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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 during 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 during customer service interactions? 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 (versus a human employee) is less effective in facilitating service evaluations because of a heightened level of expectation–disconfirmation. We further introduce a novel individual difference variable, customers' relationship norm orientation, which affects their expectations toward the AI agent and moderates the cognitive pathway. 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 they offer valuable insights for the deployment of AIs in customer service.

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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 AI use cases were related to service operations (McKinsey 2021). In particular, AI-enabled conversational agents ("AI agents" for brevity) can take the form of chatbots or voice-based AIs, and they communicate virtually with customers (Glikson and Woolley 2020). Because of their cost efficiency and growing capabilities, AI agents are increasingly deployed in customer service to reduce the burden of human labor and sometimes replace human employees (Larivière et al. 2017). Financial Digest (2017) predicts that AIs will 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 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, Yuan and Dennis 2019, Schanke et al. 2021).

Although prior research examines several aspects of AI agents and their impact on service outcomes (e.g., Araujo 2018, Luo et al. 2019, Schanke et al. 2021), less attention is paid to the AI agents' expressed emotion. Emotional expression is widely regarded as one of the foundational attributes that define human nature (Haslam 2006). However, the recent debate about the emergence of a sentient AI (i.e., a chatbot from Google 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 emergence of emotional AIs, which can recognize, interpret, process, and simulate human emotions (Huang and Rust 2018, 2021), further underscores 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 more than 30% (Global Industry Analysts 2021, Reports and Data 2021). Such emotional AI technologies are critical for developing and deploying 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 human–computer interaction and psychology provide conflicting evidence for the effectiveness of AIs expressing emotion in nonbusiness contexts (Creed et al. 2014, Stein and Ohler 2017), but little research examines the impact of AI-expressed emotion in the customer service setting. In this work, we focus on AI agents in the form of text-based chatbots that are increasingly deployed in customer service 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. Because human employees typically display positive emotion during a service encounter, we also restrict our focus to positive emotion as a first step toward achieving our primary goal. Drawing on emotional contagion and expectation–disconfirmation literature (Oliver 1977, Hatfield et al. 1993), 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 agent. On the other hand, an emotion-expressing AI agent might violate a customer's expectation that it is not capable of feeling emotion (Haslam 2006, Gray et al. 2007). This negative, cognitive pathway may cancel out the positive, affective pathway of emotional contagion, resulting in an overall weakened effect of AI-expressed 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 vary between communal- and exchange-oriented relationship norms (Clark and Mils 1993). We propose that differences in these norms lead to different expectations toward an AI 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 in which humans are service providers, the role of their displayed emotion is an important area of scholarly inquiry (Rafaeli and Sutton 1990, Pugh 2001). 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 (Pugh 2001, Tsai and Huang 2002, Barger and Grandey 2006, Verhagen et al. 2014). Emotional contagion refers to the process by 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, the customer 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 can backfire when it is perceived as inappropriate or inauthentic (Cheshin et al. 2018). In addition, expressing positive emotion through emoticons during online service interactions can enhance the perceptions of a human agent's warmth but not competence (Li et al. 2018). 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

Although prior studies provide extensive evidence for the effect of emotion expressed by a human service agent, little research examines the applicability of these findings when an AI provides the service. AIs are 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 emotional responses (Somers 2019). Thus, it is crucial to understand how, when, and why the positive emotion expressed by an AI 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. Yam et al. (2021) explore how a customer's perception of an AI agent influences service outcomes. However, this study focuses on an AI agent that is perceived to have the ability to feel rather than the agent's actual expression of emotion. A few studies examine the effects of AIs' expression of emotions mostly in nonbusiness contexts, but they provide mixed evidence partly because the contexts vary substantially. Machines displaying emotions are preferred over their neutral counterparts in certain contexts (Creed et al. 2014), but they also elicit people's negative feelings in other contexts (Stein and Ohler 2017, Kim et al. 2019). These mixed findings suggest that insights from earlier customer service studies based on humans expressing positive emotions may not apply to AIs equipped to mimic human emotions.

