: Mapping of Research Questions

3 RESEARCH DESIGN AND EMPIRICAL STUDIES

3.1 Philosophical paradigm

This research adopts a positivist perspective, grounded in the ontological assumption of realism. From this standpoint, there is “an external reality, consisting of things, and/or events and/or states of affairs, which are controlled by natural or social law” (Blaikie, 2007, p. 14). Positivism serves as a valuable framework for investigating social phenomena, emphasising observable facts, causal relationships, and adherence to the scientific method. In this section, a connection is established between the researcher’s philosophical stance and the specific research conducted by delving into the epistemological, ontological, and methodological aspects, elucidating how positivism guides and informs the course of this research.

3.1.1 Research philosophy

Positivism is a philosophical system that places significant emphasis on empirical evidence as the fundamental basis of knowledge. It perceives reality as stable and amenable to objective observation (Guba & Lincoln, 1994). The positivist paradigm maintains that facts are derived from systematic observation and measurement, forming the groundwork for reliable and valid conclusions (Holden & Lynch, 2004), while advocating for the utilisation of the scientific method and quantitative approaches generate objective, value-free knowledge (Cole, Chase, Couch, & Clark, 2011; Saunders, Lewis, & Thornhill, 2009). Positivism also believes that objectivity

enhances the credibility of social science research by producing knowledge independent of personal beliefs or preferences. In a positivist paradigm, the researcher's independence allows the data to objectively portray a measurable and external reality, emphasising that the data tells the story (Remenyi, Williams, Money, & Swartz, 1998).

3.1.2 Research process and methodology

In adopting a positivist stance, the researcher believes that a quantitative approach is essential for gaining insights, driven by the necessity to systematically test relationships between constructs and formulate hypotheses. The positivist paradigm, with its emphasis on deductive reasoning, hypothesis testing, and the exploration of causal relationships, serves as a methodological compass, ensuring a structured and objective inquiry. This research also follows the positivist principle that objectivity ensures findings that are free from personal biases or preferences. This research believes in the view that quantitative methods are indispensable for generating generalisable theories and laws that can explain social phenomena and predict their outcomes (Park, Konge, & Artino, 2020; Saunders et al., 2009).

The two research questions proposed for this research exemplify the need for a positivist approach. For instance, RQ1 delves into systematically investigating consumer preferences among established modes of contact. The adoption of a positivist paradigm, rooted in empirical evidence and objective analysis, is well-suited for the study's objectives. By focusing on

the systematic exploration of known variables, such as various modes of contact, and their impact on consumers' usage intent, the research aligns with the positivist commitment to collecting measurable, observable data. The integration of quantifiable variables and statistical analysis, inherent in positivism, resonates with RQ1's objective to measure usage intent and analyse its relationship with different modes of contact. The research design implemented for RQ1 (conjoint analysis and experimental studies) underscores positivism's foundational tenets, such as replicability and predictability, by providing consistent and generalisable results through a controlled and structured methodology. In essence, the emphasis on observable phenomena, an important aspect of positivism, is evident in RQ1's grounding in the observation and measurement of real-world consumer behaviours and preferences.

In conclusion, by adopting a positivist perspective, this research employs specific techniques, including conjoint analysis, experimental studies, and hypothesis testing experiments. These methods prioritise the systematic collection of empirical evidence, maintaining objectivity and value neutrality. The research adheres to rigorous methodologies to gather observable, measurable, and replicable data. By adhering to the positivist principles, this research contributes to the accumulation of reliable knowledge in social science. These research methodologies allow patterns to emerge, explain causal relationships, and make predictions based on empirical evidence. The use of these methods ensures the reliability and validity of findings, reinforcing the overall positivist approach adopted in this study.

3.2 STUDY 1

The use of chatbots in customer service has gained significant attention in recent years. As businesses strive to enhance customer experiences and streamline communication processes, understanding consumers' intent of using chatbots becomes crucial. This study aims to explore consumers' intent of using chatbots as compared to other modes of contact. Additionally, it also endeavours to ascertain whether usage intent for chatbots vary across distinct touchpoints within the whole customer experience.

3.2.1 Theoretical rationale and purpose of the study

To understand the customer experience of a consumer, early developments in the literature of customer experience began with the creation of models to understand the buying behaviour of consumers. These included models such as the AIDA Model (Attention, Interest, Desire, and Action) or the multichannel customer management model (Howard & Sheth, 1969; Neslin et al., 2006). The subsequent development of these models laid the groundwork for the concept of "customer purchase journey". Building on the existing models and research on customer experience, Lemon and Verhoef (2016, p. 74) defined customer experience as "a customer's journey with a firm during the purchase cycle across multiple touchpoints".

Customer journey touchpoints that constitute the customer journey are further defined as "any occasion when a consumer encounters the brand

and product- from actual experience to personal or mass communications to casual observation” (Kotler & Keller, 2016, p. 88). From an academic and a managerial perspective, past research has conceptualised customer journey touchpoints into three stages: pre-purchase, purchase, and post-purchase (Lemon & Verhoef, 2016; Neslin et al., 2006; Puccinelli et al., 2009). The pre-purchase stage involves interactions that occur before the actual purchase, while the purchase stage includes interactions related to placing the final order and payment. The post-purchase stage comprises interactions with the brand after the purchase, such as service, feedback, and repurchase. Despite the extensive research on customer journey touchpoints, the current research does not address customer journey touchpoints for interacting with a chatbot.

Another aspect of customer journey is the multichannel, which means that consumers have a choice of multiple channels to choose across different phases in the customer experience (Lemon & Verhoef, 2016). The preference and usage of these channels or modes of contact differ for consumers across the different stages of the customer journey. Kotler and Keller (2016) have identified key modes of contact in the current era, including e-mail, call centers, databases, database software, and websites. Additionally, interactions with employees play a central role in customer experiences with brands, whether it involves emailing customer support, calling customer service, or engaging with retail or sales representatives face-to-face (Meyer & Schwager, 2007). Based on these findings in the

literature, mode of contact has been defined as the different media through which customers can interact with customer service.

Existing research shows consistent and strong evidence that consumers have a lower preference for chatbots compared to interactions with human agents (Castelo et al., 2023; Sands et al., 2021; Sheehan et al., 2020). Additionally, one study has specifically compared chatbots with information on websites as an alternative medium (Sivaramakrishnan et al., 2007). There is a paucity of studies that explore the comparison between chatbots and other modes of contact for customer service.

Therefore, considering the significance of different customer journey touchpoints in the customer journey and the various modes of contact, this study aims to investigate two important aspects:

1. To determine consumers' intent to use chatbots over other available modes of contact for customer service
2. To examine whether the observed usage intent for chatbots (vs other modes of contact) varies across distinct touchpoints within the customer journey

3.2.2 Research design and sample

This study utilises two separate studies to investigate the intent of consumers using chatbots as a contact medium compared to other modes of contact, in relation to different touchpoints in the customer journey. The first study conducted is an exploratory study via a conjoint analysis. The choice of an exploratory design is based on a lack of literature examining

consumer preferences towards chatbots relative to other modes of contact. The conjoint study explores consumers' usage intent towards using chatbots as a mode of contact in comparison to other modes of contact. The second study is an empirical study through an experiment which further developed on the results of the conjoint analysis and investigates the consumer intent of using chatbots (as compared to other modes of contact) at different customer journey touchpoints.

Both the studies aim to explain the dependent variable of consumers' intent of using a specific contact medium for a given touchpoint (or stages) in the customer's journey. Additionally, the studies aim to determine if there was a difference in consumer responses based on whether the brand was luxury or affordable. Hence, three independent factors were utilised for these studies: 1) mode of contact, 2) customer journey touchpoints, and 3) brand type (luxury vs affordable). These variables are defined on different levels based on the existing literature (explained in the subsequent section).

Data for both studies were collected through Amazon's Mechanical Turk, an online platform chosen for its potential to provide a more diverse and representative sample of the population than traditional data collection methods (Buhrmester, Talaifar, & Gosling, 2018; Mason & Suri, 2012). To ensure data quality, only workers with an acceptance rate higher than 99% were distributed the survey (via Qualtrics), and a small monetary incentive was offered to participants. Prior to data collection, ethical guidelines were followed as set forth by the Trinity College Dublin Ethics Committee and Amazon MTurk. Participants voluntarily engaged in the survey through their

MTurk dashboard, with their anonymity protected by MTurk. At the start of the survey, participants were informed: "The data will be kept with the researcher solely. Data from this research project may be published in future". Data pre-processing involved two steps: 1) deleting incomplete responses and, 2) removing spurious data (responses that had same rankings for all profiles). The conjoint analysis had 513 participants, while the experimental study had 254 participants after data pre-processing (data was initially collected from 588 and 291 participants, respectively).

3.2.3 Manipulations & measurement

Customer journey touchpoints

Previous research on customer experience, such as Jüttner, Schnaffer, Windler and Maklan (2013), has identified different touchpoints in the customer journey for a hotel, including decision-making, reservations, arrival and check-in, room check-in, hotel stay, on-site experiences, check-out, and good-bye, and time after the stay. Similarly, Kotler and Keller (2016) defined the touchpoints in the customer journey for staying at a hotel as involving reservations, check-in and checkout, frequent stay programs, room service, business services, exercise facilities, laundry service, and bars. Based on these studies and the description of three stages of customer journey by Puccinelli et al. (2009) and Neslin et al. (2006), this research categorises the customer journey touchpoints for staying at a hotel and purchasing a watch and captures them as a categorical variable with different levels, as shown in Table 1.

Mode of contact

Existing research has compared chatbot interaction with alternative modes of contact, such as website content (Sivaramakrishnan et al., 2007), and human agents (Castelo et al., 2023; Sands et al., 2021; Sheehan et al., 2020). Additionally, Sampson and Chase (2020) delved into the importance of technology-mediated modes of contact, including telephone and email, as crucial modes of customer contact in the digital world. Based on existing research comparing alternative modes of contact for chatbots and those that are relevant in today's world, this study categorises modes of contact on four distinct levels as shown in Table 2.

Consumer usage intent

The dependent variable of consumer intent of using a particular mode of contact at a given touchpoint in the customer journey is measured on a Likert scale ranging from 0 (Extremely unlikely) to 10 (Extremely likely). To ensure precision and simplicity, a single-item scale was chosen for its better predictive validity and ease of study execution (Bergkvist & Rossiter, 2007; Bergkvist, 2015). Additionally, the adoption of an 11-point scale enhances sensitivity, capturing subtle variations in intent, while the 0 to 10 range is familiar and relatable to participants, promoting a more intuitive assessment and normality in data distribution (Churchill & Peter, 1984; Leung, 2011).

Variables	Purchasing a Watch	Hotel Stay
<u>Customer Journey touchpoints</u>	• <i>Pre-purchase:</i> Enquiring about product features • <i>Pre-Purchase:</i> Enquiring on Product availability • <i>Purchase:</i> Payment error during the purchase • <i>Post-purchase:</i> Enquiring about delivery/ refund/ exchange • <i>Post-purchase:</i> Providing feedback • <i>Post-purchase:</i> Seeking product service	• <i>Pre-booking:</i> Enquiring about room type & amenities offered • <i>Pre-booking:</i> Enquiring on availability of room • <i>Booking:</i> Payment error during booking • <i>Post-booking:</i> Amending the booking by cancelling or changing dates • <i>Post-booking:</i> Checking- in/ Checking- out of the hotel • <i>During Stay:</i> Ordering room service • <i>Post stay:</i> Providing feedback
<u>Mode of Contact</u>	• Chatbot (through the watch producer's website/ social media) • Customer service call • Watch producer's website/ FAQ page • Email	• Chatbot (through the hotel's website/ social media) • Customer service call • Hotel's website/ FAQ page • Email

Table 2: Study 1: Variables and its levels

3.2.4 Conjoint study

3.2.4.1 Procedure

The study employed a traditional conjoint analysis to investigate the relative importance of various attributes associated with customer service.

Conjoint analysis is a statistical technique that employs a set of attributes, each with their own levels, to generate part-worth utilities for each attribute and its components (Green & Srinivasan, 1978). The objective of this study was to investigate which attributes are deemed significant by consumers in the context of contacting customer service. The study was conducted following the procedures outlined by Green and Srinivasan (1990) for conjoint analysis.

Following the identification of the three attributes (Mode of contact, Customer journey touchpoints, brand type) and their respective levels, the study provided 48 profiles ($4 \times 6 \times 2$) for scenario of purchasing a watch and 56 profiles ($4 \times 7 \times 2$) for hotel stay. However, to eliminate potential bias and enhance efficiency, an orthogonal design that balances each attribute and its levels was developed (Carmone, Green, & Jain, 1978). This fractional factorial approach generated 32 profiles for each scenario, which were subsequently categorised into 16 profiles for luxury and 16 profiles for affordable hotels and watches, simplifying the task for the respondents. The participants were randomly assigned to the scenario of purchasing a watch ($N = 247$) or staying at a hotel ($N = 266$) and were asked to rate their usage

intent for different modes of contact at different touchpoints in the customer journey.

The traditional conjoint analysis utilised in this study adopted a decompositional approach (Rao, 2014), requiring respondents to evaluate the full description of a profile based on different attributes rather than a single attribute (Green & Srinivasan, 1978; Murry Jr & Heide, 1998). Each profile presented to the respondents comprised a combination of different levels of each attribute, and respondents ranked the intent of using a mode of contact at that particular situation on a Likert scale ranging from 0 (Extremely unlikely) to 10 (Extremely likely), as depicted in Figure 2.

Consider the case of buying a **luxury watch**, imagine you have to contact the watch producer **before purchasing to enquire about product availability in-store and online.**

0
Extremely unlikely 1 2 3 4 5 6 7 8 9 10
Extremely likely

How likely are you to contact the watch producer **via a chatbot** (through the watch producer's social media page or website)?

☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐

Figure 2: Study 1: Example of the situation presented in conjoint analysis

In order to promote thorough reading of each profile and accurate ratings, a minimum assessment time of 5 seconds was enforced for each profile. Additionally, to mitigate the influence of order effects on the results, the

order in which the 32 situations were presented to each respondent was randomised.

3.2.4.2 Data Analysis

The conjoint study utilised SPSS 26 to analyse collected data. The study rated hypothetical situations (different profiles) on the same scale to determine the relative importance of each attribute and the corresponding utility of each attribute level (Rao, 2014). To calculate the importance weights, the part-worth value of each attribute was divided by the total range of attributes (Green & DeSarbo, 1978). The results indicated that the mode of contact was the most important attribute for both the watch and hotel scenarios ($W_{\text{watch}} = 52.58$, $W_{\text{hotel}} = 54.25$) (Table 3). This means that when purchasing a watch or staying at hotel, consumers give maximum importance to the mode through which they contact the customer service.

	Hotel	Watch
<u>Mode of contact</u>	54.25	52.58
<u>Customer Journey Touchpoint</u>	36.36	36.02
<u>Brand Type</u>	9.40	11.42

Table 3: Study 1: Importance weight of attributes

Conjoint analysis also provided part-worth utilities for each level of an attribute, with higher utility indicating higher usage intent. The part-worth

utilities for the mode of contact are noted for this analysis (as the most preferred attribute and for this research) (Table 4).

	Hotel	Watch
<u>Chatbot</u>	-0.971	-0.328
<u>Customer service call</u>	1.043	-0.338
<u>Website/ FAQ</u>	0.83	1.069
<u>Email</u>	-0.902	-0.403

Table 4: Study 1: Utility scores of levels of mode of contact

The results showed that for the hotel scenario, chatbots have the lowest utility of -0.971 implying that consumers prefer chatbots the least when they contact the hotel. For the watch scenario, chatbots are the second most preferred mode of contact, but with a negative utility score of -0.328 and with a negligible difference in scores with the other two modes of contacts. Since the order of ratings for the different modes of contact are similar or with very little difference, the experiment study uses the scenario of hotel stay only.

The use of an orthogonal design and rating preferences on a scale in the conjoint study had limitations as the interaction between variables could not be evaluated. Therefore, an experimental study was conducted to address this limitation.

3.2.5 Experiment study

3.2.5.1 Procedure

The study employed a mixed experimental design with a 2 (Brand type) x 7 (Customer journey touchpoint) x 4 (Mode of contact) structure, with brand type as a between-subjects variable and customer journey and mode of contact as within-subjects variables. The use of a within-subjects design was deemed advantageous due to its ability to reduce random error and increase statistical power, while also requiring fewer participants (Singleton & Strait, 2010).

The respondents through random allocation were divided into two groups and each group received one treatment of brand type (Luxury or Affordable hotel). The treatment was explained to the participants through a vignette (Table 5).

Treatment	Vignette
<u>Luxury Hotel</u>	The survey looks at a case of booking and staying at a particular type of hotel. Each question in the survey includes situations of contacting a company for different purposes and via different media. In this part of the survey, please consider the case of booking and staying at a luxury hotel
<u>Economy Hotel</u>	The survey looks at a case of booking and staying at a particular type of hotel. Each question in the survey includes situations of contacting a company for different purposes and via different media. In this part of the survey, please consider the case of booking and staying at an economy hotel

Table 5: Study 1: Vignettes for treatment on brand type

Each respondent from both the groups was then provided with the full within-subject design (that is a total of 28 profiles (4 x 7)). These manipulations are presented in the form of situations of interacting with the customer service (through different modes of contact) of a hotel for different touchpoints in the customer journey.

The participants were asked to rate the situations on the dependent variable of consumer usage intent on the Likert scale (Figure 3). Figure 4 explains the design of this experiment.

Considering the case of booking and staying at an **economy hotel**, imagine you have to contact the hotel **after making the booking to enquire about check in and check out process.**

0
Extremely unlikely 1 2 3 4 5 6 7 8 9 10
Extremely likely

How likely are you to contact the hotel **via Email**?

☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐

Figure 3: Study 1: Example of situation presented to the respondents

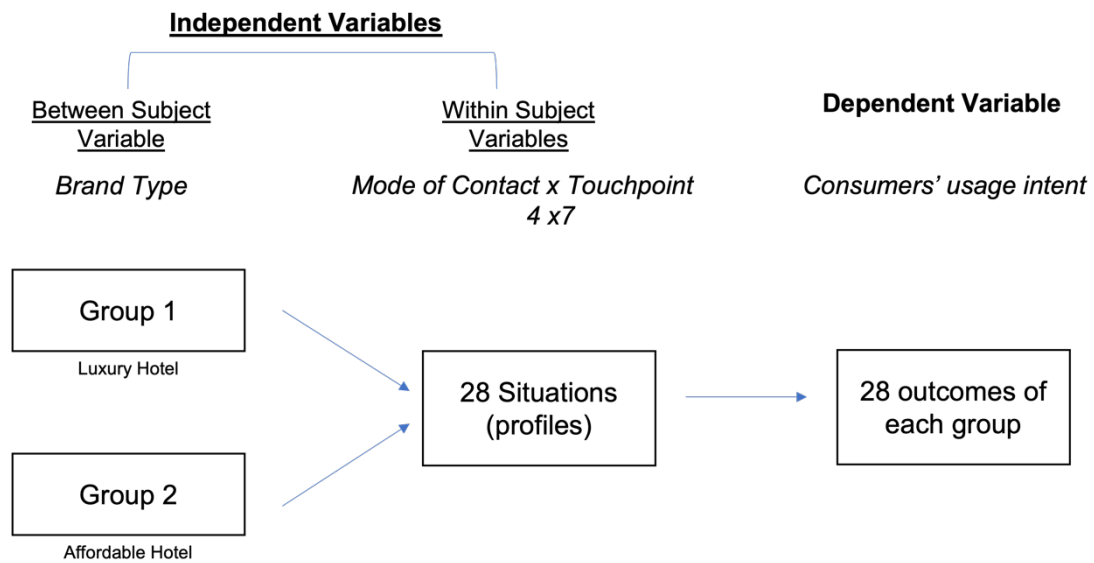


Figure 4: Study 1: Experiment design

Controls

To rule out alternative explanations for the study, the following control was used:

Order effect in Experiments

In an experimental design, the problem of question order effects may arise, which means that the response may vary on the order of the questions presented (Cook, Campbell, & Shadish, 2002). To control for these order effects, the method of randomised ordering of situations was used for each respondent.

3.2.5.2 Data Analysis

The collected data was analysed through mixed between-within subjects ANOVA. For the interaction effects, the results showed no significant three-

way interaction between brand type, mode of contact, and the customer journey touchpoint on consumer usage intent, (Wilks' Lambda = 0.94, $F(18,235) = 0.79$, $p = 0.7$, partial eta squared (η_p^2) = 0.06). However, highly significant two-way interaction is observed between the mode of contact and customer journey touchpoint (Wilks' Lambda= 0.50, $F(18,235) = 12.91$, $p < 0.005$, $\eta_p^2 = 0.50$).

In terms of main effects, type of brand was found to be insignificant ($F(1,252) = 1.095$, $p = 0.3$), which means that a consumer's usage intent does not change depending on the brand type (i.e., luxury vs. non-luxury). Hence, it has not been used in further analysis for the experiment. However, for the within-subjects variables, a significant main effect was found for both mode of contact (Wilks' Lambda = 0.73, $F(3,250) = 31.52$, $p < 0.005$, $\eta_p^2 = 0.27$) and customer journey touchpoint (Wilks' Lambda= 0.74, $F(6, 247) = 14.3$, $p < 0.005$, $\eta_p^2 = 0.26$).

Additionally, simple effects test was employed to examine the consumer intent of using a chatbot in comparison to other modes of contact at various customer journey touchpoints. The results of the simple effects test indicated that, in general, the mean difference in consumer usage intent for the chatbot was negative when compared to other modes of contact, or there was no statistically significant difference between the means (as presented in Table 6). However, it is important to note an exception in the case of ordering room service during a hotel stay. Specifically, the intent of using a chatbot in this scenario was slightly higher than using email, but

lower when compared to a customer service call or accessing the hotel's website/FAQ page.

			Mean Difference	Standard error	Significance
<i>1.Pre- booking: Room type & Amenities offered</i>	Chatbot	Customer service call	-0.504	0.262	0.056
		Email	0.232	0.241	0.336
		Website/ FAQ	-2.19	0.219	<0.001
<i>2.Booking: Payment error during booking</i>	Chatbot	Customer service call	-1.53	0.261	<0.001
		Email	-0.004	0.212	0.985
		Website/ FAQ	-1.043	0.226	<0.001
<i>3.Pre- booking: Availability of room</i>	Chatbot	Customer service call	-3.228	0.291	<0.001
		Email	-0.823	0.232	<0.001
		Website/ FAQ	-0.311	0.234	0.186
<i>4.Post- booking: Cancellation/ change in dates</i>	Chatbot	Customer service call	-2.673	0.268	<0.001
		Email	-0.929	0.233	<0.001
		Website/ FAQ	-1.394	0.233	<0.001
<i>5.Post- booking: Check in/ Check out</i>	Chatbot	Customer service call	-1.161	0.257	<0.001
		Email	-0.177	0.219	0.419
		Website/ FAQ	-1.969	0.209	<0.001
<i>6.During Stay:</i>	Chatbot	Customer	-2.075	0.248	<0.001

Room service		service call			
		Email	0.803	0.213	<0.001
		Website/ FAQ	-1.173	0.255	<0.001
7.Post stay: Feedback	Chatbot	Customer service call	0.327	0.242	0.178
		Email	-1.118	0.225	<0.001
		Website/ FAQ	-0.626	0.231	0.007

Table 6: Study 1: Mean difference of intent of using chatbot as compared to other media, at different touchpoints

Figure 5 displays that chatbot is the least preferred medium across most of the touchpoints in a customer's journey when compared to other modes of contact. Conversely, for most touchpoints, the most favoured medium is a customer service call.

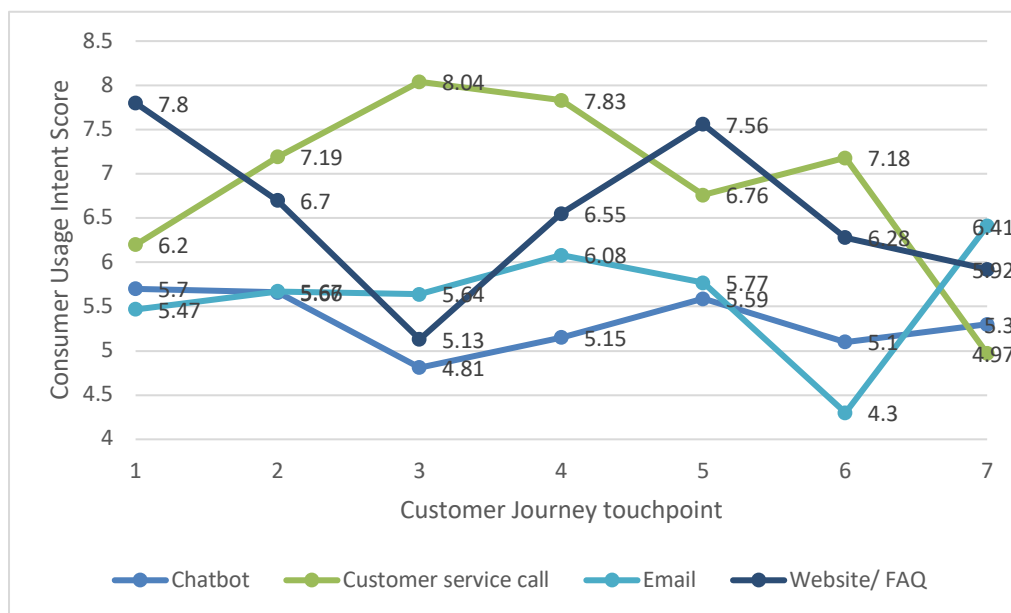


Figure 5: Study 1: Consumer usage intent score for mode of contact at different customer journey touchpoints

3.2.6 Discussion

The findings show that the primary determinant for consumers when interacting with a company is the mode of contact. Subsequently, the specific touchpoint in the customer journey for which they are reaching out to the company, is of secondary importance. The outcomes of these studies consistently demonstrate that chatbots are comparatively less favoured as a mode of contact, when compared to other alternatives. Both the conjoint analysis and the experiment corroborate this finding, indicating that chatbots are least preferred in contrast to customer service calls, emails, and accessing information on the company's website or FAQs section. These results align with existing literature that examines the comparison between chatbots, humans, and websites, with chatbots generally being less preferred for customer service interactions (Castelo et al., 2023; Sands et al., 2021; Sheehan et al., 2020; Sivaramakrishnan et al., 2007).

Furthermore, the experimental study shows a significant two-way interaction between the customer journey touchpoint and the mode of contact, with regards to usage intent. On analysing this interaction further, the findings reveal that chatbots are less preferred across most customer journey touchpoints. In contrast, other communication media such as email, website interaction, and customer service calls receive higher ratings for different touchpoints, with customer service calls being the most preferred option for most touchpoints.

Another interesting finding from this study was the effect of gender on consumer usage intent. A significant three-way interaction effect involving gender, mode of contact, and customer journey touchpoint had an impact on consumers' intent to use chatbots (Wilks' Lambda = 0.88, $F(18,235) = 1.8$, $p < 0.05$, $\eta_p^2 = 0.12$). This suggests that the impact of the mode of contact on consumers' usage intent depends on both specific customer journey touchpoints and gender. Further, examination of this effect through graphs (shown in Appendix A) revealed a pattern where men have a higher intent to use chatbots as compared to women, for all customer journey touchpoints. This pattern is justified through the existing literature explaining women are perceived to have less trust in online media than men (Garbarino & Strahilevitz, 2004).

The finding that chatbots are perceived as the least preferred mode of contact underscores the importance for marketers to proactively address this issue and enhance the service quality of chatbots to increase their intent of usage. Consequently, study 2 builds upon the findings regarding the low preference for chatbots and examines how proactively making changes to the communication style of the chatbot can enhance their performance. Since the type of brand does not significantly influence consumers' contact preferences or usage intent, it is not investigated or included as a variable in further studies.

3.3 STUDY 2

The aim of this study is to explore how to elevate the negative evaluations of chatbots in customer service. By investigating interaction content (social vs functional), the study aims to identify strategies that can improve the chatbot experience and mitigate the unfavourable perception associated with this mode of contact.

3.3.1 Theoretical rationale

The role of Interaction content in improving customer experience

The personalisation of service plays a significant role in the overall satisfaction of consumers in face-to-face service encounters, as highlighted by Surprenant and Solomon (1987). With chatbots, the inclusion of human-like attributes encourages consumers to perceive them as human entities, thereby leading them to have similar expectations as they would with human interactions (Araujo, 2018; Gelbrich et al., 2021). Hence, consumers want personalised service experiences when engaging with chatbot services, as the uniformity of chatbot interactions can diminish the emotional and social value inherent in human interactions. Therefore, personalising the service delivery of chatbots becomes crucial in enhancing the customer service experience. One possible approach to achieve this is through personalising the conversation style and conversation cues (Thomaz et al., 2020; Wilson-Nash et al., 2020). As highlighted in the literature review section, conversation cues encompass different interaction

content styles that shape the design of a chatbot. These cues can be categorised into social or functional interaction content (Chattaraman et al., 2019; Chong, Yu, Keeling, & de Ruyter, 2021; Howard & Sheth, 1969; Keeling et al., 2010). For this study, social interaction content is operationalised as “a conversational cue that highlights friendliness and emotions and delivers the message on a social level” and functional content as “a simple back-and-forth conversational message which involves only task-related dialogue and achieves functional goals”.

Use of social interaction content develops a more personal relationship than functional interaction content, making each consumer feel recognised as an individual rather than just another customer (Van Dolen et al., 2007). This is consistent with Surprenant and Solomon's (1987) concept of programmed personalisation, which emphasises customising the interactive process through the use of small talk, customary greetings, and other such elements. In addition, Van Dolen et al. (2007) show that programmed personalisation has a significant positive impact on customer satisfaction. Furthermore, customers and brands can develop affective connections with the incorporation of sensory, emotional, and social information in experiential communication (Moffett, Folse, & Palmatier, 2021). Therefore, when compared to functional interaction content, social interaction content style that encompasses emotional and social considerations provides a more experiential and engaging interaction.

The role of empathy in chatbots

Empathy has been identified as a significant determinant of customer satisfaction within the realm of customer service (Qualtrics, 2022). The report further reveals that customer service agents who display empathy have twice the impact on customer satisfaction, leading to increased expenditure by customers. This finding aligns with previous scholarly research, which suggests that customers in customer-employee interactions experience greater satisfaction when employees demonstrate empathetic behaviour (Markovic, Iglesias, Singh, & Sierra, 2018; Royne Stafford, Stafford, & Wells, 1998; Wieseke, Geigenmüller, & Kraus, 2012). Furthermore, empathetic employees elicit positive emotions in customers, thereby strengthening the customer-employee relationship and fostering satisfaction (Lee, Comer, Dubinsky, & Schafer, 2011).

Murray et al. (2019) define empathy as the capacity to comprehend, recognise, and respond to individuals' thoughts, behaviours, feelings, and experiences. Accordingly, empathy is a multidimensional concept encompassing affective, cognitive, and compassionate aspects (Powell & Roberts, 2017).

Existing literature consistently supports the notion that chatbots typically lack empathy but can enhance customer satisfaction by exhibiting empathetic characteristics. The ability of chatbots to demonstrate intuitive and empathetic intelligence, which encompasses experiential, emotional, and social capabilities, plays a crucial role in enhancing consumers' service

experiences (Huang & Rust, 2018). Additionally, the intention to use chatbots is highly influenced by the ability of robots to show empathy (Kervenoael, Hasan, Schwob, & Goh, 2020). Consumers exhibit a preference for interacting with chatbots capable of understanding their needs and providing responsive assistance, resulting in positive perceptions of chatbots possessing high levels of empathy (Chung et al., 2020). Hence, this is why brands place considerable importance on empathy, which encompasses consideration for customers and establishing a personal connection. Basis on this, studies have also suggested chatbots strive to empathise and communicate effectively with customers to enhance their satisfaction (Chung et al., 2020). Past research has also demonstrated that consumers who initially express scepticism towards machines possessing social cognitive capabilities tend to prefer empathetic interactions over unemotional provision of advice (Liu & Sundar, 2018). Similarly, engaging with an empathetic chatbot can mitigate the adverse effects of social exclusion experienced by consumers (Gennaro, Krumhuber, & Lucas, 2020).

Having established the significance of empathy in enhancing customer satisfaction and customer experience with chatbots, I propose that interaction content (social and functional) is an important factor for inducing empathy in these conversational agents. A study conducted by Yun and Park (2022) revealed that empathy and interactivity (characterised as conversational exchanges resembling human-like interactions) positively influenced customer satisfaction when chatbots utilised emotional words.

According to social impact theory, the degree of immediacy or closeness in communication plays a pivotal role in increasing the effectiveness of social interaction (Sands et al., 2021). In order to establish interpersonal connections with customers, the social interaction content style proves effective in fulfilling customers' emotional needs and personalising their interactions (Chattaraman et al., 2019). Furthermore, AI-based chatbots are perceived to possess a more engaging personality when they adopt a social-oriented interaction content as opposed to functional interaction content (Chattaraman et al., 2019). Building upon this, other studies have demonstrated that social conversations and cues such as emoticons elicit a sense of warmth (X. Li, Chan, & Kim, 2019; Xu, Niu, & Zhao, 2023), which is considered as a consequence of perceived empathy (Huang & Rust, 2018). The social interaction content conveys friendliness through elements such as greetings, small talk, encouragement, and exclamations (Keeling et al., 2010), which can be also considered as evaluations of perception of empathy from the agent.

In sum, it is rationalised that consumers interacting with a chatbot using social interaction content (vs functional interaction content) will feel more empathetic to consumers, which will enhance customer satisfaction. Thus, the following hypotheses are proposed:

H1a: The use of social interaction content (vs functional interaction content) in a chatbot leads to increased customer satisfaction.

H1b: The positive relationship between the use of social interaction content (vs functional interaction content) and customer satisfaction is mediated by the perception of empathy.

Identity disclosure of chatbots

Another factor with a significant bearing on a customer's experience with a chatbot is the (non-)disclosure of a chatbot's identity. Previous research has revealed a detrimental impact on consumer perceptions when the identity of the chatbot is disclosed, which is when the chatbot explicitly declares itself as a chatbot or not (Luo et al., 2019; Mozafari et al., 2022). For instance, Luo et al. (2019) found that disclosing the identity of chatbots significantly reduces perceived empathy, subsequently diminishing consumers' purchase intentions. Furthermore, an additional phenomenon known as 'algorithm aversion' has been observed, indicating that consumers exhibit a preference for trusting humans rather than robots (Burton, Stein, & Jensen, 2020).

However, it is also crucial to acknowledge that consumers have the right to know the entities they are engaging with, not least given business ethics considerations (Socialmediaweek, 2018). Non-disclosure of chatbot identities is in violation of legal requirements such as the B.O.T. ("Bolstering Online Transparency") Act in California and the General Data Protection Regulation (GDPR) in the European Union. These regulations demand transparency from companies regarding the use of chatbot applications during customer communication (DiResta, 2019; FTC, 2020).

Consequently, disclosing the identity of chatbots has become more of a norm, emphasising the importance of understanding how to mitigate the negative effects associated with chatbot disclosure.

This study proposes that when identity of the chatbot is disclosed, incorporating social interaction content into a chatbot can enhance empathy, leading to increased customer satisfaction. The negative effects of identity disclosure and algorithm aversion can make consumers more sensitive to the quality of customer service they are receiving. Additionally, Study 1 suggests that the medium through which consumers interact with a company's customer service is a crucial factor and chatbot is the least preferred (as compared to alternative modes available). Therefore, when consumers know they are dealing with a chatbot (i.e., the identity of the chatbot is disclosed), they have lower expectations and assume they would be speaking with a non-empathetic agent. Hence, to mitigate the negative effects of chatbot identity disclosure and capitalise on lower expectations of consumers, utilising social interaction content (as opposed to functional interaction content) would result in higher satisfaction, as consumers would perceive the chatbot to show more emotions and hence be more empathetic. However, this would apply less when the chatbot's identity is not disclosed since the consumer would have no prior assumptions that they are dealing with a non-empathetic agent. Thus, the below hypotheses are proposed:

H2a: The effect of using social (rather than functional) interaction content on customer satisfaction is stronger when the identity of a chatbot is disclosed (rather than non-disclosed).

