Bots with Feelings: Should AI Agents Express Positive Emotion in Customer Service?

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Abstract

Customer service employees are generally advised to express positive emotion in their interactions with customers. The rise and maturity of artificial intelligence (AI) powered conversational agents, also known as chatbots, beg the question: should AI agents be equipped with the ability to express positive emotion in customer service? This research explores how, when, and why an AI agent's expression of positive emotion affects customers' service evaluations. We argue that AI-expressed positive emotion can influence customers via dual pathways: an affective pathway of emotional contagion and a cognitive pathway of expectation-disconfirmation. We propose that positive emotion expressed by an AI agent (vs. a human employee) is less effective in facilitating service evaluations because of a heightened level of expectation-disconfirmation. We further introduce customers' relationship norm orientation as a novel individual difference variable that affects their expectations toward the AI agent and moderates the cognitive pathway of expectation-disconfirmation. Results from three laboratory experiments substantiate our claims. By revealing a distinctive impact of positive emotion expressed by an AI agent compared with a human employee, these findings deepen our understanding of customers' reactions to emotional AIs and offer valuable insights for the deployment of AIs in customer service.

Keywords: emotional artificial intelligence, conversation agent, chatbot, customer service, emotional contagion, expectation-disconfirmation, relationship norm orientation

**** Forthcoming at Information Systems Research ****

Introduction

With the surge of technological innovations such as machine learning and deep learning, artificial intelligence (AI) has become a major interest for researchers, practitioners, and the public. In 2020, 56% of businesses adopted AI in at least one function, and more than 50% of the AI use cases were related to service operations (McKinsey 2021). Because of the cost efficiency and growing capabilities of AI-powered conversational agents ('AI agents' for brevity) in the form of chatbots or voice-based AIs, they have been increasingly deployed in customer service to reduce the burden of human labor and often replace customer service employees (Larivière et al. 2017). Financial Digest (2017) predicted that AIs would handle 95% of customer service interactions by 2025. Recognizing the popularity and importance of using AIs in customer service, researchers have started exploring how to maximize the value of AI service agents through means such as controlling their identity disclosure or humanizing AIs through visual, auditory, and communication cues (Lucas et al. 2014; Luo et al. 2019; Schanke et al. 2021; Yuan and Dennis 2019).

While prior research has examined several aspects of AI service agents and their impact on service outcomes (Araujo 2018; Luo et al. 2019; Schanke et al. 2021), less attention has been paid to the AI agents' expressed emotion. Emotional expression is regarded as one of the foundational attributes that define human nature (Haslam 2006). However, the recent debate about the emergence of a sentient AI gaining consciousness and feelings raises the possibility that AIs can also possess the primary attributes of human beings, such as the ability to perceive, think, and feel (Tiku 2022). The emerging emotional AIs, which can recognize, interpret, process, and simulate human emotions (Huang and Rust 2018, 2021), further underscore the need to investigate how people make sense of and react to the emotional capabilities of an AI. Indeed, the global affective computing market, which develops technologies for emotional AIs, is projected to reach $100 billion by 2024 and $200 billion by 2026 at a compounded annual growth rate of over 30% (Global Industry Analysts 2021; Reports and Data 2021). Such emotional AI technologies can be critical for the development and deployment of AI service agents because human employees' positive emotions are a key driver of customer service evaluations in firm-customer encounters (Kranzbühler et al. 2020). As AI service agents grow more popular, equipping them with the capability of expressing positive emotion (e.g., being cheerful and happy) is expected to benefit businesses and enhance customer experience.

However, equipping AI service agents with this ability should be planned and rolled out cautiously because the positive effect of human-expressed positive emotion may not apply to an AI agent (Gray and Wegner 2012). Prior studies from HCI and psychology provided conflicting evidence for the effectiveness of AIs expressing emotion in non-business contexts (Creed et al. 2014; Stein and Ohler 2017). In the customer service setting, however, little research has examined the impact of AI-expressed emotion. We focus on AI service agents in the form of text-based chatbots increasingly deployed in customer service departments and explore the impact of their expressed positive emotion on service evaluations.

Our research question is the following: how, when, and why does an AI agent's expression of positive emotion influence customers' service evaluations? Our primary goal is to examine the unique impact of AI-expressed emotion that might be different from the impact of human-expressed emotion. Since human service employees typically display positive emotion during a service encounter, we also restrict our focus to positive emotion that is deemed appropriate as a first step toward achieving our primary goal. Drawing on emotional contagion and expectation-disconfirmation literature (Hatfield et al. 1993; Oliver 1977), we argue that positive emotion expressed by an AI agent can influence customers' service evaluations through dual pathways: one affective and the other cognitive. On the one hand, the affective pathway of emotional contagion that underlies the positive effect of human-expressed positive emotion, as repeatedly confirmed in the prior customer service literature (Pugh 2001; Tsai and Huang 2002), may also apply to an AI service agent. On the other hand, an emotion-expressing AI agent might violate a customer's expectation that it is not capable of feeling emotion (Gray et al. 2007; Haslam 2006). This negative, cognitive pathway may cancel out the positive, affective pathway of emotional contagion, resulting in a weakened effect of positive emotion on service evaluations. We further explore individual differences in people's norms toward their relationship with an agent—termed "relationship norm orientation"—that can be distinguished into communal-oriented and exchange-oriented relationship norms (Clark and Mils 1993). We propose that variations in these norms lead to different expectations toward an AI service agent and subsequently affect the potency of the negative pathway.

To test these hypotheses, we present three experimental studies in which participants engaged in a hypothetical customer service scenario and chatted with an agent to resolve a service-related issue. We find consistent evidence for our predictions. Our theoretical framework and findings provide three primary contributions to the literature on expressed emotion in customer service and human-AI interactions. First, this paper is among the first to investigate the role of emotion expressed by an AI service agent. Our findings extend the customer service literature by exploring the implications of expressed emotion when the service is provided by an AI rather than a human. Second, we illuminate the effect of expressed emotion on observers in human-AI interactions, which is a nascent area of research. Third, we unravel the dual pathways of expressed emotion's impact and reveal a boundary condition for the cognitive pathway, deepening our understanding of a critical but understudied phenomenon.

Theoretical Development and Hypotheses

Expressed Emotion in Customer Service

In traditional customer service settings where humans are service providers, the role of their displayed emotion has been an important area of scholarly inquiry (Pugh 2001; Rafaeli and Sutton 1990). The display of positive emotion by service employees is generally desirable as it enhances service outcomes (Kranzbühler et al. 2020). For example, displaying a smile to customers can lead to higher service evaluations in both face-to-face and online interactions because of emotional contagion (Barger and Grandey 2006; Pugh 2001; Tsai and Huang 2002; Verhagen et al. 2014). Emotional contagion refers to the process in which an individual's emotional state is transferred to an observer (Hatfield et al. 1993). The means through which emotional contagion occurs is not confined to nonverbal behaviors, such as facial, postural, or vocal expressions, and it also includes text-based computer-mediated communication (Goldenberg and Gross 2020). Thus, if a customer perceives positive emotion from a service agent, he or she can experience the same emotion and evaluate the service more positively as a result.

However, expressing positive emotion might not always be beneficial. For example, expressed emotion could backfire when it is perceived as inappropriate or inauthentic (Cheshin et al. 2018). Also, Li et al. (2018) investigated the effect of positive emotion expressed through emoticons during online service interactions and found that expressing positive emotion can enhance the perceptions of a service agent's warmth but not competence. These findings suggest a need to explore the consequences of expressing positive emotion when the service is provided by an AI agent.

AI-Expressed Emotion

While prior studies provided extensive evidence for the effect of emotion expressed by a human service agent, little research has examined the applicability of these findings when an AI provides the service. AIs have been rapidly replacing human service agents in the recent decade (Oracle 2016). Moreover, we are witnessing the development of emotional AIs that are increasingly able to recognize human emotions and simulate human's emotional responses (Somers 2019). Thus, it is crucial to understand how, when, and why the positive emotion expressed by an AI service agent can influence customers' service evaluations.

As the history of developing emotional AIs is short, research on the effect of AI-expressed emotion is nascent. The very few studies examining the effects of AIs' simulated emotions, mostly in non-business contexts, provided mixed evidence, partly because the contexts of the studies varied substantially. Machines displaying emotions were preferred over their neutral counterparts in certain contexts (Creed et al. 2014), but they also elicited people's negative feelings in other contexts (Kim et al. 2019; Stein and Ohler 2017). These mixed findings suggest that insights from earlier customer service studies based on humans expressing positive emotion may not apply to AIs equipped to mimic human emotions.

