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Completed Research Paper

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Abstract

Service failure is inevitable and service providers have a stake in minimizing the adverse consequences of service failure. As companies increasingly deploy Artificial Intelligence (AI) agents to augment or substitute conventional human customer service agents, there are growing scholarly attempts to elucidate the role of AI agents in shaping consumers' reactions to service recovery. Synthesizing extant literature on service failure and recovery with restorative justice, this study contextualizes restorative justice to service recovery and examine the interplay of recovery components with agent type (AI vs. human) on restorative justice. We then conducted a scenario-based online experiment to validate our hypothesized relationships. Analytical findings point to the positive effects of empathy and remorse on affective restorative justice, but these relationships are attenuated when they are conveyed by AI agents. Insights from this study hence extends our understanding of AI deployment in customer service and yields practical guidelines for AI agent developers.

Keywords: AI agent, restorative justice, service recovery, customer service

Introduction

Service failure is inevitable even for the best performing service providers (Schoefer and Ennew 2005). Consequently, service providers have a stake in ensuring commensurable recovery whenever service failures were to occur in order to minimize the adverse consequences arising from such failures (Hess et al. 2003). Particularly, offering effective recovery is even more critical for online service providers due to the ease with which dissatisfied consumers can switch to an alternative provider with the click of a button (Hsieh et al. 2012). Extant literature in service failure and recovery have demonstrated that effective service recovery should not only alleviate consumers' dissatisfaction with the failed service encounter (e.g., Tax and Iacobucci 2000), but it should also give rise to customer retention in the long run (e.g., Miller et al. 2000).

Past studies have yielded an abundance of evidence alluding to the vital role frontline employees play in offline service recovery, suggesting that: employees who can solve consumers' problems may enhance the service encounter (Bitner et al. 1990), while their attitudes during customer interactions exert a profound influence on the latter's evaluation of the interactive experience (Boshoff and Leong 1998). Indeed, extrapolated to the context of online services, the importance of service agents might be even more pronounced because the agent becomes the only window of opportunity for to service providers to reassure disappointed consumers in the event of a service failure (Li et al. 2018). More recently, advances in digital technologies have compelled companies to deploy Artificial intelligence (AI) agents to augment or substitute human agents in online customer service. Hiring AI agents not only culminates in cost savings of up to 30% for companies (Techlabs 2017), but it also shortens the response time during customer service interactions while simultaneously boosting the quality of these interactions (Walch and World 2019). Compared with the rapid advances in AI agents' functional capability, the development of their emotional capability lags behind. Consumers have expressed a reluctance to interact with AI agents because of their dehumanizing nature and inability to engage in meaningful content-rich interactions (Huang and Rust 2018). In service recovery, consumers are likely to be emotional and irrational, thereby demanding special care in coping with these negative emotion over and beyond solving the problem (Balaji et al. 2017). In this sense, the inaptitude of AI agents to empathize with consumers could be magnified in such context (Wirtz and Mattila 2004). This imbalance in AI agents' functional and emotional capability calls for further scrutiny of their impact on consumers' evaluation of service recovery as opposed to humans.

There is scholarly consensus that the goal of service recovery is not only to correct for manifested instances of service failure and take actions to prevent future instances of failure from reoccurring in the service delivery system, but it is also a core mission of service recovery to enhance consumers' overall evaluation of the service encounter and restore the relationship between customers and service providers to the level preceding the failure (Brown et al. 1996; Sabharwal et al. 2010). The idea of restoring the relationship matches the concept of *restorative justice* raised by the Western jurisprudence, which accentuates the restoration of a community that has been dented by crime (Van Ness and Strong 2010). Emphasizing the nature of recovery in the legal process, we argue that restorative justice can offer fresh insights for service recovery research by going beyond a single service failure encounter to take into account long-term customer retention (Latimer et al. 2005). To this end, this study endeavors to comprehend the interaction between customer reactions to service recovery and the type of service agent (i.e., human vs. AI) from a restorative justice angle. Extrapolating from past studies and practices in restorative justice and service recovery, we draw on the interplay between two dimensions of restorative justice (i.e., acknowledgment-attempt, and cognitive-affective) to derive four justice elements (e.g., cognitive acknowledgment, cognitive attempt, affective acknowledgment, and affective attempt) in the context of service failure and recovery via a scenario-based experiment. In so doing, this study strives to uncover how AI agents influence consumers' short-term and long-term reactions to service recovery.

Theoretical Background

Service Recovery

Service recovery has been touted as one of the key ingredients for alleviating consumers' negative reactions to service failures (Wirtz and Mattila 2004). Past studies have recognized the inherent dynamics of the service delivery process as an accumulation of multiple, connected service encounters (Patrício et al. 2018). Consumers experience both physical losses (e.g., products of poor quality) and psychological loss (e.g., anger, anxiety, and sadness) and seek compensation and alleviation in the recovery; the service agent's response to consumers' inquiry determines how they perceive. Therefore, well-enacted service recovery measures take care of consumers' reactions both cognitively and affectively (Miller et al. 2000). Service providers are expected to not only bolster customer satisfaction (Tax and Iacobucci 2000) but also assuage consumer anger and disappointment arising from service failures (Kuo and Wu 2012) to maintain a high level of customer retention (Miller et al. 2000).

Prior literature has documented various formats service recovery practices for amending for a service failure cognitively and affectively, and they generally comprise four principal components, including responsibility admission, offer of repair, empathy, and remorse (Scher and Darley 1997; Wirtz and Mattila 2004). On the cognitive side, *responsibility admission* refers to service providers' explanation of the responsibility locus for the service failure, which has been attested as a reliable antecedent for reducing consumers' unfavorable outcomes (Bradley and Sparks 2012). An *offer of repair* (or compensation) refers to service providers' compensation for the service failure (Seiders and Berry 1998), and can be either tangible or intangible, and monetary or nonmonetary; there has been an abundance of evidence about its effectiveness in increasing customer satisfaction and repurchase intention (Albrecht et al. 2019). On the affective side, *empathy*, referring to the provision of care and individualized attention to customers, has long been identified as a critical component for responding to customer complaints (Min et al. 2015). *Remorse*, referring to the provision of regret, was affirmed as a potent factor for obtaining forgiveness from the consumers (Fehr and Gelfand 2010). However, the effects of these four recovery components on customer reactions were examined individually or in different combinations. To the best of our knowledge, there is little research that has examined the complementary or substitutive role these components play during the service encounter. To this end, this study investigated their effects on consumer reactions holistically.

