Xingyu Wang, YooHee Hwang & Priyanko Guchait (2021) When Robot (Vs. Human) Employees Say "Sorry" Following Service Failure, International Journal of Hospitality & Tourism Administration, 24:4, 540-562, DOI: 10.1080/15256480.2021.2017812

When Robot (Vs. Human) Employees Say "Sorry" Following Service Failure

Abstract

This paper aims to understand travelers' responses to apologies of robot (vs. human) employees following service failures and how travelers' age influences their responses. Using a scenario- based between-subject experimental design, Study 1 finds that human employees' apologies (vs. no apologies) enhance travelers' revisit intention while robot employees' apologies do not have such an effect. Study 2 reveals that human employees' apologies increase satisfaction among younger travelers, whereas robot employees' apologies increase satisfaction among older travelers. Managers in the hospitality and tourism industry may train their employees (vs. design robot employees' apology messages) effectively to serve travelers in different ages.

Keywords

Service robot; service recovery; apology

This work was funded by the Hong Kong Polytechnic University (Grant #: 1-BE33, BE32)

Introduction

Geraldine Calpin, the CMO of Hilton Hotels & Resorts once said, “We are in a physical business within a digital world.” The market analysis report by Grand View Research (2020) indicates that the travel, tourism, and hospitality sectors have actively engaged in the digital transformation. Particularly, ser- vice robots are projected to account for 25% of the hotel industry personnel by 2030 (Kazandzhieva & Filipova, 2019). The COVID-19 pandemic has accelerated the proliferation of robot service employees, as travelers hold a more receptive attitude toward service that does not involve human contacts (S. Kim et al., 2021). Service robots are defined as “an automated technology in a physical embodiment with adaptable interfaces that interact, communicate, and deliver services to customers” (Ho et al., p. 1). Service robots are considered a pillar of hotel innovation (Liu & Hung, 2020). For example, Hilton Hotels & Resorts developed a robot concierge (“Connie”) that is equipped with a voice recognition system to welcome guests and respond to their questions (Revfine, 2019). “Botlr,” the concierge robot of the Aloft hotel, provides luggage service and informs the front office of guests’ arrival through artificial intelligence system.

Despite these positive implications, robotic services are not impeccable (Fan et al., 2020). For instance, in Hennna Hotel, Japan, the first hotel that fully replaced human frontline employees with robots, the concierge robot struggled in responding to guests’ complicated inquiries. In addition, an in- room voice assistant robot mistook the sound of a guest’s snoring as talking and kept asking the guest what s/he needs while the guest was in sleep (The Economist,). Service failures erode customer satisfaction, brand image, and brand patronage (McCollough et al., 2000; Norvell et al., 2018). Hence, it is important to understand customer responses to service failures from robot and human employees.

Although ample research has examined customer experiences in using service robots (e.g., McLeay et al., 2021; Tung & Au, (2018); Zalama et al., (2014)), customer reactions to service recovery enacted by robot (vs. human) employees following service failures are relatively under-examined. Emerging literature has investigated traveler characteristics (e.g., self-construal and technology self-efficacy; Fan et al., 2020; technology anxiety; B. Lee & Cranage, 2018), anthropomorphism of robot employees (Choi et al., 2020, 2019; Fan et al., 2020), and customer attributions of service failure (Belanche et al., 2020; B. Lee & Cranage, 2018). However, little is known about (1) how customers' responses to apologies differ by service agent type (robot vs. human) and (2) how customer responses to apologies of robot or human employees are contingent on customer age.

To address this research gap, the present study builds on justice theory and conducts two scenario-based experiments. Study 1 examines the interaction between an apology (present vs. absent) and service agent type (human vs. robot). Study 2 investigates how age further interacts with an apology and service agent type. Age is a readily observable characteristic of travelers with which marketers segment travelers, and older and younger travelers have different psychological and material demands in service encounters (e.g., Varela-Neira et al., 2010). To that end, the present study adds to the emerging literature in traveler responses to service recovery enacted by robot and human employees (Figure 1).

The current study makes important contributions to the hospitality and tourism literature. First, this study advances our understanding of customer experiences with service robots by comparing their attitudinal and behavioral reactions to apologies made by either human or robot employees following service failures. Advancing knowledge on this aspect is important because little research has compared human with robot employees. Emerging research has examined attributions of service failure, speed and type of service recovery by robot employees. However, the extent to which such findings are different when it comes to human employees is under-examined. Given the growth of augmented intelligence (co-existence of human and robot employees; Longoni & Cian, 2020), a direct comparison between robot and human employees helps managers in the hospitality and tourism industries know how to devise apology messages of robot employees (vs. train human employees in delivering apologies) effectively. Hence, our findings may provide important insights into how human and robotic service agents can better work in synergy to achieve the optimal service recovery. Second, this study extends previous studies on customers' reactions to service recovery by demonstrating customer age as an important demographic variable that influences reactions to apologies. Based on our findings, hospitality managers may need to take their customer age into consideration when designing apology messages of robot and human employees.

Literature Review and Hypothesis Development

Customer-Employee (Human or Robot) Interactions

Given the high-contact nature of hospitality services, considerable research has focused on customer-employee interactions (Kandampully et al., 2018). Key factors that influence customer interactions with human employees include services cape (Kaminakis et al., 2019), eye contact and courtesy (Kim & Baker, 2019), and handling of service failure (Kandampully et al., 2018). With the emergence of service robots, recent literature has examined customer-robot employee interactions (M. I. N. W. O. O. Lee & Baker, 2017). A few distinct elements related to the technology have been found to influence customer outcomes. For example, customers' technology anxiety influences their attitudes toward service robots (Meuter et al., 2003). Technical error in service delivery results in customer dissatisfaction (Zhu et al., 2013). Service robot design interface and esthetics influence customers' experience with robots (Mende et al., 2019; Shin & Jeong, 2020). Customers feel responsible for negative outcomes when perceiving high ownership of the service robots (Jörling et al., 2019).

Apology as Service Recovery

Owing to the heterogeneity of services, service failure is prevalent in the hospitality industry (Basso & Pizzutti, (2016)), and it is detrimental to firm performance (e.g., market share; Norvell et al., 2018). As such, service providers enact service recovery to restore traveler satisfaction and trust. Service failure can result from robot and human employees (Choi, Mattila, et al., (2021); Fan et al., 2020). The suboptimal performance of service robots, including machine malfunction and incorrect use by travelers, is common across hotels and restaurants (Molloy, 2016). For Fan et al. (2016), (2020)) examined service failure in airport self-service check-in where machines fail to locate travelers' booking information.

Drawing on justice theory, previous research demonstrated that travelers pursue justice/fairness in transactions/interactions with service providers (T. Kim et al., (2009, Roschk et al., 2013). Service failure undermines traveler perceptions of justice during transaction, and thus service providers initiate service recovery to restore justice perceptions. Previous research holds that service recovery comprises three dimensions of justice perceptions: distributive, procedural, and interactional justice (T. Kim et al., 2009). Three attributes of service recovery correspond with these dimensions of justice: monetary compensation (distributive justice), speed of response (procedural justice), and apology (interactional justice) (Roschk et al., 2013; Wirtz & Mattila, 2004). Interactional justice is ensured when consumers are treated with respect and dignity (Martin et al., 2018). Unlike monetary compensation and speed of response, a service employee's apology shows respect and care, thereby leading to interactional justice (Wirtz & Mattila, 2004).

An apology is a reparative behavior to sustain a relationship with the victimized party following a negative incident (Leary, 2010). An apology indicates an awareness that s/he has transgressed social norms or organizational standards (e.g., "I understand that check-in took a little longer than you may have expected.”). An apology implies an apologizer’s acknowledgment that s/he is responsible for the undesirable event that occurred and it constitutes an expression of remorse (Fehr & Gelfand, 2010). Converging evidence demonstrates that travelers exhibit higher levels of encounter satisfaction and revisit/word-of-mouth intention in the presence (vs. absence) of a service provider’s apology (T. Kim et al., 2009). Ha and Jang (2009) showed that a sincere apology (vs. no apology) is positively related to interactional justice and revisit/word-of-mouth intention. Similarly, Waldron and Kelley (2005) reveal that admitting and apologizing for wrongdoings enhances a sense of intimacy between employees and travelers after service failure.