AI-Expressed Positive Emotion and Dual Pathways

First, we believe that the impact of a service agent's expressed positive emotion in service encounters depends on the agent's identity as a human or an AI. A possible reason is that emotion-related capabilities are deemed unique capabilities of humans, such as experiencing and expressing one's own emotions as well as sharing others' emotions (i.e., empathy) (Haslam 2006). Thus, customers should have different expectations about these capabilities from a human versus an AI agent. As explained in more depth later, an AI agent is less expected to express positive emotion than a human employee because machines are generally believed to lack consciousness or feelings (Gray et al. 2007; The Economist 2022). A violation of this expectation in the case of an AI agent should weaken the positive impact of expressed positive emotion revealed in prior literature studying human agents. Thus, we propose the following:

H1*: The positive effect of positive emotion expressed by an agent on service evaluations depends on the agent's identity, such that the effect is greater for a human agent than for an AI agent.*

Because the focus of our paper is positive emotion expressed by *AI agents*, we limit our attention in the rest of theory development to *AI*-expressed positive emotion and discuss how it influences service evaluations through dual, opposing processes: one affective and the other cognitive. First, one's expressed emotion can lead an observer to feel the same emotion through emotional contagion (Hatfield et al. 1993). Prior literature in customer service showed that the display of a human employee's positive emotion provokes the positive affect of a customer, thus enhancing service evaluations (Pugh 2001). In addition, the likelihood and extent of emotional contagion may depend on various factors, such as the expresser's characteristics, the expresser-perceiver relationship, and the perceiver's susceptibility to others' emotions (Doherty 1997; van der Schalk et al. 2011).

Emotional contagion might be weakened when the expresser is an AI rather than a human agent. However, we argue that the affective process of emotional contagion can still underlie the impact of AI-expressed positive emotion. After observing another person's emotional expression, one's affective states can be automatically and subconsciously evoked without involving any cognitive resources and often, even without being aware of the origin (Neumann and Strack 2000). Moreover, prior literature on computer-mediated communication suggested that textual cues suffice for eliciting emotional contagion because affective words prime an observer with the emotion conveyed in those words (Cheshin et al. 2011; Hancock et al. 2008). This finding also implies that emotional contagion may occur through IT artifacts in digital environments that lack human presence, such as on social media (Ferrara and Yang 2015; Kramer et al. 2014).

In our context, if an AI service agent expresses positive emotion during a service interaction, the textual cues of positive emotion can prime a customer with the same emotion, thus automatically triggering positive emotion of the customer before they form any cognitive judgment towards the agent's identity. The triggered positive emotion will then serve as information for judging the service encounter. According to affect-as-information theory, one's affective states provide information about an event he or she is involved in (Schwarz and Clore 1983). Specifically, affective valence can be attributed to the value judgment of an event, such that positive (negative) emotion leads to a perception that the event is pleasant (unpleasant) (Clore et al. 2001). Thus, a customer's positive emotion triggered by emotional contagion will lead to a positive evaluation of a service encounter (Pugh 2001). Taken together, we propose that a customer's felt positive emotion can mediate the impact of AI-expressed positive emotion.

H2a (positive mediation through emotional contagion): *An AI agent's expressed positive emotion increases a customer's positive emotion, which in turn enhances service evaluations.*

In addition to the affective pathway of emotional contagion, we also propose a cognitive pathway such that AI-expressed positive emotion increases the magnitude of expectation-disconfirmation, which refers to the extent to which an individual's prior expectation does not align with the actual experience (Oliver 1977). Expectation-disconfirmation is known to influence various consumer behaviors, such as product or service evaluations, post-purchase behavior, and continuous use of information systems (Bhattacherjee 2001; Oliver 1993). During a service interaction, customers compare their expectations and the actual service experience when evaluating a service (Oliver 1993; Parasuraman et al. 1985). The impact of expectation is especially salient for interpersonal communication that involves emotion, as individuals have strong expectations toward others' emotional expressions (Burgoon 1993). Beyond interpersonal communication, an expectation has also been revealed to play an important role in the context of communication through technological artifacts (Jensen et al. 2013; Jin 2012; Kalman and Rafaeli 2011; Ramirez and Wang 2008). Overall, when the expectation is violated, especially if the observed behavior is inferior to the expected behavior (i.e., negative violation), the resulting disconfirmation and cognitive dissonance often lead people to develop negative attitudes or behaviors (Festinger 1957).

While several factors can determine the impact of expectation, one factor is a communicator's characteristics (Burgoon 1993), and we focus on the identity of a service agent as such a characteristic in our context. For an AI agent, customers should have prior expectations regarding its capability of feeling (and subsequently expressing) emotion, which should be different from that of a human agent. One of the core characteristics that define human nature and differentiate humans from machines is related to emotion, such as emotionality (i.e., experiencing or expressing one's own emotions) and emotional responsiveness (i.e., understanding or sharing others' emotions and responding accordingly) (Haslam 2006). Different from humans, machines are commonly believed to lack the mental capability of feeling various emotions (e.g., joy, fear, rage) (Gray et al. 2007; Gray and Wegner 2012), which is a necessary step before emotional display. Due to this fundamental difference in emotional capabilities between humans and machines, customers should have different expectations for the agent's emotional display, such that a human agent can and should express (supposedly positive) emotion, while an AI agent cannot. Thus, when an AI agent expresses emotion during an actual interaction, customers' expectations about its emotional expression should be disconfirmed.

While the violation of expectation can be either positive or negative, we argue that an emotion-expressing AI agent will result in a negative violation because emotionally capable machines can evoke a sense of threat to human uniqueness and lead to strong eeriness and aversion toward the machines (Stein and Ohler 2017). Such a negative violation of expectation will lead to lower service evaluations (Brady and Cronin 2001; Oliver 1993). Thus, expectation-disconfirmation can also mediate the impact of an AI agent's expressed positive emotion on service evaluations.

H2b (negative mediation through expectation-disconfirmation): *An AI agent's expressed positive emotion increases the extent of expectation-disconfirmation, which in turn reduces service evaluations.*

Accordingly, when an AI agent expresses positive emotion, the negative indirect effect through expectation-disconfirmation may cancel out the positive indirect effect through emotional contagion. The co-occurrence of these two opposing processes may explain the weaker effect of an AI agent's expressed positive emotion compared to a human agent's expressed positive emotion, as proposed in H1[1].

The Moderating Effect of Relationship Norm Orientation

While two opposing processes might underlie the impact of AI-expressed positive emotion, the pathway of expectation-disconfirmation may vary based on an individual's exact expectation. We suggest relationship norm orientation as an individual difference variable to capture the natural variation in customers' expectations. Relationship norm is used in social psychology to explain people's varying norms about two distinct types of relationships—exchange and communal—based on economic and social factors (Clark and Mils 1993). An exchange relationship is a quid pro quo relationship of exchanging a similar level of benefits. In communal relationships, however, such quid pro quo is not obligatory. Instead, benefits are given in response to a person's need or to demonstrate a general concern for another. Because this distinction is based on a rule or a norm about giving and receiving benefits, the two relationships generate different norms of behavior which, in turn, influence expectations toward another's behavior in an interpersonal relationship (Clark and Taraban 1991). Thus, the same behavior might lead to different interpersonal outcomes depending on the observer's relationship norm orientation.

Relationship norm orientation has been found to be influential beyond interpersonal relationships. For example, customers tend to form different expectations toward a brand depending on their relationship norm orientation, ultimately influencing their evaluations of the brand or its product (Aggarwal 2004; Liu and Gal 2011). These studies provide converging evidence that violating the relationship norm leads to a negative evaluation because of cognitive dissonance between expectations and actual observations. Similarly, customers' relationship norm orientation may influence how they interpret certain cues from a service agent during a service encounter (Scott et al. 2013), which in turn can alter the subsequent likelihood of expectation-disconfirmation.

[1] Note that the two proposed pathways may be interdependent due to the intertwining of affect and cognition (Izard 2011; Phelps 2006). While we acknowledge that the two processes can be mutually influential, we still treat the two pathways as distinct processes because a) such a model is more parsimonious and b) this treatment is consistent with similar theories such as the emotions as social information theory (Van Kleef 2009) and dual-process theories (Evans 2003; Petty and Cacioppo 1986).

In our context, customers can evaluate AI agents' expression of positive emotion differently depending on their relationship norm orientation. Customers with a communal relationship norm—communal-oriented customers—will expect a service agent to show a genuine concern and care like a friend or a family member (Scott et al. 2013). Because the expression of positive emotion insinuates such care and attention, it will confirm communal-oriented customers' expectations derived from their relationship norm, even if the source is an AI agent. Thus, the positive effect of AI-expressed positive emotion on expectation-disconfirmation will be weaker for communal-oriented customers.

