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From Seconds to Sentiments: Differential Effects of Chatbot Response Latency on Customer Evaluations

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ABSTRACT

Since the current literature is inconclusive on what standards best determine the optimal length of response time for chatbots, this study aims to (1) examine the effect of response latency of chatbots on customer evaluations, (2) identify the boundary conditions that moderate the effects of response latency, and (3) determine the underlying mechanism explaining the link between response latency and customer evaluations. Two scenario-based experimental studies were conducted to explore two boundary conditions, typing indicator (Study 1) and emotional support (Study 2). In Study 1, longer response latency diminished customer satisfaction, yet the presence of a typing indicator mitigated these negative effects, as customers perceived a stronger sense of social presence. In Study 2, moderate response latency combined with emotional support heightened chatbot evaluations. Findings from the current research highlight the contextual importance of response latency and human-like elements in shaping positive customer perceptions of chatbots.

KEYWORDS

Chatbot; response latency; typing indicators; emotional support; customer satisfaction

1. Introduction

Text-based chatbots have become popular communication tools for service organizations to interact with customers. These chatbots help reduce interaction costs and build positive customer relationships (Huang et al., 2024; Lee & Li, 2023; Lew et al., 2018). Despite their growing recognition, chatbot adoption rates lag behind expectations (Nordheim et al., 2019), primarily due to issues like lack of responsiveness, absence of visual and audio cues, and unnatural responses (Kim et al., 2025; Schuetzler et al., 2020). Customers naturally prefer certain social aspects of chatbots for interactive communication. Therefore, designing chatbots to foster interactivity is critical for effective online service interactions.

While previous research has identified several conversational cues that influence communication interactivity, including textual cues (Shams et al., 2024), photographic cues (Huang et al., 2021), emoticons (Huang et al., 2021), and linguistic cues (Li & Wang, 2023; Liebrecht et al., 2021), few studies have examined the role of functional cues in chatbots on online service interaction. One underdeveloped aspect of chatbot's functional cues is *chronemic cues*, which describe functions of time in online communication, such as waiting time and response time (Feine et al., 2019). The significance of time as a non-verbal yet invisible cue in communication cannot be underestimated, specifically in human–chatbot interaction. Generally, customers expect fast and efficient service from chatbots, and a delay in response time can result in frustration and dissatisfaction (Yu et al., 2020). However, there needs to be more consistency in chatbots' real-time response, whether a quick response or delayed response is appropriate. While some research argues the negativity of delayed responses, evoking negative reactions (Yu et al., 2020) and reducing the likeability of the chatbot (Schanke et al., 2021), another stream recognizes the backfiring effect of quick response times which makes the conversation seem unnatural (Crozier, 2017) and less human-like (Gnewuch et al., 2018a). Despite a lengthy debate on this issue, research is still inconclusive on what standards best determine the optimal length of response time for chatbots. Therefore, it is necessary to understand the optimal point of response time and under what conditions the negative impact of response time can be mitigated.

Managing chatbot response time involves balancing timely responses with being perceived as socially present. Because social cues can positively influence customers' perceived social presence of an online agent (Shams et al., 2024), it is important to jointly consider the interactive effect of response latency and social cues on customer evaluations of a chatbot. For example, a consumer may prefer faster responses from a chatbot, but may be willing to wait longer if a chatbot is perceived to be human-like. Therefore, in the current study, the following research questions are explored: (1) How does chatbot latency affect customer evaluations? (2) What are the boundary conditions that mitigate or enhance the varying effect of response latency on customer evaluations? (3) What is the key mechanism

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underlying the impact of response latency and customer evaluations? To summarize, the goals of the present research are to (1) examine the effect of response latency of chatbots on customer evaluations, (2) identify the boundary conditions (i.e., typing indicator and emotional support) that moderate the effects of response latency, and (3) determine the underlying mechanism explaining the link between response latency and customer evaluations.

This study contains theoretical and practical contributions in several ways. First, while the current literature has inconsistent results on the effect of response latency, our study offers empirical evidence on under what circumstances customers value different response latencies, by introducing key moderating factors: typing indicators and emotional support. Specifically, this study investigates two different interaction conditions, information provision and service failure, highlighting how customer expectations influence the effects of response latency. Second, this study suggests a better understanding of the relationship between response latency and customer evaluations by examining an important underlying mechanism which would differ for information provision (Study 1) and service failure (Study 2). Study 1 explores the role of social presence while Study 2 examines the role of rapport in customer–chatbot interaction. Finally, while conventional wisdom emphasizes instant responses, our study highlights the importance of considering context and customer needs. Our results showed deliberately delaying responses and providing emotional support can enhance customer evaluations. This approach helps service organizations effectively manage chatbot–customer interaction by suggesting the importance of introducing human-like attributes. In the sections that follow, we first provide relevant literature to formulate the conceptual framework, present two experimental studies that together support our hypotheses, and discuss the theoretical contributions, practical implications, and future research directions.

2. Literature review

2.1. Response latency

Social Information Processing (SIP) theory (Walther, 1992) posits how individuals make sense of social interactions in online environments where nonverbal cues are absent unlike face-to-face communication. According to SIP, communicators utilize available cue systems to exchange social information when physical nonverbal cues are absent. In the case of chatbots, customers rely on message-related and source-related cues such as verbal, linguistic, textual cues (Walther, 1992), as well as timing-related or chronemic cues (Walther & Tidwell, 1995).

Response latency, one of the most salient chronemic cues in computer-mediated communication (hereafter CMC) (Hesse et al., 1988; Walther & Tidwell, 1995), refers to the time taken by a system to generate a response after a request or stimulus has been received (Moon, 1999). The majority of previous studies in CMC examined response latency in the form of dynamic delays, considering message length, number of characters, and complexity (e.g., Gnewuch et al., 2018b; Holtgraves & Han, 2007; Schanke et al., 2021). Nevertheless, only a limited number of studies have explored how response time influences user's perception through static delays, yet with inconsistent research findings.

For instance, in Moon's (1999) study, information was more persuasive to the users when responses had a moderate delay (5–10 s) rather than a short delay (0–1 s) or a long delay (13–18 s). However, in Holtgraves et al. (2007) study, relatively quick responses (1 s) were perceived as more conscientious and extroverted compared to those with a slower response (10 s). Due to such inconsistent findings, we aim to unravel the contradictory effects of chatbots' response latency (e.g., in the form of static delay) presented in the existing literature. In this study, we differentiate response latency based on three durations (instant, moderate, and long) and investigate its effect on chatbot evaluation.

This study extends SIP theory by applying it to chatbot communication and incorporating interactive features such as response latency and human-like social cues that shape user perceptions in the absence of traditional nonverbal signals. According to SIP theory, users adapt to available cues in computer-mediated environments to form impressions and relational judgments (Lew et al., 2018). In the context of chatbot interactions, we propose that users interpret response latency alongside other social cues (e.g., typing indicators and emotional support) to assess the chatbot's attentiveness and intention. These cues contribute to a sense of human-like interaction, enhancing social presence or rapport, and ultimately influencing customer evaluations.

2.2. Expectancy Violations Theory (EVT)

Expectancy Violations Theory (EVT) (Burgoon & Hale, 1988) explores the consequences that arise from violations of nonverbal behavior during human-to-human interactions. EVT elucidates how individuals establish expectations in their communication with others and how they assess their communication experiences based on their evaluations of met or violated expectations (Burgoon, 1978). Essentially, EVT suggests that individuals hold expectations regarding nonverbal behaviors of non-human entities. When these expectations are not met, attention is redirected towards the source of the violation, and individuals strive to understand the meaning of the deviation. EVT asserts that positive violations yield more favorable results compared to positive confirmations, while negative deviations result in more unfavorable outcomes compared to negative confirmations (Burgoon et al., 2016).