Apology of Human Vs. Robot Employees

The golden rule among hospitality practitioners is to apologize to travelers immediately after service failure, even if the service failure results from factors out of the service provider’s control (e.g., Roschk & Kaiser, 2013). However, this golden rule assumes that apologies are from human employees. The present study postulates that robot (vs. human) employees might entail different expectations for service recovery from travelers. That is, the effective- ness of apology in generating favorable responses from customers may depend on service agent type: human vs. robot employees. An apology reflects an individual’s empathy, and empathy is a prosocial emotion that entails perspective-taking (Fehr & Gelfand, 2010; Roschk & Kaiser, 2013; Zaki, 2014). An apology results from one’s concern for others’ wellbeing, and thus a service provider’s apology reflects their care and concern for travelers who may have negative feelings because of service failure. Roschk and Kaiser (2013) suggest three elements of apology: timing, empathy, and intensity. They find that among the three elements, empathy exerts the strongest effect on traveler satisfaction.

Unlike humans, robots are not perceived as having emotions; thus, apologies from robot (vs. human) employees might not sound authentic. The victimized party responds more favorably to a sincere (vs. insincere) apology, leading to forgiveness and reconciliation (Toney & Hayes, 2017). The sincerity of apology is a function of how personalized the apology is. Emerging evidence shows that employees perceive the apologies of their supervisors as sincerer when such apologies are personalized (vs. not personalized) (Basford, 2013). Meanwhile, Fan et al. (2016) showed that travelers' willingness to use the machine again depends on voice type (anthropomorphic vs. robotic) for apology message, the presence of other travelers waiting, and the focal traveler's sense of power. Robotic (vs. anthropomorphic) voice may sound mechanical and impersonal.

This study contends that robots' scripted and programmed attributes undermine travelers' perceptions of personalization. Robots are often associated with generalization and standardization (Mechanical intelligence; Huang et al., 2020). Robots' apologies may sound mechanical or artificial (Fan et al., 2016), and consequently, we predict that robots' apologies unlikely increase revisit intention of travelers. Supporting this notion, Engelhardt et al. (2017) showed that people perceive robots' apologies as unappealing and not intelligent. Conversely, human employees' apologies are perceived to be more specific, spontaneous, warm, empathetic, and personalized. Consequently, we predict that travelers exhibit greater revisit intention when human employees make apologies (vs. no apologies) following service failure. Ultimately, the following hypotheses are proposed.

Hypothesis 1 [H1]. An interaction exists between apology and service agent type on revisit intention. Specifically,

Hypothesis 1a [H1a]. Revisit intention is higher in the presence (vs. absence) of a human service agent's apology.

Hypothesis 1b [H1b]. Revisit intention is not different regardless of the absence/presence of a robot service agent's apology.

Moderating Effect of Travelers' Age

Age is a readily observable attribute with which marketers segment travelers (Bravo et al., 2008). Emerging evidence demonstrates the importance of age in individuals' experiences of using service robots across healthcare, education, and commercial settings (Barnard et al., 2013; Cha, 2020; Ivanov et al., 2018). This stream of literature showed that age negatively influences attitudes toward technology devices. Cha (2020) demonstrated the moderating effect of customer age in the effect of customer innovativeness on attitude toward service robots. Customer age has also been discussed in the service failure and recovery context. Varela-Neira et al. (2010) revealed that younger customers exhibit negative emotions toward both procedural and outcome failures, whereas older customers are more attentive to procedural failures than outcome failures. Nevertheless, how customer age shapes their responses to human (vs. robot) employees' apologies as service recovery remains relatively unknown.

Compared with the younger generation, the older generation is generally less familiar with technology and less proactive in utilizing technology (Barnard et al., 2013). Older customers tend to be more anxious about interacting with robots and hesitant to use technology (Heerink, (2011)). Senior citizens showed unwillingness to converse with robot nurses (Song et al., 2016). Such unfamiliarity and hesitance likely lead elderly travelers to expect service robots to be proactive in communicating and interacting with them (Nomura et al., 2009). Thus, ensuring interactive justice through the apologies of robot employees may enhance encounter satisfaction among older travelers. Conversely, when it comes to human employees' apologies, older travelers are not as attentive, as they generally exhibit high levels of forgiveness in interpersonal interactions. Forgiveness is found to be positively related to age as it is continually learned and acquired with time (Ashy et al., 2010). Ashy et al. (2010) showed that age is positively associated with tendency to forgive, tolerate, and reconcile. Thus, older travelers may tolerate the absence of apologies of human employees, thereby exhibiting similar levels of encounter satisfaction, regardless of the absence or presence of human employees' apologies.

Meanwhile, younger travelers are not as likely to have high expectations for robots' interactivity (Nomura et al., 2009). Younger travelers are comfortable with and fluent in interacting with service robots (Barnard et al., 2013) and expect robotic services to be interesting and memorable (Ivanov et al., 2018). Such positive attitudes, comfort, and fluency in service robots thus likely mitigate the ill effects of the absence (vs. presence) of robots' apologies following service failure. We thus predict that encounter satisfaction of younger travelers do not differ regardless of the absence or presence of robots' apologies. However, younger travelers perceive employees' effort for service recovery as important (Mittal et al., 2001). As greater concern and care are needed for human employees' apologies, we predict that encounter satisfaction is enhanced in the presence (vs. absence) of human employees' apologies among younger travelers. The following hypotheses are proposed:

Hypothesis 2 [H2]. An interaction exists among apology, service agent type, and traveler age on encounter satisfaction. Specifically,

Hypothesis 2a [H2a]. For younger travelers, encounter satisfaction is higher when an apology (vs. no apology) is from a human service agent, whereas such a difference in encounter satisfaction is not observed with a robot service agent.

Hypothesis 2b [H2b]. For older travelers, encounter satisfaction is higher when an apology (vs. no apology) is from a robot service agent, whereas such a difference in encounter satisfaction is not observed with a human service agent.

[Insert Figure 1 here]

Method

Study 1

Design and Procedure

The purpose of Study 1 was to test H1. A 2 (apology: absent vs. present) by 2 (service agent: human vs. non-humanoid robot) between-subjects experimental design was used. A group of hospitality researchers in universities was invited to evaluate the clarity of our survey scenarios and questions. Slight changes in wording were made. Then, the participants (n = 193) were recruited via Amazon Mechanical Turk (MTurk) in 2020 and they are US residents 18 years or older. Ample evidence suggests that the data from MTurk are generally reliable (Aguinis et al., 2021; Baker & Kim, 2019). This study followed Aguinis et al. (2021) guidelines to ensure data quality. Specifically, for Studies 1 and 2, the following criteria were used to screen out participants: (1) an approval rating equal to or higher than 98%, (2) 500 or more submissions of other tasks on MTurk, and (3) previous experience of staying at least one night at a hotel in the past year.

Participants were randomly assigned to one of the four experimental conditions and asked to imagine themselves in a hypothetical hotel check-in experience. Hotel descriptions were adapted from Bolton and Mattila (2015), and the service failure/recovery scenario was adopted from Madera et al. (2020) (Appendix A). Either a robot or human agent's picture was used (e.g., Fan et al., 2020). In the scenario, upon scanning a traveler's (participant's) identification card, the service agent indicated that they were unable to locate the traveler's reservation. Our manipulation of the apology followed Scher and Darley (1997). Specifically, in the apology condition, the service agent said, "I am sorry that I am not able to find your room reservation. Let me see what I can do to solve this problem. Please key in the reservation information for the room check-in." In the no-apology condition, the service agent said, "I am not able to find your room reservation. Please key in the reservation information for the room check-in." The traveler was then asked to provide further information, such as type of the reserved room, check-in/check-out dates, and payment method. Eventually, the service agent was able to locate the traveler's reservation, issuing room keys. In the apology condition, the agent concluded the conversation by saying "I understand that check-in took a little longer than you may have expected. I promise something like this will not happen again." In contrast, in the no-apology condition, the agent did not say anything else, instead simply ending the check-in procedure.

After reading the scenario, participants indicated their intention to revisit the hotel (e.g., "I have a strong intention to visit this hotel again"; two items; $r = 0.82$, $p < .01$; T (. Kim et al., 2009). Manipulation of service agent type was assessed with one item ("In the scenario, I think the service was delivered by 1 = a robot, 7 = a human."). Similarly, manipulation of apology was assessed with one item ("In the scenario, I think the service agent apologized for the failed service."). Scenario realism was measured with two items (e.g., "I think the scenario was realistic"; $r = 0.65$, $p < .01$). We measured all items on a seven- point scale (1 = strongly disagree, 7 = strongly agree) except the question assessing manipulation of service agent type. At the end of survey, demo- graphic questions were asked.