In contrast, customers with an exchange relationship norm—exchange-oriented customers—will expect a service agent to be more transaction-focused, providing a professional and exact service (Scott et al. 2013). Because the expression of positive emotion does not satisfy such a transaction-focused norm, it will not confirm exchange-oriented customers' expectations derived from their relationship norm. As exchange-oriented customers are more likely to treat an AI agent as a machine (which is not supposed to have emotion) than a friend or family member, the positive effect of AI-expressed positive emotion on expectation-disconfirmation should be greater for them than for communal-oriented customers. Taken together, an AI agent's expression of positive emotion should enhance the service evaluations when the customers are communal-oriented (because of emotional contagion and weaker expectation-disconfirmation), but this effect should weaken or even reverse when the customers are exchange-oriented (because of emotional contagion and expectation-disconfirmation operating in opposite directions). We propose our last hypothesis below. Figure 1 depicts the complete research framework.

H3 (moderation by relationship norm orientation)*: For communal-oriented customers, an AI agent's expressed positive emotion has a positive effect on service evaluations, but for exchange-oriented customers, such an effect is non-existent or even reversed.*

To test these hypotheses, we conducted three laboratory experiments in which participants were asked to interact with a customer service agent in a hypothetical scenario. In the first study, we tested H1 by manipulating the agent's (human vs. AI) identity and the presence of positive emotional expression during the interaction. In Study 2, we focused only on the AI agent and explored the moderating role of participants' relationship norm orientations as proposed in H3. In the final study, we tested H3 as well as the underlying mechanisms as proposed in H2a and H2b.

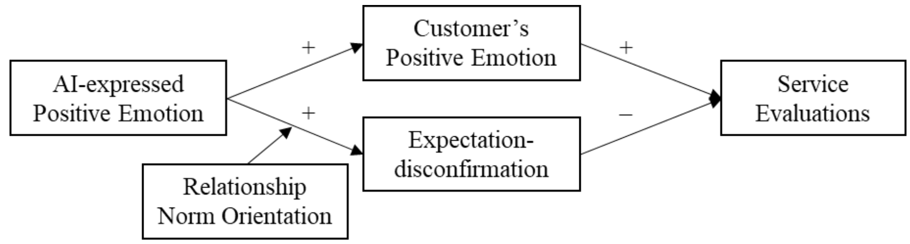

Figure 1. Research Framework

Pretest

Before the main experiments, we conducted a pretest to verify the effectiveness and validity of our key emotion manipulation in a customer service context. To achieve this goal, we varied an AI service agent's expressed positive emotion at multiple levels in a between-subjects design and kept all other aspects of the interaction identical across conditions. We focused only on the AI agent in this pretest because our primary interest is the effectiveness of AI agents expressing emotion. During the study, participants took part in a hypothetical customer service task and interacted with an AI agent via virtual chat to resolve a service-related issue. After the chat, participants evaluated the expressed emotion of the AI agent.

Stimulus Materials

To ensure that participants across conditions receive the same messages from the AI agent during the chat except for the level of expressed emotion, we used a predesigned script. The script included four messages from the agent, with two to four sentences within each message. The script was devised based on examples of best practices and canned responses for live chat from livechat.com, a popular platform that provides live chat software. Messages at the beginning (for greetings) and end of the chat followed the exact examples from the platform. The rest of the messages also followed the best practice examples from the platform but were slightly modified to fit our setting.

We manipulated expressed positive emotion at three levels by selecting one sentence from each message and varying the presence of emotional adjectives or exclamation marks in the sentence. We focused only on the positive emotion to avoid the possible confound of valence. For the low emotion condition, there were neither emotional adjectives nor exclamation marks throughout the interaction. For the intermediate emotion condition, following Yin et al. (2017), we added exclamation marks and emotional adjectives to every manipulated sentence. For the high emotion condition, we added both exclamation marks and emotional adjectives to every manipulated sentence. Furthermore, to strengthen participants' belief that they are interacting with an AI agent, we showed an introductory message of "being connected to a bot created by the customer service department" before the chat started. We also inserted a robot icon under the introductory message and next to each message from the agent. The three versions of the entire script can be found in Appendix A.

Procedure

One hundred and five subjects from Amazon Mechanical Turk (53 female) participated in the pretest. Participants were randomly assigned to one of the three conditions with different levels of expressed positive emotion. The cover story involved a hypothetical but realistic scenario that described a service-related issue. We chose the online retail industry as the setting because virtual chat is commonly deployed to communicate with customers, and this industry is at the forefront of rapidly replacing human agents with AI agents. For the service-related issue, we used one of the most common complaints in the online retail industry: a missing item from a delivery. The scenario described a recent delivery in which one of the items was missing. Participants were asked to chat with a service agent and request delivery of the missing item (see Appendix B for details). Then participants saw the introductory message that they were being connected to a customer service bot, and the chat started on a new screen.

When the chat started, the first message was displayed. Participants had to type in their response below the first message before moving on to the next screen and seeing the agent's next message. Participants were instructed to provide a response to the agent based on the cover story. Furthermore, on each screen, we provided a reminder of the facts from the cover story that pertained to the agent's question so that the chat would not go off topic, and the subsequent message from the agent would appear logical. On each screen, participants could also see the chat history up to that point. To further enhance the live chat experience, each of the agent's messages was presented with a slight delay.

To verify the effectiveness of our affect intensity manipulation (Jensen et al. 2013), we asked the participants to rate the intensity of the agent's expressed emotion after the chat concluded. Emotional intensity was measured using three items from Puntoni et al. (2008) (e.g., "very little emotion / a great deal of emotion"). We also asked participants to report the appropriateness of expressed emotion to ensure that they are similarly appropriate across conditions (Van Kleef and Côté 2007). Emotion appropriateness was measured using four items from Cheshin et al. (2018) (e.g., "The emotions the service agent expressed were appropriate."). All these questions were measured on a seven-point semantic differential scale. To identify outliers and ensure subject quality, we also asked participants to answer two attention check questions about the content of the service issue and the solution provided by the agent. All measurement items are listed in Appendix C.

Results

Out of 105 subjects, 84 subjects passed both attention check questions and were used in our analysis. We first conducted a manipulation check for the perceived intensity of the agent's expressed emotion. Analysis revealed that participants perceived the emotional intensity of the agent differently across the three conditions ($F(2, 81) = 17.324$, $p < .001$). According to a Tukey post-hoc test, the low emotion agent was perceived as less emotionally intense than the intermediate emotion agent ($M_{low} = 2.36$ vs. $M_{intermediate} = 4.01$, SDs = 1.43 and 1.53, $t(54) = 4.16$, $p < .001$) or high emotion agent ($M_{high} = 4.48$, $SD_{high} = 1.22$, $t(53) = 5.92$, $p < .001$). However, the intermediate emotion agent and the high emotion agent were not perceived differently in terms of emotional intensity ($p = .4$). Thus, our manipulations indeed varied emotional intensity successfully between low and higher levels but not between intermediate and high levels.

Next, we evaluated the appropriateness of expressed emotion to rule out this possible confound. Results revealed that subjects did not evaluate the appropriateness of emotion differently across conditions ($F(2, 81) = .878$, $p = .4$). The pairwise comparisons further confirmed that the participants did not perceive a difference in emotional appropriateness between low versus intermediate ($p = .4$), low versus high ($p = .6$), or intermediate versus high ($p = 1$) emotion conditions.

Discussion

This pretest manipulated the level of emotion expressed by a service agent and validated this key manipulation. Among the three levels, we picked the low and high levels for use in the main studies for two reasons. First, the perceived intensity of the agent's expressed emotion was the lowest in the low emotion condition and the highest in the high emotion condition, and this difference was significant. We did not choose the intermediate level of expressed emotion because we intended to strengthen the manipulation as much as possible. Second, we verified that perceived appropriateness did not differ across intensity levels. For simplicity, we will refer to the low and high levels as "emotion-absent" and "emotion-present," and the presence of positive emotion as "positive emotion" henceforth.

Study 1

In Study 1, we investigated whether the effect of expressed positive emotion depends on the service agent's identity, as suggested in H1. To do so, we varied both the presence of the expressed positive emotion and the agent's (human versus AI) identity in a between-subjects design.

Procedure and Measures

To manipulate the agent's identity, we varied the icons that appeared next to each of the agent's messages from the chat (see Figure 2). For those assigned to the human condition, the employee was either male or female (randomly determined) to reduce a possible gender effect. For manipulating the presence of emotion, we used the low and high emotional intensity scripts verified in the pretest (see Figure 3).