AI-Expressed Positive Emotion and Dual Pathways

First, we believe that the impact of an 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.

Hypothesis 1. *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 shows that the display of a human employee's positive emotion evokes 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 perceiver's susceptibility to others' emotions, and the expresser–perceiver relationship (Doherty 1997, Van der Schalk et al. 2011).

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

In our context, if an AI 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 the customer forms any cognitive judgment toward the agent's identity.[1] The triggered positive emotion then serves as information for judging the service encounter. According to the affect-as-information theory, one's affective states provide information about an event in which one is involved (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 leads 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.

Hypothesis 2a (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 this affective pathway, 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 (Oliver 1993, Bhattacherjee 2001). During a service interaction, customers compare their expectations and the actual service experience when evaluating a service (Parasuraman et al. 1985, Oliver 1993). 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 is also revealed to play an important role in the context of communication through technological artifacts (Ramirez and Wang 2008, Kalman and Rafaeli 2011, Jin 2012, Jensen et al. 2013). For example, it plays an important role during people's interactions with conversational AIs (Grimes et al. 2021). 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).

Expectation can be shaped by a communicator's characteristics (Burgoon 1993), and we focus on the identity of a service agent in our context. Customers have prior expectations of an AI agent regarding its capability of feeling (and subsequently expressing) emotion, which should be different from their expectations of a human agent. One of the core characteristics that define human nature and differentiate humans from machines is 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). Unlike humans, machines are commonly believed to lack the mental capability of feeling emotions (e.g., joy, fear, rage) (Gray et al. 2007, Gray and Wegner 2012), which is a necessary step before emotional display. Because of 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, whereas an AI agent cannot. Thus, when an AI agent expresses emotion during an interaction, customers' expectations about its emotional expression should be disconfirmed.

Whereas the violation of expectation can be either positive or negative, we argue that the emotional expression of an AI agent results 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 leads to lower service evaluations (Oliver 1993, Brady and Cronin 2001). Thus, expectation–disconfirmation can also mediate the impact of an AI agent's expressed positive emotion on service evaluations.

Hypothesis 2b (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 with a human agent's expressed positive emotion as proposed in Hypothesis 1.[2]

The Moderating Effect of Relationship Norm Orientation

As one of the two opposing processes that 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 that captures the natural variation in customers' expectations. Relationship norm describes people's norms toward relationships built upon economic and social factors, and they can vary between two distinct types: exchange and communal relationships (Clark and Mils 1993). An exchange relationship is a quid pro quo relationship of exchanging a similar level of benefits. In a communal relationship, 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 is found to be influential beyond interpersonal relationships. For example, customers with different relationship norm orientations tend to form different expectations toward a brand, ultimately influencing their evaluations of the brand or its product (Aggarwal 2004, Liu and Gal 2011). These studies provide 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.

In our context, customers can evaluate an AI agent's expression of positive emotion differently depending on their relationship norm orientation. Customers with a communal relationship norm—communal-oriented customers—expect a service agent to show a genuine concern and care like a friend or family member (Scott et al. 2013). Because the expression of positive emotion insinuates such care and attention, it confirms 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 should be weaker for communal-oriented customers.

In contrast, customers with an exchange relationship norm—exchange-oriented customers—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 does 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 final hypothesis as follows. Figure 1 depicts the complete research framework.

Hypothesis 3 (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 nonexistent 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 test Hypothesis 1 by manipulating the agent's identity (human versus AI) and the presence of positive emotional expression during the interaction. In Study 2, we focus only on the AI agent and explore the moderating role of participants' relationship norm orientations as proposed in Hypothesis 3. In the final study, we test Hypothesis 3 as well as the underlying mechanisms proposed in Hypotheses 2a and 2b.