H2b: This relationship between the use of social (vs functional) interaction content and customer satisfaction, when the identity is disclosed, is mediated by the perceived empathy displayed by the chatbot (i.e., when you know it's a chatbot, given disclosure, the social content drives perceptions of empathy)

Figure 6 summarises this conceptual framework.

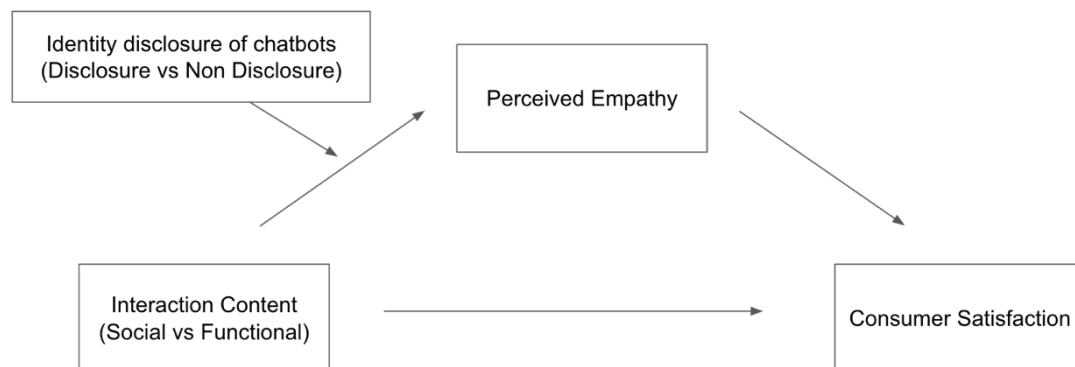


Figure 6: Study 2: Conceptual framework

3.3.2 Research sample and design

An experimental study was conducted with the purpose to find how the negative perceptions towards disclosed chatbots can be remedied using different interaction content types. The study employed a 2 x 2 between-subjects factorial design wherein participants were randomly assigned to

one of the four conditions. The two factors manipulated in the study were: the disclosure of chatbot identity (disclosure vs. non-disclosure) and the interaction content (social vs. functional). Additionally, the study explored the mediating role of perceived empathy towards the chatbot, with customer satisfaction as the dependent variable. Previous literature on chatbots have commonly adopted scenario- based manipulations and shown consumer-chatbot conversations through screenshots (Chung et al., 2020; Go & Sundar, 2019; Roy & Naidoo, 2021; Sheehan et al., 2020). Hence, a similar approach was adopted for conducting the experiment.

The research comprised two phases. Firstly, a pre-test was conducted to validate the experimental design and ensure the effectiveness of the manipulations. The study focused on online shopping, which involves a high level of interactivity and encompasses both hedonic and utilitarian aspects of consumption (Childers, Carr, Peck, & Carson, 2001; Häubl & Trifts, 2000). On this basis, a hypothetical start-up called Hound Mobility, specialising in the sale of e-bikes was selected as the context for the study.

Data for both the pre-test and main study was collected using Prolific, a recruitment platform for research participants. Prolific was chosen due to its capability to represent a diverse population in terms of factors such as geographical location and ethnicity (Palan & Schitter, 2018). Standard sampling procedures were followed, and the pre-screening process involved inviting potential participants based on the following criteria: 1) Residency in the United Kingdom and Ireland, 2) Attainment of a minimum age of 18 years, and 3) Proficiency in the English language. Participants

who had previously participated in the pre- study were excluded. Compensation in the form of £0.75 was provided to participants, and the task's completion averaged approximately 4-6 minutes per participant. A total of 401 participants took part in the study, and after applying the exclusion criteria (detailed in Appendix B) 349 participants remained in the data set (65.1% female, M_{age} = 39.8 years).

3.3.3 Procedure

The study was conducted using two research platforms: Prolific, for inviting participants and Qualtrics, for conducting the survey. Figure 7 depicts the flow of the experiment between Prolific and Qualtrics and back again to the Prolific platform.

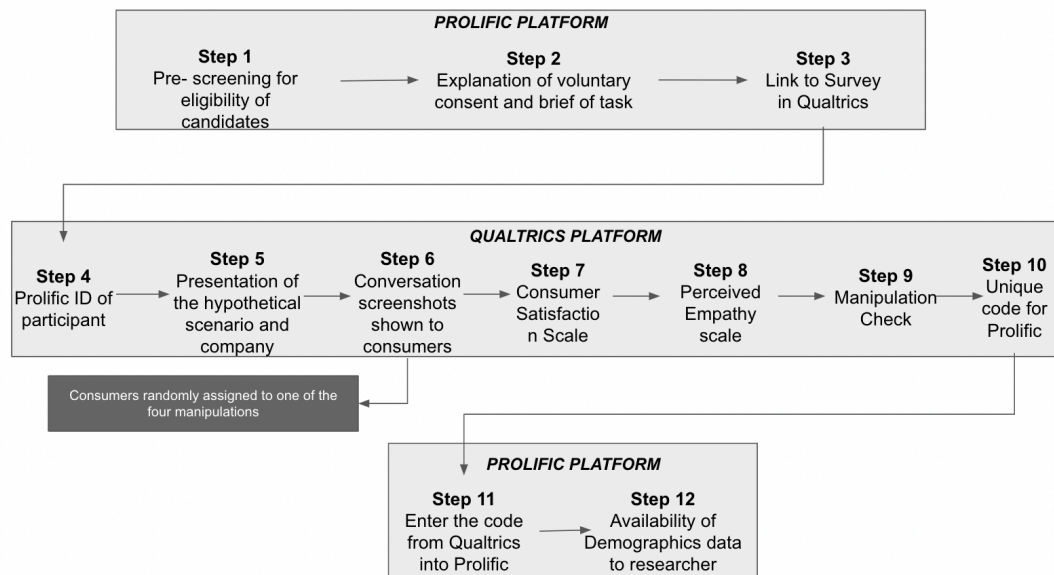


Figure 7: Study 2: Experiment design

Participants on Prolific were invited to take part in the study titled “Interact with online customer service”. The chatbot nature of the online customer

service was deliberately withheld from the study title to enable manipulation of the disclosure of identity and to prevent response bias. Prior to participating, participants were presented with ethical guidelines in accordance with the Trinity College Dublin Ethics Committee, including information on voluntary consent, data retention, and confidentiality and anonymity of their identity, which aligns with Prolific's policies. Participants were then asked to imagine themselves in a scenario where they were searching for a new e-bike and have landed on the website of Hound Mobility. A task related to this scenario was then briefly explained, and participants were directed to complete it via a Qualtrics survey link (Appendix C).

Demographic information of participants was collected from Prolific, while survey responses were obtained through Qualtrics, with both data sets linked using participants' Prolific IDs which were required on both the platforms. A unique code was provided at the end of the Qualtrics survey which participants had to enter in Prolific as proof of task completion.

In the Qualtrics survey, participants were presented a scenario in which they were interested in purchasing an e-bike for their daily commute. They were provided with information about Hound Mobility, including their offerings, website information, pre-registration, and photos from the website. Participants were then asked to express their interest in obtaining more information from the online agent about the available bikes to facilitate their purchasing decision. A detailed explanation of the scenario presented to participants can be found in Appendix D.

Participants were then shown one of four sets of manipulated screenshots depicting a conversation between an online agent and a consumer discussing different aspects of the e-bikes available on the Hound Mobility website, and the option to pre-register interest in the bike. The manipulations included chatbot identity disclosure (disclosure vs non-disclosure) and interaction content (social vs. functional). The study manipulated chatbot identity disclosure through the introductory sentence of the social agent and the chat window title, which either read "Chat with Service agent" (for non-disclosure) or "Chat with Service bot" (for disclosure). Interaction content was manipulated based on how existing literature has characterised the difference (Sheehan et al., 2020). Emojis, customary greetings, small talk and a friendlier style of conversing were used for the social interaction content, which was absent in the functional interaction content. Table 7 shows a sample of the manipulations in all four scenarios. These screenshots were designed to resemble an actual conversation with chat bubbles and logos of the brand for the online agent. To ensure participants read the conversation, a 10-second lag was implemented between each screenshot. Detailed screenshots of the conversation shown to participants for each treatment is in Appendix E.

Following the viewing of the conversation, participants were instructed to imagine themselves engaging in the same conversation, and their satisfaction with the online service was measured through a survey. The study also included the mediator question on perceived empathy.

	Disclosure & Social content	Disclosure & Functional content	Non-disclosure & Social content	Non-disclosure & Functional content
Agent	Hello👋, I am Benjamin, Hound Mobility's service chatbot. How can I help you? 😊	Hi, I am Benjamin, Hound Mobility's service chatbot. How can I help you?	Hello👋, I am Benjamin, Hound Mobility's service agent. How can I help you? 😊	Hi, I am Benjamin, Hound Mobility's service agent. How can I help you?
Customer	Hi I would like to know the difference between the N1 and N2 bikes?	Hi I would like to know the difference between the N1 and N2 bikes?	Hi I would like to know the difference between the N1 and N2 bikes?	Hi I would like to know the difference between the N1 and N2 bikes?
Agent	Sure, let me explain the differences to you! The N1 is an e- road bike specifically designed for the thrill seeker and our N2 is an e- city bike, built for a comfortable, easy cycling. 🚲	The N1 bike is an Electric Road bike & the N2 bike is an Electric City or commuter bike.	Sure, let me explain the differences to you! The N1 is an e- road bike specifically designed for the thrill seeker and N2 is an e-city bike, built for a comfortable, easy cycling 🚲	The N1 bike is an Electric Road bike & the N2 bike is an Electric City or commuter bike.

Table 7: Study 2: Sample of treatments for similar context

3.3.4 Measurement

To ensure accuracy and construct validity in measuring customer satisfaction with chatbot services, an adapted version of the American Customer Satisfaction Index (ACSI) (Fornell, Johnson, Anderson, Cha, & Bryant, 1996) was utilised for this study. The adapted ACSI scale (Nunkoo, Teeroovengadum, Ringle, & Sunnassee, 2020) was chosen due to its suitability and relevance in the context of chatbot services, as it has been previously employed in similar and more recent studies (Ruan & Mezei, 2022). The three-item scale involved participants rating each item on a 7-point Likert scale ranging from strongly disagree (1) to strongly agree (7) ($\alpha = 0.95$) (Appendix F).

In line with the previous study by Luo et al. (2019), one item was used to measure perceived empathy of the chatbot: "*The agent showed empathy towards me as a customer*". Participants were asked to rate them on 7-point Likert scale (1=strongly disagree, 7=strongly agree).

3.3.5 Pre-test

In the pre-test phase of the experiment, a manipulation check was conducted to ascertain the efficacy of the treatment involving social and functional interaction content for the participants, ensuring that it had the intended effect (Vogt, 2005). The social and functional interaction content treatment was evaluated using separate four-item scales, each employing a 7-point Likert scale (1=strongly disagree, 7=strongly agree) ($\alpha_{\text{Social}} = 0.87$,

$\alpha_{functional} = 0.75$), which were adapted from Williams and Spiro (1985) and Van Dolen et al. (2007) (Appendix F).

A total of 95 participants were recruited for the study, via Prolific (62.1% female, $M_{age} = 38.8$ years). The results demonstrated a successful manipulation of interaction content, showing a significant mean difference between the two conditions (social and functional interaction content) on the social interaction scale, $t(89) = 1.94$, $p < 0.05$. As expected, participants exposed to social interaction content ($M = 5.9$, $SD = 0.91$) reported higher social interaction scale scores compared to those exposed to functional interaction content ($M = 5.4$, $SD = 1.2$).

There was no significant mean difference observed on the functional interaction scale between the social interaction content condition ($M = 6.07$, $SD = 0.84$) and the functional interaction content condition ($M = 6.09$, $SD = 0.81$), $t(92) = -0.12$, $p = 0.451$. This lack of significance does not pose an issue for the study since both conditions presented the same functional content, with only one condition (social interaction content) enhanced by the inclusion of social cues.

The inclusion of these manipulation checks during the pre-test phase provided assurance that the independent variable (interaction content) was effectively manipulated, and any subsequent variations in customer satisfaction between the two conditions could be attributed to the content manipulation. This step ensured the validity of the study and strengthened the interpretation of the observed differences.

3.3.6 Main study analysis

Manipulation check

A manipulation check for interaction content (social vs functional) was again conducted using the same procedure as in the pre-test. The results showed a significant difference in the mean rating of social interaction scale between the two conditions, $t(348) = -2.77, p < .01$, with participants in the social interaction content condition reporting higher scores ($M = 5.82, SD = 0.85$) as compared to participants in the functional interaction content condition ($M = 5.4, SD = 1.1$). Additionally, there was no significant difference in the mean scores of the functional interaction scale for the social and functional interaction content conditions, ($t(348) = 0.62, p = 0.27$).

Customer satisfaction and Perceived empathy

In order to test for H1a, a one-way ANOVA was conducted to examine the association between the type of interaction content (social vs functional) and customer satisfaction. The results indicated that there is no statistically significant direct effect of interaction content on customer satisfaction ($F(1,348) = 1.7, p = 0.19$). However, customer satisfaction means for the social interaction content condition ($M = 6.3$) was higher as compared to functional interaction content condition ($M = 6.1$).

Additionally, a two-way ANOVA was performed to investigate the impact of chatbot interaction content (i.e., social and functional) and identity disclosure (i.e., disclosure and non-disclosure) on customer satisfaction and perceived empathy. The results of the analysis revealed significant

interaction effects between interaction content and disclosure for customer satisfaction ($F(1, 346) = 5.8, p = 0.017$) and perceived empathy ($F(1, 346) = 5.4, p = 0.021$). These findings suggest that the effect of type of interaction content on customer satisfaction and perceived empathy may differ depending on the identity disclosure of the chatbot.

Planned contrasts were employed to test for H2a, to assess the impact of each identity disclosure condition on customer satisfaction and perceived empathy. In the condition of identity disclosure of chatbot, the results showed that social interaction content condition ($M = 6.41, SD = 0.7$) resulted in higher evaluations of customer satisfaction than functional interaction content condition ($M = 6.09, SD = 0.92, F(1,346) = 7.01, p < 0.01$) and similarly, for perception of empathy, social interaction content condition ($M = 5.58, SD = 1.13$) resulted in higher evaluations than functional interaction content condition ($M = 4.76, SD = 1.4, F(1,346) = 18.75, p < 0.01$).

However, the condition of non-disclosure of chatbot identity revealed non-significant mean differences of customer satisfaction and perceived empathy between the two interaction content conditions (for customer satisfaction: $M_{social} = 6.2, SD_{social} = 0.81, M_{functional} = 6.29, SD_{functional} = 0.69, F(1,346) = 0.54, p = 0.46$; for perceived empathy: $M_{social} = 5.37, SD_{social} = 1.1, M_{functional} = 5.17, SD_{functional} = 1.29, F(1,346) = 1.22, p = 0.27$). See Figure 8 and Figure 9.

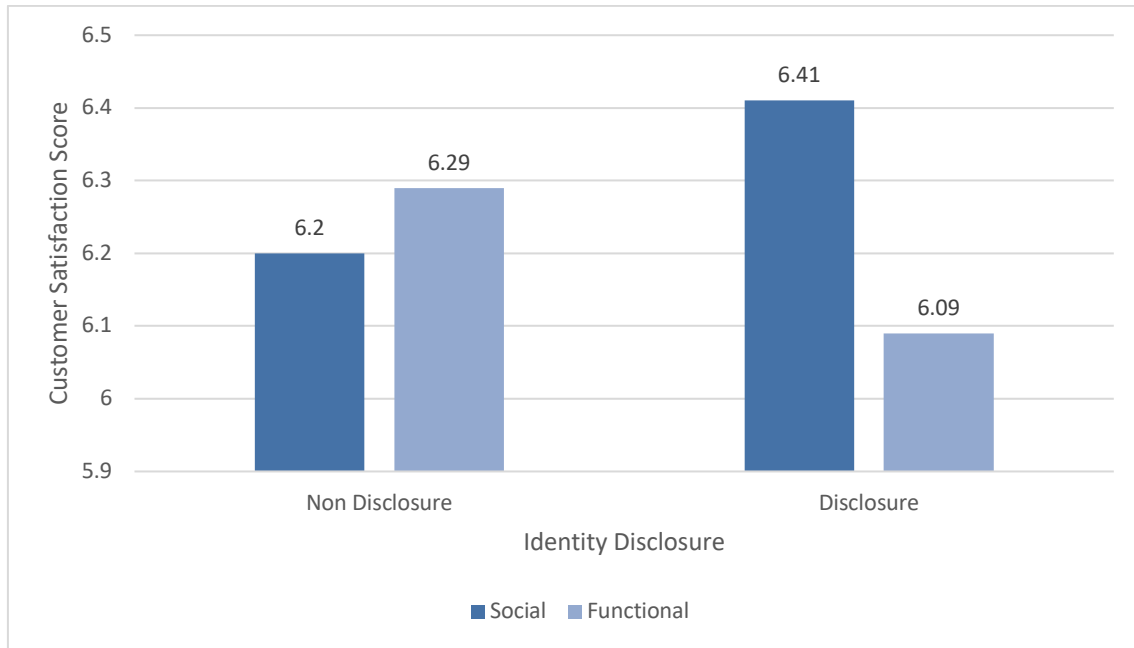


Figure 8: Study 2: Effect of interaction content and identity disclosure on customer satisfaction

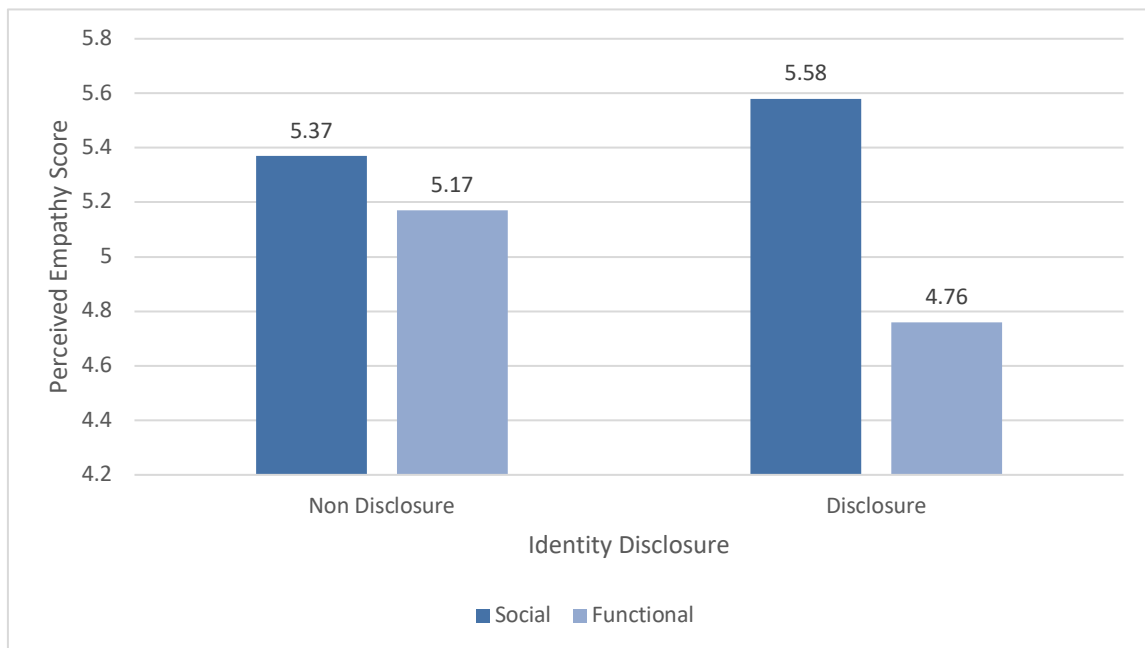


Figure 9: Study 2: Effect of interaction content and identity disclosure on perceived empathy

Mediation analysis

It was predicted that social interaction content will increase customer satisfaction and this effect will be mediated by perceived empathy (H1b). Mediation analysis of PROCESS macro in SPSS (model 4) (Hayes, 2017), with 10000 bootstrap samples, confirmed this prediction that perceived empathy mediates the effect of interaction content (social vs functional) on customer satisfaction (indirect effect = 0.14, $SE = 0.04$, 95% CI [0.07, 0.22]). Social interaction content made the chatbot seem more empathetic ($b = 0.51$, $SE = 0.13$, $t = 3.82$, $p < 0.001$), which further boosted customer satisfaction ($b = 0.27$, $SE = 0.03$, $t = 8.78$, $p < 0.001$).