Despite chatbots' ability to mimic human communication, individuals maintain distinct expectations when interacting with chatbots versus when engaging with human counterparts (Lew & Walther, 2023). Regarding expectancy violations in communication dynamics, specifically regarding variations in response latency, chatbots are generally expected to respond quickly in text-based conversation. In contrast, humans are not held to the same standard of immediacy in similar situations (Lew & Walther, 2023).

In this study, we apply EVT to examine how users react when chatbot response latency violates their expectations for efficiency. We specifically investigate whether the presence of human-like cues such as typing indicators or emotional support can help reinterpret a long delay as thoughtful or intentional, thereby reducing the negative impact of expectancy violations. Building on this theoretical foundation, our study focuses on how these cues interact with latency to influence user perceptions, and how such effects are mediated by psychological mechanisms like social presence and rapport.

2.3. Response latency and typing indicator

Response time is a quality metric for customers seeking information in the digital areas (Ranganath et al., 2015). Studies in CMC found that response time significantly affects users' perception of conversation (Holtgraves et al., 2007). Chatbots are often used for real-time engagement; however, unlike humans who require time to process a message and formulate a reply, chatbots are capable of processing user input and delivering responses instantly (Schuetzler et al., 2021). Yet, ironic delays by chatbots, despite their speed capacity, can disrupt flow and reduce effectiveness (Lew et al., 2018; Lew & Walther, 2023). Delayed response latencies have been found to evoke frustration (Yu et al., 2020), reduce likeability (Schanke et al., 2021), and impair the perceived competence of the agent (Holtgraves et al., 2007; Reinsch et al., 2008).

Typing indicators are originally developed for CMC systems to support turn-taking and create visual awareness of the other party typing (Gnewuch et al., 2018a). In human-to-human interactions, turn-taking is enabled by various social cues including body gestures, gaze direction, and facial expressions (Wiemann & Knapp, 1975). However, chatbots lack these cues, and users only see messages after typing is complete. Today, typing indicators (e.g., *three dots, person X is typing*) are used in chatbots to foster natural and human-like interactions (Appel et al., 2012). These indicators help simulate human presence, potentially reframing delays as effortful communication rather than inefficiency (Gnewuch et al., 2018a).

SIP underscores the significance of synchronizing information exchange (Walther & Tidwell, 1995). According to SIP, delays may be perceived negatively due to reduced immediacy. Especially in information-driven settings, delayed responses can signal inattentiveness or inefficiency (Zhang et al., 2018). Therefore:

H1-1: *Under the information provision context, in the absence of a typing indicator, a shorter (instant or moderate) response latency increases customer satisfaction (than a long response latency).*

Furthermore, humans are expected to take time to process a message and generate a response (Schuetzler et al., 2021), while chatbots are not. Hence, when chatbots exhibit long delays, this may violate expectations and produce a negative user experience (Lew & Walther, 2023). However, typing indicators can reframe these delays as human-like efforts and as an indication that the other party is formulating a response. According to EVT, whether latency is perceived negatively depends on available social cues. For instance, Rheu et al. (2024) found that when users' expectations—such as those shaped by a chatbot's assigned role (e.g., expert)—were violated by mismatched behavior (e.g., generic replies), users experienced stronger disappointment than when expectations were simply low. These negative expectancy violations diminished perceived trust, caring, and sincerity. This suggests that even subtle cues (like typing indicators) may mitigate negative effects by signaling engagement and responsiveness. In this case, violations are not just about delays but about failing to meet expectations of intentionality. When chatbots fail to meet interaction expectations—without signaling active effort—can damage user evaluations. However, when such violations (e.g., long delays) are accompanied by cues like typing indicators, they may be reinterpreted as thoughtful or purposeful, thereby reducing negative reactions.

H1-2: *Under the information provision context, in the presence of a typing indicator, the negative effect of a long response latency (vs. instant, moderate response latency) on customer satisfaction is attenuated.*

2.4. The mediating role of social presence

Social presence refers to the extent to which the other person is perceived as present in the interaction (Short et al., 1976). According to the Computers as Social Actors (CASA) paradigm, people often instinctively react to technology as if they were engaging with another person (Nass et al., 1994). This occurs when technologies possess social cues, such as human-like natural language, which shape the user's perception of the technology as a social actor (Nass et al., 1994; Feine et al., 2019).

Response latency and typing indicators are two social cues that evoke human-likeness (Feine et al., 2019; Grimes et al., 2021) and increase the perceived social presence (Feine et al., 2019). For instance, research has shown that typing indicators function as a social signal in human–chatbot interaction, enhancing the sense of closeness (Gnewuch et al., 2018a) and contributing to a more natural interaction (Appel et al., 2012). Similarly, in terms of response latency, compared to immediate responses, a delayed response leads to a more natural conversation (Gnewuch et al., 2022) and enhances the perception of the chatbot as being more human-like and having a stronger social presence.

Furthermore, using social cues in conversation creates an emotional bond to users and enhances the feeling of human connection, resulting in more positive attitudes such as trust, satisfaction, and positive customer responses (Go & Sundar, 2019). The strong sense of connection and human touch that results from social presence evokes feelings of intimacy and immediacy between individuals (Feine et al., 2019), which then enhances customer satisfaction (Gnewuch et al., 2018b) and usage intention (Gnewuch et al., 2022).

Thus, considering that humans naturally require time to process and respond in conversations, simulating such timing through chatbot response latency and typing indicators may enhance social presence and, in turn, increase customer satisfaction. This process aligns with SIP theory, which suggests that users adapt to available social cues (e.g., latency and typing indicators) to form impressions and relational meaning in CMC. These cues foster perceived social presence (Short et al., 1976), which then mediates the effect of chatbot behavior on satisfaction. From the perspective of EVT, longer response time may initially violate expectations of chatbot efficiency. However, when accompanied by a typing indicator (e.g., someone is typing), users may reinterpret the delay as a sign of thoughtful processing (Burgoon & Hale, 1988). In doing so, the perceived social presence increases, and the negative effect of the expectancy violation is mitigated, thereby restoring satisfaction.

H2: *The interaction effect between response latency and typing indicator on customer satisfaction is mediated by social presence.*

Figure 1 depicts the conceptual model illustrating the suggested relationships (H1 and H2) between response latency, typing indicators, social presence, and customer satisfaction.

3. Study 1

Study 1 was conducted to test the interactive effect of chatbot response latency and typing indicators on customer satisfaction (H1) and the mediating role of social presence (H2).

3.1. Methodology

3.1.1. Participants and design

Two-hundred and twenty participants were recruited from a southeastern university for a course credit. Participation in this online study was voluntary, and the study was completely anonymous. Upon completion, participants were redirected to a separate webpage to indicate their names, ensuring no identifying information was connected to their responses. They were randomly assigned to one of six conditions in a 3 (response latency: instant, moderate, long) × 2 (typing indicator: absent, present) between-subjects design and were asked to watch a pre-recorded video presenting a chatbot–customer interaction. Invalid responses based on attention check questions were eliminated to ensure data quality, leaving us with 214 respondents (49.1% male, $M_{age} = 21.64$). Despite the relative homogeneity of the sample, participants varied in terms of their previous experiences with a chatbot and technological competency in general, and thus, these variables were considered as control variables in the subsequent analyses following suggestions from Mostafa and Kasamani (2022). Table 1 depicts the demographic characteristics of the participants.

3.1.2. Materials

The context was a customer making a reservation at the ABC hotel, a fictitious brand, with a chatbot agent. An animated video presenting a chatbot–customer interaction was pre-recorded. Upon being greeted by a chatbot agent, a customer indicated preferred dates to stay, asked several questions and successfully made a reservation (see Appendix A for a complete copy of the script). The video was recorded from a customer's perspective, showing animated motion such as real-time word-by-word typing and a vibrating send button so that participants could feel as if they were interacting with a chatbot agent. In the video, the chatbot agent and the customer took turns typing. After the customer responded, the chatbot showed either a typing indicator (animated dots) suggesting that messages were being typed or nothing depending on the experimental condition. Furthermore, depending on the response latency conditions, the chatbot responded back to the customer either instantly, moderately (in 5 s), or after a long duration (in 20 s). The total duration of the video was 0:52 (instant condition), 1:32 (moderate condition), and 3:02 (long condition).