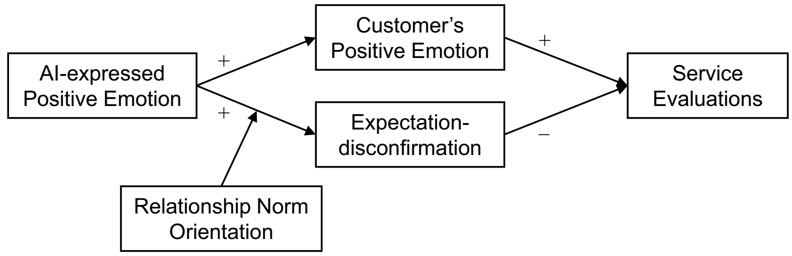
Pretest

Before the main experiments, we conducted a pretest to verify the effectiveness and validity of our key emotion manipulation in the customer service context. To achieve this goal, we varied an AI 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 emotions. 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 from livechat.com, a popular platform that provides live chat software. Messages at the beginning (for greetings) and end of

Figure 1. Research Framework



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 of the agent's messages 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/or 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 Online Appendix A.

Procedure

One hundred 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 retailers often deploy virtual chat 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 Online 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 agent's first message was displayed. Participants had to type in their response below the message before moving on to the next screen and seeing the next message from the agent. 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 about the agent's question to ensure that the chat would not go off topic and that the agent's subsequent message would appear logical. 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 emotional 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 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 Online Appendix C.

Results

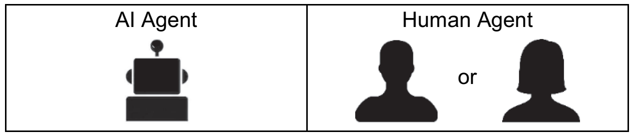
Out of 105 subjects, 84 subjects passed both attention-check questions and were used in our analyses. We first conducted a manipulation check for the perceived intensity of the agent's expressed emotion. Analysis revealed that participants perceived the agent's emotional intensity differently across the three conditions ($F(2, 81) = 17.324$, $p < 0.001$). According to a Tukey post hoc test, the low-emotion agent was perceived as less emotionally intense than the intermediate-emotion agent ($M_{low} = 2.36$ versus $M_{intermediate} = 4.01$, SDs = 1.43 and 1.53, $t(54) = 4.16$, $p < 0.001$) or the high-emotion agent ($M_{high} = 4.48$, $SD_{high} = 1.22$, $t(53) = 5.92$, $p < 0.001$), but the difference between the latter two did not reach significance ($p = 0.4$). Thus, our manipulation 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 ($F(2, 81) = 0.878$, $p = 0.4$). The pairwise comparisons further confirmed that the participants did not perceive a difference in emotional appropriateness between low- versus intermediate- ($p = 0.4$), low- versus high- ($p = 0.6$), 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

Figure 2. Agent Icons



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 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 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 Hypothesis 1. To do so, we varied both positive emotion and the agent's 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. To manipulate positive emotion, we used the low and high emotional intensity scripts verified in the pretest (see Table 1).

One hundred 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 those 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 and a key predictor of customers' intention to continue using the service (Oliva et al. 1992). Although the two are revealed to jointly influence more downstream consequences (Gotlieb et al. 1994, Cronin et al. 2000), they are distinct theoretical constructs (Anderson and Sullivan 1993, Taylor and Baker 1994, Cronin et al. 2000). We adapted existing scales from the customer service literature to measure them (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").

Table 1. Chat Scripts

Emotion-absent	Emotion-present
Hello. This is Taylor, and I am a bot created by 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.?	Hello. This is Taylor, and I am a bot created by 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.?
Participant's message	*Participant's message*
I can help you with that. What is your order number, and which item(s) is missing?	I can help you with that, and I am excited to do so! What is your order number, and which item(s) is missing?
Participant's message	*Participant's message*
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?	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 to you via one-day delivery service. Would this be okay with you?
Participant's message	*Participant's message*
I have processed your request, and the issue is resolved. Please contact us again if you need further assistance. Bye.	I have processed your request, and I am glad that the issue is resolved! Please contact us again if you need further assistance. Bye!