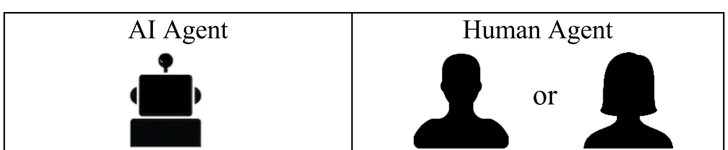

Figure 2. Agent Icons

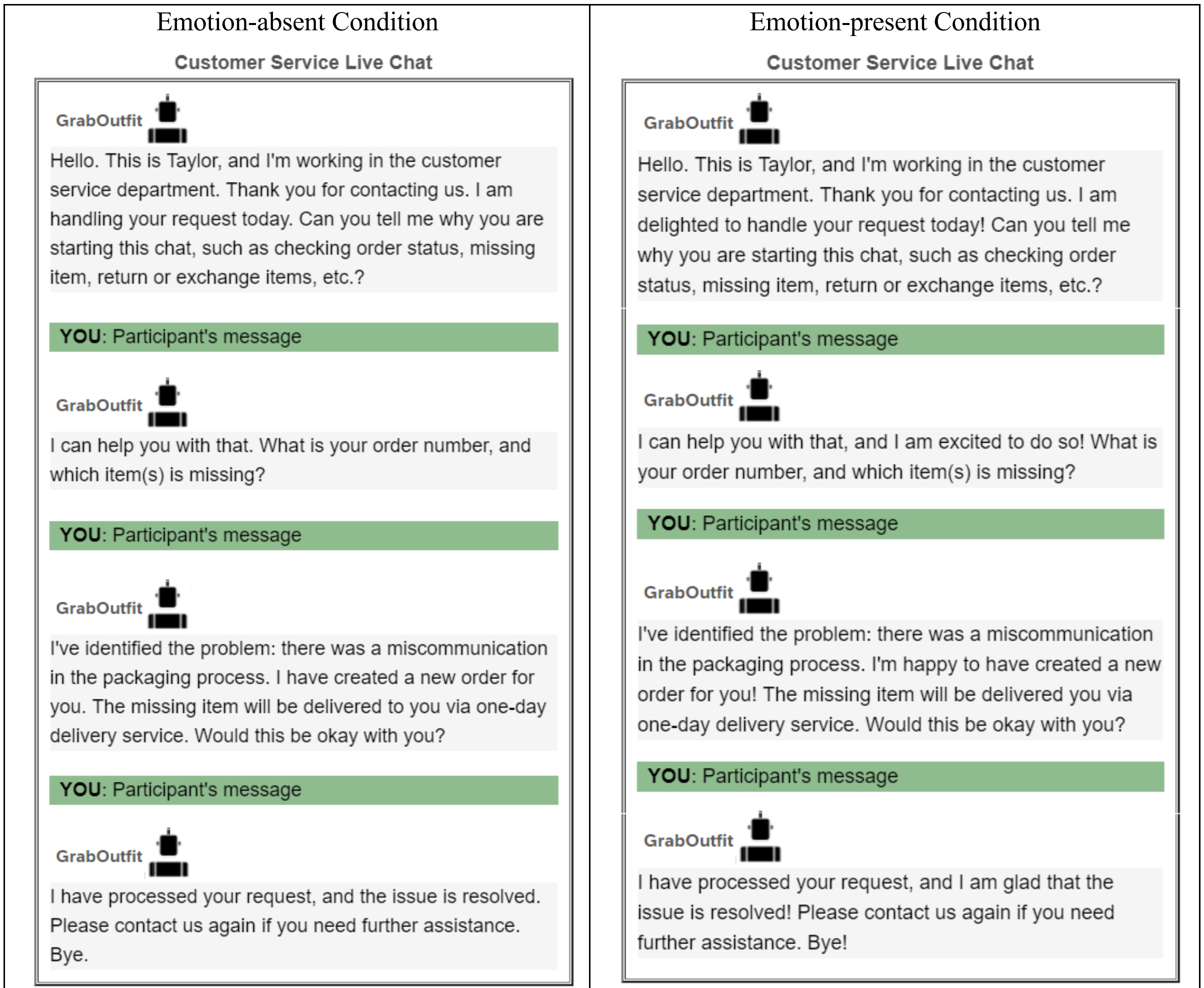

Figure 3. Chat Scripts (in AI conditions)

One hundred and fifty-eight undergraduate students (86 female) from a U.S. university participated in the study in exchange for course credit. Participants were randomly assigned to one of the four treatment conditions. The cover story and procedure were identical to that of the pretest, except that we asked the outcome variables right after participants finished their chat with the agent.

We focused on two important service evaluation outcomes: perceived service quality and satisfaction with the service. Perceived service quality is an overall evaluation of the service outcome and interaction, and it is associated with key organizational outcomes such as customer loyalty, market share, and purchase intention (Brady and Cronin 2001). Satisfaction with the service is another essential evaluation metric, as it is a key predictor of customers' intention to continue using the service (Oliva et al. 1992). Although the two have been revealed to jointly influence more downstream consequences (Cronin et al.

2000; Gotlieb et al. 1994), they are distinct constructs at the theoretical level (Anderson and Sullivan 1993; Cronin et al. 2000; Taylor and Baker 1994). To measure perceived service quality and satisfaction with the service, we adapted existing scales from the customer service literature (Cronin et al. 2000). Perceived service quality was measured using three items (e.g., "poor / excellent"). Satisfaction with the service was measured using three questions (e.g., "Overall, how satisfied or dissatisfied did your experience with the service agent leave you feeling?", "extremely dissatisfied / extremely satisfied").

After the measures for service evaluations, we asked two attention check questions as in the pretest, followed by the manipulation check questions. As a manipulation check for the presence of emotion, we used the same measure of emotional intensity from the pretest. As a manipulation check for the agent's identity, we measured the perceived human-likeness of the agent on a seven-point, semantic differential scale, using three items from MacDorman (2006) and Lankton et al. (2015) (e.g., "very mechanical / very humanlike"). All measurement items of this study and the later studies are listed in Appendix C.

Results

We used 155 subjects who passed attention checks. The analysis of the manipulation checks revealed that participants perceived the emotion-present agent as more emotionally intense than the emotion-absent agent ($M_{present} = 4.04$ vs. $M_{absent} = 2.52$, SDs = 1.35 and 1.47, $t(153) = 6.703$, $p < .001$). Also, participants perceived the human agent as more human-like than the AI agent ($M_{human} = 3.23$ vs. $M_{AI} = 2.68$, SDs = 1.79 and 1.27, $t(153) = 2.208$, $p = .029$). Therefore, both of our manipulations were deemed successful.

To test H1, we conducted a two-way ANCOVA with positive emotion and the agent's identity as between-subjects factors and gender as a covariate. We used gender as a covariate because of the prior literature indicating gender differences in emotion recognition and perception (Brody and Hall 2008; Fischer et al. 2018). Results revealed a main effect of positive emotion, such that overall, expressing positive emotion led to a more positive evaluation of service quality ($M_{absent} = 5.67$ vs. $M_{present} = 6.13$, SDs = 1.45 and 1.07, $F(1, 150) = 5.650$, $p = .019$) and greater satisfaction ($M_{absent} = 6.04$ vs. $M_{present} = 6.41$, SDs = 1.21 and .94, $F(1, 150) = 4.601$, $p = .034$). However, the main effect of agent identity was not observed (ps = .8), nor the main effect of gender (ps = .2 and .6).

Most importantly, agent identity significantly moderated the positive effect of positive emotion on perceived service quality ($F(1, 150) = 5.451$, $p = .021$) and on satisfaction ($F(1, 150) = 3.606$, $p = .059$). Pairwise comparisons showed that positive emotion from a human agent significantly increased perceived service quality ($M_{human\_absent} = 5.42$ vs. $M_{human\_present} = 6.37$, SDs = 1.25 and 1.29, $t(75) = 3.282$, $p = .001$) and satisfaction ($M_{human\_absent} = 5.86$ vs. $M_{human\_present} = 6.57$, SDs = 1.06 and 1.11, $t(75) = 2.871$, $p = .005$). In the case of an AI agent, however, the effects of positive emotion did not reach significance for service quality ($M_{AI\_absent} = 5.94$ vs. $M_{AI\_present} = 5.93$, SDs = 1.25, $t(76) = .035$, $p = 1$) or satisfaction ($M_{AI\_absent} =$ 6.27 vs. $M_{AI\_present} = 6.23$, SDs = 1.06, $t(76) = .167$, $p = .9$) (see Figure 4). These results confirmed H1.

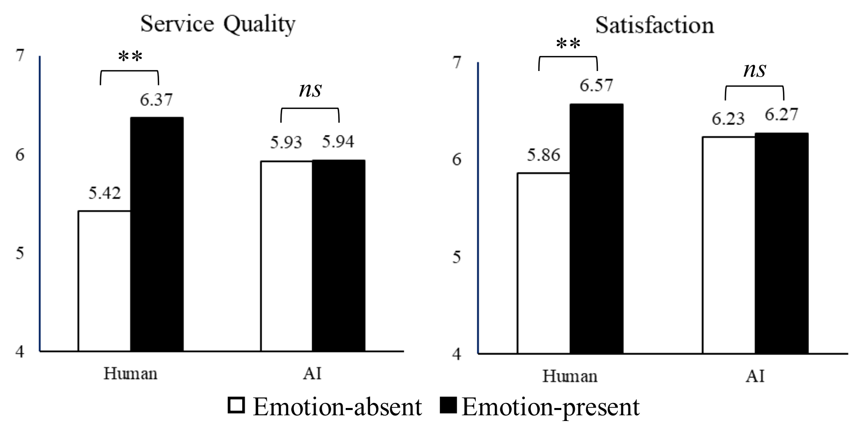

Figure 4. Interaction Effect of Positive Emotion and Agent Identity in Study 1
Note: *ns*, not significant; ** $p < .05$

Discussion

This study provides direct evidence that positive emotion expressed by a human agent can increase perceived service quality and satisfaction with the service, but such effects are absent when the emotion is expressed by an AI agent. As discussed before, prior literature on customer service has shown that positive emotional expressions by a human service agent positively influence customers' service evaluations (Kranzbühler et al. 2020). However, this study suggests that the positive impact of human's positive emotional displays is not directly applicable when AI agents replace human agents.