3.1.3. Procedure

Upon completing the consent form, participants were asked to imagine a scenario in which they were planning to go on a vacation and about to start a conversation with a chatbot agent to reserve a room. They were then asked to picture themselves in the dialogue with a chatbot by watching a video described above. After watching the video, participants responded to the survey items such as customer satisfaction with a chatbot, social presence, manipulation checks, and demographic questions.

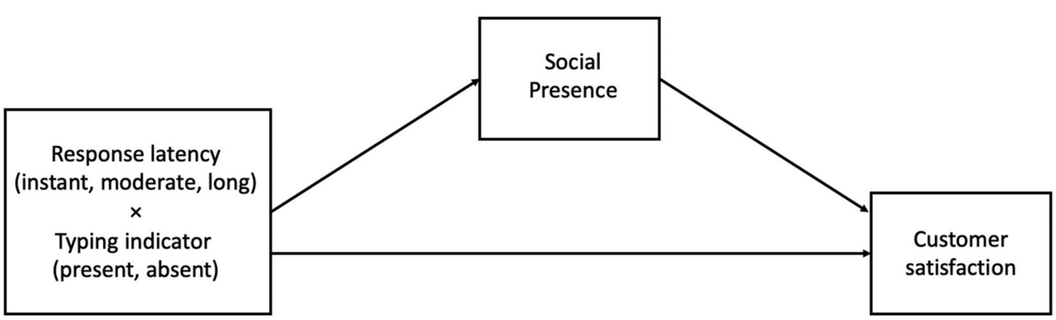

Figure 1. Conceptual model (Study 1).

Table 1. Demographic characteristics.

Variable	Study 1 (N = 214) Frequency	%	Study 2 (N = 164) Frequency	%
Age				
Under 20	70	33	54	33
21–25	119	56	62	38
26 or more	12	5	48	29
(Did not indicate)	13	6	–	–
Gender				
Male	105	49	91	55
Female	109	51	72	44
Prefer not to say	–	–	1	1
Ethnicity				
African American/Black	22	10	4	2
Asian or Pacific islander	38	18	7	4
Hispanic	15	7	19	12
White/Caucasian	134	63	134	82
Other	5	2	–	–
Previous experience with a chatbot				
Never	60	28	25	15
1–2 times	72	34	57	35
3–5 times	39	18	46	28
6–10 times	20	9	15	9
More than 10 times	23	11	21	13
Technological competency				
Learner (I am not sure how to work with a technology)	10	5	1	1
Basic (I have worked with a technology before, but might need some help)	40	19	24	14
Proficient (I can work with a technology without any assistance)	143	66	113	69
Advanced (I could train staff to work with a technology)	21	10	26	16
Total	214	100	164	100

3.1.4. Measures

All the questions were responded to a 7-point scale (1 = strongly disagree, 7 = strongly agree). Customer satisfaction with a chatbot was measured with three items ($\alpha = 0.91$) adapted from Seiders et al. (2005). Items were "I am pleased with the overall interaction provided by this chatbot," "I feel delighted with the overall interaction provided by this chatbot," and "I am completely satisfied with the experience by this chatbot." Social presence was measured with five items ($\alpha = 0.92$) adapted from Gefen and Straub (2003). Items were "I felt a sense of human contact/personalness/human warmth/sociability/human sensitivity in this chatbot." Response latency was measured with two items ($r = 0.45$), "The chatbot was prompt in responding to your inquires (reverse-coded)" and "The chatbot delayed in responding to your inquires." The presence of a typing indicator was measured with two items ($r = 0.90$), "The chatbot indicated that a response was being prepared" and "The chatbot indicated that a response was being generated" following Gnewuch et al. (2018a). Furthermore, scenario realism was measured with two items ($r = 0.77$), "This scenario was realistic" and "What happened in this scenario could happen in real life."

3.2. Results and discussion

3.2.1. Manipulation checks

A one-way ANOVA on response latency suggested a significant difference between the three response latency conditions, $F(2,211)=39.88$, $p < 0.001$. Participants perceived long (20-s) latency as significantly longer than instant latency ($M_{\text{long}} = 4.19$ vs. $M_{\text{instant}} = 2.13$, $p < 0.001$) and moderate (5-s) latency ($M_{\text{long}} = 4.19$ vs. $M_{\text{moderate}} = 2.54$, $p < 0.001$). Furthermore, an independent-samples t-test indicated that those who were presented with a typing indicator reported higher perceptions of typing indicator presence than those who were not ($M_{\text{present}} = 6.12$ vs. $M_{\text{absent}} = 4.22$, $t(212) = 7.66$, $p < 0.001$). In addition, participants felt that the given scenario was realistic, as the mean rating of 5.89 was significantly higher than the midpoint 4, $t(213)=24.36$, $p < 0.001$. Taken together, the results suggest successful manipulations of the study stimuli.

3.2.2. Hypothesis testing

A 3 (response latency) × 2 (typing indicator) ANCOVA on customer satisfaction was conducted, controlling for previous chatbot experiences and technological competency. Supporting H1, there was a significant two-way interaction effect, $F(2, 206)=4.02$, $p < 0.05$ (see Figure 2). To interpret the interaction effect, simple main effects tests were conducted. When a typing indicator was absent, customer satisfaction was significantly different across response latency conditions, $F(2, 206) = 10.95$, $p < 0.001$. Specifically, customer satisfaction was greater when the response latency was instant ($M_{\text{absent/instant}} = 5.67$) than long ($M_{\text{absent/long}}=4.40$), $p < 0.001$. Also, customer satisfaction was greater when the response latency was moderate ($M_{\text{absent/moderate}} = 5.62$) than long, $p < 0.001$. There was no significant difference between instance latency and moderate latency, $p = 0.87$. This supports H1-1.

While there was no significant effect of the typing indicator on customer satisfaction when the response latency was instant or moderate, the presence of a typing indicator significantly increased customer satisfaction when the response latency was long ($M_{\text{present/long}}=5.45$ vs. $M_{\text{absent/long}}=4.40$, $p < 0.01$), supporting H1-2. This suggests that while

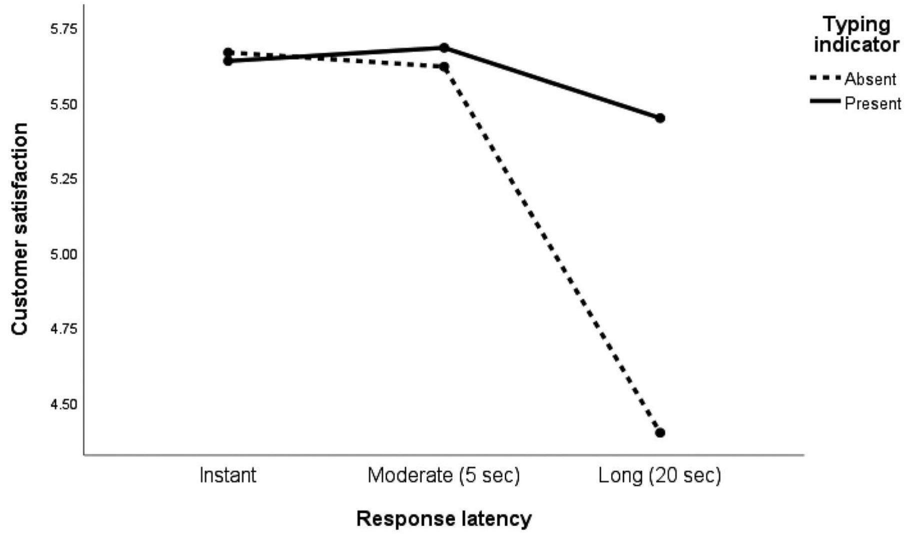

Figure 2. Interaction effect of response latency and typing indicator on customer satisfaction.

customers do not like to wait for a longer time in general, the mere presence of a typing indicator can reduce such negative effects of longer response latency on customer satisfaction.