Results

On average, participants were 37 years (standard deviation [SD] = 9.01), 65% of them were male, 48% had a college degree, and 35% had 1–3 night(s) of hotel stay in the past year. They perceived our scenarios as realistic (mean [M] = 5.70, standard deviation [SD] = 1.21). We ran a two-way ANOVA on realism and found that realism did not differ across all experimental conditions (all *p*s > 0.1). A two-way ANOVA was run to check manipulation of service agent type. Only the main effect of service agent type was significant (F (1, 189) = 333.40, p < .01, η_p^2 = 0.64; M_{human} = 6.15, M_{robot} = 1.74). The main effect of apology (F (1, 189) = 0.31, p > .1, η_p^2 = 0.00) and the interaction (F (1, 189) = 0.02, p > .1, η_p^2 = 0.00) were not significant. Similarly, a two-way ANOVA was run to check manipulation of apology. Only the main effect of apology was significant (F (1, 189) = 117.19, p < .01, η_p^2 = 0.38; $M_{apology}$ = 5.67, $M_{no\ apology}$ = 2.70). The main effect of agent type (F (1, 189) = 0.54, p > .1, η_p^2 = 0.00) and the interaction (F (1, 189) = 0.49, p > .1, η_p^2 = 0.00) were not significant. In sum, our manipulations were deemed effective.

To test H1, a two-way ANOVA on revisit intention was run. As a result, the main effect of agent type was not significant (F (1, 189) = 0.25, p> .1, η_p^2 = 0.00). The main effect of apology was significant (F (1, 189) = 15.03, p < .01, η_p^2 = 0.07). However, this main effect was qualified by the interaction between apology and agent type (F (1, 189) = 4.37, p < .05, η_p^2 = 0.02). To better understand this interaction, an analysis of simple effects was conducted (Figure 2). When a service agent was human, revisit intention was statistically higher with apology (vs. no apology) ($M_{apology}$ = 5.02, standard error $[SE]_{apology}$ = 0.27, $M_{no\ apology}$ = 3.65, $SE_{no\ apology}$ = 0.27, F (1, 189) = 12.82, p < .01, Cohen's d = 0.72), in line with H1a. When a service agent was a robot, revisit intention was not statistically different across apology (vs. no apology) conditions ($M_{apology}$ = 4.42, $SE_{apology}$ = 0.18, $M_{no\ apology}$ = 4.02, $SE_{no\ apology}$ = 0.18, F (1, 189) = 2.61, p > .1, Cohen's d = 0.32), in line with H1b. In sum, our ANOVA and simple effects results are congruent with H1.

[Insert Figure 2 around here]

Posttest

Study 1 shows that apologies of human (vs. robot) employee enhances revisit intention. In literature review, we speculate that robot (vs. human) apologies may not sound authentic and sincere because robots do not have human emotions that include empathy

(Engelhardt et al., 2017; Roschk & Kaiser, 2013). The purpose of posttest is to show differences in consumer perceptions of authenticity and empathic characteristics of human vs. robot employees.

Participants (n = 242) were recruited via MTurk and randomly assigned to either robot or human employee conditions using the same scenario as Study 1. The same prescreening criteria were used as Study 1. An item to check for manipulation of service agent type and two items for scenario realism were the same as Study 1. Authenticity of employee was measured with two items from Grandey et al. (2005) ("The front desk employee seemed to be faking how she/ he felt in this interaction," and "The front desk employee seemed to be pretending, or putting on an act, in this interaction"; 1 = strongly disagree, 7 = strongly agree; $r = 0.79$, $p < .01$). Empathic characteristics of employee were measured with three items from De Kervenoael et al. (2020) ("A front desk employee understands travelers' needs," "A front desk employee gives travelers an individual attention," and "A front desk employee is available whenever it's convenient for travelers."; 1 = strongly disagree, 7 = strongly agree; $\alpha = 0.78$).

Overall, participants perceived our scenario as realistic (M = 5.72) and found it easy to project themselves in the scenario (M = 5.94). Such mean ratings did not differ between robot and human employee conditions (all *p*s > 0.1). Also, our service agent manipulation was deemed effective ($M_{human} = 6.44$, $M_{robot} = 1.50$; t (240) = 27.01, $p < .01$). An independent samples t-test showed that participants perceived human (vs. robot) employees as more authentic ($M_{human} = 3.65$, $M_{robot} = 3.18$; t (240) = 1.94, $p = .05$) and empathetic ($M_{human} = 5.26$, $M_{robot} = 4.82$; t (240) = 2.54, $p < .05$).

Discussion

Study 1 and its posttest show that apologies of human (vs. robot) employees drive positive outcomes because of such employees' authenticity and empathic characteristics. To gain more insights on travelers' reactions to apologies from different types of service agents, study 2 further categorizes service robots into humanoid and non-humanoid robots as both types of robots are prevalent in service encounters (Choi et al., 2020; Fan et al., 2020). Therefore, we included two types of robots in study 2 to address the inconsistent previous findings and strengthen practical implications (Fan et al., 2016, 2020). Humanoid robots are robots that are anthropomorphized to mimic a human face with eyes and a smile (Fan et al., 2020). Thus, study 2 examines whether travelers' reactions to apologies from robots will be variant based on three different types of service agents and traveler age.

Study 2

Design and Procedure

The purpose of Study 2 was to test H2. A 2 (apology: absent vs. present) by 3 (agent type: human vs. humanoid robot vs. non-humanoid robot) by 2 (traveler age) between-subjects quasi-experimental design was adopted. Apology and agent type were manipulated as in Study 1, while age was measured. Our participants ($n = 235$) were US residents and they were recruited in 2020 via MTurk. They were randomly assigned to one of the six experimental conditions and asked to imagine a hypothetical hotel check-in experience. The scenarios were the same as Study 1 (Appendix A). After reading the scenario, participants indicated encounter satisfaction (e.g., "I feel unhappy about this check-in experience."; three items; $\alpha = 0.89$; Fan et al., 2020). Manipulations of agent type and apology were assessed as Study 1. Scenario realism was measured with the two items as used in Study 1 ($r = 0.66$, $p < .01$). At the end of survey, demographic questions, including age, were asked.

Results

On average, participants were 36 years ($SD = 9.88$), 60% were male, 82% had a college degree, and 35% had 1–3 night(s) of hotel stay in the past year. They perceived our scenarios as realistic (M = 5.73, SD = 1.05). We ran a two-way ANOVA on realism and found that realism did not differ across all experimental conditions (all *p*s > 0.1). A two-way ANOVA was run to check manipulation of service agent type. Only the main effect of service agent type was significant (F (2, 229) = 138.78, $p < .01$; $M_{human} = 5.92$, $M_{humanoid\text{-}robot} = 2.02$, $M_{non\text{-}humanoid\text{-}robot} = 1.94$). The main effect of apology (F (1, 229) = 0.35, $p > .1$) and the interaction (F (2, 229) = 1.71, $p > .1$) were not significant. Similarly, a two-way ANOVA was run to check manipulation of apology. Only the main effect of apology was significant (F (1, 229) = 225.70, $p < .01$, $\eta_p^2 = 0.50$; $M_{apology} = 5.85$, $M_{no\ apology} = 2.79$). The main effect of agent type (F (2, 229) = 0.22, $p > .1$, $\eta_p^2 = 0.00$) and the interaction (F (2, 229) = 1.20, $p > .1$, $\eta_p^2 = 0.01$) were not significant. In sum, our manipulations were deemed effective.

To test H2, multiple linear regression models were run on encounter satisfaction via PROCESS (Model 3; Hayes, 2017). As the comparison of our interest was made between human and robot employees (humanoid and non- humanoid robots), the Helmert contrast codes were used (Hayes & Montoya, 2017). Specifically, Contrast code 1 was human (−2/3), humanoid robot (1/3), and non-humanoid robot (1/3). Contrast code 2 was used to control for differences between humanoid robot (−1/2) and non-humanoid robot employee (1/2) and, human employee was coded with 0. Our independent variable (X) was apology, the Level 1 moderator (W) was Contrast code 1, the Level 2 moderator (Z) was age (continuous scale), a control variable was Contrast code 2, and our dependent variable (Y) was satisfaction.