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 positive 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 humanlikeness 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 Online Appendix C.

Results

We used 155 subjects who passed both attention checks in data analyses. Results for the manipulation check of emotional intensity revealed that participants perceived the emotion-absent agent as less emotionally intense than the emotion-present agent (M_{absent} = 2.52 versus $M_{present}$ = 4.04, *SD*s = 1.47 and 1.35, $t(153) = 6.703$, $p < 0.001$). In addition, results for the agent's identity revealed that participants perceived the human agent as more humanlike than the AI agent (M_{human} = 3.23 versus M_{AI} = 2.68, *SD*s = 1.79 and 1.27, $t(153) = -2.208$, $p = 0.029$). Therefore, both of our manipulations were successful.

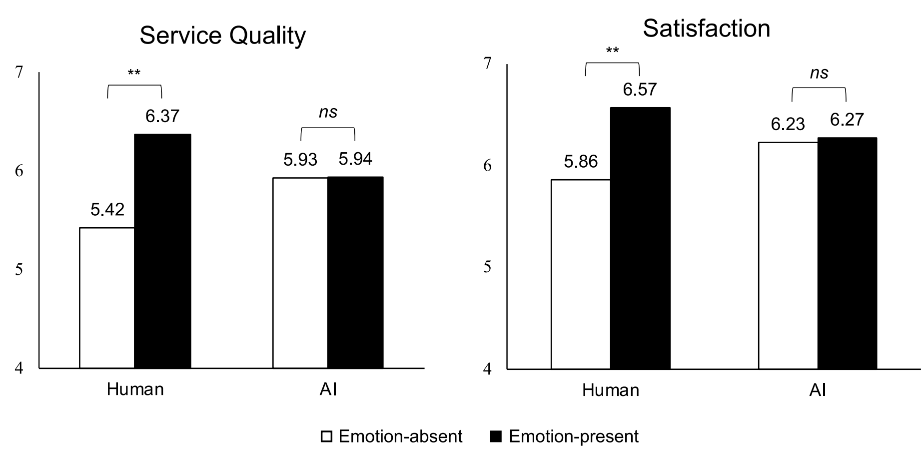
To test Hypothesis 1, we conducted a two-way analysis of covariance (ANCOVA) with positive emotion and the agent's identity as between-subjects factors and gender as a covariate. We used gender as a covariate because of the prior literature indicating gender differences in emotion recognition and perception (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 versus $M_{present}$ = 6.13, *SD*s = 1.45 and 1.07, $F(1, 150) = 5.650$, $p = 0.019$) and greater satisfaction (M_{absent} = 6.04 versus $M_{present}$ = 6.41, *SD*s = 1.21 and 0.94, $F(1, 150) = 4.601$, $p = 0.034$). However, the main effect of agent identity was not observed (*ps* = 0.8), nor was the main effect of gender (*ps* = 0.2 and 0.6).

Most importantly, agent identity significantly moderated the positive effect of positive emotion on perceived service quality ($F(1, 150) = 5.451$, $p = 0.021$) and satisfaction ($F(1, 150) = 3.606$, $p = 0.059$). Pairwise comparisons showed that positive emotion from a human agent significantly increased perceived service quality (M_{human_absent} = 5.42 versus $M_{human\_present}$ = 6.37, *SD*s = 1.25 and 1.29, $t(75) = 3.282$, $p = 0.001$) and satisfaction (M_{human_absent} = 5.86 versus $M_{human\_present}$ = 6.57, *SD*s = 1.06 and 1.11, $t(75) = 2.871$, $p = 0.005$). In the case of an AI agent, however, the effects of positive emotion did not reach significance for service quality (M_{AI_absent} = 5.93 versus $M_{AI\_present}$ = 5.94, *SD*s = 1.25, $t(76) = 0.035$, $p = 1$) or satisfaction (M_{AI_absent} = 6.23 versus $M_{AI\_present}$ = 6.27, *SD*s = 1.06, $t(76) = 0.167$, $p = 0.9$) (see Figure 3). These results confirm Hypothesis 1.