3.2.3. Moderated mediation

We conducted moderated mediation analyses to test whether the interaction effect between response latency and typing indicator on customer satisfaction is mediated by social presence (H2). PROCESS model 8 (Hayes, 2013) was used in which response latency was the independent variable, typing indicator was the moderating variable, social presence was the mediating variable, and customer satisfaction was the dependent variable, controlling for previous chatbot experiences and technological competency. Because response latency was a categorical variable with three levels, two dummy variables were created in which the reference category was instant latency. The first dummy variable represented the effect of moderate latency (coded as D_1=1, D_2=0), and the second dummy variable represented the effect of long latency (coded as D_1=0, D_2=1). When running the analyses, 95% confidence intervals with 5000 bootstrap samples were used. Table 2 summarizes the results from moderated mediation analyses.

We first compared instant latency versus moderate latency when the typing indicator was present (vs. absent). The path from response latency to customer satisfaction through social presence (indirect effect) was not significant when the typing indicator was either present (95% CI: [−0.35, 0.27]) or absent (95% CI: [−0.47, 0.12]). The index of moderated mediation (i.e., the difference between two conditional indirect effects) was not significant (95% CI: [−0.28, 0.56]), suggesting that the effects of instant latency and moderate latency on customer satisfaction do not significantly differ. We then compared instant latency versus long latency when the typing indicator was present (vs. absent). The path from response latency to customer satisfaction through social presence was not significant when typing indicator was present (95% CI: [−0.34, 0.32]) but the indirect effect was significant when typing indicator was absent (95% CI: [−0.82, −0.14]). The index of moderated mediation (i.e., the difference between two conditional effects) was 0.47, and it was significant (95% CI: [0.03, 0.95]), supporting H2.

The results from the above analyses can be summarized as follows: Customers prefer shorter response latency in general, and longer response latency reduces customer satisfaction. However, the presence of a typing indicator can mitigate the negative effects of longer response latency on customer satisfaction because consumers feel a stronger sense of social presence. This is presumably because while customers would be willing to wait for human agents to respond back, they would not expect such things from chatbot agents. When customers feel humanness out of chatbots, however, they treat them as if they are humans, and thus, they can bear longer wait times.

4. Study 2

Study 1 suggested that while customers generally prefer shorter response latency (instant or moderate) in a normal conversation with no disruption of service, the mere presence of a typing indicator can buffer the negative impact of longer response latency on customer satisfaction. When a service failure occurs, however, customers may have higher expectations for recovering from the failed service (Huang & Dootson, 2022; Song et al., 2023). In such cases, bonding with customers through sincere emotional support is more important than merely providing shorter responses or presenting a typing indicator. Therefore, Study 2 aims to demonstrate that, even with a typing indicator, the impact of response latency may vary depending on the emotional support a chatbot agent provides under a service failure situation. Furthermore, Study 2 considers the inclusion of adoption intention as a focal variable since adoption intention serves as a user-centric metric, reflecting users' willingness and eagerness to embrace and persist with chatbot interactions (Venkatesh & Davis, 2000), especially in adverse situations such as the context of service failure.

Table 2. Moderated mediation (Study 1).

DV	Predictors	b	SE	t	95% CI	Model summary
Social presence (mediator)	Constant	4.95**	0.71	6.95	(3.55, 6.36)	$R^2 = 0.06$
	PEC	−0.05	0.08	−0.68	(−0.21, 0.10)	$p = 0.09$
	TC	−0.04	0.15	−0.24	(−0.34, 0.26)	
	D_1	−0.70	0.77	−0.91	(−2.23, 0.82)	
	D_2	−2.06*	0.8	−2.58	(−3.63, −0.48)	
	Typing indicator (0 = absent, 1 = present)	−0.01	0.03	−0.21	(−0.08, 0.06)	
	D_1 × Typing indicator	0.03	0.05	0.63	(−0.07, 0.13)	
	D_2 × Typing indicator	0.10*	0.05	2.05	(0.00, 0.20)	
Customer satisfaction	Constant	2.88**	0.56	5.18	(1.78, 3.97)	$R^2 = 0.39$
	PEC	0.03	0.06	0.6	(−0.08, 0.14)	$p < 0.001$
	TC	0.2^+	0.11	1.84	(−0.01, 0.41)	
	D_1	0.19	0.54	0.34	(−0.88, 1.26)	
	D_2	−1.39*	0.57	−2.45	(−2.51, −0.27)	
	Social presence	0.46**	0.05	9.44	(0.36, 0.56)	
	Typing indicator (0 = absent, 1 = present)	0.001	0.02	0.02	(−0.05, 0.05)	
	D_1 × Typing indicator	−0.01	0.03	−0.15	(−0.07, 0.06)	
	D_2 × Typing indicator	0.06^+	0.04	1.71	(−0.01, 0.13)	

Note: PEC = previous experience with a chatbot; TC = technological competency.
$^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.10$.

4.1. Response latency and emotional support

One way to counteract the absence of human support in technology-based services is by imbuing services with social support (Rafaeli et al., 2017; Van Doorn et al., 2017). One form of social support is emotional support, an interactive strategy that is becoming popular in designing human–computer interactions (Gelbrich et al., 2021; Meng & Dai, 2021). Customers consistently anticipate and demand receiving emotional expressions of concern from the service staff (Gorry & Westbrook, 2011). Emotional support involves providing empathetic and reassuring responses to customers using body language, smiles, gestures, greetings, thanks, and empathic emotions (Gelbrich et al., 2021). While chatbots are incapable of experiencing genuine emotions (Wirtz et al., 2018), they can mimic emotions using verbal or nonverbal cues (Seeger et al., 2021).

Emotional support in chatbots involves their capacity to detect and respond suitably to the user's emotional state, creating an empathetic and understanding interaction (Diederich et al., 2020). Emotional support is particularly crucial in service failure situations, as it encompasses feelings of compassion and empathy for those in difficult situations (Ortony et al., 1988), meeting the fundamental human requirements for care and support from others (Rains et al., 2016). Previous studies show that receiving emotional support reduces stress (Duhachek, 2005; Meng & Dai, 2021) and increases service evaluation (Bagozzi et al., 1999; Menon & Dubé, 2007) and satisfaction (Gelbrich et al., 2021; Zhang et al., 2024). Therefore, we hypothesize that emotional support will shape how users interpret different chatbot response latencies in a service failure context.

Considering SIP and the aforementioned literature in Study 1, users may negatively interpret longer response times from a chatbot, as they might perceive it as a lack of attentiveness or efficiency (Zhang et al., 2018). This perception could be especially pronounced in text-based communication, where response latency is a key cue. Delays in addressing customers' concerns after failure may lead to a negative perception of the service provider. Thus, shorter response times (either instant or moderate) are expected to increase adoption intention, while longer response times may reduce adoption intention—especially in the absence of emotional support.

H3-1: *Under the service failure context, in the absence of emotional support, a shorter (instant or moderate) response latency increases adoption intention (than a long response latency).*

On the other hand, ordinary users' expectations of chatbots are to have a prompt response times, while unemotional and cold (Zhang et al., 2024). In line with EVT, when a chatbot exhibits a longer response time, it can be considered a violation of these expectations. However, introducing emotional support as an interactive strategy in human/interpersonal communication may influence users' interpretation of this violation.