Moderated mediation analysis

The conceptual framework suggested that in the case of when the identity of the chatbot is disclosed, social interaction content (vs functional interaction content) increases perceived empathy, which leads to higher customer satisfaction (H2b). In order to test this hypothesis, a moderation mediation analysis of PROCESS macro in SPSS (Model 7) (Hayes, 2017), with 10000 bootstrap samples, was used to investigate the impact of chatbot interaction content on customer satisfaction, as mediated perceived empathy. Furthermore, the study explored how this relationship was moderated by the identity disclosure of the chatbot (Figure 6) (Summary of results in Appendix G..

Effect of interaction content on customer satisfaction when mediated by perceived empathy; moderated by identity disclosure

Evidence from the estimation of the model revealed that the index of moderated mediation for identity disclosure was statistically significant and positive (index = 0.17, $SE = 0.08$, 95% CI = [0.02, 0.33]). The indirect effect of interaction content on customer satisfaction via perceived empathy was significant when the identity of the chatbot is disclosed (indirect effect = 0.22; $SE = 0.06$, 95% CI = [0.11, 0.34]) but not when identity of chatbot is not disclosed (indirect effect = 0.05, $SE = 0.05$, 95% CI = [-0.04, 0.15]). This means that when the identity of the chatbot is disclosed, social interaction content increases customer satisfaction via perceived empathy. This is not the case when chatbot identity is not disclosed.

3.3.7 Discussion

This study aimed to examine the impact of using social versus functional interaction content in chatbots on customer satisfaction, with a specific focus on the mediating role of perceived empathy and moderating role of identity disclosure of chatbots.

The empirical findings provide support for H1a and H1b, demonstrating that the nature of interaction content significantly affects customer satisfaction, with perceived empathy playing a mediating role. Specifically, chatbots with social interaction content generate higher customer satisfaction due to the perception of greater empathy compared to those chatbots with functional interaction content.

This study provides evidence in support of the proposed hypotheses, H2a and H2b, demonstrating that when the chatbot's identity is disclosed, employing social interaction content as the conversation script boosts the perceived empathy of the chatbot, resulting in higher levels of customer satisfaction. Consequently, to mitigate the negative perceptions associated with disclosing the identity of chatbots (as highlighted in the literature e.g. Luo et al. (2019); Mozafari et al. (2022)), chatbots should integrate social interaction content, which would enhance satisfaction with the service provided and also improve the overall customer experience.

However, in scenarios where the chatbot's identity remains nondisclosed, there is no difference of customer satisfaction between social and function interaction content. This means that when users are unaware that they are interacting with a chatbot, their levels of satisfaction remain relatively consistent irrespective of the type of interaction content.

It is important to note that this study focused on a specific scenario in which consumers were inquiring about pre-registering for a new product, and the chatbot successfully addressed the customer query, i.e., service success. However, the study did not account for situations in which the chatbot fails to provide answers to consumer queries, i.e., service failure. It is crucial to establish the contextual parameters within which the proposed effect can be observed and to comprehend when this effect may diminish or even exhibit a reversed trend. Therefore, the subsequent study aims to investigate an important boundary condition of the effect of using social (rather than functional) interaction content on customer satisfaction, namely if the effect

and the operation of perceived empathy still holds in conditions of service failure (rather than service success).

3.4 STUDY 3

The third and the final study for this PhD research investigates a boundary condition for the suggested mechanism in Study 2, i.e., use of social interaction content promotes perceived empathy which further yields higher customer satisfaction. This study examines whether the utilisation of social interaction content (versus functional interaction content) in chatbots amplifies customer satisfaction or if this effect is reversed, in the event of a chatbot service failure.

3.4.1 Theoretical rationale

The previous study (Study 2) provides evidence that social interaction content (characterised by greetings, friendliness, and small talk), in chatbot conversations promotes empathy, and enhance customer satisfaction. As such, customers value personalised and engaging interactions with chatbots while also expecting successful service delivery. However, this study proposes that the effect of using social (instead of functional) interaction content on customer satisfaction is reversed when a service failure occurs (i.e., the chatbot fails to answer the consumers' queries). This reversal effect may be attributed to the fact that, when faced with a service failure, consumers prefer a business-oriented relationship rather than a friendly one (Wan, Hui, & Wyer, 2011). Furthermore, the presence of social cues in a chatbot during a service failure can be perceived by customers as insincere or artificial (Gray & Wegner, 2012) as chatbots are often seen as

adhering to standardised procedures and lacking the ability to genuinely convey emotions (Malle, Scheutz, Arnold, Voiklis, & Cusimano, 2015).

Functional interaction content, which emphasises efficiency and minimisation of costs, effort, and time, is closely associated with competence, efficiency, and skilfulness (M. Li & Ma, 2022). On the other hand, social interaction content involves the use of emotional expressions through casual conversations, emojis, and informal language (Chattaraman et al., 2019; Walther & D'addario, 2001). The display of these emotions during a chatbot service failure indicates a lack of competence (X. Li et al., 2019). Additionally, the utilisation of such social cues by chatbots may be perceived as inappropriate and distracting, rather than focusing on resolving issues seriously, which subsequently diminishes their perceived competence (X. Li et al., 2019; Xu et al., 2023).

Even in the context of service recovery following a chatbot's failure, customers are more inclined to prefer human assistance over another chatbot when the chatbot employs friendly and emotional messages (Yu et al., 2022). Conversely, when a chatbot does not exhibit friendly cues during the service recovery process, customers tend to favour the chatbot (Yu et al., 2022). This suggests that when a chatbot fails to resolve customer queries, customers tend to trust a chatbot that does not utilise social cues, or rather prefers functional content.

In summary, when customers' experience service failures they have negative evaluation towards the service provided by chatbots (Choi et al.,

2021; X. Li et al., 2019). Social cues expressed by the chatbot through interaction content, such as emojis and small talk, during a failure can evoke discomfort and scepticism among customers. As a result, the impact of interaction content (social vs. functional) on customer satisfaction is reversed in the context of service failures involving chatbots. While social interaction content generally leads to higher customer satisfaction, the presence of a service failure alters this effect. Additionally, when a chatbot encounters an error, the customer's attention shifts from the agent's friendliness or empathy to the agent's competence (X. Li et al., 2019).

Hence, the following hypotheses are proposed:

H3: In the event of a service failure (rather than service success) by chatbot, the use of functional (rather than social) interaction content in chatbots leads to higher customer satisfaction of chatbot services.

H4: In the event of a service failure, perceived competence mediates the relationship between interaction content (functional vs. social) and customer satisfaction. A chatbot using functional interaction content is perceived as more competent.

As seen in Study 2, the perceived empathy of the chatbot emerges as a significant mediating factor in the relation between interaction content (social and functional) and customer satisfaction. Hence, along with perceived competence, this study also investigates the role of perceived empathy, examining whether this effect persists even in the instances of chatbot service failure.

Figure 10 summarises the proposed framework for this study.

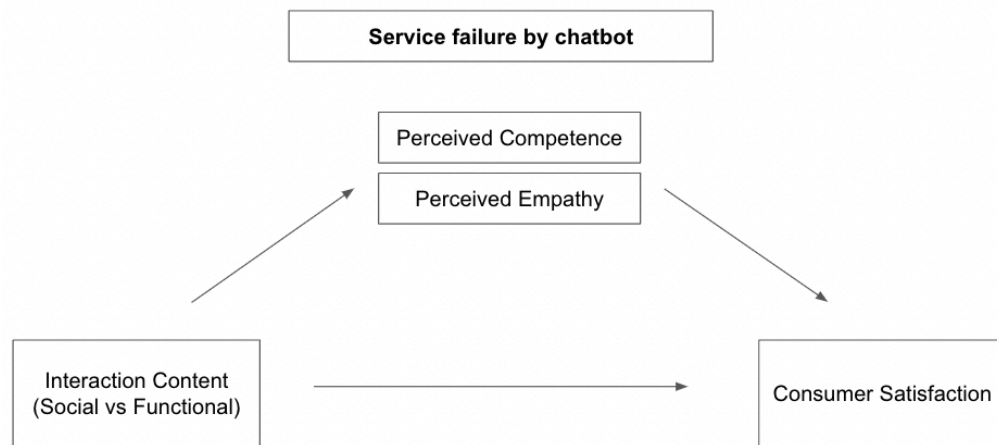


Figure 10: Study 3: Conceptual framework

Alternative explanations: Customer frustration from service failures

In addition, this study also measures customer frustration resulting from a service failure as a potential alternative explanation for the underlying mechanism that explains the effect of functional (vs social) interaction content on customer satisfaction.

Consumers may feel frustrated when encountering a service failure or negative outcome from a service bot (Roseman, 1991). Research has shown that consumers tend to hold the company responsible for service failures, rather than blaming the chatbot itself (Gray & Wegner, 2012; Lee, 2018). Consequently, in the case of AI-based service failures, individuals are more likely to experience frustration towards the situation rather than directing anger at the AI-based service agent, recognising that the events are perceived as outside the chatbot's control; (Leo & Huh, 2020; Pavone et

al., 2023). The utilisation of anthropomorphic visual cues such as the avatar of the chatbot has been found to alleviate the adverse impact of frustration experienced during a service encounter (Pavone et al., 2023). However, when consumers are already angry prior to the service encounter, the incorporation of these anthropomorphic cues may exacerbate the decrease in customer satisfaction and hinder their evaluation of future purchases (Crollic et al., 2022). The impact of conversation scripts (interaction content) on customer frustration is not evident in the literature. Therefore, this study examines this relationship and further explores whether frustration serves as an alternative explanation for the effect between interaction content (social and functional) and customer satisfaction in the context of service failures.

3.4.2 Research sample and design

Study 2 demonstrated that for a chatbot disclosing its identity, using social interaction content will yield greater customer satisfaction compared to a functional interaction content. The present study aims to examine whether this effect would be reversed in situations where the chatbot failed to fulfil the customer's service request, i.e., in cases of service failure. The study employed a between-subjects design, utilising a 2 (Interaction content: social vs. functional) x 2 (Chatbot service outcome: success vs. failure) framework. These two factors, interaction content and chatbot service type, were manipulated through the presentation of chatbot scripts to the participants. Consistent with the previous study, this study assessed the

dependent variable of satisfaction and the mediating variable of perceived empathy. Additionally, the variables of perceived competence and customer frustration were also measured. Results from study 2 revealed significant differences in satisfaction levels based on different interaction content (social and functional), when the identity of the chatbot was disclosed and not when the identity was not disclosed. Building on these results, this study uniformly disclosed the identity of chatbots across all four conditions presented to participants.

Similar to the previous experiment, this study consisted of two phases: a pre-test and the main experiment. The scenarios presented in the study focused on a consumer's attempt to purchase concert tickets through a hypothetical website called e-tix.com. Data collection was conducted using the platform Prolific, and the same criteria as Study 2 was used for pre-screening potential participants for this study. This criterion included: 1) Residency in the United Kingdom and Ireland, 2) Attainment of a minimum age of 18 years, and 3) Proficiency in the English language. Participants spent approximately 4 minutes reading the scenario and completing the questionnaire. As compensation for their participation, they received £0.75. It was ensured that participants had not taken part in any previous studies related to this PhD research. A total of 410 participants were included in the main study, with an equal distribution across all four conditions, randomly assigned to each participant. After applying the exclusion criteria (Appendix B), data from 401 participants were included in the analysis, with 52.1% identifying as female and an average age of 40.2 years.

3.4.3 Procedure

The methodology employed in this study closely followed the approach taken in Study 2, utilising the platforms Prolific and Qualtrics. However, the difference between the two studies lies in the scenario presented to the participants. While Study 2 focused on requesting pre-registration for an e-bike, this particular study revolves around the process of purchasing concert tickets. On the Prolific platform, participants were first provided with the ethical guidelines and then instructed to imagine themselves in a situation where they are purchasing concert tickets from a website called E-tix. They were informed that, during the payment process, they encountered an error and subsequently contacted the customer service chatbot of E-tix (Appendix H).

Upon transitioning to the Qualtrics platform, participants were given a clear explanation of the task they were required to complete (Appendix I). Subsequently, they were presented with one of four scenarios through conversation scripts between the chatbot and the user. These conversation scripts manipulated two variables: 1) interaction content: social or functional, and 2) service outcome i.e., whether the chatbot successfully resolved the payment issue or not. Table 8 shows a sample of the manipulations in all four conditions. Detailed screenshots of the conversations presented to participants for each treatment in Appendix J.

After reading the provided conversation, participants were asked to respond to survey questions regarding their satisfaction with the service provided by

the chatbots. Additionally, perceived empathy, perceived competence and customer frustration were also measured through the survey.

	Service Success & Social Content	Service Failure & Social Content	Service Success & Functional Content	Service Failure & Functional Content
Customer	Can you give an estimated time of when the problem will be fixed?	Can you give an estimated time of when the problem will be fixed?	Can you give an estimated time of when the problem will be fixed?	Can you give an estimated time of when the problem will be fixed?
Agent	Thank you for bearing with me. ⌚ The payment system has been updated; the payment should now work. 🇵🇸 You can refresh the page and try making the payment again. 🔄	Thank you for bearing with me. ⌚ I do not have an exact estimate at the moment, please try again later. We're working hard to resolve the issue as quickly as possible! 🙏	The payment system has been updated; the payment should now work. You can refresh the page and try making the payment again.	I do not currently have an estimate, please try again later. We're working hard to resolve the issue as quickly as possible.

Table 8: Study 3: Sample of treatments for similar context

3.4.4 Measurement

To maintain consistency, the measurement of customer satisfaction and perceived empathy in this study followed the same scale used in Study 2. The assessment of perceived competence of the chatbot relied on an established scale previously utilised in the literature pertaining to chatbot service contexts (Meyer-Waarden et al., 2020; Sirdeshmukh, Singh, & Sabol, 2002; Van Dolen et al., 2007). Participants were required to rate the five-item scale using a 7-point Likert scale ($\alpha = 0.95$) (Appendix F).

The construct of customer frustration was measured using a 3-item scale developed by Gelbrich (2010), which has been widely employed in existing research investigating customer frustration in the context of chatbots. The scale was measured using a 7-point Likert scale ($\alpha = 0.91$) (Appendix F).

3.4.5 Pre-test

The pre-test phase served two purposes in this study. Firstly, it aimed to verify whether the manipulation of interaction content (as social versus functional), in the context of a different scenario and script (compared to Study 2), still yielded the intended effect. Secondly, it aimed to preliminarily examine whether the proposed reverse effect of using social (vs functional) interaction content for higher customer satisfaction was observed in cases where the chatbot failed to provide the requested service. The design of the pre-test was consistent with the design of the main study, i.e., 2 (Interaction content: social vs. functional) x 2 (Chatbot service outcome: success vs.

failure) between subjects experiment. The interaction content and chatbot service outcome both were manipulated through the conversation scripts presented to the participant. The pre-test phase was also conducted using the Prolific platform, and a total of 101 participants were recruited ($M_{age} = 37$, 66% female).

To assess the manipulation of interaction content, a manipulation check was conducted in a similar manner to the previous study (scale in Appendix F). The results obtained were consistent with the pre-test findings of Study 2, indicating a successful manipulation of interaction content. For the social interaction scale, social and functional interaction content conditions showed a significant mean difference, ($M_{social} = 5.18$, $SD_{social} = 0.14$; $M_{functional} = 4.36$, $SD_{functional} = 0.14$; $t(99) = -3.01$, $p < 0.05$. On the other hand, for the functional interaction scale, no significant difference in means was observed between the two conditions ($M_{social} = 5.32$, $SD_{social} = 1.33$; $M_{functional} = 5.5$, $SD_{functional} = 1.09$, $t(99) = 0.76$, $p = 0.22$).

