Empathic chatbots: a double-edged sword in customer experiences

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Abstract

Recent breakthroughs in affective computing have enabled the shift from mechanical to empathic chatbots, now capable of detecting, decoding, and mimicking customers' thoughts and feelings to respond appropriately. While artificial empathy is believed to potentially bridge the human-artificial intelligence gap in customer experience, recent studies offer mixed support for its effectiveness in improving customer outcomes, leaving managers perplexed about the added value of empathic chatbots. Building on social presence theory, this paper investigates whether, how, and when empathic chatbot-led services enhance customer experience. Results from three experiments show that empathic chatbots trigger perceptions of social presence and information quality, which positively influence customer satisfaction. The findings further reveal that empathic chatbots can harm customer experience under certain conditions, particularly when customers feel time pressure. This paper provides insights into how and when to implement empathy in chatbots to enhance customer experience and boost customer satisfaction.

Keywords: artificial empathy, chatbot, customer experience, social presence, information quality, time pressure

1. Introduction

In today's fast-paced environment, customers increasingly rely on chatbots for rapid service access. For example, travelers flying with KLM Royal Dutch Airlines can interact with a chatbot to rebook their last-minute canceled flight, busy workers can use Starbucks' chatbot to order their favorite cappuccino while on the run, and healthcare chatbots help patients schedule their medical appointments faster (Singh 2021). From 2022 to 2026, it is anticipated that customer interactions with chatbots will surge from 3.5 billion to nearly 10 billion. Additionally, the chatbot market is projected to experience significant growth, soaring from $12 billion in 2023 to $72 billion in 2028, reflecting a remarkable 470% increase (Juniper 2023).

Chatbots have long been primarily limited to automatic routine tasks and perceived as deficient in human-like qualities (Davenport et al. 2020). Recent breakthroughs in computer science, however, have contributed to the development of chatbots with stronger social interaction skills, which marks a turning point in the development of artificial intelligence (AI), from *mechanical* to *empathetic AI* (Huang & Rust 2021). Artificial empathy—that is machine's capacity to detect, decode, and mimic customers' thoughts and feelings to respond appropriately—is considered as key to bridging the human-AI gap on customer experience (Liu-Thompkins et al. 2022). Many companies around the globe are therefore developing and offering their own empathic chatbots, with some even arguing that the latter have more empathy than their human service counterpart (Huang & Rust 2023).

Echoing practitioners' interest in empathic chatbots, a growing body of research examines the role of empathy in customer-chatbot service encounters. This literature consists of two main research streams. The first seeks to understand how mere and latent perceptions of empathy triggered by mechanical chatbots influence various customer outcomes (e.g., Chen et al. 2023; Liu et al. 2023). Building upon recent developments in affective computing, the second stream of research considers artificial empathy as the chatbot's core intelligence framework, with the

potential to dramatically transform communication exchanges and affect customer experiences, thus calling for increased attention (Liu-Thompkins et al. 2022). Building on social presence theory (Short et al. 1976), this paper falls into this second research stream and complements previous studies in three main ways (see Table 1).

[INSERT TABLE 1 AROUND HERE]

First, while researchers have been studying customers' reactions to chatbots for over 20 years (see Mariani et al. 2023), customer experience with artificial empathy emerged as a research stream only recently. Artificial empathy is argued to have the potential to bridge the human-artificial intelligence gap in customer experience (Liu-Thompkins et al. 2022), yet scant recent studies provide mixed support in favor of the empathic chatbot-customer evaluation linkage (e.g., Markovitch et al. 2024, Park et al. 2022). The emerging nature of empathic AI calls for more empirical verification and replication (Adler et al. 2023; Liu-Thompkins et al. 2022; Schepers et al. 2022). We conceptually replicate this linkage (Köhler et al. 2021) and constructively assess its strength and generalizability across three studies, adding new elements to the original studies and employing realistic designs, thereby advancing theory in this growing field.

Second, previous studies examining the underlying processes that explain customers' reactions to empathic chatbots exclusively considered the social aspect of the information exchange (e.g., Adam et al. 2021; Lv et al. 2022; Park et al. 2022). Customers, however, expect chatbots to not only meet their relational needs (Kull et al. 2021; Wirtz et al. 2018), but also to provide accurate and timely information that efficiently addresses their functional needs (Chen et al. 2022). Social presence theory holds that individuals assess the degree of social presence during communication exchanges, along with the richness of information delivered (Biocca et al. 2003; Straub & Karahanna 1998). Against this backdrop, we examine perceived social

presence and perceived information quality as underlying mechanisms of the empathic chatbot-customer evaluation linkage.

Third, prior research virtually ignores the extent to which individual customers' context may boost or undermine their experiences with empathic chatbots. Prior work in communication science suggests that computer-mediated communication exchanges can be shaped and affected by various contexts (Biocca et al. 2003; Lombard & Ditton 1997). Straub and Karahanna (1998), for instance, argue that social presence is deemed more or less appropriate than information richness depending on the task or context at hand. Service encounters with chatbots typically occur in time-sensitive situations (Ostrom et al. 2021; Roy & Naidoo 2021). In light of these observations, we propose that the effect of empathic chatbots on customer satisfaction depends on the level of time pressure, with artificial empathy becoming undesirable when customers feel under time constraints.

Taken together, the present results reveal that empathic chatbots can be a double-edged sword and influence customer experiences in multiple ways, thereby providing practitioners with relevant insights into how and when to implement empathy into their AI interfaces to enhance customer experience and ultimately boost satisfaction.

2. Literature review

2.1. Customer-chatbot service encounters

Chatbots are conversational system interfaces designed to communicate with customers in text-based natural language powered by AI (Wirtz et al. 2018). Among the different types of chatbots (for a taxonomy, see for instance Nißen et al. 2022), so-called *mechanical* chatbots—designed for handling short, one-time-only routine tasks (Huang & Rust 2021)—represent 84% of chatbots in use across multiple industries (e.g., retail, banking, healthcare, hospitality) (Janssen et al. 2020). These chatbots can offer companies cost-effectiveness, scalability, and flexibility,

while providing a convenient and timely solution for customers who are increasingly facing time constraints (Huang & Rust 2021).

Research on customer-chatbot service encounters has predominantly centered on comparing mechanical chatbots with their human employee counterparts and investigating the impact of various chatbot design elements on customer outcomes (for literature reviews, see De Keyser & Kunz 2022; Mariani et al. 2023; Ramesh & Chawla 2022). Specifically, previous studies have delved into how various functional (e.g., error rate) and social chatbot attributes (e.g., gender) influence customer attitudinal and behavioral outcomes (e.g., Sheehan et al. 2020; Zogaj et al. 2023). While mechanical chatbots are commonly perceived as cold and lacking affective capabilities (Huang & Rust 2023), recent studies show that imbuing chatbots with these functional and social attributes can spontaneously evoke empathy perceptions among customers, resulting in greater trust (Cheng et al. 2021), satisfaction (Liu et al. 2023) and engagement (Chandra et al. 2021). This observation encouraged service providers and computer scientists to take a step further and equip chatbots with artificial empathy to enhance the customer care journey (Huang & Rust 2023). As a result of recent advances in affective computing, empathic chatbots have recently emerged as the next promising generation of AI applications (Knight 2020).