When a chatbot provides emotional support, it adds a human-like element to the interaction (Diederich et al., 2020), and demonstrates a desire to explain and rectify service failures (Schoefer & Ennew, 2005). This emotional support may transform the nature of the expectation violation into a more acceptable or even positive one. Emotional support, acting as a social cue, signals to users that another party is actively engaged in addressing their needs. The interpretation is likely to be that they are conversing with a human agent, where longer response time is expected, and users might perceive the delay as a necessary time taken to provide a thoughtful, empathetic response.

Customers may reconcile the delay with the understanding that the system is investing extra time to provide a thoughtful response, leading to increased positive evaluation (Smith et al., 1999). In CMC, this aligns with the principles of EVT—the positive violation (receiving unexpected emotional support) can offset the adverse effects of the negative violation (longer response time). Thus, we propose that emotional support may attenuate the negative effects of long response times by providing a human-like cue that shifts users' interpretation of the delay.

H3-2: *Under the service failure context, in the presence of emotional support, the negative effect of long response latency (vs. instant, moderate response latencies) on adoption intention is attenuated.*

4.2. The optimal response latency

In handling service failure, customers value a timely response, seeing it as an appropriate way for service employees to engage with them for recovery (Liao, 2007). However, the concept of "optimal response" in human–computer interaction during service failures has not been thoroughly explored. Drawing upon the SIP Theory and the Goldilocks Principle[1], we suggest that a moderate response time can lead to the highest customer evaluation in service failure situations. SIP Theory emphasizes appropriate social cues in forming impressions (Crick & Dodge, 1994). The Goldilocks Principle suggests that people prefer conditions that are not extreme but "just right" (Kagan, 1990). An instant response may seem ideal but could be viewed as automated and impersonal, which may not fully satisfy customers who expect empathy and understanding in service failures (Appel et al., 2012; Zhang et al., 2018). Conversely, a long response time might be seen as neglectful and worsen customer dissatisfaction (Holtgraves et al., 2007). A moderate response time strikes a balance between immediacy and thoughtfulness, helping the chatbot appear competent and considerate. This could enhance customer adoption intention by giving the impression of a thoughtful, considered response. Therefore, in service recovery, a moderate response time by a chatbot may be perceived as more human-like, aligning with natural conversational rhythms and improving adoption intention.

H4: *Under the service failure context, in the present of emotional support, a moderate response latency leads to highest level of adoption intention (than instant and long response latencies).*

4.3. The mediating role of chatbot-customer rapport

Rapport is defined as a "personal connection between the two interactants, characterized by a sense of mutual attentiveness, positivity, and coordination" (Gremler & Gwinner, 2000, p. 92). Customers build rapport with service representatives through pleasant communication and mutual understanding, directly influencing customer evaluations (Delcourt et al., 2013; Fatima et al., 2024). Nonverbal cues like facial expressions and courtesy are crucial for building rapport in human interactions (Baker & Kim, 2018; Kim & Baker, 2019). In human–chatbot interactions, where facial expressions are absent, mimicking personality and emotional attributes can help foster rapport (Fatima et al., 2024; Hsu & Lin, 2023). Rapport can be built through social and emotional support, showing empathy and understanding (Street & Buller, 1987).

Research indicates that human-like cues positively affect emotional connection (Araujo, 2018) and rapport in human–AI interaction (Bailenson & Yee, 2005). Sands et al. (2021) found that emotional service scripts increase rapport and customer evaluations. Gelbrich et al. (2021) demonstrated that emotional support from digital assistants enhances perceived warmth and customer satisfaction. A chatbot's emotional support can mitigate the negative impact of long response times by increasing adoption intention through perceived rapport, as customers may view longer latency as a necessary time taken to build rapport.

Drawing from SIP theory, rapport can develop through adaptive interpretation of available cues in CMC (Walther, 1992). In the absence of nonverbal cues, users rely on emotional language and relational tone to form impressions, which over time can build rapport—a sense of mutual understanding and coordination. Emotional support provides these cues, encouraging users to perceive the chatbot as socially aware, attentive, and emotionally engaged. From the perspective of EVT (Burgoon & Hale, 1988), when chatbot latency violates expectations–especially during service failure–users may experience frustration or disappointment and respond negatively. However, if the chatbot expresses emotional support, this cue may reframe the delay as thoughtful or empathetic rather than inattentive. This reinterpretation fosters rapport by signaling human-like care, helping to recover from the negative expectancy violation. In this way, rapport serves as the key psychological mechanism through which emotional cues moderate the impact of response latency, ultimately influencing adoption intention.

H5: *The interaction effect between response latency and emotional support on adoption intention is mediated by rapport.*

Figure 3 depicts the conceptual model illustrating the suggested relationships (H3 and H4) between response latency, emotional support, rapport, and adoption intention.

4.4. Methodology

Study 2 tests the effect of response latency and the role of emotional support under a service failure condition to assess whether these social cues also affect service recovery evaluation. Therefore, Study 2 adopts a 3 (response latency: instant, moderate, long) × 2 (emotional support: absent, present) between-subjects design. Additionally, building on the customer satisfaction observed in Study 1, Study 2 uses a direct behavioral measure of adoption intention as a proxy for customer satisfaction.

4.4.1. Participants

Participants were recruited from a southeastern university using the same voluntary, anonymous, extra-credit recruitment procedure outlined in Study 1. After eliminating invalid responses based on attention check questions, the final sample consisted of 164 participants (55.5% male, $M_{age} = 24.24$; see Table 1 for demographic characteristics).

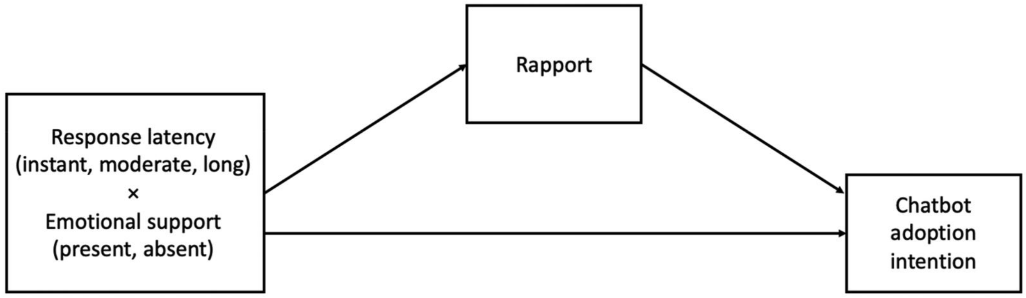

Figure 3. Conceptual model (Study 2).

4.4.2. Materials

As in Study 1, a pre-recorded video presenting a chatbot–customer interaction was displayed to participants. The video presented an angry customer complaining about unnoticed extra charges at the ABC hotel. In dealing with customer complaints, the chatbot either showed great care and compassion or plainly responded to the customer request without, depending on the emotional support conditions (see Appendix B for a complete copy of the script). In both conditions, the video ended with a chatbot agent providing a successful resolution for the customer. The format of the video was identical to Study 1. The total duration of the video was 1:13 (instant condition), 1:39 (moderate condition), and 2:39 (long condition).

4.4.3. Procedure

The procedure of Study 2 was almost the same as in Study 1. Participants were asked to imagine a scenario in which they noticed a problem with the reservation and started a conversation with a chatbot agent. They were asked to watch a video presenting a dialogue described above and then responded to the survey items, including adoption intention, rapport, manipulation checks, and demographic questions.

4.4.4. Measures

All the questions were responded to a 7-point scale (1 = strongly disagree, 7 = strongly agree). Adoption intention was measured with a single item "I would use a chatbot like this to book accommodations in the future." Chatbot-customer rapport was measured with two items ($\alpha = 0.86$) adapted from Gremler and Gwinner (2000). Items include "This chatbot creates a feeling of "warmth" in our relationship." and "In thinking about my relationship, I have a harmonious relationship with this chatbot." Perception of emotional support was measured with five items ($\alpha = 0.92$) adapted from Sherbourne and Stewart (1991). Items include "The chatbot sympathized with you about the service failure" and "The chatbot showed their understanding to you about the service failure." Other manipulation check items, such as response latency and scenario realism, were measured with the same items as in Study 1.