To examine if higher customer satisfaction ratings shift from social to functional interaction content when there is a service failure by the chatbot compared to service success, a 2x2 ANOVA was conducted. The results revealed a significant interaction effect between interaction content and chatbot service outcome condition for customer satisfaction ($F(1, 97) = 3.81$, $p = 0.05$). Planned contrasts showed that in the condition of chatbots' service outcome as successful, there was no significant difference in the mean of customer satisfaction scores between the two interaction content conditions (social and functional), ($F(1,97) = 0.92$, $p = 0.34$). However

consistent with the findings of Study 2, social interact content condition ($M = 6.45$, $SD = 0.69$) still had higher evaluations of customer satisfaction as compared to the functional interaction content condition ($M = 6.11$, $SD = 1.08$). Additionally, as theorised, in the condition of chatbots' service failure, evaluation for customer satisfaction is higher for the functional interaction content condition ($M = 3.81$, $SD = 1.74$) than social interaction content condition ($M = 3.11$, $SD = 1.43$; $F(1,97) = 3.2$, $p = 0.08$) (Figure 11).

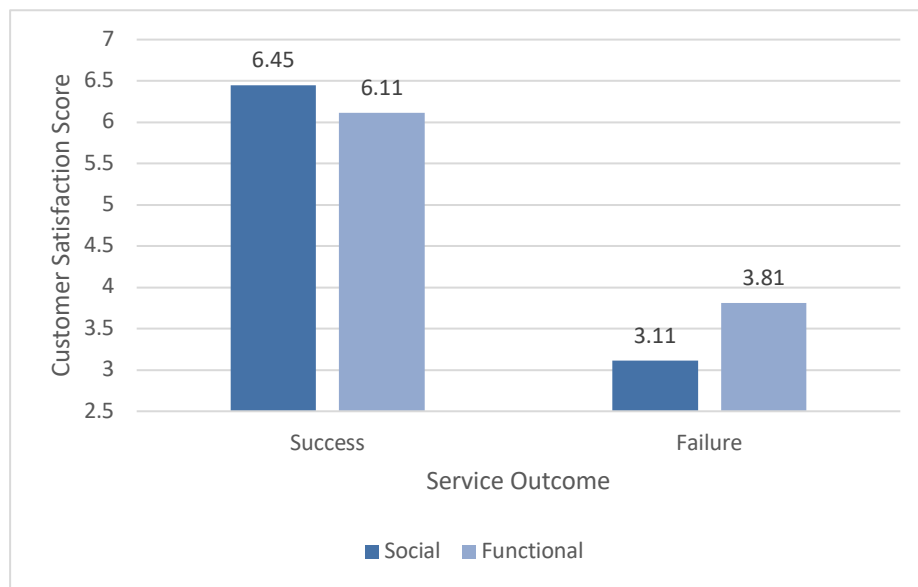


Figure 11: Study 3 Pre-test: Effect of interaction content and service outcome on customer satisfaction

3.4.6 Main study analysis

Manipulation check

Following a similar procedure as the pre-test, a manipulation check was conducted to assess the effectiveness of the social versus functional interaction conditions. The results of this manipulation check were

consistent with the pre-test findings. Specifically, participants in the social interaction content condition reported significantly higher means on the social interaction scale as compared to the participants in the functional content condition ($M_{social} = 5.18$, $SD_{social} = 1.35$ vs $M_{functional} = 4.55$, $SD_{functional} = 1.23$), $t(397) = -5.03$, $p < 0.001$. Additionally, there was also a significant difference in the mean ratings for the functional interaction scale between the two conditions ($M_{functional} = 5.5$, $SD_{functional} = 1.15$; $M_{Social} = 5.2$, $SD_{social} = 1.19$; $t(397) = 1.9$, $p = 0.03$). These results validate the intended manipulation of interaction content.

Customer satisfaction

To investigate the influence of interaction content (social vs. functional) and service outcome (success vs. failure) on customer satisfaction, a 2x2 ANOVA was performed. The results revealed a significant two-way interaction between interaction content and service outcome for customer satisfaction ($F(1, 395) = 6.3$, $p = 0.012$).

To further examine the impact of each condition of service outcome individually, planned contrasts were conducted. In the condition of chatbots' service outcome as success, there was no significant difference observed in customer satisfaction ratings between social interaction content ($M = 6.28$, $SD = 0.9$) and functional interaction content ($M = 6.23$, $SD = 0.95$; $F(1, 395) = 0.05$, $p = 0.83$). Conversely, in the condition of chatbots' service outcome as failure, a significant difference in customer satisfaction scores was observed with functional interaction content yielding higher evaluation

of customer satisfaction as compared to social interaction content ($M_{functional} = 4.1$, $SD_{functional} = 1.59$; $M_{social} = 3.48$, $SD_{social} = 1.58$; $F(1,395) = 11.15$, $p < 0.001$) (Figure 12).

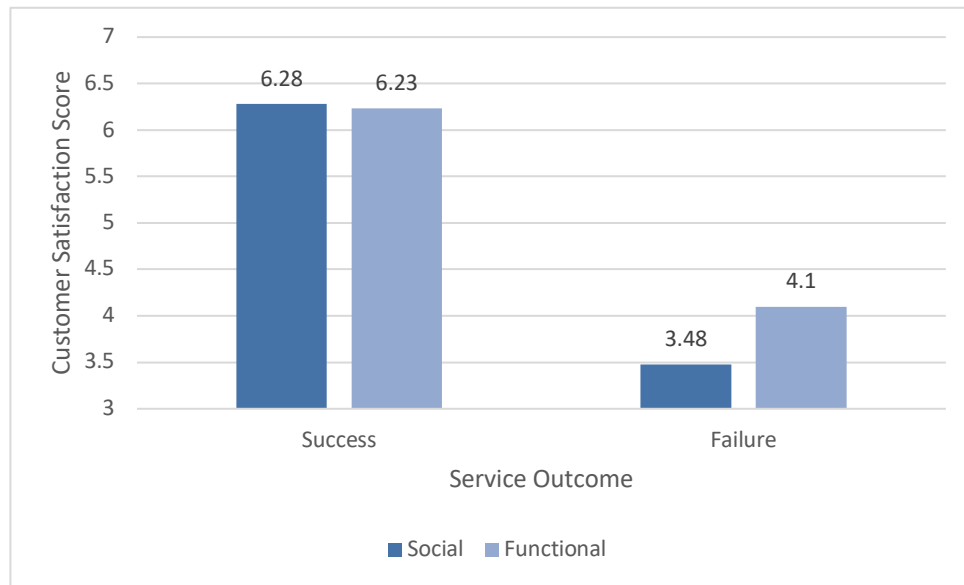


Figure 12: Study 3 Main study: Effect on interaction content and service outcome on customer satisfaction

Mediation analysis

Mediation analysis was employed using the PROCESS macro in SPSS (Model 4) (Hayes, 2017) with 10,000 bootstrap samples, in order to investigate the potential mediators underlying the reverse effect observed in the satisfaction scores for service outcome (success and failure). This statistical approach allowed for the examination of indirect effects and their significance, shedding light on the mechanisms at play between the independent variable of interaction content (social and functional) and the

dependent variable (customer satisfaction). Summary of results in Appendix K.

Condition of service outcome as success: Mediation of Empathy

In the case where the chatbot successfully completed the service request of the consumer, empathy was used as a mediating variable, as determined in study 2. Consistent with the findings of study 2, the results revealed a direct and positive effect of interaction content on empathy ($b = 1.37$, $t(197) = 7.67$, $p = 0$), showing that social interaction content increases perceived empathy. Further, empathy demonstrated a significant influence on customer satisfaction ($b = 0.40$, $t(196) = 8.97$, $p = 0$).

When assessing the mediating role of empathy between interaction content and customer satisfaction, a positive and statistically significant relationship was observed (indirect effect = 0.54, $SE = 0.1$, 95% CI = [0.35, 0.76]). This aligns with the findings of study 2, indicating that social interaction content fosters higher levels of perceived empathy, which subsequently contributes to enhanced customer satisfaction. In spite of the lack of an overall significant effect of interaction content on customer satisfaction, there is a positive significant indirect effect via perceived empathy.

Condition of service outcome as failure: Mediation of Perceived empathy,

Perceived competence, and Customer frustration

Mediation analysis was conducted to investigate the underlying factor contributing to the observed reverse effect of social versus functional

interaction content on evaluations of customer satisfaction, in the condition of chatbots' service failure.

First, the mediating role of empathy was examined. Consistent with previous findings, it was observed that interaction content (social vs functional) had a positive effect on empathy ($b = 0.82$, $t(198) = 3.87$, $p < 0.01$). Furthermore, empathy demonstrated a positive effect on customer satisfaction ($b = 0.43$, $t(197) = 6.31$, $p = 0$).

The results of the mediation analysis indicated that perceived empathy has a significant mediating role between interaction content (social vs functional) and evaluations of customer satisfaction (indirect effect = 0.36, $SE = 0.11$, 95% CI = [0.16, 0.58]). However, there also existed a significant negative main negative effect of interaction content for customer satisfaction ($b = -0.97$, $t(197) = -4.56$, $p = 0$). This implies that functional (vs social) interaction content drives higher ratings of customer satisfaction. Therefore, while empathy exhibits a positive mediating role, it does not fully account for the observed reverse effect of social versus functional content on customer satisfaction in this context.

In addition to examining empathy as a mediator, perceived competence was also included as a parallel mediator in the analysis. The results revealed that interaction content (social and functional) continued to have a positive effect on empathy ($b = 0.82$, $t(198) = 3.87$, $p < 0.01$), indicating that use of social interaction content in chatbots evokes higher levels of empathy compared to functional interaction content. However, it was

observed that interaction content had a significant negative effect on perceived competence ($b = -0.41$, $t(1,198) = -2.03$, $p < 0.05$). This suggests a chatbot using functional interaction content is perceived to be more competent than a chatbot using social interaction content, particularly in the context of service failure. As expected, a negative direct effect of interaction content (social vs functional) and customer satisfaction was observed, ($b = -0.26$, $t(196) = -1.99$, $p < 0.05$), indicating that social interaction content results in lower satisfaction while functional interaction content leads to higher satisfaction. When considering the parallel mediating roles of perceived empathy and perceived competence, it was found that perceived competence has a negative mediating role between interaction content (social vs functional) and customer satisfaction (indirect effect = -0.38 , $SE = 0.19$, 95% CI = $[-0.74, -0.01]$). This indicates that in the conditions of service failure, a chatbot using social (vs functional) interaction content is perceived as significantly less competent, leading to a significantly lower evaluations of customer satisfaction compared to chatbots adopting functional interaction content. However, in the presence of perceived competence as a mediator, the mediating role of empathy was no longer significant (indirect effect = 0.024 , $SE = 0.04$, 95% CI = $[-0.05, 0.101]$). This suggests that the strong negative mediating role of competence outweighs the positive mediating role of empathy, thus providing an explanation for the observed reverse effect in the condition of service failure (vs service success), between interaction content (social vs functional) and customer satisfaction.

Additionally, mediation analysis also examined if customer frustration operates as a competing mediator with perceived competence, aiming to explain the negative direct impact of interaction content on customer satisfaction ($b = -0.3$, $t(196) = -2.52$, $p = 0.01$). The results indicated that interaction content (social vs functional) does not influence customer frustration. The mediation analysis did not find a significant mediating effect of customer frustration between interaction content (social and functional) and customer satisfaction (indirect effect = -0.33 , $SE = 0.16$, 95% CI[-0.66, 0.01]). Hence, the possible alternative explanation of customer frustration from service failure as a mechanism to explain the effect of functional (vs social) interaction content on higher customer satisfaction was ruled out.

3.4.7 Discussion

The findings of this study reinforce the notion that customer satisfaction scores are significantly lower in the failure condition compared to the success condition. More importantly, these results are consistent with the theorisation and the hypothesis H3, which posits that functional interaction content yields higher levels of satisfaction in chatbot service failure scenarios, as opposed to social interaction content.

Within the service success condition, although there was no notable difference in customer satisfaction scores between social and functional interaction content, empathy exhibited a positive mediating role between interaction content and satisfaction. This indicates that social interaction content leads to greater satisfaction due to the presence of perceived

empathy. These findings align with the results of the previous study (Study 2) and furnish additional evidence supporting H1a, H1b, H2a and H2b.

Conversely, in the service failure condition, the findings suggest that empathy does act as a mediator in explaining why social interaction content leads to customer satisfaction. However, it does not explain the direct negative relation between interaction content (social and functional) and customer satisfaction (i.e., functional interaction provides higher customer satisfaction). Instead, the results show perceived competence as a key factor explaining the negative relationship between interaction content (social vs functional) and customer satisfaction, in cases of service failure. This means that chatbots using functional (instead of social) interaction content are perceived as more competent, which further leads to higher levels of satisfaction. This discovery aligns with the initial theoretical assumptions (and supporting H4), highlighting that the perceived competence conveyed through use of functional interaction content, rather than social interaction content, contributes to elevated levels of satisfaction.

Interestingly, the analysis further revealed that customer frustration does not mediate the relationship between interaction content and satisfaction. Despite the emphasis placed on different interaction content types (social and functional), the impact on frustration levels was not statistically significant. This suggests that the only factor explaining the higher customer satisfaction stemming from functional interaction content, in contrast to social interaction content, is the perceived competence.

To summarise, the study furnishes empirical evidence supporting the reverse effect of interaction content (social and functional) on satisfaction, in the case of a service failure by chatbot. The theoretical underpinnings corroborated by these findings have established a boundary condition for the proposed mechanism in Study 2. In situations where the chatbot service is successful, utilising social interaction content leads to increased satisfaction because it fosters a greater sense of empathy. Conversely, in cases of chatbot service failure, functional interaction content enhances satisfaction as it is associated with higher perceived competence.

4 CONCLUSION

4.1 General discussion

Customer experience from service encounters is one of the growing focuses of businesses for all service delivery aspects of the firm (Klaus & Maklan, 2013). Additionally, as technology advances, businesses are recognising the potential of chatbots to handle customer inquiries and support requests efficiently. Hence, chatbots' delivery of exceptional customer service has emerged as a critical determinant for organisational success. Both companies and consumers place great emphasis on delivering and receiving a positive customer experience respectively. However, for chatbots to effectively contribute to this goal, it is crucial that they are designed to deliver a satisfying customer experience.

This PhD research delves into the customer experience with chatbot services and addresses the challenges and potential solutions in enhancing customer satisfaction.

The initial objective of the research was to understand the extent of negative perceptions consumers hold towards chatbots compared to other modes of contact across various touchpoints in the customer journey. The findings, through a conjoint analysis and an experiment, consistently demonstrated that consumers have a lower intent to use chatbots as a mode of contact for customer service compared to alternatives like phone calls, emails, and website information. This consistent pattern of lower

preference for chatbots persists across various customer journey touchpoints. Results from this study also showed men consistently have a higher intent to use chatbots across all touchpoints compared to women.

The research then focused on improving the intention to use chatbots, which can be done by increasing customer satisfaction with the service provided by chatbots (Bolton & Lemon, 1999). Additionally, the research addressed the challenge of disclosing (vs. not disclosing) the identity of the chatbot, which is more and more a prerequisite given legal requirements. By conducting experimental studies, using consumer-chatbot conversation screenshots, the research investigated how different types of interaction content (social and functional) can mitigate the negative repercussions associated with a low intent to use chatbots (which is a consequence of low customer satisfaction) and with the identity disclosure of chatbots.

Recognising the imperative nature of chatbot identity disclosure, the results revealed that incorporating social interaction content, which encompasses elements such as greetings, emojis, and acknowledging previous messages, contributes significantly to positive customer outcomes, specifically customer satisfaction. This positive impact is attributed to consumers perceiving the chatbot as empathetic when the chatbot's conversation script utilises social (rather than functional) interaction content.

However, results also showed that the use of social interaction content is not effective in all situations. When a service by chatbot fails to deliver the desired outcome, customer satisfaction naturally diminishes compared

to instances where the chatbot service is successful. Moreover, the study demonstrated that in such chatbot failure scenarios, the usage of social interaction content in the conversation script of chatbots aggravates the decrease in customer satisfaction. Conversely, the utilisation of functional interaction content yields higher satisfaction levels. This happens because consumers perceive chatbots that use functional interaction content to be more competent, proving more effective in handling failure situations than chatbots that use social interaction content.

Overall, the three studies conducted in this research have provided consistent and valuable insights into consumers' experience with chatbot services. These findings contribute to academic research by expanding the understanding of consumer perceptions and preferences towards chatbots while also offering practical implications for businesses aiming to design and deploy chatbots that deliver exceptional customer service.

4.2 Theoretical contributions

In recent years, research on chatbots and related areas has experienced notable growth. Since 2019, there has been an increasing interest in understanding the perceptions and implications of chatbot interactions in various business contexts (Mariani et al., 2023). This growth is attributed to the rising prominence of chatbots in the digital landscape and the recognition of their potential to revolutionise customer service and enhance customer experiences. However, despite the growing body of research in this field, certain gaps and limitations still need to be addressed. These

caveats hinder a comprehensive understanding of chatbot interactions and their impact on customer experience. By recognising and addressing these caveats, this research contributes to understanding a more holistic and robust perception of chatbot interactions in business contexts. The research conducted for this PhD makes valuable contributions through a theory-driven framework to multiple literature streams within the field of business. These include the areas of Human-Computer Interaction, Customer Experience, and Agent-customer Interaction.

First and foremost, this research provides valuable insights into the prevalent negative perceptions surrounding chatbots in today's digital era. Prior studies in the realm of human-computer interaction have consistently shown that consumers prefer human agents and information on websites over chatbots in customer service interactions (Castelo et al., 2023; Sands et al., 2021; Sheehan et al., 2020; Sivaramakrishnan et al., 2007). This research extends this comparison to encompass other modes of contact, offering a comprehensive examination of consumer preferences. It shows that consistent with comparison to human agents, other modes of contact (email, customer service call and website) are more likely to be used over chatbots if customers are given the chance. Furthermore, the research also addresses another notable gap in the current literature by examining the intent to use chatbots across various touchpoints throughout the customer journey in comparison to alternative modes of contact. While previous studies predominantly focused on analysing a single stage within the customer journey, this research expands on this by investigating multiple

customer journey touchpoints at the same time. Moreover, it aims to determine whether the preference for chatbots (vs other modes of contact) varies across these touchpoints stages of the customer journey.