2.2. Artificial empathy

Empathy is inherently an intertwined process of cognition and affect (Wieseke et al. 2012). A commonly accepted conceptualization of empathy identifies two key components: Perspective-taking—the cognitive component—is the capacity to put oneself in someone else's shoes and understand another's situation, point of view and needs (de Waal 2008). The affective component is reflected in empathic concern and emotional contagion (McBane 1995). Empathic concern is the ability to intuit others' emotional condition, demonstrate care and consideration, and to communicate in a way that makes others feel better (Wieseke et al. 2012). Emotional

contagion is the automatic and unconscious response of sharing the other person's emotions when these emotions occur (Hatfield et al. 1993).

Until recently, empathy was considered an area where humans were superior to technology and a key difference that would prevent frontline employees from being replaced by AI (Robinson et al. 2020). Nonetheless, recent technological progress enables chatbots to be empathic by detecting, decoding, and mimicking customers' thoughts and feelings to respond appropriately (Liu-Thompkins et al. 2022; Zhou 2020). To date, two approaches exist for the implementation of artificial empathy into chatbots. The first approach consists of providing a fixed emotion architecture inspired by theories and models of biological systems (Leite et al. 2013). The second approach is the creation of a software architecture that mirrors the human brain and continuously learns from its environment (Lim & Okuno 2015). In either case, chatbots cannot truly feel empathic but only behave as though they have empathy feelings (Airenti 2015). In contrast with mechanical chatbots, empathic chatbots engage in perspective-taking by discovering customers' motivations in a specific situation and inferring their preferences based on their behaviors and choices (Fan et al. 2023). Empathic chatbots can also automatically detect customers' emotions using sentiment analysis (Sidaoui et al. 2020), respond with appropriate emotional responses through natural language processing, and express both care and concern, as well as simulate sharing similar emotions (Casas et al. 2021).

2.3. Artificial empathy in customer-chatbot service encounters

Scant research has started to study the role of artificial empathy in customer-chatbot service encounters. Overall, prior research suggests that empathic chatbots trigger mixed responses among customers (see Table 1). Lv et al. (2022), for instance, show a positive effect of empathic chatbots on customers' continuous usage intention of hospitality services. Similarly, Markovitch et al. (2024) provide support for a positive effect of artificial empathy on customer satisfaction in a retail context. In contrast, Park et al. (2022) find that chatbots' cognitive

empathy fails to heighten social presence and willingness to participate in fundraising projects. Liu and Sundar (2018) demonstrate that medical empathic chatbots can trigger feelings of uncanniness, while Fan et al. (2023) show that misalignment between empathic chatbots and employees undermines customer retention. Taken together, these inconsistent findings cast doubts about the effectiveness of artificial empathy, prompting calls for more empirical research on the topic (Liu-Thompkins et al. 2022; Schepers et al. 2022).

3. Theoretical framework

We next present our theoretical framework for the effects of artificial empathy on customer satisfaction, its mediation via perceived social presence and perceived information quality, and the moderation by time pressure. Figure 1 illustrates the hypothesized effects. Given the communicational nature of chatbot-customer exchanges, we build on communication science literature and social presence theory to develop our hypotheses. Social presence theory is one of the most widely recognized communication theories (Moffet et al. 2020) and has rapidly become one of the most prominent theoretical frameworks in service robot research (Mariani et al. 2023). Originally conceived in communication science as a framework to understand how communication media transmit nonverbal and social cues (Short et al. 1976), this theory provides a foundation for computer-mediated communication research examining how an online user's "sense of being with another" and perceptions of information richness are shaped and influenced by various interfaces, content and contexts (Biocca et al. 2003; Hayes et al. 2020; Straub & Karahanna 1998).

[INSERT FIGURE 1 AROUND HERE]

3.1. The effect of empathic chatbot on customer satisfaction

Studies on customer-chatbot service encounters highlight the lack of chatbot empathy as a significant barrier to customer satisfaction (Puntoni et al. 2021). Customers often find

interactions with mechanical chatbots monotonous and emotionless, which contrasts sharply with their experiences with human employees (Subramony et al. 2021). The social skills of the organizational frontline, particularly empathy, exert a strong influence on customers' service quality evaluations (Parasuraman et al. 1988). Empathy traditionally enables employees to deliver higher quality service by better understanding and adapting to customers' needs, ultimately resulting in higher satisfaction (Wieseke et al. 2012). This is especially true when customers express empathic opportunities, defined as "clear and direct statements of emotion, progress or challenge" (Bylund & Makoul 2002, p. 209). A lack of empathy in response to these opportunities often leads to undesirable outcomes such as misunderstandings, hostility, and frustration (Huang & Rust 2023). Given the importance customers place on empathy in interpersonal communication exchanges (Chen et al. 2022), developing chatbots capable of taking customers' perspectives and communicating concern and emotion—that is artificial empathy—holds promise for bridging the human-AI gap and generate value for customers (Liu-Thompkins et al. 2022). Building on these theoretical arguments, alongside social presence theory—which highlights the significance of the interface's intelligence as the primary driver of individuals' reactions (Biocca et al. 2003)—we hypothesize:

H1: Empathic chatbots (vs. mechanical) increase customer satisfaction

3.2. The mediating role of perceived social presence and perceived information quality

The well-established social presence theory (Short et al. 1976) has paved the way for numerous studies providing evidence on how individuals apply social rules to computers and AI-enabled technologies, spontaneously perceiving them as social actors (van Doorn et al. 2017), even when the artificial nature of the agent is disclosed (Araujo et al. 2018). According to social presence theory, this sense of social presence originates from the immediate activation of a mental model upon the detection of intelligence during interactions in mediated environments (Biocca et al. 2003). Prior research suggests options to heighten levels of social presence by

enhancing communication formats and contents with specific characteristics, such as adding social human-like cues (Konya-Baumbach et al. 2023; Moffet et al. 2020). Rapp et al. (2021), for instance, show that social presence increases when chatbots exhibit human-like qualities and behaviors in service exchanges. Chatbots adopting a social-oriented (vs. task-oriented) communication style enhance customers' feelings of social presence (De Cicco et al. 2020). Similar effects on social presence occur when chatbots delay their response time to imitate human behavior (Gnewuch et al. 2022) or provide feedback along the conversation to acknowledge mutual understanding (Liu et al. 2023). By shifting from mechanical to empathetic AI, empathic chatbots can bring AI-enabled social customer experiences closer to those with human agents (Liu-Thompkins et al. 2022). They are likely to create a sense of synchrony and immediacy, which are key to social presence (Short et al. 1976). In turn, social presence increases satisfaction by helping customers successfully make sense and take ownership of their service interactions with an artificial entity (Biocca et al. 2003; van Doorn et al. 2017). This leads to the following hypothesis:

H2: The effect of empathic chatbots on customer satisfaction is mediated by perceived social presence

As per social presence theory, technologies offer individuals the opportunity to interact with others in a variety of ways to not only access social, but also task-related information (Biocca et al. 2003; Straub & Karahanna 1998). In technology-enabled service interactions, customers attach great importance to the quality of the information they receive to solve their issues quickly (Chen et al. 2022). Inadequate information typically leads customers to seek assistance from employees, which undermines the very purpose of employing a technological solution in the first place and is consequently viewed as a time-wasting, dissatisfying experience (Holloway & Beatty 2008). Perceived information quality refers to a customer's assessment of how effectively the system conveys semantic meaning and imparts knowledge (Xu et al. 2013);

it encompasses various facets of information, including relevance, accuracy, completeness, and timeliness (Wixom & Todd 2005).