AI Customer Service Agent

Recent service encounters have witness the rise of AI to augment customer service, which has been enabled by automated sensing, learning, and problem-solving, to add value to service encounters through flexible adaptation to consumer needs (Bock et al. 2020). Assuming the form of both tangible (e.g., humanoid service robots) and intangible (e.g., virtual avatars) entities, AI agent is increasingly becoming part and parcel of routine service encounters (Mende et al. 2019). Apart from systemic features expected of information technology (e.g., instantaneous and standardized responses), AI agents are endowed with anthropomorphic and self-learning capabilities (Huang and Rust 2021), leading consumers to experience human-like (Kim et al. 2019), personalized (Chung et al. 2016) exchanges when interacting with them. AI agents is not only capable of ensuring consistent quality in consumers interactions and scaling up when necessary (Wirtz et al. 2018) but also replacing human contact in projecting social presence (Van Doorn et al. 2017). The increasing capability of AI agents in dealing with various service encounters has led practitioners and scholars to question whether AI can perfectly substitute humans in customer service encounters (Bock et al. 2020).

Contemporary knowledge about human-algorithm interaction has uncovered that individuals' interactions with algorithms are different from those with human assistants (e.g., Dietvorst et al. 2015; Mozafari et al. 2021). On the one hand, individuals do not demonstrate distinct differences in evaluating cognitive outcomes when interacting with algorithms. In addition to appreciating their accuracy and immediacy, consumers perceive algorithms to exert less efforts when generating a recommendation (Bechwati and Xia 2003). On the other hand, individuals profess to have difficulty in experiencing a sense of humanness or building up emotional attachment with AI (Schroll et al. 2018) because of the latter's dehumanizing nature (Highhouse 2008). Consumers report a sense of discomfort and eeriness whenever AI agent acts like humans during interactions (Mende et al. 2019). System users further explain that they have more difficulty in rebuilding trust with algorithms than humans once they offer suggestions leading to adverse outcomes. We contend that the absence of humanness and loss of emotional attachment in AI agents may shape customer reactions in terms of emotional outcomes, whereas the rational customer reactions would be less likely to be affected by agents' identities.

Restorative Justice

Western court-based judicial systems propose a notion of justice, *restorative justice*, as a humanistic reaction to rule-breaking behaviors (Van Ness and Strong 2010). Restorative justice refers to the repair of justice by reaffirming a shared value consensus in a bilateral process of reparation and rehabilitation that actively involves victims and offenders (Wenzel et al. 2008). The purpose of a restorative justice process is "through vindication and reparation, to restore a community that has been sundered by crime" (Van Ness and Strong 2010, p. 8). It emphasizes the harmful effects of offenders' actions and actively involves victims and offenders in the process of reparation and rehabilitation (Eglash 1958). It makes the appeal that victims, offenders, and communities should have the opportunity to be actively involved in the judicial process as early and as fully as they want (Van Ness and Strong 2010). Restorative justice has been affirmed to possibly reduce substantial crime and victim's post-traumatic stress (Sherman and Strang 2007).

Because restorative justice stresses the importance of obligations to make things right, it is applicable to service failures. A service failure is a violation of consumers and their relationship with the service providers and creates obligations for the service to be delivered smoothly. Therefore, the role of the restoration of justice in crime is analogous to the role of recovery in a service failure. Besides, the ultimate goal of service recovery is to enhance consumers' overall perceptions of the service and restore the customer relationship to the level preceding the failure (Brown et al. 1996; Sabharwal et al. 2010), which perfectly matches the core of restorative justice (Van Ness and Strong 2010); so to using restorative justice as a lens to view service recovery might provide fresh insights to service recovery research (Latimer et al. 2005). Larsen and Lawson (2013) indicated that restorative justice is concerned with the customer's rights, such as, receiving a fair settlement to just claims, including compensation for misrepresentation, shoddy goods, or unsatisfactory service. Liu et al. (2019) disentangled the trade-off between compensation and promptness in the context of service recovery for online review sites through a restorative justice angle. They viewed the review site as a mediating platform between consumers and hotels; consumers actively reported service failures on the review sites, and the hotel strove to deliver justice to consumers who had given negative reviews through online communication (Liu et al. 2019). However, although these two studies employed restorative justice as a powerful theoretical instrument, but they did not contextualize the construct in service recovery, undermining its power to reveal the secrets behind a satisfying service recovery. To this end, the present study sought to decrypt restorative justice in the context of service recovery.

According to extant literature on restorative justice, there are generally two focuses in justice restoration, one concentrating on the nature of the loss and the other focusing on the type of amends. Individuals suffer from physical loss and psychological loss and judicial systems treat these two types of loss both seriously. Analogously, prior service recovery literature has already documented that a satisfying recovery should also take care of consumers' negative emotions (e.g., anger and disappointment) (Kuo and Wu 2012) in addition to the damage caused by failure. Therefore, a comprehensive recipe for pursuing restorative justice in service recovery should stress a constructive way to not only mitigate the consumers' physical loss caused by the service failure but also alleviate their psychological loss simultaneously.

For types of amends, judiciaries allow for various formats of amends and we consolidate them into the following two types, *acknowledgement* and *attempt*. On the one hand, both the victim and offender are given a voice to express their views and emotions (Wenzel et al. 2008). Restorative justice is geared toward making the offender take responsibility and accept accountability for their actions (Wenzel et al. 2008). The victim is encouraged to express willingness to forgive the offender and show respect to the offender as an individual capable of redemption and moral transformation (Govier 2002). Consistent with this, we label service providers' *acknowledgment* of a consumers' loss caused by the service failure as one principle amend for service failure. On the other hand, offenders are expected to take steps to better adjust to society, including learning new skills, expanding their behavioral repertoire, and changing their attitudes (Wenzel et al. 2008). In service recovery, service providers take the initiative to make amends for consumers for a failure that causes loss and they promise to make improvements in future service to ensure a lower possibility of failure. We define the service providers' initiative to offer better service and amend for a present failure as an *attempt*.