Previous literature has highlighted how social and visual cues, conversation styles, gender, and anthropomorphism of a chatbot can help improve perceptions towards them (Araujo, 2018; Borau, Otterbring, Laporte, & Fosso Wamba, 2021; Go & Sundar, 2019; Roy & Naidoo, 2021). Building upon these findings, this research specifically focuses on the conversation cues in the context of chatbots (Chattaraman et al., 2019; Go & Sundar, 2019; Williams & Spiro, 1985). While prior studies that have explored the influence of conversation styles on aspects such as relationship building, trust and social presence (as highlighted in the literature review), this study looks at a significant gap regarding how the overall customer satisfaction of chatbots can be improved using different types of conversation styles (social or functional). This research introduces a novel framework that combines different types of interaction content, perception of empathy, customer satisfaction and the issue of chatbot identity disclosure. The framework reveals that using social interaction content, particularly in relation to chatbots disclosing their identity, fosters higher levels of customer satisfaction with the chatbot service. Consequently, this heightened satisfaction further increases consumers' intention to utilise chatbots. The field of identity disclosure is relatively under-researched, making this contribution particularly valuable. Previous studies have looked at the effects of identity disclosure (Luo et al., 2019; Mozafari et al., 2022),

but this study further advances the understanding of how these negative effects can be mitigated.

This research also make a noteworthy contribution to the existing body of literature on empathy in chatbots, as it represents one of the few studies in this specific domain. Previous research has acknowledged the significance of empathy in the context of customer service and customer satisfaction (Markovic et al., 2018; Royne Stafford et al., 1998; Wieseke et al., 2012), and specifically in the context of chatbots (Chung et al., 2020), this research extends this literature by delving deeper into the role of social interaction content in facilitating empathic perceptions among consumers. Notably, the findings from this study shed light on the crucial positive relationship between the utilisation of social interaction content in chatbot interactions and the consumers' perception of empathy. This insight adds substantial value to the existing literature, as it emphasises the pivotal role of empathic interactions in enhancing customer satisfaction—a factor that has been consistently identified as negatively affected by the absence of empathy in chatbots (Chung et al., 2020).

Furthermore, another significant theoretical contribution is made to the growing literature on chatbot service failure. Unlike previous studies that primarily focus on traditional service recovery mechanisms (Choi et al., 2021; Pavone et al., 2023; Sun & Guan, 2022), this research explores how dissatisfaction resulting from service failures can be mitigated through the utilisation of distinct types of interaction content. In particular, the findings from Study 3 demonstrate that consumers perceive chatbots employing

functional interaction content as more competent than those employing social interaction content. Consequently, this perception of competence contributes to increased customer satisfaction in the event of a service failure. By highlighting the efficacy of functional interaction content, the results from this research enhance the understanding of how chatbots can effectively address service failures and improve customer experiences. Furthermore, it builds upon the role of perceived competence in chatbots, as discussed in existing literature (X. Li et al., 2019).

The study undertaken offers valuable insights into the mediating role of empathy and competence in the relationship between interaction content and customer satisfaction with chatbot services. Existing literature has established that the perception of warmth is an outcome of perceived empathy (Huang & Rust, 2018). By considering this association, this research also contributes to the growing body of literature on the 'Dimensions of Social Cognition: Warmth and Competence' (Cuddy, Fiske, & Glick, 2008). While prior research has examined this model in the context of customer-employee relation, this research extends its application to understand the influence of warmth and competence on different service outcomes (success and failure) for chatbots.

In summary, this research significantly contributes to the chatbot literature by elucidating how chatbots can effectively increase customer satisfaction. By exploring the role of interaction content, this study addresses how to mitigate negative perceptions of chatbot identity disclosure and service failure.

4.3 Managerial implications

This PhD thesis has yielded crucial marketing implications that can significantly benefit managerial practices. It provides actionable insights for managers to navigate challenges effectively for ethical and design issues faced when deploying chatbots.

Firstly, managers need to recognise the prevailing negative perceptions towards chatbots and acknowledge that consumers often prefer alternative media for their customer service interactions, if given the option to choose between different media. By understanding the factors that contribute to these perceptions, such as concerns about impersonality or the perception of limited understanding, businesses can design strategies to address them effectively. Additionally, organisations must also contemplate the ethical development of chatbots in terms of disclosing the identity of the chatbot. In addition to being an ethical consideration, it is now mandatory (in several countries) for companies to disclose the identity of their chatbots. This legal requirement adds an extra layer of importance to understand how to alleviate the negative feelings that consumers may experience when they interact with a chatbot. The findings of this research offer valuable guidance to firms on how to enhance satisfaction among consumers when disclosing the identity of chatbots. By incorporating social cues such as greetings, emojis, and engaging in small talk, chatbots can create a perception of empathy, leading consumers to believe that the chatbot has emotions and understands their needs.

However, managers should exercise caution when using social cues, especially in cases where this is a high likelihood of chatbots not being able to deliver customer requests. In such situations, the presence of social cues can inadvertently amplify consumer perceptions of the chatbot's incompetence, leading to decreased satisfaction. Therefore, it is essential to carefully calibrate the use of social cues, ensuring they align with the chatbot's capabilities.

Additionally, this research highlights the importance of understanding the customer journey touchpoints in the context of contacting customer service. Managers can gain insights into at which touchpoints customers are more likely to engage with chatbots (when alternative channels are available for customer service) and can optimise the functionality of chatbots accordingly.

In summary, this research offers valuable guidance for managers seeking to leverage chatbot technology and improve customer experiences. By recognising and addressing negative perceptions, ethical considerations of chatbot identity disclosure, incorporating social cues appropriately, and aligning chatbot functionality with customer preferences, managers can more readily harness the potential of chatbots as a valuable customer service tool. This comprehensive approach will result in enhanced customer satisfaction, increased usage of chatbots, and ultimately, improved business outcomes.

4.4 Limitations and avenues for future research

Despite the valuable insights gained from this research, there are certain limitations to acknowledge.

One notable limitation of this research is its limited external validity. The data collection method employed in this study, namely the screenshot method, is a common approach found in the existing literature (Chung et al., 2020; Go & Sundar, 2019; Roy & Naidoo, 2021). Due to the challenges associated with persuading companies to modify their chatbot functionalities for research purposes (which is an issue that this doctoral research has faced), the use of screenshots remains a popular alternative. However, it is important to acknowledge that this simulated approach may not fully capture the real-world dynamics of chatbot interactions, and the nuanced responses users provide in real-time. To enhance the generalisability of the findings from this research, future studies could consider adopting a real-time research design that involves manipulating chatbots of actual companies, as has been done in recent studies (Luo et al., 2019; Yu et al., 2022). By incorporating a real-world setting, such studies could provide a more authentic representation of user experiences and potentially uncover novel insights. Having said that, the conversation scripts utilised in the studies hold the assumption that chatbots have a strong ability to comprehend consumers (irrespective of being able to solve the customer issue, or not). However, such an assumption holds even more truer into practice these days than before (for instance, ChatGPT, an

unsupervised language model, can demonstrate a very good understanding of consumers' queries).

Another limitation of this research is the specific context of consumer inquiries that were examined. They primarily concentrated on two predetermined scenarios: pre-registering for a new product and addressing a payment issue (Study 2 and Study 3 respectively). However, it is worth considering that addressing a payment problem entails a higher level of psychological risk compared to pre-registering for a product (Park and Tussyadiah, 2016). Therefore, future studies could explore the use of different types of interaction content (social and functional) to enhance customer experience within the context of situations with varying degrees of psychological risk. In addition, within the broader context of risks associated with chatbot interactions, existing literature underscores concern about perceived privacy risk and perceived time risk. In the context of chatbots, users may encounter increased privacy concerns, especially in activities involving personal data collection for product or service advisory purposes (Ischen et al., 2019). Research on perceived risks associated with chatbots reveals that perceived privacy risk can negatively impact the intention and frequency of chatbot use. This concern arises due to some chatbots collecting and accessing users' personal information, including personal data and geolocations (Rese et al., 2020). Furthermore, chatbot latency emerges as a notable limitation affecting chatbot adoption (Pillai & Sivathanu, 2020). Consequently, users may perceive chatbots as more time-consuming than human conversations. Future research could explore

how these risk factors can be mitigated with the use of different types of interaction content and their implications for the effective deployment of chatbots and user acceptance.

Additionally, the research identified customer journey touchpoints as an important factor for consumers to contact customer service. Future research in the field of chatbots could delve deeper into this aspect by examining the different touchpoints and exploring how companies can develop tailored strategies to optimise the customer experience by chatbots at each touchpoint of the customer journey. By expanding the scope of inquiry, the generalisability of findings to diverse contexts can be better understood, and organisations can gain insights on maximizing customer satisfaction at various stages of the customer journey.

The third constraint of this research is its exclusive focus on individuals residing in the United Kingdom and Ireland. While this study yielded valuable insights within the specific geographical context, it is essential to acknowledge that cultural elements can significantly influence how customers perceive, prefer, and accept chatbots. In order to obtain a more comprehensive comprehension, future studies could explore the impact of cultural differences on chatbot usage and identify effective strategies for cultural adaptation of chatbot conversation scripts. Additionally, forthcoming research could also examine the effect of other demographic factors, such as gender. The study's findings indicated a disparity in chatbot's usage intent between men and women, but further exploration is needed to provide a more in-depth explanation for this difference. By comparing

variances across cultures and genders, researchers can contribute to a more profound understanding of the global applicability of chatbots and assist organisations in tailoring their chatbot implementations to diverse demographics.

This research focused solely on text-based chatbots, and an interesting avenue for future research lies in exploring the effectiveness of voice-based chatbots. Voice assistants and voice-activated devices have gained significant popularity in recent years (Fernandes & Oliveira, 2021; McLean & Osei-Frimpong, 2019). While chatbots on platforms like Facebook messenger, websites, and WhatsApp might incorporate social cues such as emoticons, these elements might come across as less natural or more unexpected in voice chatbots and might not be conveyed through voice very well. Therefore, it would be valuable to investigate how the absence of these cues affects user interactions in voice- based chatbot conversations.

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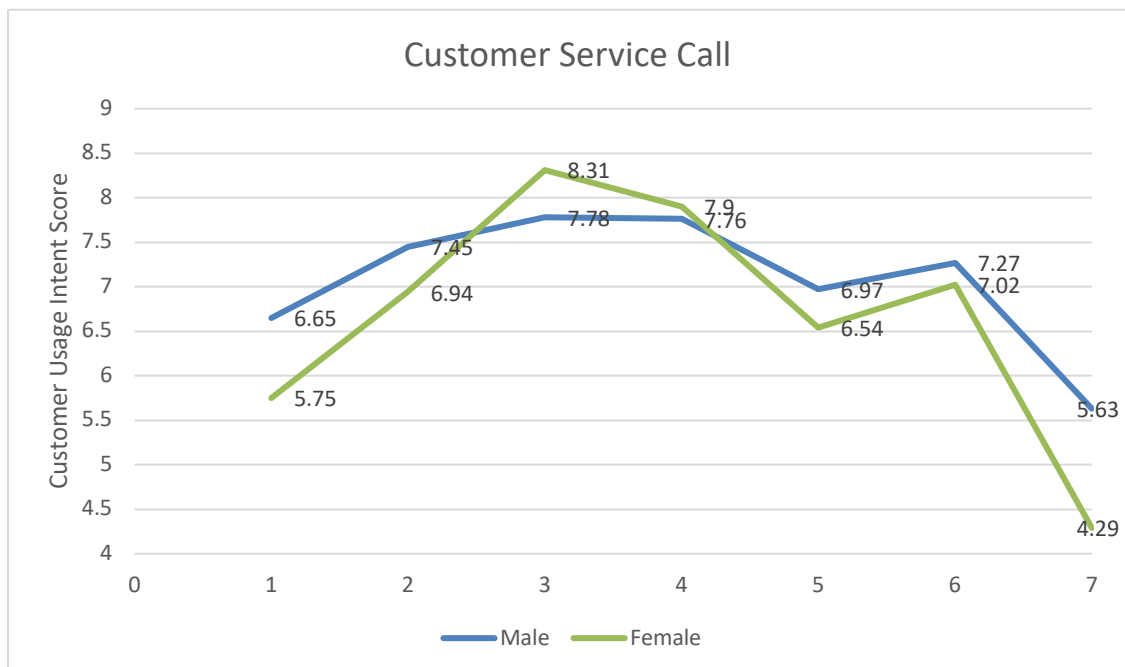
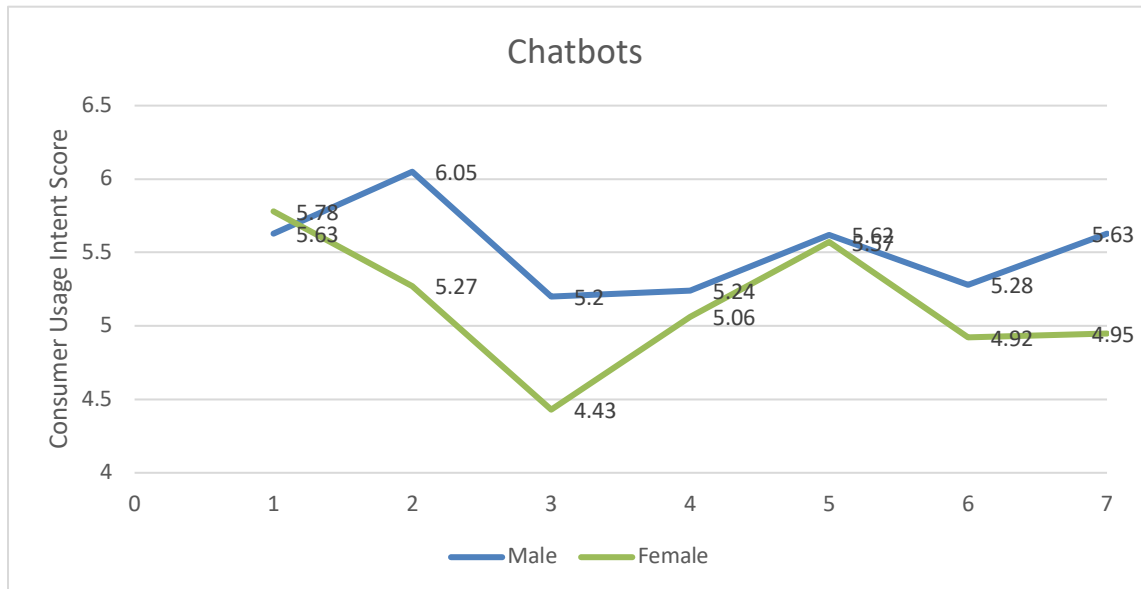
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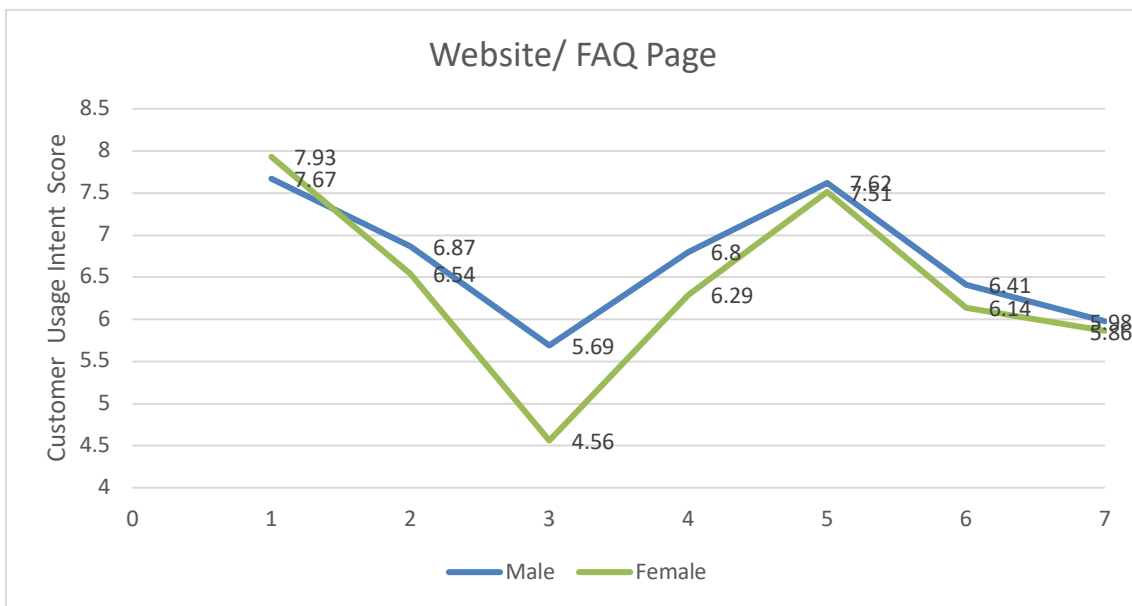
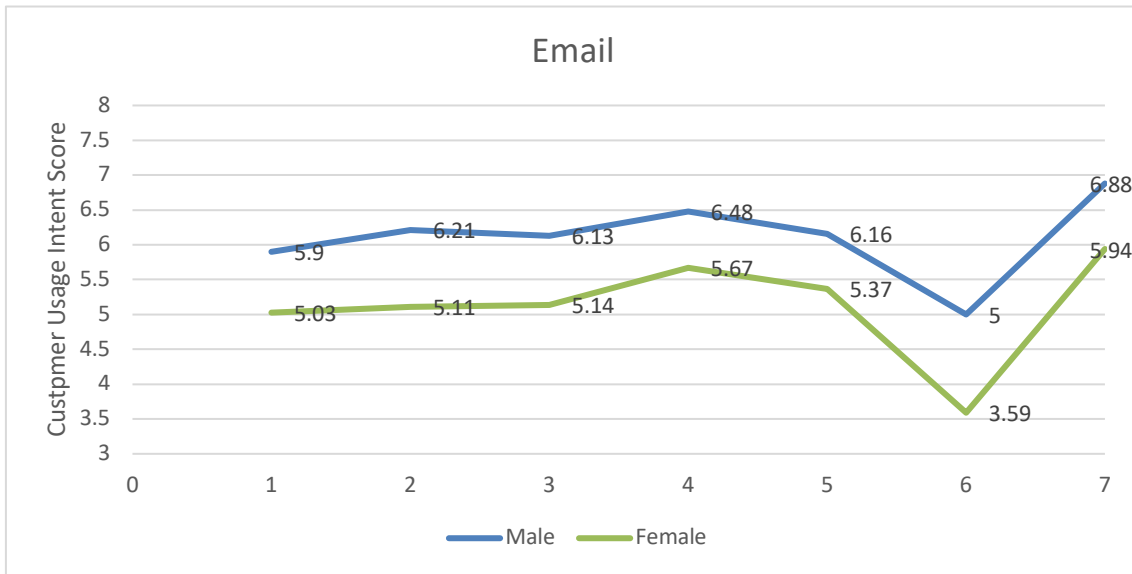
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APPENDICES

Appendix A - Study 1: Usage intent ratings by male and female respondents based on different medium of contact at different stages





Appendix B - Study 2 & 3: Exclusion criteria for removing participants from the dataset

To facilitate the analysis process of Study 2 & 3, a series of data cleaning procedures were performed, which involved the removal of multiple participants from the primary dataset. The rationale behind this decision, as well as the specific exclusion criteria utilized, are provided in the table below.