Perceptions of information quality typically rely on the attributes of the system responsible for its delivery. Research, for instance, shows that certain characteristics of websites, such as their design (Ha & Im 2012) and personalization (Pappas et al. 2017), influence how information quality is perceived. Within the chatbot domain, artificial empathy stands out as a core attribute that has the potential to transform both the content and semantic meaning of the information conveyed to customers (Liu-Thompkins et al. 2022). Specifically, the capacity for perspective-taking empowers empathic chatbots to consider customers' behaviors, preferences, and personality traits to tailor the conversation's content, likely resulting in richer, more accurate and relevant information (Shumanov & Johnson 2021). Moreover, empathic concern and emotional contagion add an emotional layer to the information through the use of emotional words and emoticons, making the information delivered by empathic chatbots even more appropriate and complete (Coyle & Carmichael 2019). Because greater information quality is commonly associated with positive post-service evaluations (e.g., Holloway & Beatty 2008), this study hypothesizes:

H3: The effect of empathic chatbots on customer satisfaction is mediated by perceived information quality

3.3. The moderating role of time pressure

Customers often engage with chatbots under time constraints, expecting faster responses than those provided by human agents (Ostrom et al. 2021). Considered as one of the most influential contextual factors affecting customer experiences (Belk 1975), time pressure is defined as the perceived limitation of time available to consider information, make decision and/or perform a specific task (Suri & Monroe 2003).

Under time pressure, social presence theory suggests that customers prefer less socially oriented technology because social presence is not as important as efficiency, that is the richness of the information requirements of the task (Fulk et al. 1987; Straub & Karahanna 1998). In such situations, individuals paradoxically exhibit heightened motivation to process all information necessary for task completion while having fewer cognitive resources to do so (Pieters & Warlop 1999). As a consequence, individuals tend to prioritize immediate task-related needs over relational aspects (Hamilton et al. 2019), making the social experience derived from the empathic chatbot likely less valuable for customers. Along those lines, Liu (2022), for instance, show that time pressure undermines the positive social effect of humorous responses from the chatbot. Moreover, under time pressure, customers' information-seeking behaviors shift towards seeking clear, certain, and task-relevant information that helps them solve their issue quickly (Kruglanski & Freund 1983). In such contexts, social cues like artificial empathy can divert customers' attention (Pieters & Warlop 1999), be treated as distraction, and hinder both information quality and related customer outcomes (Fei et al. 2021). This leads to the following hypotheses:

H4a: The effect of empathic chatbots on customer satisfaction is negatively moderated by high (vs. low) time pressure

H4b: The effect of empathic chatbots on customer satisfaction through perceived social presence is negatively moderated by high (vs. low) time pressure

H4c: The effect of empathic chatbots on customer satisfaction through perceived information quality is negatively moderated by high (vs. low) time pressure

4. Overview of studies

This paper investigates the proposed framework and hypotheses in three studies, across various service contexts (travel insurance, car rental and accommodation booking) (see Figure 1). Study

1 conceptually replicates the empathic chatbot–customer satisfaction linkage. Study 2 examines the impact of empathic chatbots on customer satisfaction by testing the parallel mediation mechanism of perceived social presence and perceived information quality. Study 3 investigates the moderating role of time pressure. All study materials (e.g., experimental video stimuli and scripts, preregistered protocols) and datasets are available on a dedicated OSF page: https://osf.io/ga5b8/?view_only=5ff2d13296db4e8d98c66e1ae4120bbc.

5. Study 1

5.1. Method

Data. Study 1 uses a single-factor (chatbot: empathic vs. mechanical) scenario-based, between-subjects experiment. A total of 159 U.K. participants were recruited from Prolific. Following Aguinis et al.'s (2021) best-practice recommendations to ensure good data quality when using crowdsourced online samples, *all* respondents were paid £9 per hour for their participation, which was above the minimum wage at the time of data collection. We then excluded participants who failed the attention checks (n=9). The final sample includes 150 participants (65.33% female, 0.02% non-binary; M_{age} = 37.10, SD_{age} = 11.83).

Procedures. First, participants were instructed that they were planning to travel soon and that they purchased travel insurance. They were asked to imagine navigating a fictitious insurance provider's website and interacting with the customer service chatbot to get help with their insurance policy. Second, participants were randomly assigned to one of the two conditions (empathic vs. mechanical chatbot); they were invited to watch a video of the conversation with the chatbot and to picture themselves as the customer of the conversation. We used a video-based approach to enhance the realism of the experiment and the likelihood of providing insights into real customer behavior (Morales et al. 2017). Evidence indeed shows that video-based experiments entail a more naturalistic setting and induce similar psychological responses compared to studies conducted in real service settings (Bateson & Hui 1992).

For both conditions, the script includes the following line of events: (i) the chatbot greets the customer and offers its help, (ii) the customer requests assistance to better understand travel insurance, (iii) the chatbot supports the customer, and (iv) ends the interaction. The customer messages and the outcome of the service encounter are identical across conditions; only the way the chatbot interacts with the customer varies, according to different demonstrations of artificial empathy. To manipulate the level of artificial empathy, we followed Suchman et al.'s (1997) model of empathic communication and adapted Liu-Thompkins et al.'s (2022) original study materials. In doing so, we also used procedures from prior work in computer science (Sharma et al. 2020) and medicine (Bylund & Makoul 2002) on empathic communication coding systems. Specifically, the empathic chatbot simulates perspective-taking by "putting itself" in the customer's shoes, acknowledging the customer's situation and providing more personalized answers (e.g., "I understand your concern about the refund"); emotional contagion by using emoticons; and empathic concern by using sentences such as "don't worry, I'm sure I can help you". In contrast, typical responses from mechanical chatbots consist of informational-driven sentences focused on problem-solving (Nißen et al. 2022), reflecting its inability to adapt the conversation to customers' situations and emotional states (e.g., "For more information about insurance, write your questions here and I'll look for answers") (Huang & Rust 2023) (for the conversation scripts, see Appendix A; a detailed description of the manipulation procedures is also available on the dedicated OSF page).