A reason for this lack of effect in the case of an AI agent might be that customers differ in perceived norms regarding their relationships with the AI agent and thus have different expectations toward the AI agent's expressed emotion. Such different expectations may lead to different reactions, as we proposed in H3. Thus, we focused only on AI agents in the next study and tested this hypothesis.

Study 2

The goal of Study 2 was to investigate whether the effect of AI-expressed positive emotion is dependent on customers' individual differences in their relationship norm orientation as proposed in H3. Because we shifted our focus to only the AI agent, we varied the presence of positive emotion as a single between-subjects factor and measured participants' relationship norm orientation.

Stimulus Materials, Procedure, and Measures

We changed our predesigned script by switching to a different service-related issue and extending the length of the conversation. We asked participants to request an exchange for a textbook they had already ordered, as this scenario is more relevant to student subjects. We also added one more message to the conversation to enhance participant engagement. This additional message, which was inserted after the greetings message, asked why a participant wanted an exchange. Manipulation of emotional intensity was also implemented in this additional message and all other messages as in the first study.

Ninety-two undergraduate students (49 female) from a U.S. university participated in this study in exchange for course credit. Participants were randomly assigned to either the emotion-absent or the emotion-present condition. The cover story and procedure were identical to those of Study 1. In addition to the measures used in Study 1, we added a new scale measuring participants' individual differences in relationship norm orientation. We used a seven-point, semantic differential scale with three items, describing the kind of relationship a participant would want with an online customer service agent (e.g., "strictly for business / bonded like family and friends") (Aggarwal 2004; Li et al. 2018).

Results

We used the responses from 88 subjects who passed both attention checks. Analysis of the manipulation check for emotional intensity revealed that participants perceived the emotion-present agent as more emotionally intense than the emotion-absent agent ($M_{present} = 4.22$ vs. $M_{absent} = 2.86$, *SD*s = 1.27 and 1.39, $t(86) = 4.791$, $p < .001$). Therefore, this manipulation was deemed successful.

To test the moderation effect proposed in H3, we conducted a one-way ANCOVA with positive emotion as a between-subjects factor, relationship norm orientation as a continuous moderator, and gender as a covariate. First, replicating the AI-related findings from Study 1, we did not find any significant main effect of positive emotion on perceived service quality (M_{absent} = 5.98 versus $M_{present}$ = 6.02, *SDs* = .93 and .94, $F(1, 83) = .667$, $p = .4$) or satisfaction (M_{absent} = 6.25 versus $M_{present}$ = 6.33, *SDs* = .96 and .73, $F(1, 83) = 1.836$, $p = .2$). Meanwhile, we observed a significant effect of gender on satisfaction, such that females tended to be more satisfied with the service than males ($F(1, 83) = 6.140$, $p = .015$), but not on service quality ($F(1, 83) = 1.426$, $p = .2$).

Most importantly, we discovered that relationship norm orientation significantly moderated the effect of positive emotion on perceived service quality ($F(1, 83) = 12.744$, $p = .001$) and on satisfaction ($F(1, 83) = 14.066$, $p < .001$). In order to probe the pattern of the interaction, we conducted a simple slope analysis and examined the marginal effect of positive emotion at one standard deviation above and below the mean of relationship norm orientation. For exchange-oriented individuals (relationship norm orientation = 1.10, -1 SD), AI-expressed positive emotion has a significant, negative effect on perceived service quality ($\beta = -.57$, $t(86) = -2.12$, $p = .037$) and satisfaction ($\beta = -.44$, $t(86) = -1.88$, $p = .06$). On the other hand, for communal-oriented individuals (relationship norm orientation = 3.95, +1 SD), AI-expressed positive emotion had a significant, positive effect on perceived service quality ($\beta = .89$, $t(86) = 3.04$, $p = .003$) and satisfaction ($\beta = .89$, $t(86) = 3.52$, $p < .001$). Figure 5 illustrates the simple slope analyses. Taken together, these results indicate that the effect of positive emotion from an AI agent on service evaluations depends on an individual's relationship norm orientation, thus confirming H3.

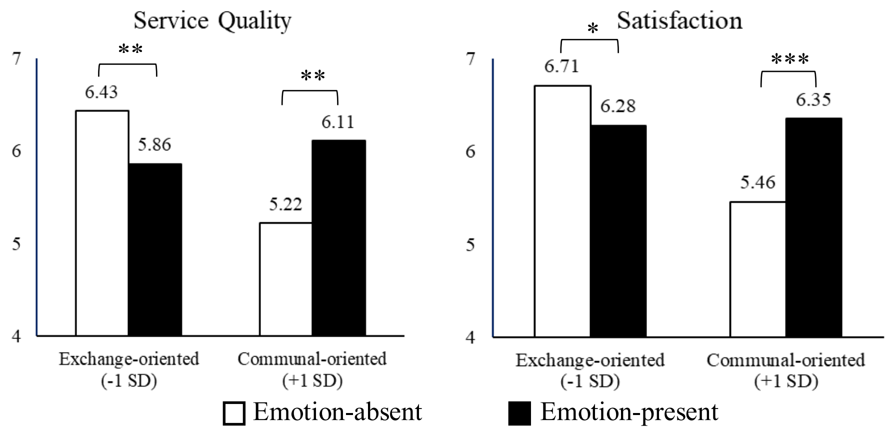

Figure 5. Moderating Effect of Relationship Norm Orientation in Study 2
Note: * $p < .1$; ** $p < .05$; *** $p < .001$

Discussion

Study 2 extends our previous findings by revealing the moderating role of a theoretically relevant individual difference variable, relationship norm orientation. Individuals with a communal-oriented norm evaluated an AI agent's service more positively when the agent expressed positive emotion than when it did not. Conversely, individuals with an exchange-oriented norm evaluated an AI agent's service more negatively when the agent expressed positive emotion than when it did not. Despite the revelation of the moderating role of relationship norm orientation in this study, we have not explored the underlying mechanisms, which we turn to in the final study.

Study 3

In Study 3, we delved into the mechanisms proposed in H2a and H2b. Similar to Study 2, we focused only on AI agents and manipulated the presence of positive emotion as a single between-subjects factor. To test the proposed mechanisms, we added new measures for the subject's felt positive emotion and the extent of expectation-disconfirmation to capture the opposing pathways.

Procedure and Measures

One hundred and eighty-six undergraduate students (93 female) from a U.S. university participated in this study in exchange for course credit. Similar to Study 2, participants were randomly assigned to either the emotion-absent or emotion-present condition. We used the predesigned script from Study 1 to vary the presence of positive emotion. The cover story and procedure were similar to those of prior studies. After the service interaction, participants reported service evaluations, followed by attention checks, mechanism measures, manipulation checks, and individual difference measures of relationship norm orientation.

To measure the mechanisms, we asked participants' felt positive emotions to quantify emotional contagion because measuring one's emotion right after an emotion-invoking stimulus can capture affective transfer (Hasford et al. 2015). We used five items from Pham (1998) to measure participants' felt emotions (e.g., "sad / joyful"). We also measured the extent to which participants confirmed their expectations toward the service agent, using three items from Bhattacherjee (2001). We modified the original items to tailor to our need to capture the specific expectations about the level of emotion expressed by the service agent (e.g., "The level of the chatbot's emotional display was exactly what I expected"). In data analysis, we reversed these items' scores to represent expectation-disconfirmation.

Results

One hundred and seventy-seven subjects passed the attention checks and thus were used in the following analyses. We first analyzed the perceived emotional intensity of the service agent as a manipulation check. We found that participants perceived the emotion-present agent as more emotionally intense than the emotion-absent agent (M_{absent} = 3.11 vs. $M_{present}$ = 5.19, *SD*s = 1.25 and 1.22, $t(175)$ = 11.194, $p < .001$), indicating that our manipulation of the presence of positive emotions was successful.