In line with the previous discussion, we conceive that restorative justice can be delineated by the *cognitive–affective* and *acknowledgment–attempt* dimension into four constituent elements (see Table 1). We attempt unravel the interplay between recovery components and service agent on justice elements in service recovery in the next section.

Definition	Acknowledgment	Attempt
Cognitive	Cognitive acknowledgment refers to the acknowledgment of physical loss that consumers suffered in the service failure	Cognitive attempt refers to the initiative to amend for the physical loss caused by the service failure
Affective	Affective acknowledgment refers to the acknowledgment of psychological loss caused by the service failure	Affective attempt refers to the initiative to amend for the psychological loss caused by the service failure

Table 1. Restorative Justice

Hypotheses Development

Recovery Components and Restorative Justice

Implementing restorative justice in service recovery primarily relies on recovery practices by service agent during the recovery process. Responsibility admission, as one of the principal recovery components, requires the service providers to give an acceptable explanation of the service failure during the communication with the customer and validate the internal information sources. Regardless of whether the service failure is attributed to the service provider, if the service agent proactively takes the responsibility on behalf of the service provider, and recognizes the consumer's physical loss caused by the service failure (e.g., wasted time, monetary loss, disrupted schedule), the customer will be impressed. The legitimacy of consumers' asking for recovery is acknowledged after a series of steps, including problem identification and validation, providing a solid basis for later claims of compensation. We therefore hypothesize that:

> *Hypothesis 1: Consumers' perception of cognitive acknowledgement will increase when the agent admits responsibility.*

Offer of repair, the essential component of recovery, signifies the service providers' intention to restore a relationship with consumers. The details of the offer of repair, such as its format and amount, present the consumer with a conscientious consideration by the service agent, on behalf of the service providers to amend the negative evaluations caused by the service failure. Providing the consumer with commensurable compensation would induce a positive conjecture the service agent has taken steps to compensate for the service failure. In addition, to promise an improvement in future service and that failure will be less likely to occur also increases the reliability of the service provider's attempt to rebuild the customer relationship. We therefore hypothesize that:

> *Hypothesis 2: Consumers' perception of cognitive attempt will increase when the agent provides an offer of repair.*

Providing empathy in the communication with the consumers suggests the service agent is fully aware of the consumer's emotional dilemma. Although individuals might have various demands for emotional care during the predicament, offering an appropriate level of empathy demonstrates the service agent's attention to the consumer's psychological predicament and their acknowledgment of the psychological loss caused by the service failure. We therefore hypothesize that:

> *Hypothesis 3: Consumers' perception of affective acknowledgment will increase when the agent provides empathetic statements.*

Expressing remorse by the service agent in the recovery conveys their sincerity to alleviate the consumers' negative emotions. Immediately after the service failure, consumers are swamped in the emotional difficulties and turn to the service agent for help. When the service agent indicates negative feelings about the consequences of the service failure, the consumer tends to view this remorse as a confession for the failure and an attempt to make up for the psychological loss caused by it. We therefore hypothesize that:

> *Hypothesis 4: Consumers' perception of affective attempt will increase when the agent provides remorse statements.*

Moderating Role of Agent Type

AI has obtained unprecedented advancement and has been deployed in various industries to assist, augment and even acts as substitute for their human colleagues (Bock et al. 2020; Huang and Rust 2021). Because AI has long been accused of its dehumanizing nature and weak ability to generate and understand emotions, AI developers endeavor to empower AI with emotional competence. Recent customer service AI agents have acquired a certain level of capability to comprehend the emotional intensity and valence of consumers and respond to the them adaptively (Peng and Zhao 2020).

However, emotional AI have been not embraced by the market as expected. Educated by the life experience and the environment where they grew up, contemporary consumers possess preconceived notions about AI, ranging from its dehumanizing nature to its inability to comprehend personalized needs, cope with qualitative data (e.g., customer opinions), and learn (Highhouse 2008). These preconceived notions are so entrenched that they cannot be reversed by several interactions. Consequently, it is inevitable that consumers will discount the effects of emotion-related expressions during communications. In service recovery, consumers hold the notion that AI agents cannot empathize with their emotional needs, resulting in them being less likely to perceive these agents as genuine. The empathy and remorse conveyed in the expressions by AI agents are more likely to be perceived as compulsory or the result of templates rather than sincere interpersonal concerns. Therefore, consumers are not inclined to believe the service agent has put forth effort to achieve affective restorative justice via communication. Similarly, Choi et al (2020) also found that humanoid (vs. non-humanoids) robots can recover a service failure by themselves via sincere apologies, restoring perceptions of warmth. We therefore hypothesize that:

> *Hypothesis 5: The agent type moderates the effects of empathy and remorse in terms of affective restorative justice. Specifically, the positive effects of (a) empathy on affective acknowledgment and (b) remorse on affective attempt are attenuated when the consumers interact with an AI agent.*

Restorative Justice and Customer Attitudes

According to the previous literature, service providers should take care of consumers' cognitive and affective reactions to gain a higher evaluation in the post-recovery phase (Miller et al. 2000; Van Vaerenbergh et al. 2019). Following the trend in recovery research, we found customer satisfaction plays an essential role in describing consumers' attitudes toward the service encounter (Bhandari et al. 2007). However, because satisfaction, a customer judgment about service fulfillment (Oliver 2014), is an outcome of their reflection on the recovery (Jang and Feng 2007) and has been found to be strongly correlated to the level of the consumer's expectation, we argue that satisfaction has a cognitive nature. To fit the recovery context, we employ *dissatisfaction* in this study to obtain an exact measure of consumers' perception. Moreover, alleviating negative emotions has been characterized as a crucial part of service recovery (Ozgen and Duman Kurt 2012; Schoefer and Ennew 2005). To measure the effectiveness of the recovery practices in terms of affect, we use *affective alleviation* to describe the extent to which consumers' negative emotions and mental stress has been relieved during the recovery phase.