Step	Description
<i>Step 1: Tackling Incorrect Prolific Id or Missing Unique code</i>	Participants whose Prolific ID did not match between the two platforms (Prolific and Qualtrics) were removed from the data set. Participants that did not enter the unique code (from Qualtrics) into Prolific were removed as well.
<i>Step 2: Deleting spurious data</i>	Each response was looked at and the one's with the same ratings for all survey questions or alternating between two or three rankings were deleted. For e.g., if a participant had ranked all Customer satisfaction and Manipulation check questions as 6 were deleted.
<i>Step 3: Passing the attention check</i>	An 'Attention check' question was also added at the end of the manipulation check scale: " <i>For this specific statement, please choose 'Strongly disagree'. This is an attention check</i> ". All participants who had not ranked the scale correctly for this question were also removed.
<i>Step 4: Checking previous records of participants</i>	In the final step, the previous participation record of participants on Prolific was checked. This was provided by Prolific in the demographic data. If a participant had less than 95% approval rate or had been rejected previously (from other studies) more than 3 times, the submission was deleted from the main data set.

Appendix C - Study 2: Ethics information and task scenario presented in Prolific

You are invited to participate in this research project, which is being carried out by Chetna Johar from Trinity Business School, Dublin.

Your participation is voluntary. Even if you agree to participate now, you can withdraw at any time without consequence.

You will be asked to imagine you are researching buying a new e-bike. From a search on Google, you click on an ad and are brought to the website of Hound Mobility. Your task is to read a conversation that represents the type of interaction you may have with the online customer service of Hound Mobility. This interaction includes questions and answers about specific features of the e-bikes available through Hound Mobility. After looking at the conversation, you will be asked some questions regarding your experience of the conversation. The time duration of the whole task will be 4-6 minutes.

Any identifiable information or data which we obtain from you during this research with you will be treated confidentially. We will do this by treating all responses anonymously. The data will be kept with the researcher solely. Data from this research project may be published in future.

The original data will be available only to the present investigator: Chetna Johar. If you have any questions about this research, please contact at: joharc@tcd.ie.

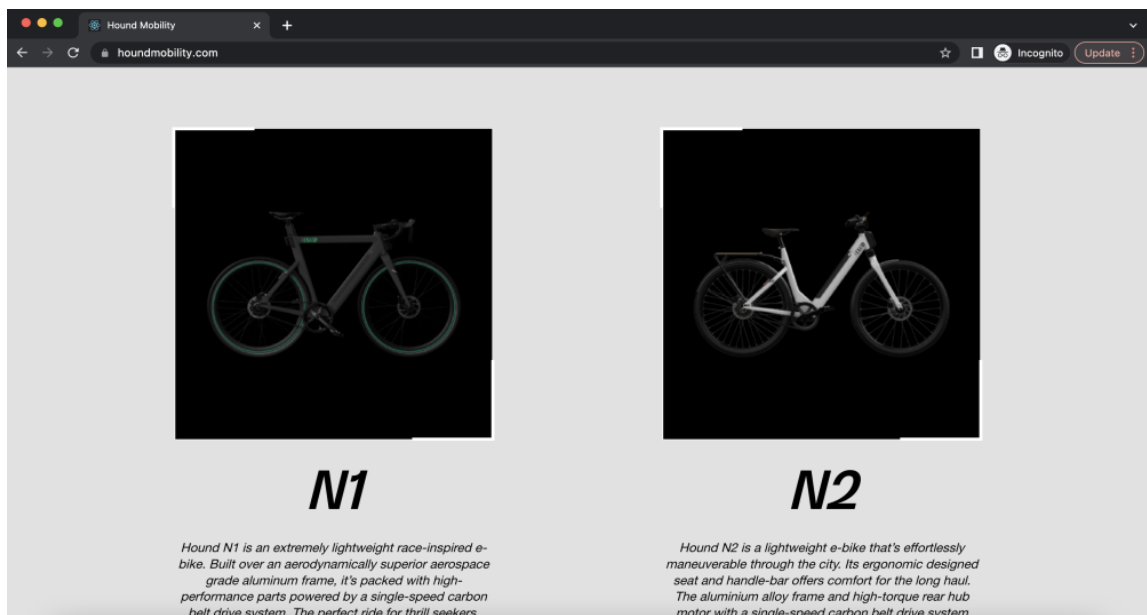
Appendix D - Study 2: Explanation of task and scenario to participants

Thank you for taking part in this study.

The task for this research requires you to imagine yourself in a situation where you are interested in purchasing an e-bike, which you will use for your daily commute to work.

Hound Mobility is a cutting-edge new e-bike company, which will be launching in the UK and Europe in the next few months. They are bringing two exciting e-bike options to the market: Hound N1 and Hound N2. The website of the company provides details about the company ownership, company ethos and values and provides specifications and highlights key features of the bikes. The website also allows potential customers to pre-register their interest for an e-bike. Pre-registering for the e-bike means you will be the first to know about the launch date, any upcoming offers and have early access to purchase your preferred bike.

The images below provide a glimpse of the website:



You find the website interesting and are intrigued by the features of the bikes. However, you would like to probe for more information, for you to make a choice about pre-registering for the bike or not.

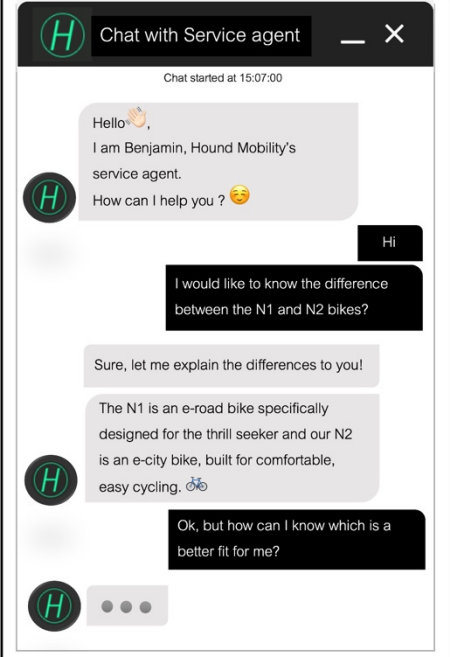
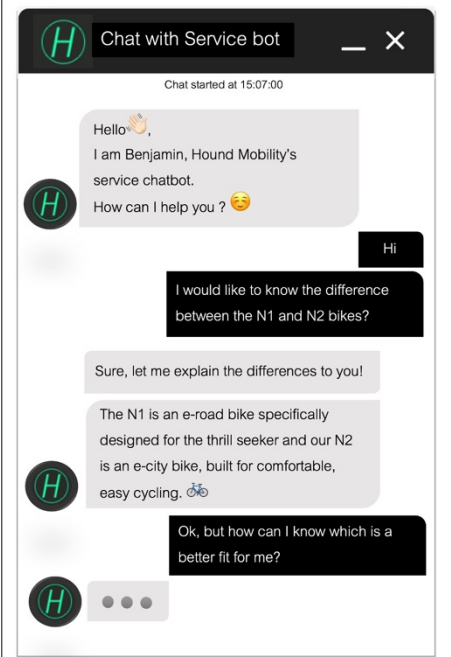
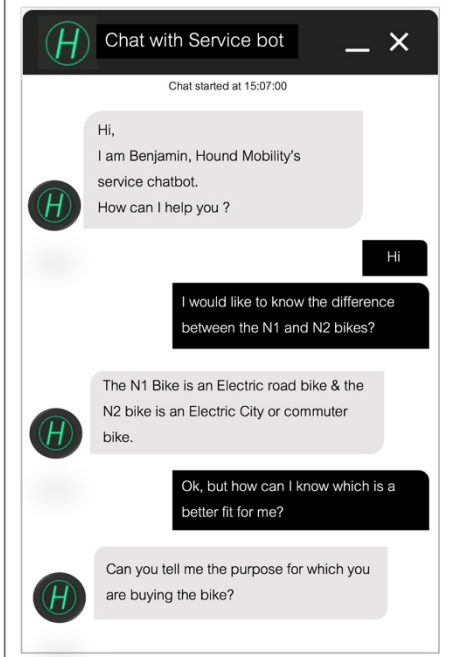
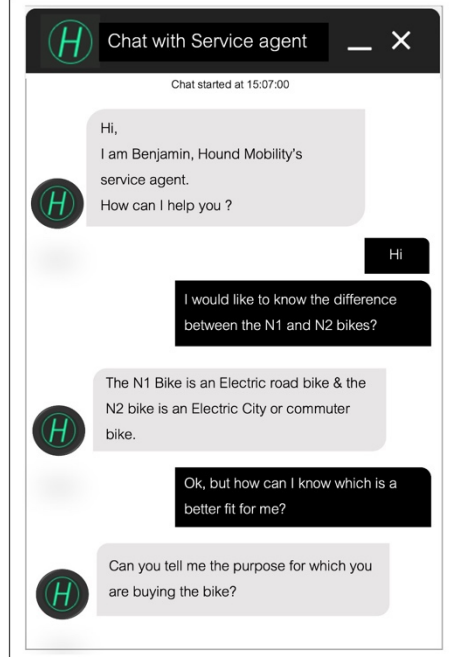
In particular, you wish to know more about the differences between the two bike models and which of the two bikes is more suitable for your needs. To get these answers, imagine you are having a conversation with the online customer service available on the website, and that this conversation is described below.

This conversation is described via screenshots on the following pages of this questionnaire.

Please read the conversation script below, carefully.

You will be able to go to the next screen of the conversation after at least 10 seconds, to allow enough time for you to read.

Appendix E – Study 2: Screenshots shown to participants for each condition

Non-Disclosure & Social Interaction content (1/5)	Disclosure & Social interaction content (1/5)	Non-disclosure & Functional interaction content (1/5)	Disclosure & Functional interaction content (1/5)
 Chat started at 15:07:00 Hello 🙋, I am Benjamin, Hound Mobility's service agent. How can I help you ? 😊 Hi I would like to know the difference between the N1 and N2 bikes? Sure, let me explain the differences to you! The N1 is an e-road bike specifically designed for the thrill seeker and our N2 is an e-city bike, built for comfortable, easy cycling. 🚲 Ok, but how can I know which is a better fit for me? ...	 Chat started at 15:07:00 Hello 🙋, I am Benjamin, Hound Mobility's service chatbot. How can I help you ? 😊 Hi I would like to know the difference between the N1 and N2 bikes? Sure, let me explain the differences to you! The N1 is an e-road bike specifically designed for the thrill seeker and our N2 is an e-city bike, built for comfortable, easy cycling. 🚲 Ok, but how can I know which is a better fit for me? ...	 Chat started at 15:07:00 Hi, I am Benjamin, Hound Mobility's service chatbot. How can I help you ? Hi I would like to know the difference between the N1 and N2 bikes? The N1 Bike is an Electric road bike & the N2 bike is an Electric City or commuter bike. Ok, but how can I know which is a better fit for me? Can you tell me the purpose for which you are buying the bike?	 Chat started at 15:07:00 Hi, I am Benjamin, Hound Mobility's service agent. How can I help you ? Hi I would like to know the difference between the N1 and N2 bikes? The N1 Bike is an Electric road bike & the N2 bike is an Electric City or commuter bike. Ok, but how can I know which is a better fit for me? Can you tell me the purpose for which you are buying the bike?

Non-Disclosure & Social Interaction content (2/5)	Disclosure & Social interaction content (2/5)	Non-disclosure & Functional interaction content (2/5)	Disclosure & Functional interaction content (2/5)
 Chat with Service agent — X  I can help you with that. But first, could you please tell me the purpose for which you are buying the bike? 😊 I need it for cycling to office. That's great, the N2 bike is perfectly suited for everyday use! It is designed as an e-city bike that's effortlessly manoeuvrable making it perfect for everyday urban commute! 🚲 Its features include intelligent pedal assist, a carbon fibre belt drive system, anti-theft protection, it provides an overall connected experience. It also comes with a lighting and indicator system.  And what material is the bike made of?	 Chat with Service bot — X  I can help you with that. But first, could you please tell me the purpose for which you are buying the bike? 😊 I need it for cycling to office. That's great, the N2 bike is perfectly suited for everyday use! It is designed as an e-city bike that's effortlessly manoeuvrable making it perfect for everyday urban commute! 🚲 Its features include intelligent pedal assist, a carbon fibre belt drive system, anti-theft protection, it provides an overall connected experience. It also comes with a lighting and indicator system.  And what material is the bike made of?	 Chat with Service agent — X I need it for cycling to office. The N2 bike would be a good fit for you. It is designed as an e-city bike that's effortlessly manoeuvrable making it perfect for everyday urban commute. Its features include intelligent pedal assist, a carbon fibre belt drive system, anti-theft protection, it provides an overall connected experience. It also comes with a lighting and indicator system.  And what material is the bike made of?  ...	 Chat with Service bot — X I need it for cycling to office. The N2 bike would be a good fit for you. It is designed as an e-city bike that's effortlessly manoeuvrable making it perfect for everyday urban commute. Its features include intelligent pedal assist, a carbon fibre belt drive system, anti-theft protection, it provides an overall connected experience. It also comes with a lighting and indicator system.  And what material is the bike made of?  ...

Non-Disclosure & Social Interaction content (3/5)	Disclosure & Social interaction content (3/5)	Non-disclosure & Functional interaction content (3/5)	Disclosure & Functional interaction content (3/5)
 Chat with Service agent — ×  Sure thing! The bike is made from aerospace grade aluminium alloy.  And how long does the battery last? That's a good question! 🌱 Our bikes use lithium-ion batteries from Samsung. They will last for around 80-100 kms. Also, the batteries are compact and removable, which means you can charge anywhere, anytime.  Ok and when would I get the bike delivered? Our bikes are currently in the pre-production stage, which means it will take 6-8 months for them to be available.  Coming to you guys soon!! ➡️ SOON	 Chat with Service bot — ×  Sure thing! The bike is made from aerospace grade aluminium alloy.  And how long does the battery last? That's a good question! 🌱 Our bikes use lithium-ion batteries from Samsung. They will last for around 80-100 kms. Also, the batteries are compact and removable, which means you can charge anywhere, anytime.  Ok and when would I get the bike delivered? Our bikes are currently in the pre-production stage, which means it will take 6-8 months for them to be available.  Coming to you guys soon!! ➡️ SOON	 Chat with Service agent — ×  The bike is made from aerospace grade aluminium alloy.  And how long does the battery last? All the bikes use lithium-ion batteries from Samsung. They will last for around 80-100 kms. Hound bikes come with a compact and removable battery.  Ok and when would I get the bike delivered? Our bikes are in the pre-production stage, which means it will take 6-8 months for them to be available.  What's the price?  ...	 Chat with Service bot — ×  The bike is made from aerospace grade aluminium alloy.  And how long does the battery last? All the bikes use lithium-ion batteries from Samsung. They will last for around 80-100 kms. Hound bikes come with a compact and removable battery.  Ok and when would I get the bike delivered? Our bikes are in the pre-production stage, which means it will take 6-8 months for them to be available.  What's the price?  ...

Non-Disclosure & Social Interaction content (4/5)	Disclosure & Social interaction content (4/5)	Non-disclosure & Functional interaction content (4/5)	Disclosure & Functional interaction content (4/5)
 Chat with Service agent What's the price?  If you opt for a N2 bike, it will cost you approximately 1800 GBP/EUR 📄 However, if you pre-register you will be the first one to hear of any offers and updates about the launch!! Okay, how can I pre-register?  Great question! Please provide your email id and we can add you to our pre-registration list 📄 biker.345@gmail.com Thank you. Just give me a few moments; I will get this done ⌚ 	 Chat with Service bot What's the price?  If you opt for a N2 bike, it will cost you approximately 1800 GBP/EUR 📄 However, if you pre-register you will be the first one to hear of any offers and updates about the launch!! Okay, how can I pre-register?  Great question! Please provide your email id and we can add you to our pre-registration list 📄 biker.345@gmail.com Thank you. Just give me a few moments; I will get this done ⌚ 	 Chat with Service agent  Hound N2 bike costs 1800 GBP/EUR However, if you pre-register you will be the first one to hear of any offers and updates about the launch!! Okay, how can I pre-register?  Remember to provide your email id and we can add you to our mailing list. biker.345@gmail.com Thank you. A few moments while I upload this on the system.  Can you check if you have received a confirmation email? Yes, got it	 Chat with Service bot  Hound N2 bike costs 1800 GBP/EUR. However, if you pre-register you will be the first one to hear of any offers and updates about the launch. Okay, how can I pre-register?  Remember to provide your email id and we can add you to our mailing list. biker.345@gmail.com Thank you. A few moments while I upload this on the system.  Can you check if you have received a confirmation email? Yes, got it

Non-Disclosure & Social Interaction content (5/5)	Disclosure & Social interaction content (5/5)	Non-disclosure & Functional interaction content (5/5)	Disclosure & Functional interaction content (5/5)
 Chat with Service agent — ✕  You're now on our pre-registration list. Can you check if you have received a confirmation email? Yes, got it Awesome! Welcome to the Hound Mobility- family! 🐾  Is there anything else you'd like to know about the company or the product? 📄 I am happy to help with anything! 😊 No that's it.  Thank you for contacting us today! Hope I was able to help you 😊 Chat ended at 15:10:05	 Chat with Service bot — ✕  You're now on our pre-registration list. Can you check if you have received a confirmation email? Yes, got it Awesome! Welcome to the Hound Mobility- family! 🐾  Is there anything else I can help you with? 📄 No that's it.  Thank you for contacting us today! Hope I was able to help you 😊 Chat ended at 15:10:05	 Chat with Service agent — ✕ Thank you. Welcome to the Hound Mobility- family!  Is there anything else you'd like to know about the company of the product? I am happy to help with anything! No that's it.  Thank you for contacting us today. Chat ended at 15:10:05	 Chat with Service bot — ✕ Thank you. Welcome to the Hound Mobility- family!  Is there anything else I can help you with? No that's it.  Thank you for contacting Hound Mobility today. Chat ended at 15:10:05

Appendix F - Study 2 & 3: Measurement scales

Dependent Variable: Customer Satisfaction

The three-item scale involved participants rating each item on a 7-point Likert scale ranging from strongly disagree (1) to strongly agree (7).