In developing the video material, we took several initiatives to minimize the potential for confounds. Both videos had the same duration (1 min 16 seconds), the same number of messages (number of messages: customer 12, chatbot 12), sent in the same order, at the same speed (between 3 and 5 seconds according to the size of the speech bubble). The script lengths vary slightly (number of words: 204 in the mechanical chatbot condition, 197 in the empathic chatbot condition), but we balanced this by maintaining equivalent speech bubbles across both

conditions. Additionally, we used the gender-neutral name Jordan for the chatbot and provided no other gender cues, as these can influence perceptions of the chatbot's abilities (Zogaj et al. 2023). Finally, after refining the manipulations based on expert feedback, we used a computational approach to pretest the experimental material and check whether the manipulation of artificial empathy worked as intended. Specifically, we followed Sharma et al. (2020) procedures and applied a natural language processing model (i.e., multi-task RoBERTa-based bi-encoder model) to analyze our customer-chatbot conversations and identify empathy communication mechanisms within them. The model provides an empathy score comprised between 0 (no empathy at all) and 6 (strong empathy) (for more details, see Sharma et al. 2020). This computational approach indicated a higher level of empathy in the empathic chatbot condition (total score = 3) than in the mechanical chatbot condition (total score = 0).

Measures. The respondents rated their satisfaction on a 3-item scale developed by Gelbrich et al. (2021). We also measured several control variables that may influence individuals' reactions to chatbots (Blut et al. 2021), including prior experience with chatbots, need for interaction, age, and gender. The former two control variables were respectively measured using scales adopted from Reinders et al. (2008) and Dabholkar and Bagozzi (2002). In addition to Sharma et al.'s (2020) computational approach described above, we used Liu-Thompkins et al.'s (2022) 9-item scale to measure perceived artificial empathy and check our manipulations. Finally, a 2-item scale by Liao (2007) was also presented to measure scenario realism. All constructs were measured with 7-point Likert scales (1= strongly disagree; 7 = strongly agree). Table 2 provides an overview of the different measures and their Cronbach's α. All measures have reliabilities greater than the recommended .7 threshold.

[INSERT TABLE 2 AROUND HERE]

5.2. Results

Manipulation checks. Results show that the manipulation worked as intended. Further confirming the computational approach (empathic chatbots = 3; mechanical chatbot = 0), the self-reported scale of artificial empathy showed a significant difference between the two conditions ($M_{Empathic\ chatbot}$ = 4.16, SD = 1.13; $M_{Mechanical\ chatbot}$ = 2.64, SD = 1.22; $F(1,148)$ = -7.946, $p < .001$). Respondents also perceived the scenarios as realistic ($M_{Empathic\ chatbot}$ = 5.82, $M_{Mechanical\ chatbot}$ = 5.69; $F(1,148)$ = -.801, p = .212).

Analysis. To investigate the effects of empathic chatbot on customer satisfaction (H1), we conducted a one-way ANCOVA. Empathic chatbot served as the independent variable and customer satisfaction as the dependent variable. Prior experience, need for interaction, gender and age served as control variables.

Direct effects. The one-way ANCOVA revealed significant effects of empathic chatbot ($F(1,148)$ = 9.138, p = .003, η^2 = .06) and need for interaction ($F(1,148)$ = 10.761, p = .00, η^2 = .07). The effects of prior experience ($F(1,148)$ = .126, p = .723, η^2 = .001), age ($F(1,148)$ = .526, p = .469, η^2 = .004), and gender ($F(1,148)$ = .981, p = .324, η^2 = .007) were not significant. These results indicate that, even when controlling for individual characteristics, empathic chatbot has a favorable impact on customer satisfaction, providing support for H1.

5.3. Discussion

Study 1 conceptually replicates the empathic chatbot–customer satisfaction linkage, using a research context (travel insurance) different than that of prior research and a realistic video-based experimental design. Consistent with the original study of Liu-Thompkins et al. (2022), our findings provide support for the positive effect of artificial empathy on customer experience, such that empathic (vs. mechanical) chatbot results in greater customer satisfaction. According to social presence theory, technologies offer individuals the opportunity to interact with others in a variety of ways to access both social and task-related information (Biocca et al.

2003). Therefore, Study 2 examines the mediating role of perceived social presence and perceived information quality.

6. Study 2

6.1. Method

Data. Study 2 uses a single-factor (chatbot: empathic vs. mechanical) scenario-based, between-subjects experiment. A total of 201 U.K. participants were recruited from Prolific. All respondents were paid above the minimum wage at the time of the data collection. We then excluded participants who failed the attention check (n=2) or completed the questionnaire with an unusual fast response time (n=1; less than 3 minutes). The final sample includes 198 participants (50.5% female, 0.5% non-binary; M_{age} = 42.49, SD_{age} = 12.67).

Procedures. The procedure and manipulation of artificial empathy were kept identical to that of Study 1, albeit adapted to a new service context. Specifically, participants were informed that they were relocating to a new apartment and required a rental removal van.

Measures. Study 2 used the measures of Study 1. In addition, respondents rated their perceived social presence on Gefen and Straub's (2003) 5-item scale and perceived information quality with 8 items adapted from Kim and Niehm (2009). All constructs were measured with 7-point Likert scales (1= strongly disagree; 7 = strongly agree). All measures have reliabilities greater than the recommended .7 threshold (see Table 2).

6.2. Results

Manipulation checks. Artificial empathy was manipulated as intended. The computational approach indicated a higher level of empathy in the empathic chatbot condition (total score = 3) than in the mechanical chatbot condition (total score = 0). In addition, the self-reported scale of artificial empathy showed a significant difference between both conditions ($M_{Empathic\ chatbot}$ = 4.31, SD = 1.22; $M_{Mechanical\ chatbot}$ = 2.22, SD = .99; $F(1,196)$ = -13.198, $p < .001$). Finally, respondents perceived both scenarios as realistic ($M_{Empathic\ chatbot}$= 5.93, $M_{Mechanical\ chatbot}$ = 5.50),

albeit with a small difference in favor of the empathic chatbot condition ($F(1,196) = -2.957$, $p = .002$). Adding realism as covariate did not change the findings (see the OSF page); thus, we do not discuss this issue further.

Analysis. We analyzed the data with PROCESS model 4 with 10,000 bootstrapped samples (Hayes 2017) to examine the parallel mediation effect of empathic chatbot on customer satisfaction through perceived social presence and perceived information quality. Empathic chatbot served as the independent variable; perceived social presence and perceived information quality as parallel mediators; and customer satisfaction as the dependent variable. Prior experience, need for interaction, gender and age served as control variables.