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. Prior literature on customer service shows that positive emotional expressions by a human service agent enhance customers' service evaluations (Kranzbühler et al. 2020). However, this study suggests that the positive impact of human positive emotional displays is

Figure 3. Interaction Effect of Positive Emotion and Agent Identity in Study 1



Note. *ns*, not significant.
**$p < 0.05$.

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 propose in Hypothesis 3. Therefore, we focus only on AI agents in the next study and test 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 Hypothesis 3. Because we shifted our focus to only the AI agent, we varied 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 conversation's length. 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 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. We first analyzed the perceived emotional intensity of the AI agent as a manipulation check, finding that participants perceived the emotion-absent agent as less emotionally intense than the emotion-present agent (M_{absent} = 2.86 versus $M_{present}$ = 4.22, *SD*s = 1.39 and 1.27, $t(86) = 4.791$, $p < 0.001$). Therefore, this manipulation was successful.

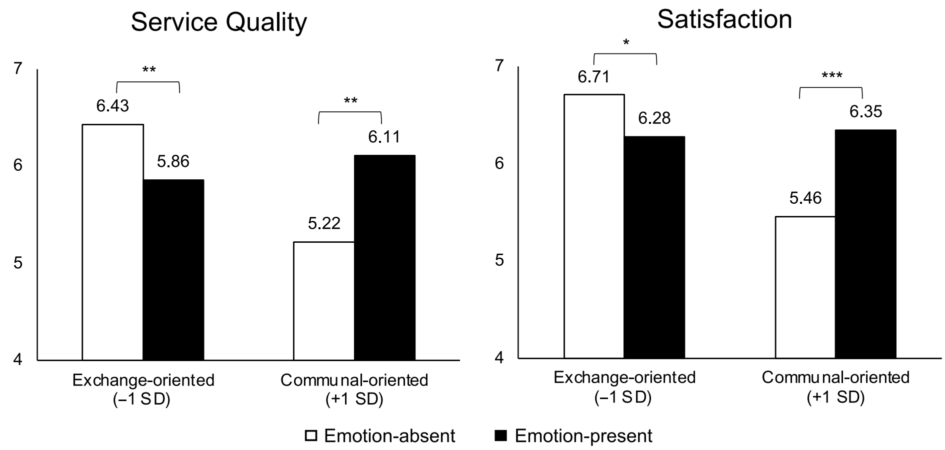
To test the moderation effect proposed in Hypothesis 3, we conducted a one-way ANCOVA with positive emotion as a between-subjects factor, relationship norm orientation as a continuous moderator, and gender as a covariate. First, replicating the AI-related findings from Study 1, we did not find any significant main effect of positive emotion on perceived service quality (M_{absent} = 5.98 versus $M_{present}$ = 6.02, *SD*s = 0.93 and 0.94, $F(1, 83) = 0.667$, $p = 0.4$) or satisfaction (M_{absent} = 6.25 versus $M_{present}$ = 6.33, *SD*s = 0.96 and 0.73, $F(1, 83) = 1.836$, $p = 0.2$). Meanwhile, gender had a significant effect on satisfaction such that females tended to be more satisfied with the service than males ($F(1, 83) = 6.140$, $p = 0.015$), but its effect on service quality did not reach significance ($F(1, 83) = 1.426$, $p = 0.2$).