Next, we conducted a one-way ANCOVA to replicate prior findings, with positive emotion included as a between-subjects factor, relationship norm orientation as a continuous moderator, and gender as a covariate. Results revealed that AI-expressed positive emotion did not significantly influence perceived service quality (M_{absent} = 6.13 vs. $M_{present}$ = 6.26, *SD*s = 1.02 and .82, $F(1, 172) = .726$, $p = .4$) or satisfaction with the service (M_{absent} = 6.33 vs. $M_{present}$ = 6.44, *SD*s = .93 and .75, $F(1, 172) = .404$, $p = .5$). We did not find any significant effect of gender on service evaluations (*p*s = .4 and .9). These results replicated the lack of effect of AI-expressed positive emotion in the earlier studies.

We also discovered a significant moderation by relationship norm orientation for the effect of positive emotion on perceived service quality ($F(1, 172) = 3.738$, $p = .055$) and on satisfaction ($F(1, 172) = 6.683$, $p = .011$). Simple slope analysis showed that, for communal-oriented individuals (relationship norm orientation = 4.54, 1 SD above the mean), AI-expressed positive emotion significantly increased perceived service quality (β = .41, $t(172) = 1.99$, $p = .049$) and satisfaction (β = .43, $t(172) = 2.30$, $p = .023$). However, for exchange-oriented individuals (relationship norm orientation = 1.67, 1 SD below the mean), positive emotion did not have any effect on perceived service quality (β = -.16, $t(172) = -.76$, $p = .45$) or on satisfaction (β = -.26, $t(172) = -1.37$, $p = .17$). Figure 6 illustrates the simple slope analyses. These results, once again, confirmed H3.

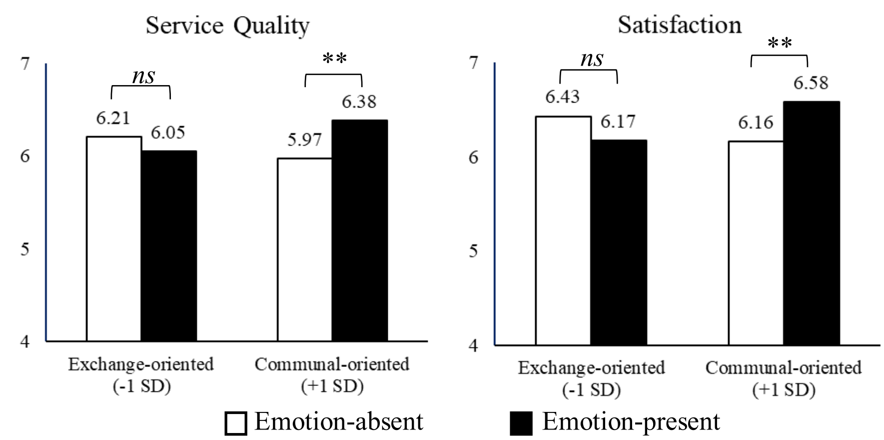

Figure 6. Moderating Effect of Relationship Norm Orientation in Study 3
Note: *ns*, not significant; ** $p < .05$

To determine if the effect of AI-expressed positive emotion on service evaluations is mediated by emotional contagion and expectation-disconfirmation, we used PROCESS Model 4 (parallel mediation model) with gender as a covariate and a bootstrapped sample of 5,000 (Hayes 2013). Results revealed the lack of total effects and direct effects of AI-expressed positive emotion on perceived service quality (ps = .3 and 1) and satisfaction (ps = .4 and .9). However, AI-expressed positive emotion increased customers' positive emotions (β = .26, $t(175) = 1.737$, $p = .084$), implying emotional contagion. An increase in felt positive emotion further led to greater perceived service quality (β = .62, $t(173) = 11.498$, $p < .001$) and greater satisfaction (β = .52, $t(173) = 10.362$, $p < .001$). The test of indirect effects revealed a marginally significant, positive indirect effect of AI-expressed positive emotion through participants' felt positive emotion on perceived service quality (β = .16, SE = .097, 90% CI = [.006, .332]) and on satisfaction (β = .14, *SE* = .082, 90% CI = [.007, .277]). These results provide suggestive evidence for the positive, affective pathway of emotional contagion as hypothesized in H2a.

On the other hand, positive emotion increased expectation-disconfirmation (β = .32, $t(175)$ = 1.859, p = .065), which further reduced perceived service quality (β = -.083, $t(173)$ = -1.759, p = .080) and satisfaction (β = -.13, $t(173)$ = -3.074, p = .003). The test of indirect effects confirmed a marginally significant, negative indirect effect of AI-expressed positive emotion through expectation-disconfirmation on satisfaction (β = -.043, *SE* = .033, 90% CI = [-.106, -.002]), but not on perceived service quality (β = -.026, *SE* = .023, 90% CI = [-.074, .001]). These results partially support the negative, cognitive pathway of expectation-disconfirmation proposed in H2b. Overall, our results suggest that the two opposing pathways may explain the lack of total effects of AI-expressed positive emotion on service evaluations.[2] Figure 7 shows the summary of the mediation model along with the results.[3]

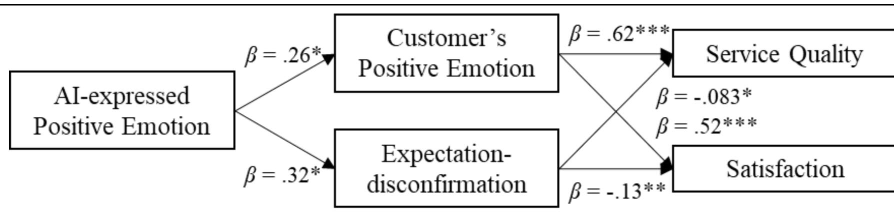

Figure 7. Mediation Analysis in Study 3
Note: * $p < .10$; ** $p < .05$; *** $p < .001$

Discussions

[2] We tested an additional model that accounts for the interdependencies of the two mediating processes. We believe that expectation-disconfirmation influencing a customer's felt positive emotion is more likely than vice versa. Expectation-disconfirmation is derived from a cognitive evaluation of comparing the expected and the actual experiences (Oliver 1980). This indicates that the process of expectation-disconfirmation is unlikely to be driven by emotion. On the other hand, expectation-disconfirmation can influence affective judgment (Oliver 1977), and thus may affect positive emotion. After adding a path from expectation-disconfirmation to felt positive emotion, we found this additional path to be significant. However, our findings regarding the parallel model still held. We also tested whether expectation-disconfirmation moderates the effect of AI-expressed positive emotion on felt positive emotion, but we did not find any evidence. These findings indicate the robustness of treating the two paths as dual processes and mitigate the concerns of their potential interdependencies.

[3] We also tested whether relationship norm orientation moderates the two pathways proposed in our hypotheses. We found a significant interaction between the presence of positive emotion and relationship norm orientation on expectation-disconfirmation ($F(1,173)$ = 8.823, p = .003), such that, for exchange-oriented individuals, the presence of positive emotion significantly increased the extent of expectation-disconfirmation (M_{absent} = 1.98 versus $M_{present}$ = 2.81, $F(1, 172)$ = 10.757, p = .001), whereas for communal-oriented individuals, such an effect was not observed (M_{absent} = 2.58 versus $M_{present}$ = 2.35, $F(1, 172)$ = .833, p = .4). These findings suggested a potential reason for the moderating role of relationship norm orientation revealed in Study 2 and Study 3. Meanwhile, we did not find any significant interaction effect on customer's positive emotion.

Study 3 unraveled how individuals might react to AI agent's expressed positive emotion affectively and cognitively, thus illuminating the potential reasons for the lack of effect of AI-expressed positive emotion on service evaluations. Although positive emotion expressed by an AI agent could be transferred to customers through emotional contagion, it violated the customers' expectations toward the agent (e.g., machines are not supposed to have emotions). Therefore, the positive affective pathway and negative cognitive pathway may have canceled out each other's effects.

However, our hypotheses regarding the indirect effects obtained only marginal statistical support, as the effects of AI-expressed positive emotion on the two mediators were marginally significant. First, the marginally significant indirect effect through expectation disconfirmation is not unexpected. The reason is that based on findings from Studies 2-3, the impact of positive emotion on expectation disconfirmation was revealed to depend on participants' relationship norm orientation. In addition, as revealed in footnote 2, the indirect effect through expectation-disconfirmation was present and significant for exchange-oriented individuals, but such an indirect effect was absent for communal-oriented individuals, exactly as we expected. Thus, the overall indirect effect through expectation disconfirmation is expected to be weak if we disregard this interaction in a pure-mediation model. Second, the marginal support for the indirect effect through emotional contagion may arise from different reasons, including the relatively subtle manipulation of expressed positive emotion, our focus on measuring the valence (but not other aspects) of felt emotion, and the presence of other mechanisms not captured in our dual-pathway model.