Implementing cognitive acknowledgment in service recovery reinforces the proactive nature of the agents in assuming responsibility and consumers enjoy the sincerity they display. Consumers will deem that the service agents are willing to embrace their viewpoints and work with them to cope for the service failure, rather than being only representative of the service providers. The appreciation for courage and honesty will motivate consumers to decrease their dissatisfaction while alleviating their negative emotions. We therefore hypothesize that:

> *Hypothesis 6: Cognitive acknowledgment (a) decreases customer dissatisfaction but (b) increases their affective alleviation.*

The cognitive attempt to amend the service failure serves as the dominant means to restore the equity in the consumer-service provider relationship. The reconstruction of just principles exerts potent effects on improving negative evaluations towards the service providers (Jung and Seock 2017). Furthermore, the cognitive attempt also generates positive ones and offsets negative emotions because it presents the consumer with the service provider's strong willingness to improve the difficult situation via an actual resolution (Xu et al. 2019). We therefore hypothesize that:

> *Hypothesis 7: Cognitive attempt (a) decreases customer dissatisfaction but (b) increases their affective alleviation.*

Providing an affective acknowledgment and an affective attempt to consumers help them view the service failure as an aberrant instance (Fehr and Gelfand 2010) and leads to a higher likelihood of forgiveness (Wang et al. 2020). This emotional resonance will make consumers treat the service agent as an ally for dealing with the service failure; therefore, they would consider the solution positively rather than critically while considering it commensurate to the loss they suffered. Further, an affective acknowledgment might help the consumer to overcome the urge to avoid the service providers or seek revenge and become more prosocial toward the service provider. It will also relieve the negative emotions aroused by prior service failure (Tomlinson and Mryer 2009). We therefore hypothesize that:

Hypothesis 8: Affective acknowledgment (a) decreases customer dissatisfaction but (b) increases their affective alleviation.

Hypothesis 9: Affective attempt (a) decreases customer dissatisfaction but (b) increases their affective alleviation.

Revisit intention is identified as a crucial indicator of customer loyalty (Benbasat et al. 2007; Evanschitzky et al. 2012) and has long been employed to describe the consumer's ultimate attitude toward the service providers because it guarantees the future revenue of the service providers. The relationship between (dis)satisfaction and revisit intention has been explored in various product and service markets, and previous studies have almost unanimously found that satisfaction positively affected revisit intention (Fang et al. 2014; Um et al. 2006). Consumers are more likely to visit a service provider again if they have had satisfactory past service experience with it (c.f. Huang and Hsu 2009). In the context of the present study, consumers with a lower level of dissatisfaction have had a similar recovery experience to their expectation, thereby finding the service providers reliable and trustworthy and resulting in higher revisit intention. We therefore hypothesize that:

Hypothesis 10: Customer dissatisfaction decreases their revisit intention.

Alleviating consumers' negative affective experiences has been recognized as an important antecedent in achieving a successful recovery (Xu et al. 2019). Customers become more critical in their assessment of a service when they are in a negative emotional state (McColl-Kennedy and Sparks 2003) and tend to become more detail-oriented and systematic while using complex judgment processes to evaluate the service failure recovery process (Forgas 1994). Thus, they might overemphasize the service failure while ignoring the effort the service providers have made to correct the failure, which results in a lower possibility of revisiting the service provider. Additionally, consumers who had their negative emotions relieved during the service failure recovery process usually express a more positive evaluation toward the service provider and thus, are more likely to revisit the service provider in the future (Yalch and Spangenberg 2000). We therefore hypothesize that:

Hypothesis 11: Affective alleviation increases their revisit intention.

Figure 1 depicts our proposed research model and illustrates how recovery components contribute to restorative justice, thereby influencing dissatisfaction, affective alleviation, and revisit intention. Furthermore, we hypothesize the agent (human vs. AI) moderates the effects exerted by recovery components on restorative justice elements.

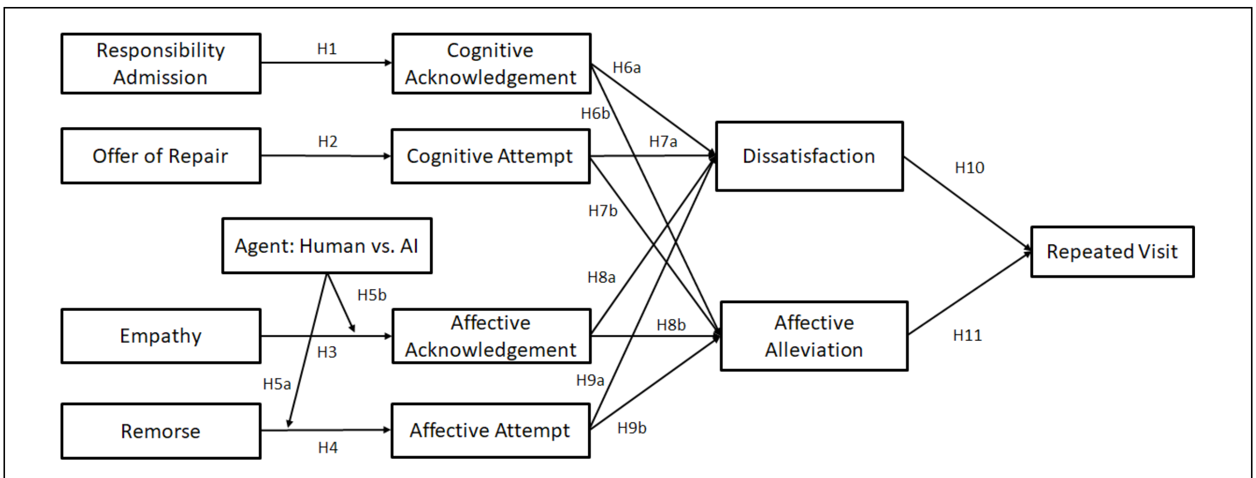


Figure 1. Research Model

Experiment Design

Stimuli

We employed 2 (customer service agent: AI vs. human) × 2 (responsibility admission: presence vs. absence) × 2 (offer of repair: high vs. low) × 2 (empathy: presence vs. absence) × 2 (remorse: presence vs. absence) between-subject full-factorial-design experiment to validate our research model. Participants were exposed to a common service failure on an online travel agency (OTA) platform. We chose OTA platforms as our context for the following two reasons: 1) many OTA platforms have integrated AI into their customer services, for example, Booking, Airbnb, guaranteeing the realism of the scenario; 2) OTA platform, other than the customer and the hotel, plays a mediating role in hotel reservation. Consequently, chatbots in OTA could have the flexibility of blaming the failure on the platform itself to blaming the hotel, thereby providing a realistic scenario for manipulating responsibility admission.