Most importantly, we discovered that relationship norm orientation significantly moderated the effect of positive emotion on perceived service quality ($F(1, 83) = 12.744$, $p = 0.001$) and satisfaction ($F(1, 83) = 14.066$, $p < 0.001$). In order to probe the pattern of this 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* below the mean), AI-expressed positive emotion had a significant, negative effect on perceived service quality ($\beta = -0.57$, $t(86) = -2.12$, $p = 0.037$) and satisfaction ($\beta = -0.44$, $t(86) = -1.88$, $p = 0.06$). On the other hand, for communal-oriented individuals (relationship norm orientation = 3.95, 1 *SD* above the mean), AI-expressed positive emotion had a significant, positive effect on perceived service quality ($\beta = 0.89$, $t(86) = 3.04$, $p = 0.003$) and satisfaction ($\beta = 0.89$, $t(86) = 3.52$, $p < 0.001$). Figure 4 illustrates the simple slope analysis. Taken together, these results indicate that the effect of AI-expressed positive emotion on service evaluations depends on an individual's relationship norm orientation, thus confirming Hypothesis 3.

Discussion

Study 2 extends our previous findings by revealing the moderating role of relationship norm orientation, a theoretically relevant individual difference variable. 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 this interaction effect, we

Figure 4. Moderating Effect of Relationship Norm Orientation in Study 2



Note. *$p < 0.1$; **$p < 0.05$; ***$p < 0.001$.

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 Hypotheses 2a and 2b. Similar to Study 2, we focused only on AI agents and manipulated positive emotion as a single between-subjects factor. To test the proposed mechanisms, we added new measures for the subjects' felt positive emotion and the extent of expectation–disconfirmation to capture the opposing pathways.

Procedure and Measures

One hundred 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 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 because we needed 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.

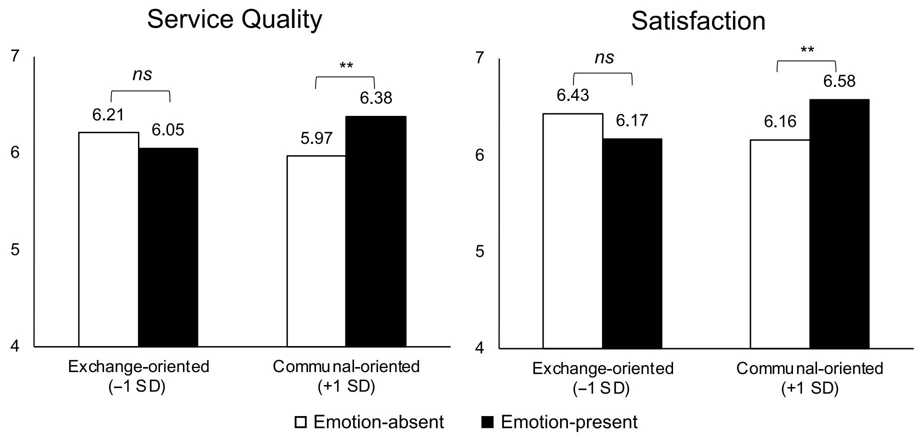
Results

One hundred seventy-seven subjects passed both attention checks and, thus, were used in the following analyses. Analysis of the manipulation check for emotional intensity revealed that participants perceived the emotion-absent agent as less emotionally intense than the emotion-present agent ($M_{absent} = 3.11$ versus $M_{present} = 5.19$, SDs = 1.25 and 1.22, $t(175) = 11.194$, $p < 0.001$), indicating that our manipulation of positive emotion was successful.

Next, we conducted a similar ANCOVA as in Study 2 to replicate prior findings. Results revealed that AI-expressed positive emotion did not significantly influence perceived service quality ($M_{absent} = 6.13$ versus $M_{present} = 6.26$, SDs = 1.02 and 0.82, $F(1, 172) = 0.726$, $p = 0.4$) or satisfaction with the service ($M_{absent} = 6.33$ versus $M_{present} = 6.44$, SDs = 0.93 and 0.75, $F(1, 172) = 0.404$, $p = 0.5$). We did not find any significant effect of gender on service evaluations (ps = 0.4 and 0.9). These results replicated the lack of effect of AI-expressed positive emotion in the earlier studies.