Direct effects. First, empathic chatbot (B = 2.07, $t(192) = 10.764$, $p = .000$) and need for interaction (B = -.28, $t(192) = -3.208$, $p = .002$) significantly predicted perceived social presence. The effects of prior experience (B = -.02, $t(192) = -.229$, $p = .820$), age (B = -.01, $t(192) = -.749$, $p = .455$) and gender (B = .08, $t(192) = .428$, $p = .669$) were not significant. Second, empathic chatbot (B = .80, $t(192) = 5.607$, $p = .000$) and age (B = -.02, $t(192) = -3.275$, $p = .001$) significantly predicted perceived information quality. The effects of prior experience (B = .01, $t(192) = .150$, $p = .881$), need for interaction (B = -.08 , $t(192) = -1.218$, $p = .225$) and gender (B = -.05, $t(192) = -.363$, $p = .717$) were not significant. Third, perceived social presence (B = .23, $t(192) = 4.733$, $p = .000$), perceived information quality (B = .98, $t(192) = 14.801$, $p = .000$) and age (B = -.01, $t(192) = -2.051$, $p = .042$) significantly predicted customer satisfaction. Empathic chatbot (B = .09, $t(192) = .641$, $p = .53$), prior experience (B = -.05, $t(192) = -1.21$, $p = .228$), need for interaction (B = -.08, $t(192) = -1.619$, $p = .11$) and gender (B = -.06, $t(192) = -.540$, $p = .59$) were not significant.

Indirect effects. The results of the bootstrapping mediation showed a significant total effect of empathic chatbot on customer satisfaction (B = 1.36, $SE = .20$, $p = .000$), a non-significant direct effect (B = .09, $SE = .14$, $p = .523$) and a significant parallel mediation through perceived

social presence (B = .48, *SE* = .14, 95% bootstrap CI = [.24, .77]) and perceived information quality (B = .79, *SE* = .14, 95% bootstrap CI = [.52, 1.06]). These results support H2 and H3.

6.3. Discussion

Study 2 revealed that empathic chatbots influence customer satisfaction through both perceived social presence and perceived information quality. When interacting with empathic (vs. mechanical) chatbots, customers experience higher perceptions of social presence and of information quality, which in turn results in greater satisfaction. Moreover, Study 2 replicates the direct effect of empathic chatbot on customer satisfaction, in a different context, providing additional support for the strength and generalizability of this linkage.

As per social presence theory, customers' responses and information processing behaviors can vary according to the context in which the computed-mediated interaction takes place (Biocca et al. 2003). We propose that the effect of empathic chatbot on customer satisfaction depends on the level of time pressure, with empathic chatbot becoming undesirable when customers feel under time constraints. Study 3 tests this prediction and examines the moderating role of time pressure.

7. Study 3

7.1. Method

Data. Study 3 uses a 2 (chatbot: empathic vs. mechanical) × 2 (time pressure: high vs. low) scenario-based, between-subjects experiment. A total of 250 U.S. participants were recruited from Prolific. As in Study 1 and Study 2, all respondents were paid above the minimum wage at the time of the data collection. We then excluded participants who failed the attention check (n=3) or completed the questionnaire with an unusual fast response time (n=1; less than 3 minutes). The final sample includes 246 participants (female 50,41%, M_{age} = 40.74, SD_{age} = 13.22).

Procedures. Participants were randomly assigned to one of the four experimental conditions (empathic vs. mechanical chatbot; high vs. low time pressure). They were instructed that they had booked accommodation a few days ago and that they needed to cancel it. They were asked to imagine navigating the website of a fictitious company that offers short-term stays, and interacting with the customer service chatbot to help with the cancellation. We manipulated time pressure in line with prior research (Song et al. 2023). Specifically, participants in the high time pressure conditions were informed that they had only 5 minutes left to cancel the accommodation and get the full refund, while participants in the low time pressure conditions had one month left. Participants were invited to watch a video of the conversation with the chatbot and to picture themselves as the customer of the conversation. The manipulation of artificial empathy was kept identical to that of Study 1 and Study 2, albeit adapted to the new service context.

Measures. In addition to the scales used in Study 2, we assessed the manipulation of time pressure with a 1-item scale from Song et al.'s (2023) ("How much time did you feel at your disposal to cancel your reservation?"). We also measured situational involvement using 5 items adapted from Mehta et al. (2017) to control for potential confounding effect, as situational involvement may increase with time pressure (Sharma et al. 2020) and ultimately moderate customers' reactions to empathic chatbots (Liu-Thompkins et al. 2022). By doing so, we ensured that only time pressure moderated the empathic chatbot–customer satisfaction relationship, and not an increased situational involvement due to time pressure[1]. All constructs were measured with 7-point Likert scales (1= strongly disagree; 7 = strongly agree). All measures have reliabilities greater than the recommended .7 threshold (see Table 2).

7.2. Results

[1] A one-way ANOVA showed no significant effect of time pressure on situational involvement ($F(3,242) = 1.012$, $p = .388$). Bonferroni post hoc comparisons further confirmed no significant difference across conditions in term of situational involvement (all $p > .05$). In addition, excluding situational involvement as a covariate from the analysis does not alter the conclusions. These additional tests have been included on the OSF page.

Manipulation checks[1]. Artificial empathy was manipulated as intended. The computational approach indicated a higher level of empathy in the empathic chatbot condition (total score = 2) than the mechanical chatbot condition (total score = 0). In addition, the self-reported scale of artificial empathy showed a significant difference between the conditions ($M_{Empathic\ chatbot}$ = 4.26, SD = 1.38; $M_{Mechanical\ chatbot}$ = 3.03, SD = 1.30; $F(3,242) = -7.204$, $p < .001$). Results also indicated that time pressure manipulations worked as intended. Time pressure was considered as higher in the high-time-pressure conditions ($M_{high\text{-}time\text{-}pressure}$ = 6.15, SD = 1.37) than in the low-time-pressure conditions ($M_{low\text{-}time\text{-}pressure}$ = 2.85, SD = 1.53; $F(3,242) = -17.744$, $p < .001$). Finally, respondents perceived the scenarios as realistic ($M_{Empathic\ chatbot;\ high\ time\ pressure}$= 5.71, $M_{Empathic\ chatbot;\ low\ time\ pressure}$ = 5.90, $M_{Mechanical\ chatbot;\ high\ time\ pressure}$= 6.07, $M_{Mechanical\ chatbot;\ low\ time\ pressure}$ = 5.99; $F(3, 242) = 2.07$, $p = .105$).

Analysis. To examine the conditional parallel mediation of empathic chatbots on customer satisfaction through perceived social presence and perceived information quality according to time pressure, we conducted two ANCOVAs and used PROCESS model 8 with 10,000 bootstrap samples. Empathic chatbot served as the independent variable; perceived social presence and perceived information quality as parallel mediators; time pressure as the moderator; and customer satisfaction as the dependent variable. Prior experience, need for interaction, situational involvement, gender and age served as control variables.