The service failure is based on a scenario whereby a customer has paid for a room reservation on the platform, but the room reservation did not come through at the hotel's end. The main reason we chose it is that we wanted to exclude participants' alternative option of turning to another OTA platform for room reservation when confronted with a service failure. Payment would lock participants to the platform and compel them to contact customer services in the event of service failure. In this way, we can not only ensure a high degree of realism for the service failure encounter but also have a valid reason for why participants have no choice but to contact the OTA platform for assistance.

Consistent with our research model, we manipulated the service recovery components (i.e., responsibility admission, offer of repair, empathy, and remorse) via the conversation between the customer service agent and the consumer[1] (Min et al. 2015; Scher and Darley 1997; Tan 2011). The participant would receive a bundle of various apology components from the service agent in his/her assigned corresponding condition, including admitting responsibility for the encountered service failure, expressing its empathy or remorse, and providing a corresponding level of compensation. Specifically, the service agent would offer an alternative plan for reserving an upper-grade room in another hotel of the same level for free in the high offer-of-repair condition, whereas it would only refund the payment in seven workdays in the low offer-of-repair condition. Moreover, customer service agents were manipulated through an avatar. Participants were exposed to a cartoon of a real person in the human agent condition, while their counterparts in the AI agent condition were presented with a robot avatar instead. To ensure that participants were fully aware of the identity of the agent, it would introduce itself at the very beginning of the conversation.

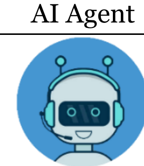
Condition	Human Agent	AI Agent
Avatar		
Self-Introduction	Hello, I am Turi from Customer Service and I am here to help you today.	Hello, I am Turi. I am an intelligent chatbot from Customer Service and I am here to help you today.

Table 2. Manipulation of Service Agent

Procedure

Participants for the experiment were recruited from Amazon Mechanical Turk (AMT), a crowd-working marketplace that connects Human Intelligence Task (HIT) requesters with individual workers. Researchers have increasingly recognized AMT as a viable avenue for gaining access to a massive and unbiased pool of participants for academic research (Paolacci and Chandler 2014). AMT is appropriate for this study due to the diversity in workers' demographic composition and their rich experience with digital services (Paolacci

[1] For more details of stimuli design in each experiment group, please visit online Appendix A at https://github.com/CYFileSpace/Conference/blob/main/ICIS2022-Appendix_A.pdf

and Chandler 2014). After eliminating 104 data-runners (e.g., extreme long/short duration), our final sample comprises 1,031 participants who are randomly assigned to each condition. The differences of demographics across conditions are not significant.

To begin, potential participants were directed from our HIT page on AMT to an introductory page containing a detailed description of the study procedures. Participants were randomly assigned to one of the experimental conditions. They were asked to put themselves into the failure scenario and then were directed to go through the service recovery process via reading. Next, participants were presented with an online survey questionnaire to evaluate their attitudes towards this service encounter and the agent. Demographic data were extracted at the end of the questionnaire. Upon the completion of the questionnaire, participants obtained a completion code to claim their reward on AMT.

Measurement

Manipulation checks. We included several manipulation checks at the beginning of the questionnaire to ensure the participants were aware of the exposure to the stimuli in various conditions. We first asked the participant to indicate the identity of the agent (AI/human/not sure). Then we requested the participant to choose the response that he/she did not receive from the customer service agent during the recovery process. Participants who could not pass these two manipulation checks were immediately directed to the end of the survey and therefore eliminated from the final sample.

Constructs[2]. Measurements items to capture participants' evaluation of the service recovery experience were solicited from past studies whenever plausible. Items for measuring participants' restorative justice perceptions (i.e., cognitive acknowledgment, cognitive attempt, affective acknowledgment, and affective attempt) were newly developed based on discussions of the authors. Guided by the concept of alleviation in Davis et al. (2010's work, new measures were developed to assess participants' affective alleviation. Measurement items for revisit intention and dissatisfaction were adapted from prior operationalization of related constructs (Evanschitzky et al. 2012; Goodwin and Ross 1992). Moreover, we also included commensurability as a control variable to exclude the confounding downstream effects brought by different offer-of-repair levels. The measurement items were developed based on the prior discussion on the commensurability in service recovery (Radin 1993). Additionally, we measured participants' recency with the mentioned spot in the scenario (i.e., Telluride) and previous experience with the service failure and OTA platforms as controls to eliminate the effect of familiarity on customer reactions. We also incorporated measures for task realism to verify whether participants were engaged in the scenario.

We assessed the reliability and internal consistency of all measurement items, as well as the convergent and discriminant validity of all latent constructs. The quality indices for all latent constructs far exceed recommended thresholds (Cronbach's alpha > 0.7, CR > 0.7, and AVE > 0.5), implying adequate internal consistency of our measures for the constructs.

Results

ANOVA Results

We first examined how the provision of each recovery component affects participants' perceptions of restorative justice. Particularly, we compared participants' restorative justice perceptions (i.e., cognitive acknowledgment, cognitive attempt, affective acknowledgment, and affective attempt) across the treatment groups via a five-way ANOVA. As demonstrated in Table 3 and Table 4, providing different recovery components enables corresponding restorative justice elements. Consistent with Hypothesis 1, participants receiving responsibility admission from the agent would perceive high cognitive acknowledgment ($M[\text{cognitive acknowledgement}]_{RA\text{-}A} = 4.139$, $M[\text{cognitive acknowledgement}]_{RA\text{-}P} = 5.303$, $p < .001$). In support of Hypothesis 2, offering better compensation to participants facilitates cognitive attempt perceptions ($M[\text{cognitive attempt}]_{OR\text{-}L} = 3.840$, $M[\text{cognitive attempt}]_{OL\text{-}H} = 5.612$, $p < .001$). Besides, the provision of empathetic statement and remorse contributes to affective acknowledgment and affective attempt respectively ($M[\text{affective acknowledgement}]_{EM\text{-}A} = 4.040$, $M[\text{affective acknowledgement}]_{EM\text{-}P}$ =

[2] We included all the measurement items in the online Appendix B (https://github.com/CYFileSpace/Conference/blob/main/ICIS2022-Appendix_B.pdf).