As a result, the three-way interaction between apology, Contrast code 1, and age was significant ($b = 0.10$, t (226) = 2.21, 95% C.I. = [0.01–0.19]; Table 1). To better understand this interaction, we conducted a floodlight analysis via Johnson-Neyman technique (Table 2; Spiller et al., 2013). For participants whose age is 23 or younger, the sign of the interaction between Contrast code 1 and apology is negative. For participants whose age is 65 or older, the sign of such an interaction is positive. To better understand different signs of such an interaction, we showcase findings based on ±1 standard deviation from the mean age. Specifically, for the group one standard deviation lower than the mean age (26 years old), when a service agent was human, satisfaction was statistically higher with apology (vs. no apology) (effect = 1.18, t (226) = 2.19, 95% C.I. = [0.12–2.25]). When a service agent was robot, such a difference in satisfaction was not statistically significant (effect = 0.00, t (226) = −0.01, 95% C.I. = [−0.72 to 0.72]), in line with H2a. For the group one standard deviation higher than the mean age (46 years old), when a service agent was robot, satisfaction was statistically higher with apology (vs. no apology) (effect = 1.18, t (226) = 2.71, 95% C.I. = [0.32–2.05]). When a service agent was human, such a difference in satisfaction was not statistically significant (effect = 0.42, t (226) = 0.95, 95% C.I. = [−0.44–1.28]), in line with H2b. In sum, our results from regression and floodlight analyses are consistent with H2.

[Insert Table 1 around here]

[Insert Table 2 around here]

Discussion and Conclusions

Theoretical Contributions

This study extends the literature on service failure and recovery in the context of human-robot hospitality services (Tuomi et al., 2021). A few recent studies have articulated traveler responses to service failure and recovery that involve robot employees (e.g., Fan et al., 2016, 2020; Leo & Huh, 2020). For instance, Leo and Huh (2020) compared traveler responses to service failures caused by either a human or robot employee and found that travelers blame the human (vs. robot) employee to a larger extent. Fan et al. (2020) examined the moderating effects of customers' technological self-efficacy and interdependent self-construal on the relationship between robot employees' service failures and customer dissatisfaction. Leo and Huh (2020) found that customers attribute less responsibility toward robot employees' service failures compared to human employees' service failures. The present study extends this line of work by shifting our focus to robot employees' service recovery (i.e., apology) following service failure.

Previous findings regarding the effectiveness of robot employees' apology are mixed (Engelhardt et al., 2017; Sebo et al., 2019). Sebo et al. (2019) found that individuals perceive robots' apology as helpful to reestablish trust following a competence-based failure. In contrast, Engelhardt et al. (2017) showed that individuals consider robots' apology unappealing. The results of the current research indicate that travelers' revisit intention is not improved with robot employees' apology. This is aligned with previous literature conceptualizing service robots being scripted and programmed, and associated with standardization, thereby rendering robot apology mechanical and less effective (e.g., Fan et al., 2016; Huang et al., 2020; Toney & Hayes, 2017).

Although some studies showed that humans interact with robots as if robots were humans (Van Doorn et al., 2017), the present study demonstrates that when it comes to apology, travelers did not respond to robot and human employees invariantly. Thus, the present study addresses Bock et al. (2020) call for research on the downstream consequences of robots' service failures and types of service recovery that can buffer the ill effects of such service failures. Specifically, the current study documents joint effects of the presence of an apology and service agent type on travelers' satisfaction and revisit intention. We find that human apology increases travelers' revisit intention, whereas robot apology do not increase revisit intention following a service failure. Such results are in line with the resource exchange principles that apology is used to compensate for psychological loss from service failure and that apology is more effective when it comes from a human (vs. robot) given the empathic nature of apology (Roschk & Kaiser, 2013; Smith et al., 1999).

Furthermore, the current study categorizes service robots into humanoid and non-humanoid robots (Choi et al., 2020; Fan et al., 2020). Additional analyses with Contrast code 2 as a moderator and Contrast code 1 as a covariate show that the three-way interaction is not significant. That is, we do not observe differences in travelers' encounter satisfaction between non- humanoid and humanoid service robots. This finding diverges from those of Fan et al. (2016), (2020)) who demonstrated different responses of travelers to non-humanoid and humanoid robots (i.e., anthropomorphism) following a service failure. This divergence of findings might be due to different contexts, as the current study focuses on apology as service recovery, whereas Fan et al. (2016), (2020)) involved scenes of service failures.

Last, this paper contributes to the literature showcasing the importance of individuals' age in technology adoption and perception of service recovery (Cha, 2020; Ivanov et al., 2018). This stream of literature is convergent in discovering the negative relationship between traveler age and traveler attitude toward service robots. The current study extends this line of work by integrating traveler age into the framework for understanding traveler satisfaction and revisit intention upon apologies of human vs. robot employees. Specifically, Study 2 finds that human employees' apologies increase younger travelers' satisfaction, whereas robot employees' apologies enhance older travelers' satisfaction. Such findings are congruent with previous studies suggesting that given unfamiliarity and anxiety, older travelers favor service robots' proactive and amiable communications (e.g., Nomura et al., 2009). In com- parison, previous research revealed that as younger travelers skillfully use technology, they are less keen to the presence of robot apology (e.g., Barnard et al., 2013; Ivanov et al., 2018; Nomura et al., 2009). Taken together, the current research provides useful insight into apology as a service recovery strategy in the midst of technological transformation occurring in the hospitality industry.

Practical Implications

The hospitality industry has integrated service robots into service production and delivery. Service robots increasingly replace human employees, as exemplified by the robot-serviced restaurant in India, Hai Di Lao, China, the FlyZoo Hotel – Alibaba Future Hotel, HIS Hotel Holdings in Japan, to name a few (Choi et al., 2019; Kuo et al., 2017). Particularly, the adoption of service robots has been accelerated since the COVID-19 pandemic outbreak. Recent research showed that travelers hold more positive attitudes toward robot-staffed (vs. human-staffed) hotels after the COVID-19 (S. Kim et al., 2021). Not only do service robots enable social distancing and touchless service delivery, but also address the long-standing issue, such as high labor cost. Given the increasing adoption of service robots in delivering service, it is of critical importance for practitioners to understand this new service ecosystem involving customers and robot employees. Our findings allude to the importance of how apologies should be made (vs. what is said when apologizing). Although humans can use verbal and facial expressions when apologizing, robot employees lack such expressions. Therefore, apology statements from service robots should be more thoroughly designed than their human employee counterparts.

Posttest after Study 1 shows that human (vs. robot) apologies enhance satisfaction due to empathy and sincerity in human apologies. In other words, hospitality and tourism managers may need to train their employees to focus on empathy and sincerity when apologizing. Another implication is that human employees may need to supplement (vs. replace) robot employees because human (vs. robot) apology is more effective following service failure. Hospitality managers may also need to attend to travelers' individual factors in robots' service delivery. Specifically, hospitality organizations may need to find ways to understand and meet the needs of travelers of different ages to better adjust the service recovery strategies. Our results suggest that human apologies are effective in driving younger travelers' satisfaction as they are in need of greater social support than elderly travelers.

Meanwhile, robot apologies are effective in inducing older travelers' satisfaction as they have high expectations for robots' proactive communications.

Older travelers' increasing exposure to technology may change their attitudes toward robots, possibly decreasing curiosity that may alter their reactions to apologies from robot employees (Woods et al., 2007). Ultimately, hospitality managers may want to carefully assess the age range of their target traveler group. If the target travelers are generally elderly, managers need to thoroughly design robots' apology statements. Conversely, if the target travelers are relatively young, managers may need to train their human employees on delivering sincere and empathic apologies. It is also crucial for hospitality and tourism managers to attend to hotel context. Customers have different expectations based on hotel type. Personalized and high-touch services are highly expected in luxury hotels while standardized services and convenience are expected in budget hotels (Kim & Baker, 2021; Shin & Jeong, 2020). As such, human employees may be preferred to present a more authentic apology following a service failure in luxury hotels. Conversely, service robots might fit non-luxury hotels.