Direct effects. The one-way ANCOVA revealed significant effects of empathic chatbot ($F(3, 242) = 16.246$, $p < .001$, $\eta^2 = .064$), need for interaction ($F(3, 242) = 5.553$, $p = .019$, $\eta^2 = .023$) and situational involvement ($F(3, 242) = 6.674$, $p = .01$, $\eta^2 = .027$) on customer satisfaction. The effects of prior experience ($F(3, 242) = .211$, $p = .646$, $\eta^2 = .001$), gender ($F(3,$

[1] A one-way ANOVA with artificial empathy condition as the IV and perceived time pressure as the DV showed no significant effect ($F(3,242) = .612$, $p = .435$). Similarly, a one-way ANOVA with time pressure condition as the IV and perceived artificial empathy as the DV also showed no significant effect ($F(3,242) = .958$, $p = .329$), confirming no interaction effect between the manipulation checks.

242) = 1.262, p = .262, η^2 = .005) and age (F(3, 242) = .049, p = .825, η^2 = .00) were not significant.

Interaction effects. The two-way ANCOVA showed significant effects of empathic chatbot (F(3, 242) = 16.826, p < .001, η^2 = .066), need for interaction (F(3, 242) = 5.583, p = .019, η^2 = .023) and situational involvement (F(3, 242) = 7.839, p = .006, η^2 = .032), as well as a significant interaction effect between empathic chatbot and time pressure (F(3, 242) = 6.593, p = .011, η^2 = .027) on customer satisfaction. Time pressure (F(3, 242) = 1.995, p = .159, η^2 = .008), prior experience (F(3, 242) = .083, p = .773, η^2 = .00), gender (F(3, 242) = .998, p = .319, η^2 = .004) and age (F(3, 242) = .019, p = .89, η^2 = .00) were not significant. Bonferroni post hoc comparisons indicated that customer satisfaction with empathic chatbots is significantly lower in high (vs. low) time pressure ($M_{Empathic\ chatbot;high\ time\ pressure}$ = 5.16, SD = 1.36 vs. $M_{Empathic\ chatbot;low\ time\ pressure}$ = 5.69, SD = 1, p = .046), while no significant differences were observed between mechanical chatbot conditions ($M_{Mechanical\ chatbot;high\ time\ pressure}$ = 6.12, SD =.92 vs. $M_{Mechanical\ chatbot;low\ time\ pressure}$ = 5.95, SD = 1.09, p = 1)

Conditional direct and indirect effects. The results revealed a significant negative conditional direct effect of empathic chatbot on customer satisfaction when time pressure is high (B = -.55, SE = .15, t = -3.65, p = .000) but no effect when time pressure is low (B = -.19, SE = .15, t = -1.30, p = .193). H4a is supported. Further, the results showed a significant positive conditional indirect effect through perceived social presence when time pressure is low (B = .10, SE = .05, 95% bootstrap CI = [.01, .21]) but no effect when time pressure is high (B = .04, SE = .04, 95% bootstrap CI = [-.01, .13]). H4b is supported. Finally, the results revealed a significant negative conditional indirect effect through perceived information quality when time pressure is high (B = -.42, SE = .13, 95% bootstrap CI = [-.69, -.18]) but no effect when time pressure is low (B = -.12, SE = .12, 95% bootstrap CI = [-.36, .10]). H4c is supported.

7.3. Discussion

In Study 3, we found support for the negative moderating effects of time pressure on empathic chatbot-customer experience linkage. As predicted by social presence theory, customers are less satisfied with empathic chatbots when facing time constraint because of two reasons. First, customers prioritize immediate task-related needs over relational aspects under time pressure, negating the effect of artificial empathy through perceived social presence. Second, customers shift towards seeking clear, certain, and task-relevant information in situations of time pressure, making the effect of artificial empathy through perceived information quality negative. Overall, these results suggest that interacting with empathic chatbots becomes undesirable when customers feel under time constraints.

8. General discussion

8.1. Theoretical contributions

Despite the potential of artificial empathy for bridging the human-AI gap in technology-mediated exchanges (Liu-Thompkins et al. 2022), empirical work investigating the impact of empathic chatbots on customer experience remains scarce. By integrating fundamental premises of social presence theory (Short et al 1976; Biocca et al. 2003), this study addresses this void in the literature and empirically examines whether, how and when empathic chatbots influence customer satisfaction. In doing so, this research responds to recent calls for more research on customers' responses to feeling AI (Huang & Rust 2023; Schepers et al. 2022) and contributes in three main ways.

First, scant recent research has started examining the impact of empathic chatbots on customer evaluations, providing mixed support for the effectiveness of artificial empathy (e.g., Markovitch et al. 2024, Park et al. 2022). These inconsistent findings, coupled with the observation that artificial empathy is an emerging phenomenon, call for more empirical verification and replication (Adler et al. 2023; Liu-Thompkins et al. 2022). By analyzing the

relationship between empathic chatbots and customer satisfaction in different contexts (insurance, retail, hospitality), adding new elements to the original studies (the mediating role of social presence and information quality, and the moderating role of time pressure as extensions) and using realistic experimental designs, this paper conceptually replicates prior research and provides theoretical insights about the strength and generalizability of this relationship (Köhler et al. 2021).

Second, previous studies examining the underlying mechanisms behind customers' reactions to empathic chatbots have primarily built upon the CASA paradigm, focusing on the social aspects of information exchanges (e.g., Adam et al. 2021; Lv et al. 2022). Relying on social presence theory, we argue that customers not only assess the degree of social presence triggered by empathic chatbots during those exchanges, but also the richness of the information delivered (Straub & Karahanna 1998). By considering and testing the parallel mediation mechanism of perceived social presence and perceived information quality, this paper adds to the nascent literature on feeling AI (Huang & Rust 2023) and provides a more comprehensive understanding of how empathic chatbots influence customer experience.

Third, we uncover a new boundary condition of the effect of empathic chatbots on customer satisfaction and find that this effect depends on individual customers' context (here, the level of time pressure). This aligns with social presence theory, which holds that the mediated communication context in which individuals exchange information influences individuals' information processing behaviors (Biocca et al. 2003). Our findings reveal that, under high time pressure, empathic chatbot can be detrimental and undermine customer experience. These results complement previous studies that mainly considered chatbot-, customer- and employee-related characteristics as contingencies (e.g., Fan et al. 2023; Liu & Sundar 2018; Park et al. 2022). Taking a broader perspective, this paper questions whether artificial empathy is recommended in all situations. In line with Castelo et al.'s (2023) research on customers'

reactions to service robots, the present results suggest that researchers and practitioners should avoid over-generalizing artificial empathy appreciation, recognizing instead that consumers sometimes react positively to empathic chatbots, while at other times the exact opposite is true.