4.5. Results and discussion

4.5.1. Manipulation check

A one-way ANOVA on response latency suggested a significant difference between the three response latency conditions, $F(2,161)=6.01$, $p < 0.01$. Participants perceived long latency as significantly longer than instant latency ($M_{long}=3.14$ vs. $M_{instant}=2.44$, $p < 0.05$) and moderate latency ($M_{long}=3.14$ vs. $M_{moderate}=2.28$, $p < 0.01$). In addition, participants felt higher levels of emotional support when emotional support was present compared to when it was absent ($M_{support}=5.60$ vs. $M_{nosupport}=3.71$, $t(162)=9.00$, $p < 0.001$). Furthermore, participants felt that the given scenario was realistic, as the mean rating of 5.81 was significantly higher than the midpoint 4, $t(163)=20.51$, $p < 0.001$. Taken together, the results suggest successful manipulations of the study stimuli.

4.5.2. Hypothesis testing

A 3 (response latency) × 2 (emotional support) ANCOVA on adoption intention was conducted, controlling for previous chatbot experiences and technological competency. The predicted two-way interaction between response latency and emotional support was significant, $F(2, 156)=3.96$, $p < 0.05$, supporting H3. As shown in Figure 4, longer response latency decreased adoption intention when emotional support was absent, but when emotional support was present, moderately delaying response time increased adoption intention. Specifically, simple main effects tests revealed that under no emotional support condition, adoption intention was significantly higher when response latency was instant (vs. long; $M_{instant}=4.43$ vs. $M_{long} = 3.25$, $p < 0.05$); and adoption intention was marginally significantly higher when response latency was moderate (vs. long; $M_{moderate} = 4.15$ vs. $M_{long}=3.25$, $p = 0.09$); adoption intention was not significantly different between instant latency and moderate latency ($p = 0.58$). This supports H3-1. Also, when the response latency was long, adoption intention was significantly higher in the emotional support condition ($M_{support/long}=5.13$) compared to the no support condition ($M_{nosupport/long}=3.25$), $p < 0.001$, supporting H3-2. Under emotional support condition, adoption intention was higher when response latency was moderate ($M_{moderate}=5.80$) compared to when response latency was instant ($M_{instant} = 4.44$, $p < 0.01$); adoption intention was not significantly different between instant latency and long latency ($M_{long} = 5.13$,

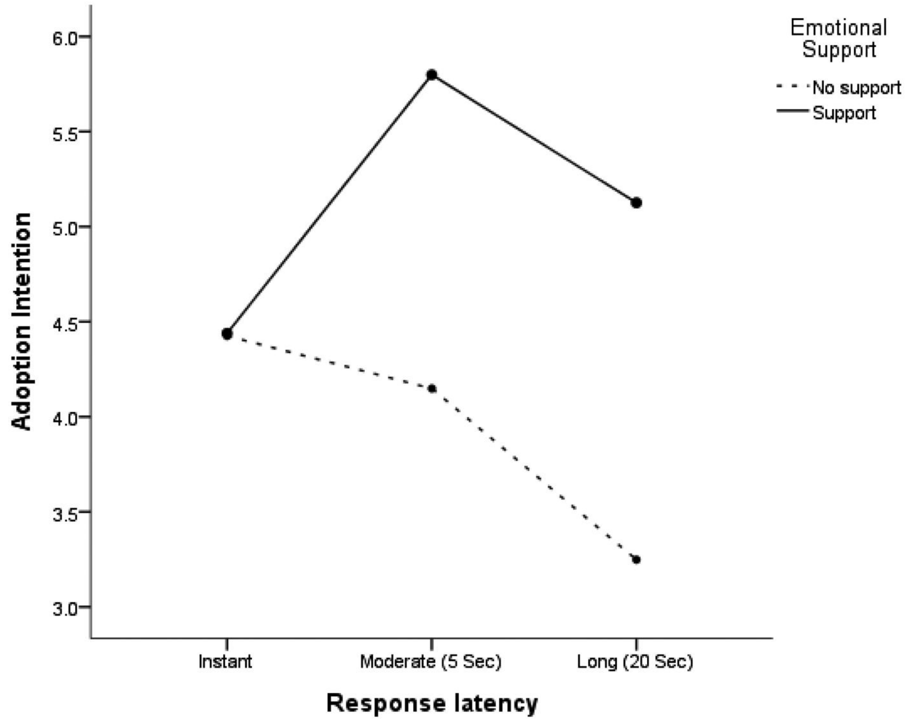

Figure 4. Interaction effect of response latency and emotional support on adoption intention.

Table 3. Moderated mediation (Study 2).

DV	Predictors	*b*	SE	*t*	95% CI	Model summary
Rapport (mediator)	Constant	2.29***	0.66	3.45	(0.98, 3.60)	R^2=0.35
	PEC	−0.02	0.09	−0.19	(−0.20, 0.16)	$p < 0.001$
	TC	0.00	0.20	0.02	(−0.40, 0.40)	
	D_1	−0.34	0.37	−0.91	(−1.08, 0.40)	
	D_2	−0.34	0.40	−0.86	(−1.12, 0.44)	
	Emotional support (0 = absent, 1 = present)	1.29***	0.38	3.40	(0.54, 2.03)	
	D_1 × Emotional support	1.42**	0.54	2.63	(0.35, 2.50)	
	D_2 × Emotional support	0.38	0.54	0.71	(−0.68, 1.45)	
Adoption intention	Constant	3.32***	0.77	4.29	(1.79, 4.85)	R^2=0.41
	PEC	−0.01	0.10	−0.05	(−0.21, 0.20)	$p < 0.001$
	TC	−0.17	0.23	−0.75	(−0.62, 0.28)	
	D_1	−0.03	0.42	−0.07	(−0.86, 0.81)	
	D_2	−0.93*	0.45	−2.09	(−1.81, −0.05)	
	Rapport	0.72***	0.09	8.02	(0.54, 0.90)	
	Emotional support (0 = absent, 1 = present)	−0.91*	0.44	−2.08	(−1.79, −0.04)	
	D_1 × Emotional support	0.61	0.62	0.97	(−0.62, 1.84)	
	D_2 × Emotional support	1.59*	0.61	2.60	(0.38, 2.79)	

Note: PEC = previous experience with a chatbot; TC = technological competency.
***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.

$p = 0.17$) and between moderate latency and long latency ($p = 0.19$). This provides partial support for H4.

4.5.3. Moderated mediation

We conducted moderated mediation analyses to test whether rapport can mediate the interaction effect between response latency and emotional support on adoption intention (H5). PROCESS model 8 (Hayes, 2013) was used in which response latency was the independent variable, emotional support was the moderating variable, rapport was the mediating variable, and adoption intention was the dependent variable, controlling for previous chatbot experiences and technological competency. As in Study 1, two dummy variables (D_1 and D_2) were created for the response latency variable. When running the analyses, 95% confidence intervals with 5000 bootstrap samples were used. Table 3 summarizes the results from moderated mediation analyses.

We first compared instant versus moderate latency when emotional support was absent (vs. present). While the path from response latency to adoption intention through rapport (indirect effect) was not significant under the emotional support absent condition (95% CI: [−0.67, 0.18]), the indirect effect was significant under the emotional support present condition (95% CI: [0.15, 1.45]). The index of moderated mediation (i.e., the difference between two conditional indirect effects) was 1.03 (95% CI: [0.27, 1.83]), suggesting that emotional support increased rapport when response latency was moderate (vs. instant), which subsequently increased adoption intention. Next, we compared instant latency and long latency under different emotional support conditions. The path from response latency to adoption intention through rapport was not significant when emotional support was either absent (95% CI: [−0.70, 0.24]) or present (95% CI: [−0.60, 0.69]). The moderated mediation index was not significant (95% CI: [−0.54, 1.07]). Together, this supports H5.