We also discovered that relationship norm orientation significantly moderated the effect of positive emotion on perceived service quality ($F(1, 172) = 3.738$, $p = 0.055$) and satisfaction ($F(1, 172) = 6.683$, $p = 0.011$). 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 ($\beta = 0.41$, $t(172) = 1.99$, $p = 0.049$) and satisfaction ($\beta = 0.43$, $t(172) = 2.30$, $p = 0.023$). However, for exchange-oriented individuals (relationship norm orientation = 1.67, 1 SD below the

Figure 5. Moderating Effect of Relationship Norm Orientation in Study 3



Note. ns, not significant.
**$p < 0.05$.

mean), positive emotion did not have any effect on perceived service quality ($\beta = -0.16$, $t(172) = -0.76$, $p = 0.45$) or satisfaction ($\beta = -0.26$, $t(172) = -1.37$, $p = 0.17$). Figure 5 illustrates the simple slope analysis. These results, once again, confirm Hypothesis 3.

To explore 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 a lack of total and direct effects of AI-expressed positive emotion on perceived service quality ($ps = 0.3$ and 1) and satisfaction ($ps = 0.4$ and 0.9). However, AI-expressed positive emotion increased customers' positive emotions ($\beta = 0.26$, $t(175) = 1.737$, $p = 0.084$), implying emotional contagion. An increase in felt positive emotion further led to greater perceived service quality ($\beta = 0.62$, $t(173) = 11.498$, $p < 0.001$) and greater satisfaction ($\beta = 0.52$, $t(173) = 10.362$, $p < 0.001$). 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 ($\beta = 0.16$, $SE = 0.097$, 90% confidence interval (CI) = [0.006, 0.332]) and satisfaction ($\beta = 0.14$, $SE = 0.082$, 90% CI = [0.007, 0.277]). These results provide suggestive evidence for the positive, affective pathway of emotional contagion as hypothesized in Hypothesis 2a.

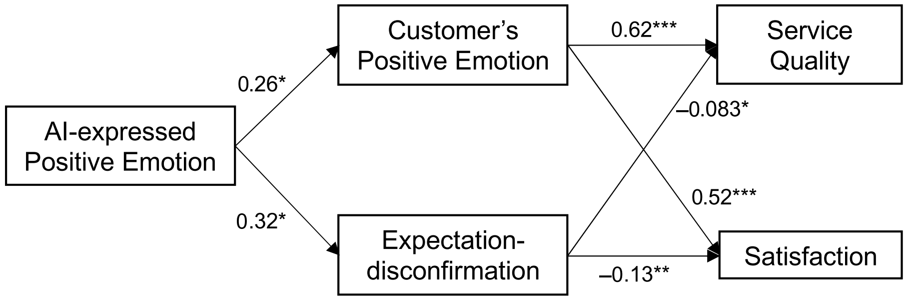
On the other hand, positive emotion increased expectation–disconfirmation ($\beta = 0.32$, $t(175) = 1.859$, $p = 0.065$), which further reduced perceived service quality ($\beta = -0.083$, $t(173) = -1.759$, $p = 0.080$) and satisfaction ($\beta = -0.13$, $t(173) = -3.074$, $p = 0.003$). The test of indirect effects confirmed a marginally significant, negative indirect effect of AI-expressed positive emotion through expectation–disconfirmation on satisfaction ($\beta = -0.043$, $SE = 0.033$, 90% CI = [−0.106, −0.002]) but not on perceived service quality ($\beta = -0.026$, $SE = 0.023$, 90% CI = [−0.074, 0.001]). These results provide partial support for the negative, cognitive pathway of expectation–disconfirmation proposed in Hypothesis 2b. Overall, our results suggest that the two opposing pathways may explain the lack of total effects of AI-expressed positive emotion on service evaluations.[3] Figure 6 shows the summary of the mediation model along with the estimated coefficients.[4]