8.2. Managerial implications

This research carries several implications for service providers who incorporate (or consider incorporating) chatbots into their frontline. First, service providers traditionally deploy mechanical chatbots with low socio-emotional behaviors to handle short, one-time-only routine task interactions (Nißen et al. 2022). Recent studies, however, show that this type of chatbot may lead to customer frustration and perceptions of cost-cutting motivations (Castelo et al. 2023). The present study findings suggest that managers could deploy empathic chatbots instead, even for these short interactions, as implementing artificial empathy into chatbots generally enhances customer experience (i.e., perceptions of social presence and information quality) and satisfaction. Various approaches exist for implementing artificial empathy into chatbots, including providing a fixed emotion architecture (Leite et al. 2013) or creating a continuously learning architecture (Lim & Okuno 2015). In any case, managers might use our study material as a guide to design the three dimensions of artificial empathy. Specifically, chatbots can simulate perspective-taking by acknowledging customers' situations and giving more personalized answers; emotional contagion by using emoticons; and empathic concern by using sentences such as "don't worry".

Second, this study outlines the need to align chatbot empathy with the customer's situational context, specifically the level of time pressure. The present findings reveal that a higher level of artificial empathy is less suitable for customers who are in situations of high time pressure. Service providers could therefore consider this contextual element when deciding which type of chatbot to incorporate into their frontline. A solution could be to implement mechanical chatbots for service requests typically made under high time pressure, while

deploying empathic chatbots for other service requests. Another solution is to ensure that empathic chatbots can assess customers' time pressure during the initial stages of interaction using NLP techniques and adjust the displayed level of empathy accordingly.

8.3. Limitations and future research

Some limitations should be considered when interpreting the results, some of which provide fruitful opportunities for future research. First, this study manipulated the three dimensions of artificial empathy altogether. Early conceptual research by Liu-Thompkins et al. (2022) suggests that one dimension does not necessarily require the presence of the two others to work, although their synergy is expected to benefit each other's. For instance, a chatbot could take the perspective of customers without mimicking their emotions, yet doing so could enhance customers' perception of perspective-taking. Future research could separately manipulate the dimensions of artificial empathy, assess their relative importance, and find the optimal combination.

Second, this study finds a positive main effect of empathic chatbot on customer satisfaction in Study 1 and Study 2. Surprisingly though, Study 3 did not replicate this main effect in the low-time pressure condition. One explanation for this may be that there were fewer empathic opportunities (i.e., "clear and direct statements of emotion, progress or challenge", Bylund & Makoul 2002, p. 209) included in the customer scripts of Study 3, likely decreasing the added value of artificial empathy. Future research could therefore investigate the effect of artificial empathy according to the properties of these empathic opportunities, particularly in terms of frequency (e.g., few vs. many) and length (e.g., short vs. long).

Third, this study focuses on time pressure given its central role as a key driver for customer interaction with chatbots (Ostrom et al. 2021). Other relevant contextual factors may exist and influence customers' reactions to empathic chatbots. Future research, for instance, could investigate the effectiveness of empathic chatbots in emotionally charged encounters such as

medical assistance, car breakdown assistance or funeral services. In such emotionally-charged settings, customers typically expect service agents to display authentic empathy (Delcourt et al. 2016). Building upon prior conceptualizations of authenticity in human interactions (e.g. Carroll & Wheaton 2009), one may assume that machines may appear less authentic on certain dimensions (e.g. moral authenticity) and equally or more authentic on others (e.g. type authenticity). However, scholars have not yet fully explored what it means to consider an AI-enabled interface as authentic or sincere, with some even arguing that it differs from the concept of authenticity in human service interactions (e.g., Jago 2019). Conceptual work is required to advance our understanding of this issue. As a logical next step, future research could examine when customers perceive artificial empathy as (in)authentic and how these perceptions affect their experience and satisfaction.

Declaration of generative AI and AI-assisted technologies in the writing process
During the preparation of this work the authors used ChatGPT in order to improve readability and language. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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Figure 1: Conceptual framework and overview of studies

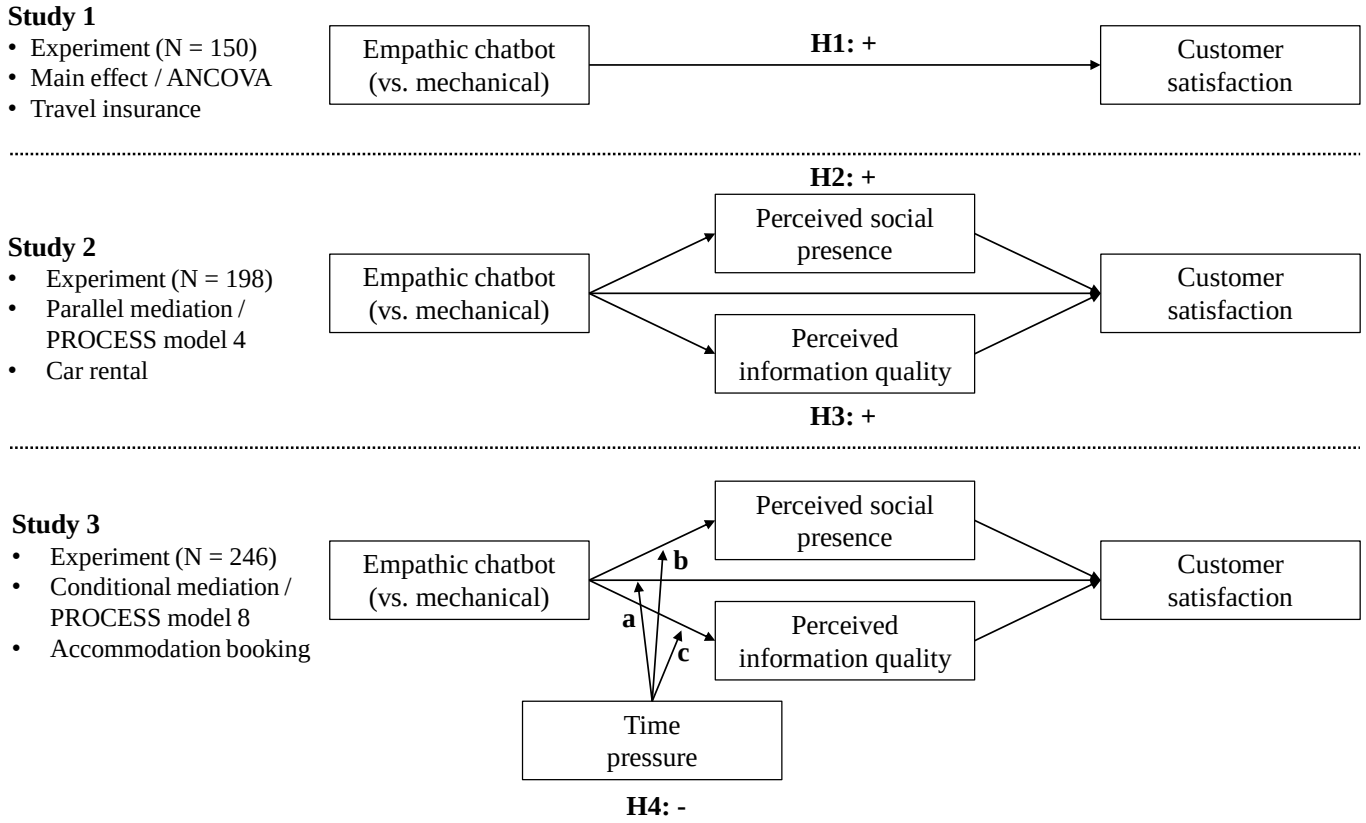


Table 1: Synthesis of prior research on artificial empathy in customer-chatbot service encounters