4.598, p < .001; M[affective attempt]$_{RM\text{-}A}$ = 4.199, M[affective attempt]$_{RM\text{-}P}$ = 4.580, p < .001), thereby substantiating Hypothesis 3 and Hypothesis 4.

In addition to hypothesized relationships, the analytical results also reveal the spillover effects of these recovery components on restorative justice (see Table 3). Responsibility admission by the agent would also increase cognitive attempt, affective acknowledgment, and affective attempt. This implies that taking the blame plays an important role in boosting consumers' justice perceptions. It is regarded as the agent's (on behalf of the platform) resolution to solve the adverse outcome caused by the failure, thus resulting in an increased cognitive attempt (M[cognitive attempt]$_{RA\text{-}A}$ = 4.565, M[cognitive attempt]$_{RA\text{-}P}$ = 4.867, p < .001). Besides, attributing the failure to the agent (on the half of the platform), likewise, makes the consumers feel being treated carefully, thus mitigating the affective restorative justice perceptions (M[affective acknowledgement]$_{RA\text{-}A}$ = 4.159, M[affective acknowledgement]$_{RA\text{-}P}$ = 4.475, p < .001; M[affective attempt]$_{RA\text{-}A}$ = 4.168, M[affective attempt]$_{RA\text{-}P}$ = 4.609, p < .001). Furthermore, offer of repair is an overwhelming antecedent for restorative justice. This suggested that consumers would regard a high offer of repair as a behavioral acknowledgment of responsibility admission (M[cognitive acknowledgement]$_{OR\text{-}L}$ = 4.190, M[cognitive acknowledgement]$_{OR\text{-}H}$ = 5.267, p < .001) and are more likely to forgive the failure and let the negative emotions go for the sake of commensurable compensations (M[affective acknowledgement]$_{OR\text{-}L}$ = 3.797, M[affective acknowledgement]$_{OR\text{-}H}$ = 4.850, p = .000; M[affective attempt]$_{OR\text{-}L}$ = 3.801, M[affective attempt]$_{OR\text{-}H}$ = 4.990, p < .001).

The spillover effects of empathy are limited in affective perceptions of restorative justice. Expressing empathy to consumers would slightly improve their perceptions of affective attempt (M[affective attempt]$_{EM\text{-}A}$ = 4.225, M[affective attempt]$_{EM\text{-}P}$ = 4.555, p < .001) while the positive effect of sincere apology by the agent is also extended to affective acknowledgment (M[affective acknowledgement]$_{RM\text{-}A}$ = 4.199, M[affective acknowledgement]$_{RM\text{-}P}$ = 4.580, p < .001). Surprisingly, an increase in cognitive acknowledgment is found when the agent provides a remorse statement (M[cognitive acknowledgement]$_{RM\text{-}A}$ = 4.570, M[cognitive acknowledgement]$_{RM\text{-}P}$ = 4.876, p = .001), indicating that apologizing serves as a behavioral cue for cognitive acknowledgment.

Condition	N	Cognitive Acknowledgment	Cognitive Attempt	Affective Acknowledgment	Affective Attempt
RA-A	517	4.139 (1.648)	4.565 (1.556)	4.159 (1.620)	4.168 (1.639)
RA-P	514	5.303 (1.335)	4.867 (1.529)	4.475 (1.553)	4.609 (1.597)
OR-L	521	4.190 (1.628)	3.840 (1.445)	3.797 (1.626)	3.801 (1.701)
OR-H	510	5.267 (1.391)	5.612 (1.064)	4.850 (1.371)	4.990 (1.312)
EM-A	518	4.678 (1.603)	4.685 (1.589)	4.040 (1.623)	4.225 (1.677)
EM-P	513	4.769 (1.613)	4.749 (1.509)	4.598 (1.515)	4.555 (1.570)
RM-A	516	4.570 (1.664)	4.658 (1.605)	4.100 (1.587)	4.199 (1.653)
RM-P	515	4.876 (1.535)	4.775 (1.491)	4.535 (1.573)	4.580 (1.590)

Table 3. Group Means (Standard Deviations) by Recovery Components

Notes: RA = Responsibility Admission, OR = Offer of Repair, EM = Empathy, RM = Remorse; A = Absence, P = Presence, L = Low, H = High.

We examined the moderating role of delivery agent in the hypothesized relationships via ANOVA. As the results showed (see Table 5), the interaction effects of delivery agent and empathy as well as remorse were significant, thereby confirming Hypothesis 5a and Hypothesis 5b. Delivering empathy and remorse by human agents would significantly increase affective acknowledgment and affective attempt respectively (M[affective acknowledgement]$_{EM\text{-}A}$ = 4.226, M[affective acknowledgement]$_{EM\text{-}P}$ = 4.976, p < .001; M[affective attempt]$_{RM\text{-}A}$ = 4.295, M[affective attempt]$_{RM\text{-}P}$ = 4.964, p < .001). However these emotional expressions' effects on affective restorative justice were far attenuated if they were delivered by AI agents (M[affective acknowledgement]$_{EM\text{-}A}$ = 3.850, M[affective acknowledgement]$_{EM\text{-}P}$ = 4.222, p = .002; M[affective attempt]$_{RM\text{-}A}$ = 4.099, M[affective attempt]$_{RM\text{-}P}$ = 4.203, p = .287). Additionally, we also found the effect of remorse on affective acknowledgment is mitigated when it is conveyed by an AI agent (M[affective acknowledgement]$_{RM\text{-}A}$ = 3.932, M[affective acknowledgement]$_{RM\text{-}P}$ = 4.137, p = .445), since providing remorse served as a reliable driver for affective acknowledgment when being expressed by a human agent (M[affective acknowledgement]$_{RM-A}$ = 4.263, M[affective acknowledgement]$_{RM-P}$ = 4.941, $p < .001$).