General Discussion

Extending the concept of expectation-disconfirmation (Oliver 1977), we propose that positive emotional expressions of AI service agents may not be as effective as those of human service employees in enhancing customers' service evaluations. Despite customers' increased positive feelings triggered by emotional contagion, there is also a risk of emotion-expressing AI service agents violating customers' expectations, thus weakening the positive effect of positive emotion. We further propose relationship norm orientation as a moderator because it might influence the likelihood of customers' expectation-disconfirmation as customers hold different norms regarding their relationship with service agents. Three experimental studies provided converging evidence for our predictions. Table 1 summarizes our findings.

Table 1. Summary of Findings

	Study 1	Study 2	Study 3
H1: *The positive effect of positive emotion expressed by an agent on service evaluations depends on the agent's identity, such that the effect is greater for a human agent than for an AI agent.*	Supported	-	-
H2a (positive mediation through emotional contagion): *An AI agent's expressed positive emotion increases a customer's positive emotion, which in turn enhances service evaluations.*	-	-	Supported
H2b (negative mediation through expectation-disconfirmation): *An AI agent's expressed positive emotion increases the extent of expectation-disconfirmation, which in turn reduces service evaluations.*	-	-	Partially supported
H3 (moderation by relationship norm orientation): *For communal-oriented customers, an AI agent's expressed positive emotion has a positive effect on service evaluations, but for exchange-oriented customers, such an effect is non-existent or even reversed.*	-	Supported	Supported

Note: "-" indicates that the hypothesis was not explored in that study.

Theoretical Implications

Prior investigations of the effect of emotional expressions by a customer service agent have focused entirely on human employees (Barger and Grandey 2006; Cheshin et al. 2018; Kranzbühler et al. 2020; Li et al. 2018). However, the rapid deployment of AIs for handling a service encounter calls for extending the study of emotions to AI service agents. Addressing this emerging phenomenon, we discover that the commonly observed positive effect of positive emotion from human service employees is not directly applicable to AI service agents. To the best of our knowledge, this paper is the first in the customer service literature to examine the role of emotion expressed by an AI service agent, illustrating the need to study the unique impacts of AI-expressed emotion in service encounters.

This research also contributes to the burgeoning human-AI interaction literature, in which the exploration of interactions between emotional AIs and humans has just started to emerge (Creed et al. 2014; Melo et al. 2013; Stein and Ohler 2017). Most of the research examining factors that influence the effectiveness of human-AI interactions focused on the transparency of an AI's decision-making process and an AI's behaviors that can enhance its social presence or conformity to the norms (Amershi et al. 2019; Velez et al. 2019). On the other hand, emotional AIs have been increasingly popular in automated chatbots or conversational agents, and their expressed emotions can potentially influence various business outcomes. However, the impact of AI-expressed emotion, especially in business domains, has not received much attention from scholars studying human-AI interactions. Our research underscores the importance of incorporating emotional factors in future investigations of human-AI interactions.

At a broader level, we supplement the emotion literature by delving into how, when, and why emotions from an AI, a new entity, are perceived by the observers. Emotion has been known to serve an important role in interpersonal relationships (Van Kleef et al. 2010). Prior research has extensively documented how various aspects of emotion influence interpersonal outcomes (Lazarus 2006; van Kleef and Côté 2022). As emotion is universally considered a unique capability of human beings, emotion scholars rarely acknowledged the possibility of AI agents or machines expressing emotions. However, the latest technological innovations have enabled AI agents to mimic a human's emotion-related capabilities, raising the need to study emotions in human-AI relationships. Our study addresses this need by discovering the distinct role of emotion expressed by human vs. non-human agents. Thus, this research opens up exciting opportunities for further studies to explore the impact of emotion in novel contexts.

Also, our finding that emotional expressions from an AI agent may trigger emotional contagion extends this well-documented phenomenon beyond interpersonal relationships. Although prior literature suggested various boundary conditions of emotional contagion related to the characteristics of the expresser, the perceiver, and their relationship (Doherty 1997; van der Schalk et al. 2011), we confirm the existence of emotional contagion even when the expresser is an AI agent. This finding also contributes to the information systems literature on emotional contagion by supplementing prior findings on how emotional contagion may occur through IT artifacts that lack human presence, such as on social media and via instant messaging (Cheshin et al. 2011; Ferrara and Yang 2015; Goldenberg and Gross 2020).

Finally, this paper unravels the underlying mechanisms and a boundary condition for the unique impact of AI-expressed positive emotion in customer service. Our findings of expectation-disconfirmation as an underlying pathway contribute to the emotion literature by highlighting the role of expectations in the social impact of emotions when the expresser is not a human. Prior literature has shown that various norms or display rules exist regarding emotional expressions (Ekman et al. 1969; Heise and Calhan 1995). Such norms are also present when communicating with others, and others' emotions are one of the key expectations that significantly impact interpersonal outcomes (Burgoon 1993). Our work extends these prior findings by providing empirical evidence for the mediating role of expectation-disconfirmation in human-AI interactions and suggesting relationship norm orientation as a novel boundary condition.

Practical Implications

This work provides valuable guidance for practitioners who are interested in deploying emotional AIs in customer service. The argument of an AI becoming sentient has evoked a contentious debate not only about whether the argument is true, but also about the benefits and costs of deploying AIs (The Economist 2022). AI service agents can save costs—both economic costs and emotional labor of human employees—and streamline firm-customer interactions. However, one of the primary goals of customer service is to maximize customers' service evaluations through their experience and interaction with a service agent. Our findings suggest that the positive effect of expressing positive emotion on service evaluations may not materialize when the source of the emotion is not a human. Practitioners should be cautious about the unique impact of equipping AI agents with emotion-expressing capabilities.

In addition, our findings indicate that an AI agent expressing positive emotion is beneficial when customers expect a communal relationship, but such a beneficial effect may not exist or even backfire when they expect an exchange relationship from the interaction. Companies can design emotional AIs in such a way that they are context-aware and express positive emotion only when the expression effectively facilitates service outcomes. For example, they may benefit from switching on or off the emotion-expressing capabilities of AI agents based on the type of customers that could be determined through past communication histories. Alternatively, companies can selectively deploy emotion-expressing AIs based on the nature of their tasks because different tasks may activate different relationship norms. For instance, AIs dealing with personalized tasks (activating a communal-oriented relationship norm) might benefit by expressing positive emotion, whereas AIs dealing with more standardized tasks (activating an exchange-oriented norm) might not. Companies may also set up a more communal environment beforehand to nudge customers' expectations in such a way that can reduce their expectation disconfirmation when encountering emotional expressions of an AI agent.

Limitations and Future Research

Several opportunities present themselves for future research. First, our findings for the moderating role of relationship norm orientation can be extended to various avenues. For instance, researchers can examine how customers' norms toward their relationship with a brand (Aggarwal 2004) can influence the impact of AI-expressed emotion. A brand that oversees close interactions with customers and holds a communal relationship (e.g., in healthcare and education markets) may benefit from AI-expressed emotion. However, a brand with a pure exchange relationship (e.g., in finance markets) may not witness such a beneficial impact. In addition to relationship norm orientation, future research can also explore other factors that may vary the impact of AI-expressed emotion on customers' expectations and norms during a service interaction, such as price, culture, etc.

Second, our manipulation of emotional intensity is restricted to emotional phrases that are expressed normally or appropriately because companies are unlikely to configure AIs to express extremely intense emotion. Still, varying emotional intensity at a more granular level may yield interesting findings not uncovered in this research. Furthermore, emotional intensity can be manipulated through various vocal qualities (Murray and Arnott 1993). As voice-based AIs are another emerging trend in both personal lives (e.g., virtual assistants such as Apple's "Siri" and Amazon's "Alexa") and customer service interactions (during phone calls), future research can look into the impact of emotions expressed through the voice.

Third, our proposed theoretical model does not address the interdependencies of affective and cognitive processes. Due to the complex relationship between affect and cognition (Izard 2011; Phelps 2006), it is likely for our two proposed mechanisms to influence each other. Although this work provides suggestive evidence for our parallel model after accounting for possible interdependencies (see footnote 1), future research can attempt to disentangle affective and cognitive processing more clearly.

Fourth, in addition to relationship norm orientation, other boundary conditions for our proposed mechanisms are worthy of further exploration. Because the likelihood and extent of the emotional contagion process in human relationships depend on the expresser, the perceiver, and the relationship between the two, it is also possible that boundary conditions exist for emotional contagion between an AI and a human. For instance, emotional contagion may be stronger for those individuals who have more experience with AI agents or feel more attached to AIs. Furthermore, the expectation-disconfirmation process may depend on when and how expectations are formed. Whereas our studies disclosed the AI agent's identity before the interaction, a disclosure during or after the interaction may lead to different expectations toward the agent, which can, in turn, influence the extent of expectation-disconfirmation and customers' reactions to the agent's emotional expression.