Limitations and Future Research Suggestions

This study has the following limitations that merit further investigations. First, we used encounter satisfaction and revisit intention as dependent variables. Future research may consider exploring other attitudinal variables (e.g., sincerity, forgiveness) and discrete emotions (e.g., anger, and frustration) that may underlie traveler responses to robot vs. human employees' apologies. This study used pictures to manipulate service agent type following previous research (e.g., Choi et al., 2020; Fan et al., 2020). In future research, video- taped vignettes could be used to operationalize the multiple dimensions of apology, such as intensity and timing (e.g., Roschk et al., 2013). Particularly, the use of human voice and motion may enhance of the degree of anthropomorphism to improve the effectiveness of robot apology, in addition to the humanoid appearance of robots. Moreover, this study involves US travelers. Thus, it might be illuminating to explore cross-cultural/cross-country differences in traveler responses to apologies by human and robot employees. In countries where technology is widely adopted, traveler expectations for robot employees' apology might differ from those of travelers in other countries where technology adoption lags. Last, building from previous research (e.g., Shin & Jeong, 2020), future research may examine whether hotel type (e.g., luxury, mid-scale, economy) alters customers' perception of apologies from human or robot employees.

References

Aguinis, H., Villamor, I., & Ramani, R. S. (2021). MTurk research: Review and recommendations. *Journal of Management*, *47*(4), 823–837. https://doi.org/10.1177/0149206320969787

Ashy, M., Mercurio, A. E., & Malley-Morrison, K. (2010). Apology, forgiveness, and reconciliation: An ecological world view framework. *Individual Differences Research*, *8*(1), 17–26. https://www.researchgate.net/profile/Majed-Ashy/publication/289151266_Apology_forgiveness_and_reconciliation_an_ecological_world_view_framework/links/5d7c233492851c87c38800d5/Apology-forgiveness-and-reconciliation-an-ecological-world-view-framework.pdfs

Baker, M. A., & Kim, K. (2019). Value destruction in exaggerated online reviews. *International Journal of Contemporary Hospitality Management*, *31*(4), 1956–1976. https://doi.org/10. 1108/IJCHM-03-2018-0247

Barnard, Y., Bradley, M. D., Hodgson, F., & Lloyd, A. D. (2013). Learning to use new technologies by older adults: Perceived difficulties, experimentation behaviour and usability. *Computers in Human Behavior*, *29*(4), 1715–1724. https://doi.org/10.1016/j.chb. 2013.02.006

Basford, T. E. (2013). Leader apologies: How content and delivery influence sincerity appraisals. *International Journal of Business and Social Science*, *4*(5), 9–26. https://doi.org/10.1007/s10551-012-1613-y

Basso, K and Pizzutti, C. (2016). Trust Recovery Following a Double Deviation. *Journal of Service Research*, *19*(2), 209–223. https://doi.org/10.1177/1094670515625455

Belanche, D., Casaló, L. V., Flavián, C., & Schepers, J. (2020). Service robot implementation: A theoretical framework and research agenda. *The Service Industries Journal*, *40*(3–4), 203–225. https://doi.org/10.1080/02642069.2019.1672666

Bock, D. E., Wolter, J. S., & Ferrell, O. C. (2020). Artificial intelligence: Disrupting what we know about services. *The Journal of Services Marketing*, *34*(3), 317–334. https://doi.org/10. 1108/JSM-01-2019-0047

Bolton, L. E., & Mattila, A. S. (2015). How does corporate social responsibility affect consumer response to service failure in buyer–seller relationships? *Journal of Retailing*, *91*(1), 140–153. https://doi.org/10.1016/j.jretai.2014.10.001

Bravo, R., Fraj, E., & Montaner, T. (2008). Family influence on young adult's brand evaluation. An empirical analysis focused on parent-children influence in three consumer packaged goods. *The International Review of Retail, Distribution and Consumer Research*, *18*(3), 255–268. https://doi.org/10.1080/09593960802113752

Cha, S. S. (2020). Customers' intention to use robot-serviced restaurants in Korea: Relationship of coolness and MCI factors. *International Journal of Contemporary Hospitality Management*, *32*(9), 2947–2968. https://doi.org/10.1108/IJCHM-01-2020-0046

Choi, S., Liu, S. Q., & Mattila, A. S. (2019). "How may I help you?" Says a robot: Examining language styles in the service encounter. *International Journal of Hospitality Management*, *82*, 32–38. https://doi.org/10.1016/j.ijhm.2019.03.026

Choi, S., Mattila, A. S., & Bolton, L. E. (2021). To err is human(-oid): How do consumers react to robot service failure and recovery? *Journal of Service Research*, *24*(3), 354–371. https://doi. org/10.1177/1094670520978798

Choi, Y., Choi, M., Oh, M., & Kim, S. (2020). Service robots in hotels: Understanding the service quality perceptions of human-robot interaction. *Journal of Hospitality Marketing & Management*, *29*(6), 613–635. https://doi.org/10.1080/19368623.2020.1703871

De Kervenoael, R., Hasan, R., Schwob, A., & Goh, E. (2020). Leveraging human-robot interaction in hospitality services: Incorporating the role of perceived value, empathy, and information sharing into visitors' intentions to use social robots. *Tourism Management, 78*, *78*, 104042. https://doi.org/10.1016/j.tourman.2019.104042

Engelhardt, S., Hansson, E., & Leite, I. (2017, August). Better faulty than sorry: Investigating social recovery strategies to minimize the impact of failure in human-robot interaction Cafaro, Angelo, Coutinho, Eduardo, Gebhard, Patrick, and Potard, Blaise. In *WCIHAI@ IVA* (pp. 19–27).

Fan, A., Wu, L. L., & Mattila, A. S. (2016). Does anthropomorphism influence customers' switching intentions in the self-service technology failure context? *Journal of Services Marketing*, *30*(7), 713–723. https://doi.org/10.1108/JSM-07-2015-0225

Fan, A., Wu, L., Miao, L., & Mattila, A. S. (2020). When does technology anthropomorphism help alleviate customer dissatisfaction after a service failure?–The moderating role of consumer technology self-efficacy and interdependent self-construal. *Journal of Hospitality Marketing & Management*, *29*(3), 269–290. https://doi.org/10.1080/19368623.2019.1639095

Fehr, R., & Gelfand, M. J. (2010). When apologies work: How matching apology components to victims' self-construals facilitates forgiveness. *Organizational Behavior and Human Decision Processes*, *113*(1), 37–50. https://doi.org/10.1016/j.obhdp.2010.04.002

Grand View Research. (2020). *Professional service robots market size, share & trends analysis report by application (logistics, healthcare, traveler service, field robots), by region, and segment forecasts, 2020 – 2027*", from https://www.grandviewresearch.com/industry-analysis/professional-service-robots-market

Grandey, A. A., Fisk, G. M., Mattila, A. S., Jansen, K. J., & Sideman, L. A. (2005). Is "service with a smile" enough? Authenticity of positive displays during service encounters. *Organizational Behavior and Human Decision Processes*, *96*(1), 38–55. https://doi.org/10.1016/j.obhdp.2004. 08.002

Ha, J., & Jang, S. (2009). Perceived justice in service recovery and behavioral intentions: The role of relationship quality. *International Journal of Hospitality Management*, *28*(3), 319–327. https://doi.org/10.1016/j.ijhm.2008.12.001

Hayes, A. F., & Montoya, A. K. (2017). A tutorial on testing, visualizing, and probing an interaction involving a multicategorical variable in linear regression analysis. *Communication Methods and Measures*, *11*(1), 1–30. https://doi.org/10.1080/19312458. 2016.1271116

Hayes, A. F. (2017). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach*. Guilford publications.

Heerink, M. (2011, March). Exploring the influence of age, gender, education and computer experience on robot acceptance by older adults. In 2011 6th ACM/IEEE International Conference on Human-Robot Interaction (HRI) (pp. 147–148). IEEE.