Independent Variables	Cognitive Acknowledgment	Cognitive Attempt	Affective Acknowledgment	Affective Attempt
RA	.000***	.000***	.000***	.000***
OR	.000***	.000***	.000***	.000***
EM	.228	.332	.000***	.000***
RM	.000***	.116	.000***	.000***
Agent	.001***	.354	.000***	.000***
Agent x RA	.218	.776	.940	.628
Agent x OR	.256	.195	.063	.240
Agent x EM	.579	.891	.037*	.279
Agent x RM	.281	.475	.016*	.004**

Table 4. Five-Way ANOVA Results (p-Value)

Notes: RA = Responsibility Admission, OR = Offer of Repair, EM = Empathy, RM = Remorse

Conditions		N	Cognitive Acknowledgment	Cognitive Attempt	Affective Acknowledgment	Affective Attempt
Human	RA-P	256	4.335 (1.683)	4.594 (1.545)	4.443 (1.516)	4.430 (1.525)
	RA-A	261	5.385 (1.233)	4.905 (1.483)	4.749 (1.470)	4.817 (1.526)
AI	RA-P	258	3.945 (1.591)	4.536 (1.570)	3.878 (1.674)	3.908 (1.708)
	RA-A	256	5.220 (1.430)	4.829 (1.577)	4.195 (1.588)	4.397 (1.643)
Human	OR-H	262	4.383 (1.568)	3.928 (1.454)	4.161 (1.514)	4.093 (1.582)
	OR-L	255	5.361 (1.396)	5.596 (1.053)	5.046 (1.346)	5.172 (1.276)
AI	OR-H	259	3.996 (1.668)	3.751 (1.434)	3.429 (1.655)	3.506 (1.767)
	OR-L	255	5.174 (1.382)	5.627 (1.078)	4.653 (1.370)	4.808 (1.324)
Human	EM-P	261	4.795 (1.597)	4.726 (1.574)	4.226 (1.596)	4.411 (1.630)
	EM-A	256	4.937 (1.527)	4.777 (1.466)	4.976 (1.291)	4.844 (1.403)
AI	EM-P	257	4.559 (1.603)	4.643 (1.605)	3.850 (1.631)	4.037 (1.705)
	EM-A	257	4.601 (1.680)	4.721 (1.553)	4.222 (1.626)	4.266 (1.675)
Human	RM-P	262	4.661 (1.664)	4.709 (1.556)	4.263 (1.553)	4.295 (1.615)
	RM-A	255	5.074 (1.425)	4.794 (1.485)	4.941 (1.362)	4.964 (1.372)
AI	RM-P	254	4.477 (1.663)	4.605 (1.655)	3.932 (1.607)	4.099 (1.688)
	RM-A	260	4.681 (1.616)	4.757 (1.499)	4.137 (1.664)	4.203 (1.698)

Table 5. Descriptive Statistics

Notes: RA = Responsibility Admission, OR = Offer of Repair, EM = Empathy, RM = Remorse; A = Absence, P = Presence, L = Low, H = High

Regression Results

We then employed linear regression models to examine the rest of the hypotheses with dissatisfaction, affective alleviation, and revisit intention as dependent variables respectively in a confirmatory fashion (see

Table 6 to Table 8)[3]. Consistent with Hypotheses 6a, 7a, and 9a, restorative justice components negatively influenced dissatisfaction, suggesting that restoring justice via recovery practices was effective in decreasing customer dissatisfaction induced by a prior service failure. On the contrary, the affective acknowledgment was marginally positively associated with consumers' dissatisfaction, indicating that the expression of empathy would induce consumer dissatisfaction to some extent, thereby rejecting H8a. The adverse relationship could be accounted for by the magnifying effect of affective acknowledgment. The acknowledgment of psychological loss in the service failure consolidated consumers' negative feelings and therefore induced higher dissatisfaction.

Independent Variables	Model 1			Model 2		
	Beta	S.E.	Sig.	Beta	S.E.	Sig.
Cognitive Acknowledgment				-0.064	0.030	0.031*
Cognitive Attempt				-0.186	0.041	0.000***
Affective Acknowledgment				0.084	0.045	0.063
Affective Attempt				-0.249	0.049	0.000***
Commensurability	-0.691	0.022	0.000***	-0.466	0.032	0.000***
Recency of Telluride	-0.335	0.046	0.000***	-0.366	0.044	0.000***
Experience in Incident	-0.073	0.099	0.460	-0.078	0.094	0.412
Experience in OTA	-0.204	0.041	0.000***	-0.215	0.039	0.000***
Gender	0.067	0.080	0.403	0.138	0.077	0.072
Age	-0.004	0.003	0.235	-0.004	0.003	0.271
Education	0.178	0.062	0.004**	0.190	0.059	0.001***
Income	-0.049	0.037	0.191	-0.028	0.036	0.429
Constant	9.630	0.363	0.000***	10.554	0.365	0.000***
Observations		1031			1031	
Adjusted R square		0.522			0.564	

Table 6. Regression Results on Dissatisfaction

As displayed in Table 7, restorative justice elements positively influence affective alleviation except for cognitive acknowledgment, confirming Hypotheses 7b, 8b, and 9b whereas rejecting Hypothesis 6b. The insignificant relationship between cognitive acknowledgment and affective alleviation alluded to the distinction between physical loss and psychological loss consumers suffered during the service failure. Furthermore, a simple acknowledgment of the physical loss had nothing to do with the final mitigation of the psychological loss. In addition, a post-hoc analysis indicated that affective attempt has a stronger effect on affective alleviation than cognitive attempt (t value = 2.963, p < .005).

Independent Variables	Model 1			Model 2		
	Beta	S.E.	Sig.	Beta	S.E.	Sig.
Cognitive Acknowledgment				0.003	0.025	0.894
Cognitive Attempt				0.220	0.035	0.000***
Affective Acknowledgment				0.077	0.039	0.046*
Affective Attempt				0.382	0.042	0.000***
Commensurability	0.790	0.020	0.000***	0.492	0.027	0.000***
Recency of Telluride	-0.109	0.042	0.009**	-0.065	0.038	0.086
Experience in Incident	-0.018	0.090	0.845	0.007	0.081	0.931

[3] To eliminate confounding factors, we included customers' commensurability towards to compensation, familiarity with the experimental scenario (i.e., the spot, the OTA platform and the incident) and descriptive statistics (gender, age, education level and income level) as control variables.