				Mediator(s)			
Authors	**Theory**	**Design**	**Sector(s)**	**Social-related**	**Information quality**	**Moderator(s)**	**Outcome(s)**
Liu & Sundar (2018)	CASA	Experimental	Healthcare	X		Customer-related	Overall evaluation, uncanniness
Adam et al. (2021)	CASA	Experimental	Banking	X			User compliance
Liu-Thompkins et al. (2022)	Customer experience	Experimental	Retail				Customer experience
Lv et al. (2022)	CASA	Experimental	Airline, entertainment, hospitality	X		Chatbot-related	Continuous usage intention
Park et al. (2022)	CASA	Experimental	Charity	X		Chatbot-related	Willingness to donate
Fan et al. (2023)	Expectation confirmation theory	Experimental	Hospitality			Chatbot & employee-related	Customer retention
Markovitch et al. (2024)	Attribution theory	Experimental	Retail			Chatbot-related	Customer satisfaction
This study	*Social presence theory*	*Experimental*	*Hospitality, insurance, retail*	*X*	*X*	*Context-related (time pressure)*	*Customer satisfaction*

Table 2: Measurement scales used across studies

	Cronbach's α		
Measures	**S1**	**S2**	**S3**
Customer satisfaction adopted from Gelbrich et al. (2021)	.984	.977	.960
- I am satisfied with the service provided			
- I am happy with the service provided			
- I think the service provided is satisfactory			
Perceived social presence adopted from Gefen & Straub (2003)	N.A.	.960	.934
- There is a sense of human contact in the interaction with [X]			
- There is a sense of personalness in the interaction with [X]			
- There is a sense of sociability in the interaction with [X]			
- There is a sense of human warmth in the interaction with [X]			
- There is a sense of human sensitivity in the interaction with [X]			
Perceived information quality adopted from Kim & Niehm (2009)	N.A.	.944	.932
- The interaction with [X] provides accurate information			
- The interaction with [X] is informative			
- The interaction with [X] provides updated information			
- The interaction with [X] provides high quality information			
- The interaction with [X] provides timely information			
- The information in the interaction with [X] is relevant to me			
- I can find what I need in the interaction with [X]			
- The interaction with [X] provides relevant information			
Situational involvement adopted from Mehta et al. (2017)	N.A.	N.A.	.710
- How important was the cancellation for you?			
- How relevant was the cancellation for you?			
- How appealing was the cancellation for you?			
- How much effort did you spend on the cancellation?			
- How much did the cancellation mean to you?			
Artificial empathy adapted from Liu-Thompkins et al. (2022)	.946	.962	.958
- [X] tried to understand me better by imagining how things look from my perspective			
- [X] tried to "put themselves in my shoes"			
- [X] tried to imagine how he would think in my place			
- [X] recognized my emotions			
- [X] expressed concerns about my experience			
- [X] tried to make me feel better			
- [X] easily got affected by my emotions			
- [X] seemed to feel bad when I was concerned / [X] seemed to feel the way I felt			
- It worried [X] when I was distressed / [X] was worried about how I felt			
Prior experience with chatbots adapted from Reinders et al. (2008)	.878	.891	.917
- I commonly interact with many chatbots			
- I do not have much experience interacting with chatbots			
- I interact a lot with chatbot-based customer service			
Need for interaction adopted from Dabholkar & Bagozzi (2002)	.826	.752	.822
- Human contact in providing services makes the process enjoyable for the consumer			
- I like interacting with the person who provides the service			
- Personal attention by the service employee is not very important to me			
- It bothers me to use a machine when I could talk to a person instead			
Realism of the scenario adopted from Liao (2007)	.812	.927	.796
- This scenario seems realistic			
- What happens in this scenario could also happen in real life			

Note. [X] should be replaced by chatbot's name.

Appendices

Appendix A: Conversation script (Study 1)

Mechanical chatbot	Empathic chatbot
Agent: Good afternoon. I'm Jordan, your customer service chatbot **Agent:** How can I help you? **Customer:** Hi, I'm going on holiday, and I purchased World HT a few days ago **Customer:** I'm worried because I realize that not everything is clear to me at this point **Customer:** Can you help me, please? **Agent:** For more information about insurance, write your questions here and I'll look for answers **Customer:** Well, I feel quite confused about what is covered if I'm sick or injured **Customer:** I don't want to end up at the hospital with no coverage **Customer:** It stresses me out **Agent:** Each insurance policy has its own coverage 📝 **Agent:** Click on the link below. You will be redirect to a webpage that includes a summary **Agent:** www.vevris.com/McwHT **Customer:** Ok, thanks **Customer:** I'm also concerned about the refund process **Customer**: I had a bad experience in the past **Agent:** Please find the link about the refund policy below **Agent**: The last section includes a 4-step guide to getting a refund **Agent:** www.vevris.com/refund **Customer**: And what if something goes wrong anyway? **Agent**: In case of questions during the refund process, ask them here **Customer:** Ok. If I run into any issues, I'll reach out for assistance **Agent:** Do you have another question? **Customer:** No, thanks **Agent**: Ok. Thanks for contacting us! Goodbye	**Agent:** Good afternoon. I'm Jordan, your customer service chatbot **Agent:** How can I help you? **Customer:** Hi, I'm going on holiday, and I purchased World HT a few days ago **Customer:** I'm worried because I realize that not everything is clear to me at this point **Customer:** Can you help me, please? **Agent:** Don't worry, I'm sure I can help you. Tell me, which parts of your insurance are not clear? **Customer:** Well, I feel quite confused about what is covered if I'm sick or injured **Customer:** I don't want to end up at the hospital with no coverage **Customer:** It stresses me out **Agent:** You are right; coverage can be confusing 😕 **Agent:** Rest assured, this short summary clarifies what is covered if you are sick or injured **Agent:** www.vevris.com/McwHT **Customer:** Ok, thanks **Customer:** I'm also concerned about the refund process **Customer**: I had a bad experience in the past **Agent:** I understand your concern about the refund **Agent:** The link below includes a 4-step guide to obtaining a hassle-free refund **Agent:** www.vevris.com/refund **Customer**: And what if something goes wrong anyway? **Agent:** I'll be here to help you with any concerns along the refund process **Customer:** Ok. If I run into any issues, I'll reach out for assistance **Agent:** Do you have another question? **Customer:** No, thanks **Agent**: Ok. Thanks for contacting us! Have a safe trip