Huang, M., Liu, Z., & Tao, Y. (2020). Mechanical fault diagnosis and prediction in IoT based on multi-source sensing data fusion. *Simulation Modelling Practice and Theory*, *102*, 101981. https://doi.org/10.1016/j.simpat.2019.101981

Ivanov, S., Webster, C., & Garenko, A. (2018). Young Russian adults' attitudes towards the potential use of robots in hotels. *Technology in Society*, *55*, 24–32. https://doi.org/10.1016/j. techsoc.2018.06.004

Jörling, M., Böhm, R., & Paluch, S. (2019). Service robots: Drivers of perceived responsibility for service outcomes. *Journal of Service Research*, *22*(4), 404–420. https://doi.org/10.1177/ 1094670519842334

Kaminakis, K., Karantinou, K., Koritos, C., & Gounaris, S. (2019). Hospitality servicescape effects on customer-employee interactions: A multilevel study. *Tourism Management*, *72*, 130–144. https://doi.org/10.1016/j.tourman.2018.11.013

Kandampully, J., Zhang, T. C., & Jaakkola, E. (2018). Customer experience management in hospitality: A literature synthesis, new understanding and research agenda. *International*

Journal of Contemporary Hospitality Management, *30*(1), 21–56. https://doi.org/10.1108/IJCHM-10-2015-0549

Kazandzhieva, V., & Filipova, H. (2019). Customer attitudes toward robots in travel, tourism, and hospitality: A conceptual framework Ivanov, S., and Webster, C. In *Robots, artificial intelligence, and service automation in travel, tourism and hospitality*. Emerald Publishing Limited. pp. 79-92 https://doi.org/10.1108/978-1-78756-687-320191004

Kim, K., & Baker, M. A. (2021). Luxury branding in the hospitality industry: The impact of employee's luxury appearance and elitism attitude. *Cornell Hospitality Quarterly*, https://doi.org/10.1177/19389655211022660 .

Kim, K., & Baker, M. A. (2019). How the employee looks and looks at you: Building customer– employee rapport. *Journal of Hospitality & Tourism Research*, *43*(1), 20–40. https://doi.org/ 10.1177/1096348017731130

Kim, S., Kim, J., Badu-Baiden, F., Giroux, M., & Choi, Y. (2021). Preference for robot service or human service in hotels? Impacts of the COVID-19 pandemic. *International Journal of Hospitality Management*, *93*, 102795. https://doi.org/10.1016/j.ijhm.2020.102795

Kim, T., Kim, W. G., & Kim, H.-B. (2009). The effects of perceived justice on recovery satisfaction, trust, word-of-mouth, and revisit intention in upscale hotels. *Tourism Management*, *30*(1), 51–62. https://doi.org/10.1016/j.tourman.2008.04.003

Kuo, C.-M., Chen, L.-C., & Tseng, C.-Y. (2017). Investigating an innovative service with hospitality robots. *International Journal of Contemporary Hospitality Management*, *29*(5), 1305–1321. https://doi.org/10.1108/IJCHM-08-2015-0414

Leary, M. R. (2010 Affiliation, acceptance, and belonging Fiske, Susan T., Gilbert, Daniel T., and Lindzey, Gardner Handbook of Social Psychology 5th 2 (John Wiley & Sons) 864–897. ISBN: 978-0-470-13749-9).

Lee, B., & Cranage, D. A. (2018). Causal attributions and overall blame of self-service technology (SST) failure: Different from service failures by employee and policy. *Journal of Hospitality Marketing & Management*, *27*(1), 61–84. https://doi.org/10.1080/19368623. 2017.1337539

Lee, M. I. N. W. O. O., & Baker, M. A. (2017 Technology, customer satisfaction and service excellence. Koc, Erdogan). . Service Failures and Recovery in Tourism and Hospitality: A Practical Manual (Oxfordshire, UK: CABI Publishing), 83–99 ISBN 13: 978 1 78639 067 7 .

Leo, X., & Huh, Y. E. (2020). Who gets the blame for service failures? Attribution of responsibility toward robot versus human service providers and service firms. *Computers in Human Behavior*, *113*, 106520. https://doi.org/10.1016/j.chb.2020.106520

Liu, C., & Hung, K. (2020 Self-service Technology Preference During Hotel Service Delivery: A Comparison of Hoteliers and Customers Information and Communication Technologies in Tourism 2020 January 08–10, 2020 Surrey, United Kingdom,). Neidhardt, Julia, and Wörndl, Wolfgang. In (pp. 267–279). Springer.

Longoni, C., & Cian, L. (2020). Artificial intelligence in utilitarian vs. hedonic contexts: The “word-of-machine” effect. *Journal of Marketing 86*(1):91–108 . https://doi.org/10.1177/ 0022242920957347

Madera, J. M., Taylor, D. C., & Barber, N. A. (2020). Customer service evaluations of employees with disabilities: The roles of perceived competence and service failure. *Cornell Hospitality Quarterly*, *61*(1), 5–18. https://doi.org/10.1177/1938965519882315

Martin, B., Strong, C., & O’Connor, P. (2018). How psychologically entitled shoppers respond to service recovery apologies. *European Journal of Marketing*, *52*(9/10), 2173–2190. https:// doi.org/10.1108/EJM-02-2017-0165

McCollough, M. A., Berry, L. L., & Yadav, M. S. (2000). An empirical investigation of customer satisfaction after service failure and recovery. *Journal of Service Research*, *3*(2), 121–137. https://doi.org/10.1177/109467050032002

McLeay, F., Osburg, V. S., Yoganathan, V., & Patterson, A. (2021). Replaced by a robot: Service implications in the age of the machine. *Journal of Service Research*, *24*(1), 104–121. https:// doi.org/10.1177/1094670520933354

Mende, M., Scott, M. L., van Doorn, J., Grewal, D., & Shanks, I. (2019). Service robots rising: How humanoid robots influence service experiences and elicit compensatory consumer responses. *Journal of Marketing Research*, *56*(4), 535–556. https://doi.org/10.1177/ 0022243718822827

Meuter, M. L., Ostrom, A. L., Bitner, M. J., & Roundtree, R. (2003). The influence of technology anxiety on consumer use and experiences with self-service technologies. *Journal of Business Research*, *56*(11), 899–906. https://doi.org/10.1016/S0148-2963(01)00276-4

Mittal, V., Katrichis, J. M., & Kumar, P. (2001). Attribute performance and customer satisfac- tion over time: Evidence from two field studies. *Journal of Services Marketing*, *15*(5), 343–356. https://doi.org/10.1108/EUM0000000005655

Molloy, M. (2016), "*Useless robot waiters fired for incompetence in China* The Telegraph ", (Retrived 15 October 2020). from https://www.telegraph.co.uk/technology/2016/04/11/use less-robot-waiters-fired%20forincompetence-in-China

Nomura, T., Kanda, T., Suzuki, T., & Kato, K. (2009). Age differences and images of robots: Social survey in Japan. *Interaction Studies*, *10*(3), 374–391. https://doi.org/10.1075/is.10.3. 05nom

Norvell, T., Kumar, P., & Dass, M. (2018). The long-term impact of service failure and recovery. *Cornell Hospitality Quarterly*, *59*(4), 376–389. https://doi.org/10.1177/ 1938965518762835

Revfine. (2019). *How artificial intelligence is changing the travel industry*, (Retrived 24 April 2020, from https://www.revfine.com/artificial-intelligence-travelindustry

Roschk, H., & Kaiser, S. (2013). The nature of an apology: An experimental study on how to apologize after a service failure. *Marketing Letters*, *24*(3), 293–309. https://doi.org/10.1007/s11002-012-9218-x

Roschk, H., Müller, J., & Gelbrich, K. (2013). Age matters: How developmental stages of adulthood affect customer reaction to complaint handling efforts. *Journal of Retailing and Consumer Services*, *20*(2), 154–164. https://doi.org/10.1016/j.jretconser.2012.11.002

Scher, S. J., & Darley, J. M. (1997). How effective are the things people say to apologize? Effects of the realization of the apology speech act. *Journal of Psycholinguistic Research*, *26*(1), 127–140. https://doi.org/10.1023/A:1025068306386

Sebo, S. S., Krishnamurthi, P., & Scassellati, B. (2019, March). “I Don’t Believe You”: Investigating the effects of robot trust violation and repair. In *2019 14th ACM/IEEE International Conference on Human-Robot Interaction (HRI)* Daegu, Korea (South), 57–65. IEEE.