The above results suggest the importance of appropriate use of emotional support and response latency within a service recovery context. While customers generally appreciate instant responses from a chatbot, instant latency combined with emotional support can backfire because customers would not feel the sincerity and genuineness of such a response. Customers would prefer to wait a few seconds for a response characterized by care and compassion, fostering the development of rapport with a chatbot agent—a key factor in achieving interaction satisfaction.

5. General discussion

This research examines how chatbot response latency influences customer evaluations by exploring how two human-like social cues–typing indicators and emotional support–interact with response delays to either buffer or amplify their effects. Across two experimental studies, we demonstrate the context-dependent role of these cues in shaping customer satisfaction and adoption intention. Study 1 reveals that in routine, information-provision scenarios, customers generally prefer immediate chatbot responses; however, incorporating a typing indicator, a subtle yet effective social cue, mitigates dissatisfaction associated with longer response latencies by enhancing perceived social presence. Study 2 extends these findings by focusing on service recovery contexts, showing that instant responses paired with emotional support may unintentionally appear insincere. Instead, a moderate delay combined with emotional support signals empathy and thoughtfulness, thereby fostering chatbot-customer rapport and enhancing customers' intentions to adopt chatbot services. Taken together, the two studies offer a more comprehensive understanding of how users interpret chatbot latency across distinct service contexts. Both studies highlight that response latency is neither inherently positive nor negative; instead, its impact is influenced by the presence of human-like social cues that shape how users interpret the delay. Ultimately, this research underscores the nuanced interplay between response latency and human-like design elements, highlighting the importance of aligning timing and social cues to the specific conversational context.

5.1. Theoretical contributions

This research makes several theoretical contributions. First, by differentiating response latencies into instant, moderate, and long durations, it offers a nuanced understanding of how response times affect user evaluations of chatbots. Previous research on static response latency effects has been inconsistent, showing both positive and negative outcomes (Holtgraves et al., 2007; Moon, 1999). This study provides empirical evidence on whether and under what circumstances customers value different response latencies, by introducing key moderating factors: typing indicators and emotional support. By examining two distinct scenarios (information provision and service failure) this study shows that the effects of response latency are context-dependent, shaped by users' expectations, interaction goals, and the availability of human-like social cues.

Second, this research extends the anthropomorphism literature by empirically examining how human-like cues embedded in chatbot interactions influence customer evaluations. Anthropomorphism is the tendency to assign human characteristics such as physical appearance, behaviors, and ways of communicating to non-human entities (Epley et al., 2007, 2008). Specifically, our study explores two distinct forms of anthropomorphic design: (1) typing indicators, which visually mimic human typing behavior, and (2) emotional support messages, which convey human-like empathy and care. Prior research highlights the positive impact of anthropomorphic features on customer trust, engagement, and satisfaction by making digital agents appear more relatable and socially competent (Blut et al., 2021; Konya-Baumbach et al., 2023). In line with this, our findings demonstrate that subtle anthropomorphic cues–specifically typing indicators and emotional support language–can positively shape users' evaluations of chatbots, particularly when aligned with the interaction context. By strategically aligning these cues with response latency, chatbot designers can either mitigate or intensify users' reactions to delays in communication. By showing how these cues influence user evaluations under different latency conditions, our research deepens the understanding of chatbot anthropomorphism in dynamic interactions.

Furthermore, our findings contribute to the emerging concept of *anthropotheism*–users' attribution of not only human traits but also human-like intentionality, emotional depth, and moral awareness to artificial agents (Coeckelbergh, 2010; Waytz et al., 2014). In emotionally sensitive contexts such as service recovery, chatbots that express emotional support and exhibit moderate response latency may be perceived not merely as human-like, but as socially and morally attuned agents. In such cases, emotional support cues may trigger interpretations of care and empathy, leading users to assess chatbot responses through a human moral lens, thereby assigning intentionality or even moral agency to the chatbot (Banks, 2019; Nass & Moon, 2000; Waytz et al., 2014). These interpretations reflect a shift from surface-level anthropomorphism toward *anthropotheism*, where digital agents are evaluated through human relational, emotional, and ethical frameworks.

Third, the study contributes to Social Information Procession (SIP) theory (Walther, 1992), which posits that individuals form impressions and relational meaning in computer-mediated environments by adapting to the limited social cues available. Our research extends SIP theory by demonstrating how both visual (typing indicators) and verbal (emotional support) cues compensate for the lack of nonverbal information in chatbot interactions. Specifically, the findings show that users interpret these cues as signals of presence and effort, which enhance social presence (Study 1) and rapport (Study 2), depending on the communication context. This highlights that the same underlying cognitive mechanism–adaptive cue processing–can manifest in different forms depending on interaction goals and task context. This advances SIP by identifying distinct psychological mechanisms that mediate customer responses in chatbot interactions.

Fourth, the research advances Expectancy Violations Theory (EVT) (Burgoon & Hale, 1988) to human–computer interaction, examining how response latency and social cues jointly shape customer expectations and interpretations of chatbot interactions. In both studies, longer delays were initially perceived as negative expectancy violations. However, the presence of human-like cues reframed these violations, making them appear intentional, thoughtful, or emotionally responsive, rather than inattentive (Burgoon & Hale, 1988; Rheu et al., 2024), which is consistent with positive expectancy violations in EVT. Importantly, we contribute to EVT by showing that the interpretation of violations depends not just on the deviation from expectations, but on the presence of compensatory cues that alter the perceived intent behind the deviation. This also aligns with Maister's (1984) psychology of waiting, suggesting that perception of wait time is shaped by accompanying signals of attention and care.

Fifth, the study introduces emotional support as a key relational component in chatbot design, especially during service failures. It enhances understanding of how verbal emotional support can mitigate the negative effects of delayed responses. This finding aligns with research in human communication showing that emotional support reduces stress and enhances service evaluations (Bagozzi et al., 1999; Duhachek, 2005; Meng & Dai, 2021; Menon & Dubé, 2007). Our findings suggest that in the absence of human presence, emotionally supportive chatbot responses can fulfill relational expectations, improving user experience even in challenging service contexts such as service failure.

Finally, the study incorporates the Goldilocks Principle into response latency dynamics, suggesting that moderate delays may be ideal in emotionally sensitive settings such as during service failures. This principle emphasizes an optimal balance, suggesting that non-extreme response delays align with natural conversational rhythms and improve customer evaluations. Accordingly, instant responses in service recovery may seem insincere, while long delays frustrate users. Moderation combined with social cues signals thoughtfulness and aligns with natural conversational expectations. This reinforces the idea that effective digital communication is not just about speed, but about the alignment between timing and perceived intention.

5.2. Practical implications

Findings from this research offer valuable practical and managerial insights for business providers seeking to optimize chatbot design and user experience. First, it is crucial for service providers and chatbot programmers to recognize that the ideal response latency is not "one-size-fits-all," but context-dependent. For simple information requests or straightforward commands, instant responses align well with customer expectations and enhance satisfaction. However, in service failure situations or emotionally sensitive exchanges, instant replies may be perceived as automated and insincere. Our findings suggest that deliberately embedding moderate delays in these contexts, especially when paired with emotional support, can convey thoughtfulness, empathy, and genuine care, thereby boosting customer evaluations and adoption intentions (Study 2).