Experience in OTA	-0.070	0.037	0.064	-0.055	0.034	0.101
Gender	0.021	0.072	0.769	-0.082	0.065	0.208
Age	0.008	0.003	0.014*	0.007	0.003	0.017*
Education	0.122	0.056	0.031	0.098	0.051	0.053
Income	0.020	0.034	0.565	-0.005	0.030	0.879
Constant	0.904	0.330	0.006**	-0.191	0.311	0.539
Observations		1031			1031	
Adjusted R square		0.621			0.696	

Table 7. Regression Results on Affective Alleviation

Independent Variables	Model 1			Model 2		
	Beta	S.E.	Sig.	Beta	S.E.	Sig.
Dissatisfaction				-0.170	0.028	0.000***
Affective Alleviation				0.607	0.031	0.000***
Commensurability	0.511	0.021	0.000***	0.149	0.031	0.000***
Recency of Telluride	-0.375	0.045	0.000***	-0.252	0.040	0.000***
Experience in Incident	0.129	0.096	0.178	0.152	0.082	0.062
Experience in OTA	-0.200	0.040	0.000***	-0.123	0.035	0.000***
Gender	-0.015	0.078	0.843	-0.040	0.066	0.549
Age	0.005	0.003	0.105	0.001	0.003	0.611
Education	0.195	0.060	0.001***	0.091	0.052	0.079
Income	-0.040	0.036	0.276	-0.043	0.031	0.163
Constant	3.083	0.353	0.000***	0.900	0.412	0.029*
Observations		1031			1031	
Adjusted R square		0.467			0.615	

Table 8. Regression Results on Revisit Intention

Discussion

Theoretical Contributions

This study contributes to the extant literature on three fronts. First, the proliferation of AI agents in customer services has challenged contemporary knowledge about service encounters in offline contexts (Bock et al. 2020). In this vein, this study can be deemed as a response to the call for further examination on the role AI agents play in service encounters (Bock et al. 2020). This study thus contributes to the preceding research stream by revealing how AI agents influence consumers' reactions (i.e., dissatisfaction, affective alleviation, and revisit intention) to service recovery via a restorative justice angle. Echoing past studies' findings that AI agents are characterized by dehumanizing and emotionless nature (Highhouse 2008), this study identifies that AI agents could perform as well as their human counterparts in eliciting cognitive restorative justice but are flawed when enhancing consumers' affective restorative justice. In this sense, this study enlightens the extant research stream by validating prior conceptual propositions with empirical tests.

Second, though past studies have used the justice angle to probe consumer behaviors in service recovery (e.g., Turel et al. 2008; Wetsch 2006), this study introduced restorative justice into the context of service failure and recovery. Restorative justice corresponds with the pursuit of service recovery. We introduce restorative justice supplements the conventional justice perspective and provides further details for understanding consumers' behavioral intentions. The study contextualizes restorative justice in service recovery and delineates its concept into four elements (i.e., cognitive acknowledgment, cognitive attempt, affective acknowledgment, and affective attempt). By mapping recovery components with restorative justice elements, this study introducing a brand new perspective to look through the recovery process and reveals how to implement restorative justice in this context.

Third, this study extends previous work in service recovery by jointly examining the cognitive and affective outcomes in the recovery and comparing their effects on consumer behaviors. Specifically, we employed dissatisfaction to represent the cognitive side while affective alleviation to depict the emotional side. The results revealed that both cognition and affects influence consumers' revisit intention, but the latter effect weighs more than the former. Although past studies have affirmed that a well-enacted service recovery should take care of consumers' cognitive loss and affective loss (Miller et al. 2000), few have examined them jointly or compared their effect size. The findings showed that although both cognition and consumers' affect matter in a single service encounter, a pleasant experience might result in a greater possibility of customer retention.

Practical Implications

This study also bears critical managerial implications. First, our finds emphasize the moderating role of AI agents in the relationship between emotional expressions in the recovery and affective restorative justice, revealing that the expression of remorse and empathy has smaller effects when they are conveyed by AI agents. Recent AI designers spend enormous efforts in endowing AI agents with emotions while contemporary consumers hardly embrace emotional AI agents. In service recovery, instead of diagnosing the emotions by these artificial machines with anthropomorphic behaviors, consumers tend to ignore these and consider the compensation as it stands. On the contrary, the effects of explanations and compensation on cognitive restorative justice have no difference between human agents and AI agents. Based on these findings, the service providers could reconsider the human-AI collaboration and work division in customer service. The most efficient strategy to cope with service recovery might be having AI undertake less emotion-loaded tasks while still employing human representatives to communicate with consumers to handle their emotions.

Second, our findings show that a commensurable compensation in service recovery has dominant effects on both dissatisfaction and affective alleviation than other recovery components, indicating the importance of commensurability in service recovery. However, our results also reveal that consumers' affective alleviation weigh more than dissatisfaction when influencing revisit intention. Therefore, customer service agents should pay exceptional attention to consumers' feelings to maintain a higher level of customer retention, especially when they are confined to providing satisfactory compensations.

Limitations and Future Research

There are three caveats to this study that should be noted. First, this study employed an online experiment to validate our proposed research model, and participants were shown the experimental scenario via texts and pictures, resulting in a relatively low level of immersion. Besides, the inherent flaw of the experiment, the generalizability issue, was not fully addressed, although we have obtained acceptable ratings on the realism of the scenario. Future studies are encouraged to employ field experiment or secondary data that could reflect participants' perceptions in real situations to validate the conclusions drawn in this study.

Second, the study did not investigate the boundaries of the focal effects. However, previous studies have shown that factors, such as failure severity, play moderating roles in customer reactions in terms of service recovery. Besides, we have not examined the interplay between recovery components. Future studies are encouraged to examine the potential interaction between the agent type, recovery components and boundary conditions of service recovery effects.

Third, this study considered the service recovery performed by human or AI agents solely to magnify the effect of interest. However, the contemporary deployment of AI agent in customer service is more diversified. For example, human and AI agents cooperate to any extent to complete one task. Future studies are encouraged to examine how to optimize the efficacy of human-AI cooperation in service recovery.

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