Shin, H. H., & Jeong, M. (2020). Guests’ perceptions of robot concierge and their adoption intentions. *International Journal of Contemporary Hospitality Management*, *32*(8), 2613–2633. https://doi.org/10.1108/IJCHM-09-2019-0798

Smith, A. K., Bolton, R. N., & Wagner, J. (1999). A model of customer satisfaction with service encounters involving failure and recovery. *Journal of Marketing Research*, *36*(3), 356–372. https://doi.org/10.1177/002224379903600305

song, A., Wu, C., Ni, D., Li, H., & Qin, H. (2016). One-therapist to three-patient telerehabilitation robot system for the upper limb after stroke. *International Journal of Social Robotics*, *8* (2), 319–329. https://doi.org/10.1007/s12369-016-0343-1

Spiller, S. A., Fitzsimons, G. J., Lynch, J. G., Jr, & McClelland, G. H. (2013). Spotlights, floodlights, and the magic number zero: Simple effects tests in moderated regression. *Journal of Marketing Research*, *50*(2), 277–288. https://doi.org/10.1509/jmr.12.0420

Toney, D. E., & Hayes, L. J. (2017). A behavioral analysis of apologies, forgiveness, and interpersonal conflict. *Behavior and Social Issues*, *26*(1), 128–155. https://doi.org/10.5210/bsi.v26i0.7425

Tung, V Wing and Au, N. (2018). Exploring customer experiences with robotics in hospitality. *IJCHM*, *30*(7), 2680–2697. https://doi.org/10.1108/IJCHM-06-2017-0322

Tuomi, A., Tussyadiah, I. P., & Stienmetz, J. (2021). Applications and implications of service robots in hospitality. *Cornell Hospitality Quarterly*, *62*(2), 232–247. https://doi.org/10.1177/1938965520923961

Van Doorn, J., Mende, M., Noble, S. M., Hulland, J., Ostrom, A. L., Grewal, D., & Petersen, J. A. (2017). Domo arigato Mr. Roboto: Emergence of automated social presence in organiza- tional frontlines and customers' service experiences. *Journal of Service Research*, *20*(1), 43–58. https://doi.org/10.1177/1094670516679272

Varela-Neira, C., Vázquez-Casielles, R., & Iglesias, V. (2010). The effects of customer age and recovery strategies in a service failure setting. *Journal of Financial Services Marketing*, *15*(1), 32–48. https://doi.org/10.1057/fsm.2010.2

W., A. Why the world's first robot hotel was a disaster. *The Economist*. May 27 2019. Retrieved15 October 2021 https://www.economist.com/gulliver/2019/03/27/why-the- worlds-first-robot-hotel-was-a-disaster

Waldron, V. R., & Kelley, D. L. (2005). Forgiving communication as a response to relational transgressions. *Journal of Social and Personal Relationships*, *22*(6), 723–742. https://doi.org/10.1177/0265407505056445

Wirtz, J., & Mattila, A. S. (2004). Consumer responses to compensation, speed of recovery and apology after a service failure. *International Journal of Service Industry Management*, *15*(2), 150–166. https://doi.org/10.1108/09564230410532484

Woods, S., Dautenhahn, K., Kaouri, C., Boekhorst, R. T., Koay, K. L., & Walters, M. L. (2007). Are robots like people?: Relationships between participant and robot personality traits in human–robot interaction studies. *Interaction Studies*, *8*(2), 281–305. https://doi.org/10. 1075/is.8.2.06woo .

Zaki, J. (2014). Empathy: A motivated account. *Psychological Bulletin*, *140*(6), 1608. https://doi. org/10.1037/a0037679

Zalama, E., García-Bermejo, J. G., Marcos, S., Domínguez, S., Feliz, R., Pinillos, R., & López, J. (2014). Sacarino, a service robot in a hotel environment. In *ROBOT2013: First Iberian robotics conference* (pp. 3–14). Springer, Cham

Zhu, Z., Nakata, C., Sivakumar, K., & Grewal, D. (2013). Fix it or leave it? Customer recovery from self-service technology failures. *Journal of Retailing*, *89*(1), 15–29. https://doi.org/10. 1016/j.jretai.2012.10.004

Table 1. Results from Study 2

	B	*SE*	*t*-value	95% CI
Constant	3.51**	1.28	2.75	[1.00, 6.02]
Apology	-0.31	0.84	-0.37	[-1.97, 1.35]
Contrast code 1	2.76	2.63	1.05	[-2.42, 7.95]
Contrast code 2	0.25	0.26	0.98	[-0.25, 0.76]
Age	-0.02	0.03	-0.69	[-0.09, 0.04]
Apology x Contrast code 1	-3.76*	1.69	-2.22	[-7.09, -0.42]
Apology x Age	0.03	0.02	1.17	[-0.02, 0.07]
Contrast code 1 x Age	-0.07	0.07	-1.03	[-0.21, 0.07]
Apology x Contrast code 1 x Age	0.10*	0.04	2.21	[0.01, 0.19]
Adjusted R^2	.10			
F (8, 226)	2.80**			

Note. CI = confidence interval, *$p < .05$. **$p < .01$.

Table 2. Conditional interaction between Contrast code 1 and apology at different ranges of age

Age	Effect	*se*	*t*	*p*	LLCI	ULCI
20.00	-1.78	0.86	-2.06	0.04	-3.48	-0.08
22.50	-1.53	0.77	-1.99	0.05	-3.05	-0.01
22.99	-1.48	0.75	-1.97	0.05	-2.97	0.00
25.00	-1.29	0.68	-1.88	0.06	-2.63	0.06
27.50	-1.04	0.60	-1.72	0.09	-2.23	0.15
30.00	-0.79	0.54	-1.47	0.14	-1.85	0.27
32.50	-0.54	0.49	-1.12	0.27	-1.50	0.42
35.00	-0.30	0.46	-0.65	0.52	-1.20	0.61
37.50	-0.05	0.46	-0.11	0.91	-0.95	0.85
40.00	0.20	0.48	0.41	0.68	-0.75	1.15
42.50	0.44	0.53	0.84	0.40	-0.60	1.49
45.00	0.69	0.60	1.16	0.25	-0.48	1.87
47.50	0.94	0.67	1.39	0.17	-0.39	2.27
50.00	1.19	0.76	1.56	0.12	-0.31	2.68
52.50	1.43	0.85	1.68	0.09	-0.25	3.11
55.00	1.68	0.95	1.77	0.08	-0.19	3.55
57.50	1.93	1.05	1.84	0.07	-0.14	3.99
60.00	2.17	1.15	1.89	0.06	-0.09	4.44
62.50	2.42	1.25	1.93	0.05	-0.05	4.89
65.00	2.67	1.36	1.96	0.05	-0.01	5.35
65.72	2.74	1.39	1.97	0.05	0.00	5.48
67.50	2.91	1.47	1.99	0.05	0.03	5.80
70.00	3.16	1.57	2.01	0.05	0.06	6.26

Note. *se* = standard error, LLCI = lower level of 95% confidence interval, ULCI = upper level of 95% confidence interval. Gray areas indicate that the two-way interaction between Contrast code 1 and apology is significant. White areas indicate that such a two-way interaction is not significant.