Items	Cronbach alpha
I feel satisfied with the performance of the agent	0.95
The performance of the agent has met my expectations	
My satisfaction level with the performance of the agent is quite close to my ideal online shopping assistance service	

Manipulation Check: Social and Functional Content

The social and functional content treatment was evaluated using a four-point scale each (1=strongly disagree, 7=strongly agree).

Items	Cronbach alpha
Social interaction content	
The agent was easy to talk with	0.87
When conversing with the agent, it felt like the company was genuinely interested to help me	
The agent appeared to be pretty talkative	
When conversing with the agent, the company seemed interested in me not only as a consumer but also as a human	
Functional interaction content	
The agent primarily focused on the details pertaining to the bike	0.75
The agent tried their best to provide information to answer my queries	

The agent mainly provided factual information	
Based on the conversation with the agent, it felt like the company wanted to make sure I have all the information that I need to make a choice about the e-bike	

Mediators: Perceived competence and consumer frustration

Both the scales involved participants rating each item on a 7-point Likert scale ranging from strongly disagree (1) to strongly agree (7).

Items	Cronbach alpha
Perceived competence	
The chatbot was efficient	0.95
The chatbot met my needs	
The chatbot was thorough	
The chatbot performed as I expected	
The chatbot competently handled my request	
Customer frustration	
I felt frustrated about the situation	0.91
I felt disturbed by the situation	
I felt annoyed at the situation	

Appendix G - Study 2: Results summary from SPSS Process Macro by Hayes (Model 7)

Model summary

	Mediator: Perceived empathy				Dependent variable: Customer satisfaction			
<i>Variables</i>	b	SE	t	p	b	SE	t	p
Interaction Content	-0.41	0.41	-0.99	0.32	-0.03	0.08	-0.33	0.74
Identity Disclosure	-1.02	0.42	-2.46	0.02				
Interaction Content x Identity Disclosure	0.61	0.26	2.33	0.02				
Perceived Empathy					0.27	0.03	0.78	0

Conditional effect of Content on Mediator (perceived empathy) at values of the moderator (identity disclosure)

	Effect	SE	t	p	LLCI	ULCI
	Mediator: Perceived empathy					
Non-disclosure	0.20	0.18	1.10	0.27	-0.16	0.57
Disclosure	0.82	0.19	4.33	0	0.45	1.19

Conditional indirect effect of Content on Customer satisfaction via the mediator (perceived empathy) at values of the moderator (identity disclosure)

	Effect	BootSE	BootLLCI	BootULCI
	Mediator: Perceived empathy			
Non-disclosure	0.06	0.05	-0.04	0.15
Disclosure	0.22	0.07	0.11	0.34

Appendix H - Study 3: Ethics information and task scenario presented in Prolific

You are invited to participate in this research project, which is being carried out by Chetna Johar from Trinity College Business School.

Your participation is voluntary. Even if you agree to participate now, you can withdraw at any time without consequence.

You will be asked to imagine that you are trying to purchase concert tickets from an online website, e-tix.com. Your task is to read a conversation that represents an interaction you had with the online customer service agent at E-tix. This interaction includes you discussing the payment error you are facing when trying to purchase your concert tickets. After looking at the conversation, you will be asked some questions regarding your experience of the conversation. The time duration of the whole task will be 5 minutes.

Any identifiable information or data which we obtain from you during this research with you will be treated confidentially. We will do this by treating all responses anonymously. The data will be kept with the researcher solely. Data from this research project may be published in future.

The original data will be available only to the present investigator: Chetna Johar. If you have any questions about this research, please contact me at: joharc@tcd.ie.

Appendix I - Study 3: Explanation of task and scenario to participants

The task for this research requires you to imagine yourself in a situation where you are trying to purchase tickets for a concert but keep getting an error message at the payment gateway.

You are planning to attend a Coldplay concert with your friend. After looking for tickets online and through offline vendors, you find a good deal for two tickets on e-tix.com.

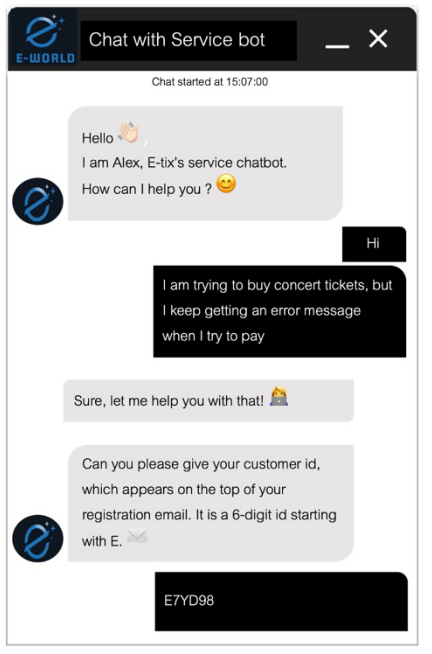
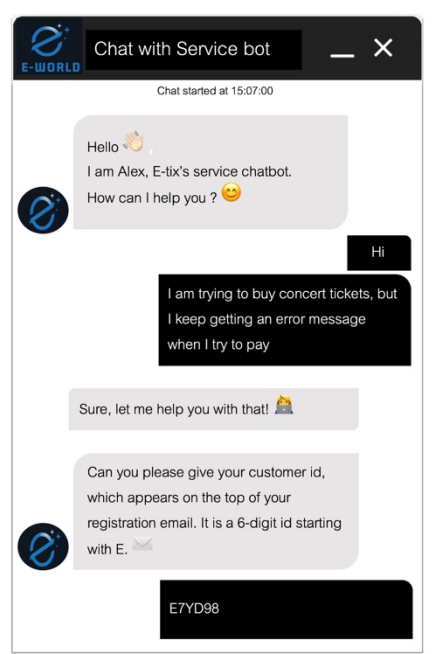
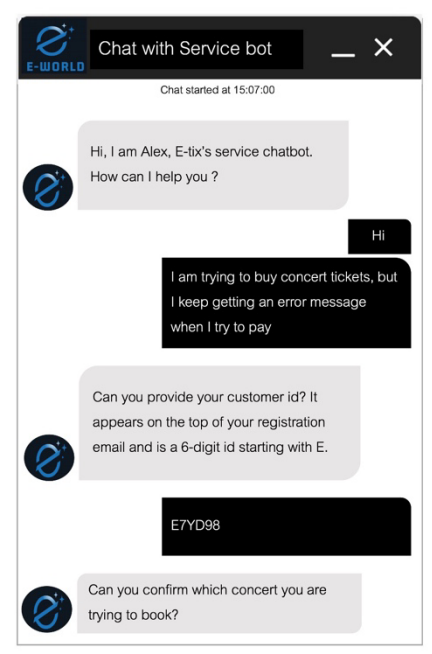
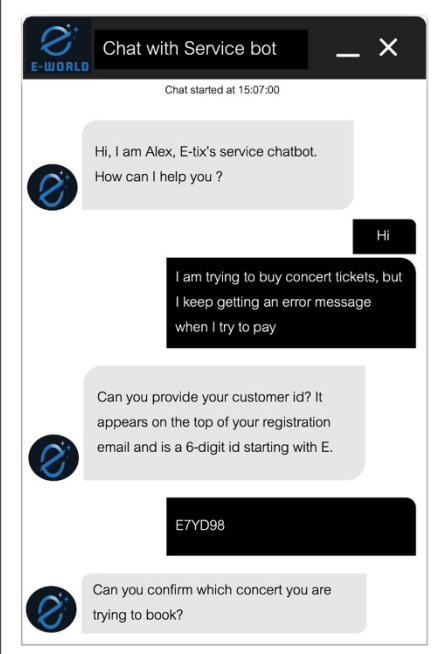
However, when trying to make the payment, you keep getting an error message and it takes you back to the home page. Hence, you decide to contact the online service agent to solve this issue.

This conversation is described via screenshots on the following pages of this [questionnaire](#).

Please read the conversation script below, carefully. You will be able to go to the next screen of the conversation after 8 seconds, to allow enough time for you to read.

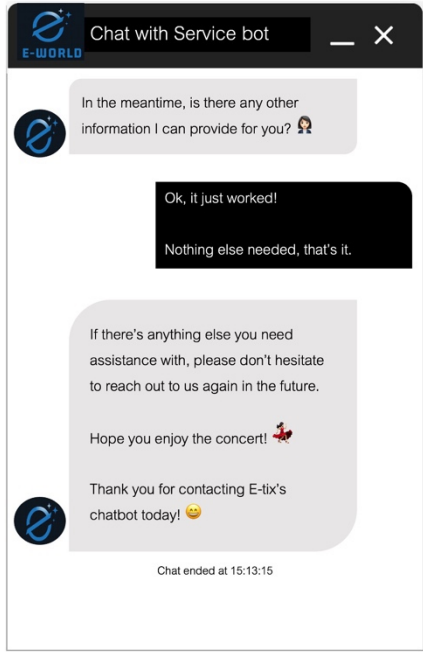
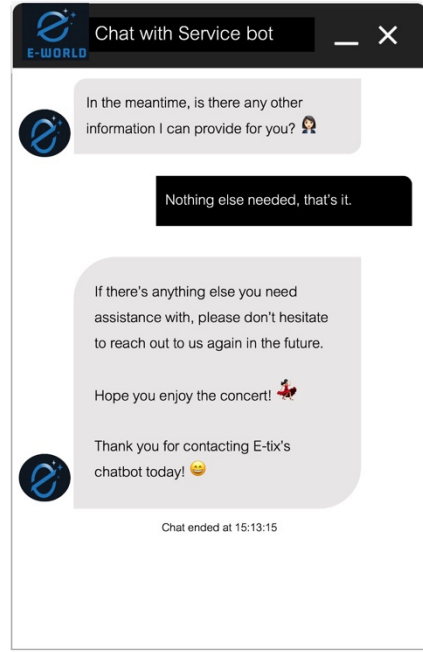
You will now see screenshots of the conversation you are having with the chatbot.

Appendix J – Study 3: Screenshots shown to participants for each condition

Service success & Social Interaction content (1/4)	Service failure & Social interaction content (1/4)	Service success & Functional interaction content (1/3)	Service failure & Functional interaction content (1/3)
 Chat with Service bot Chat started at 15:07:00 Hello 🙋 I am Alex, E-tix's service chatbot. How can I help you? 😊 Hi I am trying to buy concert tickets, but I keep getting an error message when I try to pay Sure, let me help you with that! 🙋 Can you please give your customer id, which appears on the top of your registration email. It is a 6-digit id starting with E. ✉ E7YD98	 Chat with Service bot Chat started at 15:07:00 Hello 🙋 I am Alex, E-tix's service chatbot. How can I help you? 😊 Hi I am trying to buy concert tickets, but I keep getting an error message when I try to pay Sure, let me help you with that! 🙋 Can you please give your customer id, which appears on the top of your registration email. It is a 6-digit id starting with E. ✉ E7YD98	 Chat with Service bot Chat started at 15:07:00 Hi, I am Alex, E-tix's service chatbot. How can I help you? Hi I am trying to buy concert tickets, but I keep getting an error message when I try to pay Can you provide your customer id? It appears on the top of your registration email and is a 6-digit id starting with E. E7YD98 Can you confirm which concert you are trying to book?	 Chat with Service bot Chat started at 15:07:00 Hi, I am Alex, E-tix's service chatbot. How can I help you? Hi I am trying to buy concert tickets, but I keep getting an error message when I try to pay Can you provide your customer id? It appears on the top of your registration email and is a 6-digit id starting with E. E7YD98 Can you confirm which concert you are trying to book?

Service success & Social Interaction content (2/4)	Service failure & Social interaction content (2/4)	Service success & Functional interaction content (2/3)	Service failure & Functional interaction content (2/3)
 Chat with Service bot Thank you! 😊  Also, can you please confirm which concert you are trying to book? 🎫 Coldplay in London on 10/10/23 That sounds like fun! 😊 I will look into this for you...  I can see in your account you were trying to book two tickets for £85 each. Is that right? 👤 Yes  I'm sorry you're having trouble with making the payment. 😞	 Chat with Service bot Thank you! 😊  Also, can you please confirm which concert you are trying to book? 🎫 Coldplay in London on 10/10/23 That sounds like fun! 😊 I will look into this for you...  I can see in your account you were trying to book two tickets for £85 each. Is that right? 👤 Yes  I'm sorry you're having trouble with making the payment. 😞	 Chat with Service bot Coldplay in London on 10/10/23  I see you were trying to book two tickets for £85 each. Is this correct? Yes I am sorry you cannot make the payment. We are experiencing technical difficulties that are affecting our ability to process payments.  I will convey this to our payment system. Can you give an estimated time of when the problem will be fixed?	 Chat with Service bot Coldplay in London on 10/10/23  I see you were trying to book two tickets for £85 each. Is this correct? Yes I am sorry you cannot make the payment. We are experiencing technical difficulties that are affecting our ability to process payments.  I will convey this to our payment system. Can you give an estimated time of when the problem will be fixed?

Service success & Social Interaction content (3/4)	Service failure & Social interaction content (3/4)	Service success & Functional interaction content (3/3)	Service failure & Functional interaction content (3/3)
 Chat with Service bot — ✕ We have been experiencing technical difficulties that have been affecting our ability to process payments 🖨️  I will convey this to our payment system...👤 Can you give an estimated time of when the problem will be fixed? Thank you for bearing with me. 🙏 The payment system has been updated; the payment should now work. 🖨️ You can refresh the page and try making the payment again. 🔄  ⋮	 Chat with Service bot — ✕ We have been experiencing technical difficulties that have been affecting our ability to process payments 🖨️  I will convey this to our payment system...👤 Can you give an estimated time of when the problem will be fixed? Thank you for bearing with me. 🙏 I do not have an exact estimate at the moment, please try again later. We're working hard to resolve the issue as quickly as possible! 🙏  ⋮	 Chat with Service bot — ✕ The payment system has been updated; the payment should work now. You can refresh the page and try making the payment again.  Is there any other information I can provide? Ok, it just worked! Nothing else needed, that's it. For further assistance, contact us here.  Thank you for contacting E-tix's chatbot. Chat ended at 15:10:15	 Chat with Service bot — ✕ I do not currently have an estimate, please try again later. We're working hard to resolve the issue as quickly as possible.  Is there any other information I can provide? Nothing else needed, that's it. For further assistance, contact us here.  Thank you for contacting E-tix's chatbot. Chat ended at 15:10:15

Service success & Social Interaction content (4/4)	Service failure & Social interaction content (4/4)		
			

Appendix K - Study 3: Results summary from SPSS Process Macro by Hayes (Model 4)

Service Outcome: Success

Model summary for mediator Perceived empathy

Direct Effects

	Mediator: Perceived empathy				Dependent variable: Customer satisfaction			
<i>Variables</i>	b	SE	t	p	b	SE	t	p
Interaction content	1.37	0.18	7.67	0	-0.51	0.13	-3.4	0.0001
Perceived empathy					0.4	0.04	8.97	0

Indirect Effects of Interaction content on Customer Satisfaction

Mediation: Perceived empathy			
Effect	BootSE	BootLLCI	BootULCI
0.54	0.1	0.35	0.76

Service Outcome: Failure

1. Model summary for mediator Perceived empathy

Direct Effects

	Mediator: Perceived empathy				Dependent variable: Customer satisfaction			
<i>Variables</i>	b	SE	t	p	b	SE	t	p
Interaction content	0.82	0.21	3.87	0.0001	-0.97	0.21	-4.56	0
Perceived empathy					0.43	0.07	6.31	0

Indirect Effects of Interaction content on Customer Satisfaction

Mediation: Perceived empathy			
Effect	BootSE	BootLLCI	BootULCI
0.36	0.11	0.16	0.58

2. Model summary for parallel mediators Perceived empathy & Perceived competence

Direct Effects

	Mediator: Perceived empathy				Mediator: Perceived competence				Dependent variable: Customer satisfaction			
Variables	b	SE	t	p	b	SE	t	p	b	SE	t	p
Interaction Content	0.82	0.21	3.87	0	-0.41	0.2	-2.03	0.04	-0.26	0.13	-1.99	0.05
Perceived empathy									0.03	0.05	0.64	0.53
Perceived competence									0.93	0.05	19.54	0

Indirect Effects of Interaction content on Customer Satisfaction

Mediation: Perceived empathy			
Effect	BootSE	BootLLCI	BootULCI
0.02	0.04	-0.05	0.1
Mediation: Perceived competence			
Effect	BootSE	BootLLCI	BootULCI
-0.38	0.18	-0.74	-0.01

3. Model summary for parallel mediators Perceived competence & Customer frustration

Direct Effects

	Mediator: Perceived competence				Mediator: Customer frustration				Dependent variable: Customer Satisfaction			
Variables	b	SE	t	p	b	SE	t	p	b	SE	t	P
Interaction Content	-0.41	0.2	-2.03	0.04	-0.06	0.2	-0.29	0.78	-0.3	0.12	-2.52	0.01
Perceived Competence									0.81	0.05	15.6	0.0001
Customer Frustration									-0.22	0.05	-4.14	0

Indirect Effects of Interaction content on Customer Satisfaction

Mediation: Perceived competence			
Effect	BootSE	BootLLCI	BootULCI
-0.33	0.16	-0.66	-0.09
Mediation: Customer Frustration			
Effect	BootSE	BootLLCI	BootULCI
0.01	0.05	-0.07	0.11