Lastly, emotion is a complex concept that comprises various aspects, such as other dimensions (e.g., valence) and discrete emotions. The ability of an AI to express emotion has just started to emerge, and further research into other aspects of emotional expressions can provide additional insights into the best ways of deploying emotionally intelligent AIs. For example, AI agents may empathize with customers' concerns by expressing sadness or responding to customers' anger in an apologetic manner. Delving into other emotions can help draw a comprehensive picture of the unique impact of AI-expressed emotions. The emotion used in our work is also fixed to be appropriate because we primarily investigate the unique impact of emotion expressed by an AI rather than a human. AIs may be prone to errors or express irrelevant emotions, so exploring the consequences of inappropriate emotional expressions can have significant implications. Our work opens up exciting opportunities for future research to look into the role of emotion in this nascent but essential area.

Conclusion

Considering the recent trend in the rapid deployment of AIs across various industries and the growing capabilities of emotional AIs, this research points to the importance of studying the unique impact of AI-expressed emotion. Our paper provides experimental evidence that the emotional expressions of an AI service agent have a distinct impact on customers' evaluations of service outcomes compared to those of a human agent. We also reveal a novel individual-difference variable, relationship norm orientation, further enriching our theoretical framework. We believe this work represents an initial step into a nascent yet critical area of human-AI interactions. We anticipate future research to further expand our understanding of the role of an AI's emotional expressions in diverse contexts.

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Appendix A: Chat Scripts Used in Pretest

I. Low emotion

Customer Service Live Chat

GrabOutfit

Hello. This is Taylor, and I'm working in the customer service department. Thank you for contacting us. I am handling your request today. Can you tell me why you are starting this chat, such as checking order status, missing item, return or exchange items, etc.?

YOU: Participant's message

GrabOutfit

I can help you with that. What is your order number, and which item(s) is missing?

YOU: Participant's message

GrabOutfit

I've identified the problem: there was a miscommunication in the packaging process. I have created a new order for you. The missing item will be delivered to you via one-day delivery service. Would this be okay with you?

YOU: Participant's message

GrabOutfit

I have processed your request, and the issue is resolved. Please contact us again if you need further assistance. Bye.

II. Intermediate emotion

Customer Service Live Chat

GrabOutfit

Hello. This is Taylor, and I'm working in the customer service department. Thank you for contacting us. I am delighted to handle your request today! Can you tell me why you are starting this chat, such as checking order status, missing item, return or exchange items, etc.?

YOU: Participant's message

GrabOutfit

I can help you with that! What is your order number, and which item(s) is missing?

YOU: Participant's message

GrabOutfit

I've identified the problem: there was a miscommunication in the packaging process. I have created a new order for you! The missing item will be delivered you via one-day delivery service. Would this be okay with you?

YOU: Participant's message

GrabOutfit

I have processed your request, and I am glad that the issue is resolved! Please contact us again if you need further assistance. Bye!

III. High emotion

Customer Service Live Chat

GrabOutfit

Hello. This is Taylor, and I'm working in the customer service department. Thank you for contacting us. I am delighted to handle your request today! Can you tell me why you are starting this chat, such as checking order status, missing item, return or exchange items, etc.?

YOU: Participant's message

GrabOutfit

I can help you with that, and I am excited to do so! What is your order number, and which item(s) is missing?

YOU: Participant's message

GrabOutfit

I've identified the problem: there was a miscommunication in the packaging process. I'm happy to have created a new order for you! The missing item will be delivered you via one-day delivery service. Would this be okay with you?

YOU: Participant's message

GrabOutfit

I have processed your request, and I am glad that the issue is resolved! Please contact us again if you need further assistance. Bye!

Appendix B: Cover Stories Used in the Experiments

Pretest, Study 1, and Study 3

Internet has changed how customers contact a company for questions related to the company's products. Thanks to Internet, customers can simply use their electronic devices to communicate with a customer service agent. The most popular form of such communications is an online live chat. Through a live chat with a customer service agent, customers can inquire about product and shipping issues, and the customer service agent may help address those issues.

In particular, online live chat is widely used in the retail industry. Your task in this study is to resolve an issue about a recent order by communicating with a service agent via a live chat.

---------------------- Page break ----------------------

Imagine the following:

Two weeks ago, you ordered a pair of jeans, a navy sweater, and a baseball cap through an online apparel store that you have used often. Your order number was 6322, and your order was delivered three days ago. However, you found that although the jeans and the sweater were delivered, the baseball cap was missing. When you checked your bill, you saw that you already paid for everything, including the baseball cap. You would like to get the baseball cap delivered as soon as possible.

--------------------- Page break ---------------------

So you decided to contact their customer service department. You open the store's website and notice a chat window (named "Contact Us via Live Chat") at the bottom right of the webpage. You decide to try this method to get in contact with a customer service agent.

On the following screens, you will chat with a customer service agent from the apparel store.

- In each screen, you will see a message from the agent and then type your response. Your responses should be based on the scenario that you read just now. <u>Please make sure you read all the available information on the page before you type your response.</u>
- As you communicate with the agent, please treat it as if it is actually happening. Simply read and respond to the agent as you would normally do.

Study 2

Internet has changed how customers contact a company for questions related to the company's products. Thanks to Internet, customers can simply use their electronic devices to communicate with a customer service agent. The most popular form of such communications is an online live chat. Through a live chat with a customer service agent, customers can inquire about product and shipping issues, and the customer service agent may help address those issues.

In particular, online live chat is widely used in the retail industry. Your task in this study is to resolve an issue about a recent order by communicating with a service agent via a live chat.

--------------------- Page break ---------------------

Imagine the following:

You are enrolled in a class that requires a textbook. The professor has required you to buy the latest edition (3rd edition) of the book. However, when you visit your usual online secondhand bookstore, you notice that there is a 2nd edition, which is $50 cheaper than the 3rd edition. So you decide to buy the 2nd edition instead. You have your order number, G2029.

However, during the first week of class, you realize that the 2nd edition does not have some of the materials from the 3rd edition, which are needed for your first quiz. You decide to contact the bookstore to see if you can exchange for the 3rd edition (by paying $50 more) with a free shipping or get a refund (in case the 3rd edition is not in stock). In either case, you would also want to find out whether you can get a free shipping label to send your 2nd edition back.

--------------------- Page break ---------------------

You open the bookstore's website and notice a chat window (named "Contact Us via Live Chat") at the bottom right of the webpage. You decide to try this method to get in contact with a customer service agent.

On the following screens, you will chat with a customer service agent from the bookstore.

- In each screen, you will see a message from the agent and then type your response. Your responses should be based on the scenario that you read just now. Please make sure you read all the available information on the page before you type your response.
- As you communicate with the agent, please treat it as if it is actually happening. Simply read and respond to the agent as you would normally do.

Appendix C: Variables Measured in the Experiments

Service Quality (7-point scale): (Cronin et al. 2000)
Please rate the service provided by the customer service agent in each of the following items below.
- Poor / excellent
- Inferior / superior
- Low standards / high standards

Satisfaction (7-point scale): (Cronin et al. 2000)
- Overall, how satisfied or dissatisfied did your experience with the customer service agent leave you feeling? (extremely dissatisfied / extremely satisfied)
- How well did this service experience with the customer service agent meet your needs? (extremely poor / extremely well)
- To what extent do you agree or disagree that overall, you are satisfied with the experience of interacting with the customer service agent? (strongly disagree / strongly agree)

Human-likeness (7-point scale): (Lankton et al. 2015; MacDorman 2006)
Using the following scale, how would you evaluate the customer service agent?
- Very humanlike / very mechanical
- Has many more human qualities / has many more techno qualities
- Very person-like / very machine-like

Emotional intensity (7-point scale): (Puntoni et al. 2008)
In your opinion, how much emotion was expressed by the customer service agent during your conversation?
- Very little emotion / a great deal of emotion
- Very few feelings / a lot of feelings
- Expressed very few sentiments / expressed many sentiments

Relationship norm orientation (7-point scale): (Aggarwal 2004; Li et al. 2018)
If you were to interact with an online customer service agent in general, you would want the relationship with the customer service agent to be...
- Strictly for business / bonded like family and friends
- Formal and professional / informal and friendly
- Purely transactional / based on friendship

Participants' felt emotion (7-point scale): (Pham 1998)
Please indicate how you felt right after your interaction with the service chatbot.
- Depressed / cheerful
- Sad / joyful
- Annoyed / pleased
- Unhappy / happy

- In a bad mood / in a good mood

Expectation-confirmation (7-point scale; reversed in the analyses to measure expectation-disconfirmation): (Bhattacherjee 2001)
Below are statements dealing with your perception of the chatbot you've just interacted with. Please indicate to what extent you agree or disagree with each statement.

- The level of the chatbot's expressed emotion is how you would expect most chatbots to behave.
- The level of the chatbot's emotional display was exactly what I expected.
- Overall, most of my expectations regarding the level of the chatbot's expressed emotion were confirmed.