Discussions

Study 3 unravels 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 can be transferred to customers through emotional contagion, it also violates the customers' expectations toward the agent (e.g., machines are not supposed to have emotions). Therefore, the positive affective and negative cognitive pathways may cancel 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 an exploratory analysis of Study 3 (see Endnote 4), the impact of positive emotion on expectation–disconfirmation was dependent on participants' relationship norm orientation such that this impact was absent for communal-oriented

Figure 6. Mediation Analysis in Study 3



Note. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.001$.

individuals. 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 be caused by 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 agents may not be as effective as those of human employees in enhancing customers' service evaluations. Despite customers' increased positive feelings triggered by emotional contagion, there is also a risk of emotion-expressing AI 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 AI agents. Three experimental studies provide converging evidence for our predictions. Table 2 summarizes our findings.

Theoretical Implications

Prior investigations of the effect of emotional expressions by a customer service agent focus entirely on human employees (Barger and Grandey 2006, Cheshin et al. 2018, Li et al. 2018, Kranzbühler et al. 2020). However, the rapid deployment of AIs for handling a service encounter calls for extending the study of emotions to AI 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 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 agent, illustrating the need to study the unique impacts of AI-expressed emotion in service encounters.

Table 2. Summary of Findings

	Study 1	Study 2	Study 3
Hypothesis 1	Supported	—	—
Hypothesis 2a	—	—	Supported
Hypothesis 2b	—	—	Partially supported
Hypothesis 3	—	Supported	Supported

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

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 (de Melo et al. 2013, Creed et al. 2014, Stein and Ohler 2017). Most of the research examining factors that influence the effectiveness of human–AI interactions focuses 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 are 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 novel entity, are perceived by the observers. Emotion is known to serve an important role in interpersonal relationships (Van Kleef et al. 2010). Prior research extensively documents 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 acknowledge the possibility of AI agents or machines expressing emotions. However, the latest technological innovations enable 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 versus nonhuman 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 suggests 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 shows 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. Thus, practitioners should be cautious about the promises 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, companies 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 to 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 benefits. 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 expressed at a normal level 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. Because of the complex relationship between affect and cognition (Phelps 2006, Izard 2011), 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 Endnote 3), 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 disclose 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 expressions.

Finally, 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 more comprehensive picture of the unique impact of AI-expressed emotions. The emotion used in our work is also fixed to be appropriate, but 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 highlights the necessity and importance of studying the unique impact of AI-expressed emotion. Our paper provides experimental evidence that the emotional expressions of an AI agent can have a distinct impact on customers' service evaluations compared with those of a human agent. We also reveal relationship norm orientation, a novel individual difference variable, to moderate the impact of AI-expressed emotion, 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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Endnotes

[1] Although we assume that emotional contagion occurs automatically before any cognitive evaluations, we do not imply that the emotion triggered as a result of emotional contagion is invariable over time. Because of the intertwining of affect and cognition, it is possible that the emotional state changes after cognitive evaluations. This possibility is explored empirically in the final study.

[2] The two proposed pathways may be interdependent because of the intertwining of affect and cognition (Phelps 2006, Izard 2011). Although we acknowledge that these two pathways can influence each other, we treat them as parallel 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 (Petty and Cacioppo 1986, Evans 2003).

[3] 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 expected and 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.

[4] We also tested whether relationship norm orientation moderates the two pathways proposed in our hypotheses. We found a significant interaction between positive emotion and relationship norm orientation on expectation–disconfirmation ($F(1,173) = 8.823$, $p = 0.003$) such that, for exchange-oriented individuals, positive emotion significantly increased the extent of expectation–disconfirmation ($M_{absent} = 1.98$ versus $M_{present} = 2.81$, $F(1, 172) = 10.757$, $p = 0.001$),

whereas for communal-oriented individuals, such an effect was not observed (M_{absent} = 2.58 versus $M_{present}$ = 2.35, $F(1, 172) = 0.833$, p = 0.4). These findings suggest a potential reason for the moderating role of relationship norm orientation revealed in Studies 2 and 3. Meanwhile, we did not find any significant interaction effect on customer's positive emotion.

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