Second, our research underscores the importance of integrating subtle, human-like cues into chatbot interactions. Beyond typing indicators and emotional support as the present research shows, other possible strategies include using interactive and relational cues like emojis and humor (Shams et al., 2024; Xie et al., 2024), mirroring human dialogues, and incorporating anthropomorphic elements such as human names or avatars to signal social presence. These features are especially helpful when delays are inevitable, as they help shape customers' interpretations of wait time and maintain engagement in communication. Aligning these elements with task type (e.g., immediate response with information-provision tasks and a moderate response with service recovery messages) can strengthen perceived conversational appropriateness.

Third and relatedly, our findings indicate practical opportunities to refine how human-like cues are implemented, especially in the detailed design of typing indicators and the content of emotional support that adds a human touch. Chatbot developers could diversify typing indicators by closely mimicking human typing patterns, such as varying typing speed or simulating natural pauses, to make typing indicators feel more realistic, enhancing the sense of "someone thinking" behind the message (Study 1). Similarly, incorporating insights from psychological theories (e.g., politeness theories, emotional contagion) could help make chatbot messages more emotionally resonant. This approach allows chatbots to genuinely console, reassure, and support customers during interactions, further strengthening customer-brand relationships.

Finally, while embedding human-like attributes in chatbots has become a widely accepted practice and is viewed positively in general (Huang et al., 2024; Schanke et al., 2021), our findings caution against over-humanization without thoughtful response latency design. For instance, a highly humanized chatbot featuring human names, images, and conversational language might perceive inauthentic if it consistently replies instantaneously, potentially undermining perceived sincerity. Conversely, a chatbot that appear overly mechanical (e.g., robotic name such as "bot," generic interface) may frustrate users if the response delays are excessively long. Service designers should therefore thoughtfully calibrate chatbot humanness alongside latency, ensuring alignment with customer expectations and context-specific needs.

5.3. Limitations and future research directions

While this study makes significant theoretical contributions and offers practical implications, several limitations suggest avenues for future research. First, the use of a scenario-based experiment with pre-recorded chatbot interactions, though beneficial for experimental control, which may not fully capture realism and complexity of real-time engagements. Future research could address this limitation by involving live interactions with chatbots to provide more accurate insights and enhance ecological validity.

Second, focusing exclusively on the hotel industry context may restrict the broader applicability of the results. Future research should investigate various industries such as medical services, legal consultancy, finance, and general retail. Different customer needs and urgency levels across sectors should be considered. For instance, urgent medical advice requires instant responses, while legal consultations may prioritize objective solutions over empathy. Exploring these variations will provide a more nuanced understanding of how response latency aligns with industry-specific demands and customer expectations.

Third, this study did not examine dynamic aspects of chatbot interactions, such as gender, names, and humor (Xie et al., 2024; Xu et al., 2023). Previous research indicates that chatbot gender can influence customer responses, with female chatbots more effective in calming angry customers during service failures (Liang et al., 2024). Future studies should investigate how these dynamic features interact with response time to optimize customer interactions and satisfaction.

Fourth, Studies 1 and 2 utilized different dependent variables–customer satisfaction in Study 1 and adoption intention in Study 2–to examine user responses. Although diversifying dependent variables can enhance the robustness of findings, this inconsistency may limit direct comparability across the two studies. Future research should consider consistent metrics across different studies or incorporate multiple outcome measures within each study to establish clearer connections between response latency and customer evaluation outcomes. For instance, simultaneously examining both attitudinal (e.g., satisfaction, trust) and behavioral (e.g., actual usage, recommendation intentions) responses can provide a more thorough understanding of how chatbot latency influences customer evaluations.

Finally, although this study categorized response latency into three distinct levels (instant, moderate, and long), these definitions were set somewhat arbitrarily. Perceptions of "moderate" or "long" response delays may vary among individuals. For example, a 10-s delay might be perceived as moderate by some customers but excessively long by others. Therefore, future studies could empirically determine precise thresholds for different latency levels, examining how varying durations of response delays influence customer perceptions and evaluations.

6. Conclusion

To summarize, this research reveals that chatbot response latency significantly influences customer evaluations, with human-like cues (typing indicators and emotional support) playing critical moderating roles. Typing indicators mitigate negative reactions to delayed responses by enhancing social presence in information-focused interactions. In service recovery situations, moderate response delays combined with emotional support signal empathy and authenticity, fostering rapport and greater chatbot adoption.

Note

1. The Goldilocks principle, derived from a children's story where the character Goldilocks favored porridge that was "just right" (neither too hot nor too cold), has found application in various fields such as economics, biology, psychology, and more.

Author contributions

CRediT: **Kaeun Kim**: Conceptualization, Data curation, Investigation, Methodology, Supervision, Writing – original draft, Writing – review & editing, Conceptualization, Data curation, Formal analysis, Methodology, Writing – original draft, Writing – review & editing; **Ghazal Shams**: Conceptualization, Writing – original draft, Writing – review & editing; **Kawon Kim**: Conceptualization, Data curation, Investigation, Methodology, Supervision, Writing – original draft, Writing – review & editing, Conceptualization, Data curation, Formal analysis, Methodology, Writing – original draft, Writing – review & editing.

Disclosure statement

The authors report there are no competing interests to declare.

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Appendix A. The script used for Study 1

Chatbot: Hello, welcome to ABC hotel. How can I help you today?

Customer: I want to book a room at your hotel.

Chatbot: Sure, I would be happy to assist you. When are you looking to checkin?

Customer: December 2

Chatbot: How long are you planning to stay?

Customer: 2 nights

Customer: Oh no, I meant 3 nights

Chatbot: Sure, we have a standard room available for 3 nights, from December 2 to December 5 for $199 per night.

Customer: That works. Is there a place to park?

Chatbot: Yes, we do have a parking garage next to our hotel which is free of charge for our guest.

Customer: Great. Can I reserve a non-smoking room for that dates?

Chatbot: Of course. I can secure a non-smoking room on those dates for you.

Customer: Please reserve the room for me.

Chatbot: Your reservation has been successfully confirmed. Please click the button below to proceed your transaction. We look forward to welcoming you and your guests on December 2nd.

Appendix B. The script used for Study 2

Emotional support presence condition

Chatbot: Hello, welcome to ABC hotel booking. How can I help you today?

Customer: I reserved a room at your booking site. However, when I checked my email confirmation, the amount charged to the credit card was almost double what the room was displayed as on your website! There were substantial "cleaning deposit" charges that were never clearly shown when I was checking out on your website!!

Chatbot: I feel really sorry that it happened to you. I sincerely apologize for the miscommunication during your reservation process.

Customer: I feel being cheated and taken advantage of. There was nothing during my check out process that clearly noted this additional massive cost!!!

Chatbot: I totally understand how you feel about what happened. I'm here to listen to and take care of you. I will try my best to assist you with your situation. What would be the best way to make you feel better?

Customer: I would like to cancel this reservation.

Chatbot: Not a problem. I am going to cancel your reservation without any cost on your end. Can I get your confirmation number?

Customer: Confirmation # 11111111111.

Chatbot: Your reservation has been successfully canceled. Again, I deeply apologize for your inconvenience. I just want you to know that you are a valuable customer that I care. Should you have any further problems, please let me know. I will always be available to listen to you and help you.

Emotional support absence condition

Chatbot: Hello, welcome to ABC hotel booking. How can I help you today?

Customer: I reserved a room at your booking site. However, when I checked my email confirmation, the amount charged to the credit card was almost double what the room was displayed as on your website! There were substantial "cleaning deposit" charges that were never clearly shown when I was checking out on your website!

Chatbot: Ok. Sorry for the miscommunication.

Customer: I feel cheated and taken advantage of. There was nothing during my check out process that clearly noted this additional massive cost!!!!

Chatbot: Let's see what I can do. How do you want me to handle this situation?

Customer: I would like to cancel this reservation.

Chatbot: Ok. I will cancel your reservation. Can I get your confirmation number?

Customer: Confirmation # 11111111111.

Chatbot: Your reservation has been canceled. Let me know if you have any further problems.