Figure 1a. Conceptual model for Study 1

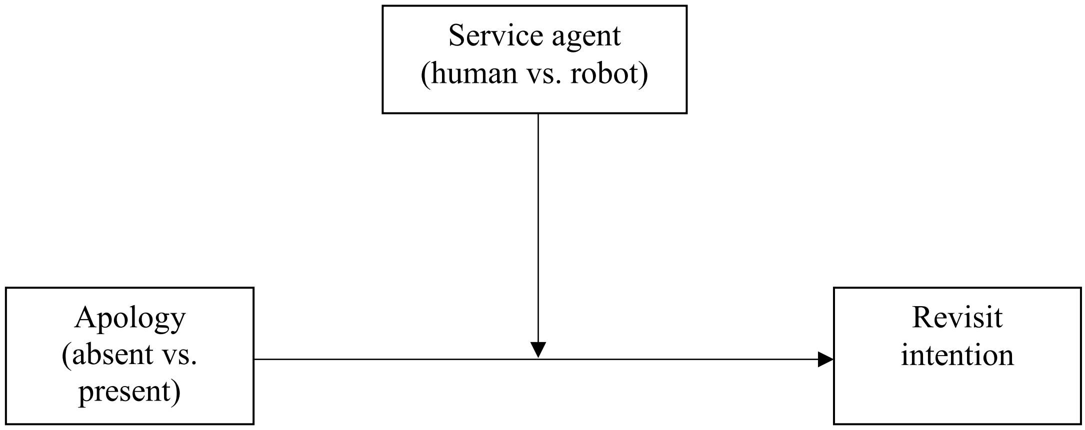


Figure 1b. Conceptual model for Study 2

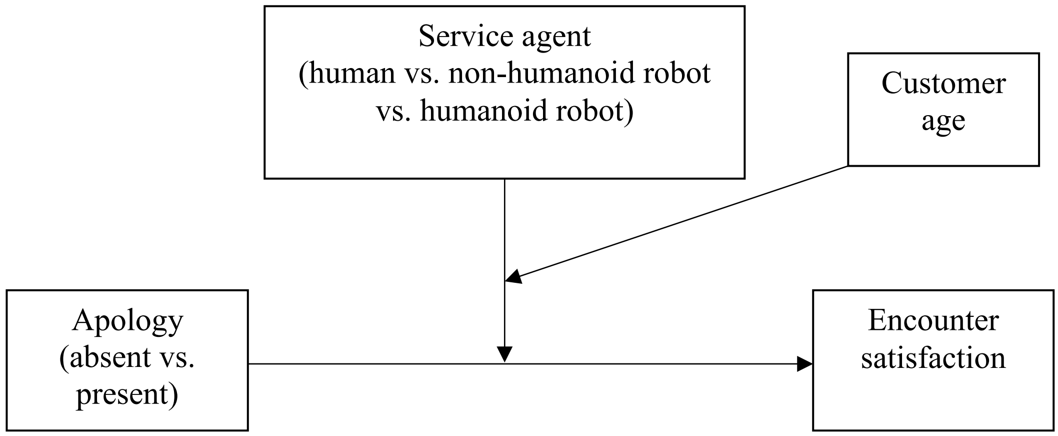
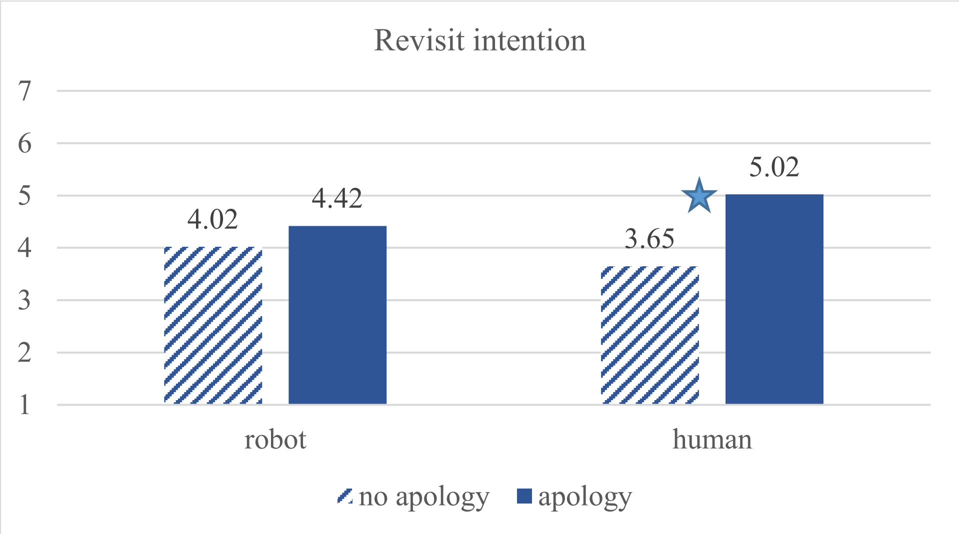


Figure 2. Interaction plot from Study 1

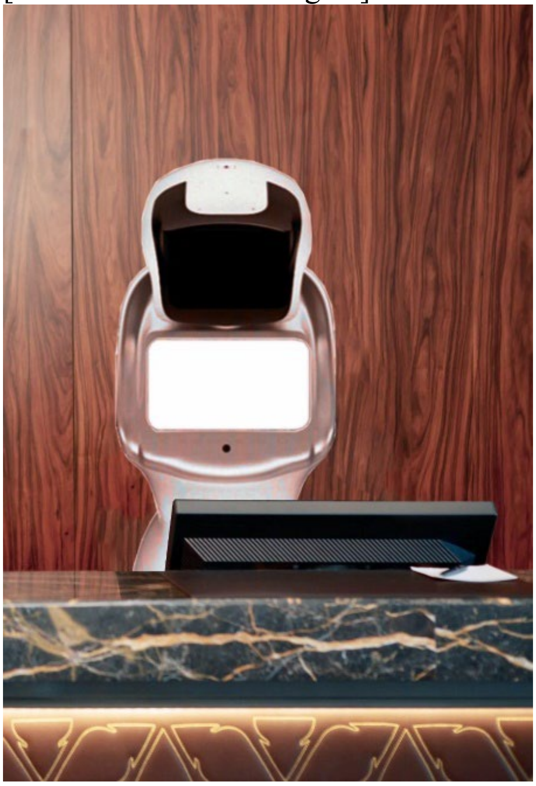


Note. The robot condition indicates non-humanoid robots. Star indicates statistical significance at the α = 0.05 level.

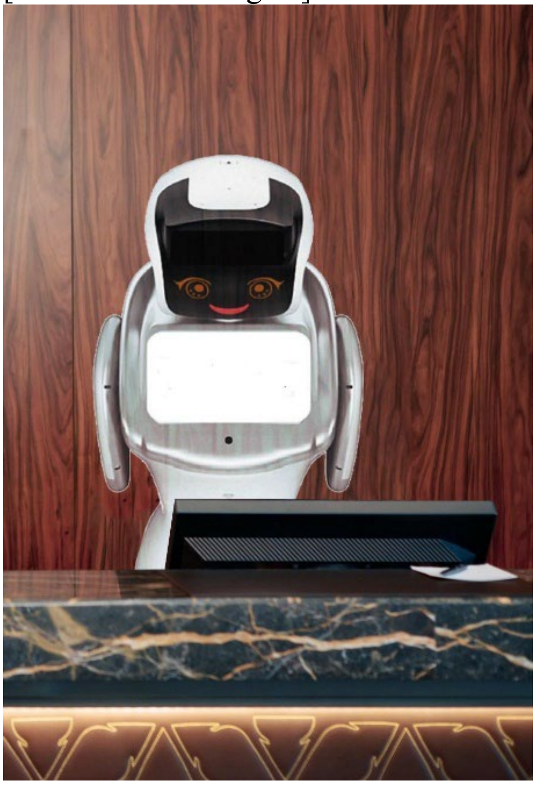
Appendix A. Experimental stimuli

Hotel XYZ is a mid-scale hotel chain with multiple locations in North America. The hotels are typically located in major cities, often near tourist attractions, business area, and downtown. The hotels feature medium-sized restaurants, fitness centers. It is Wednesday, you are on a trip in a major south-western city in the United States, and just arrive at a XYZ hotel in the evening. As you walk in, you see a service robot [receptionist] at the hotel front desk.

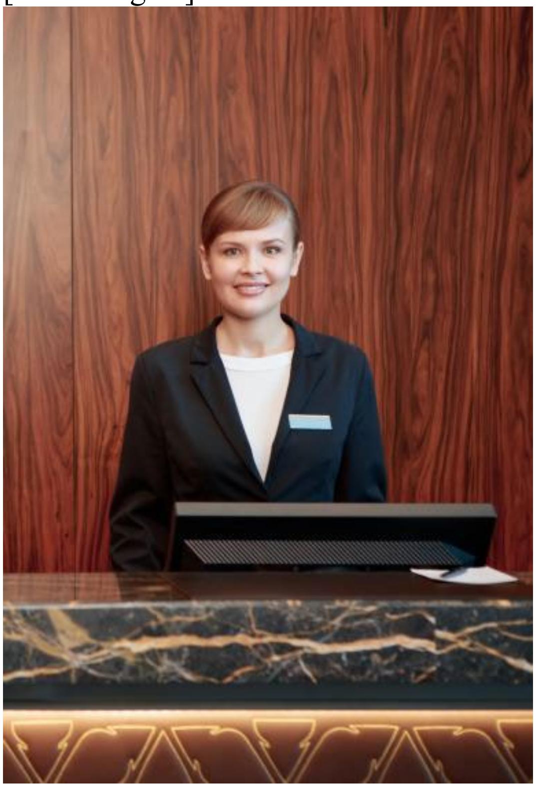
[Non-humanoid robot agent]



[Humanoid robot agent]



[Human agent]



You approach the service robot [receptionist] for check-in. The robot [receptionist] greets you and ask you to scan your ID on a self-service kiosk. Once you put your ID on the self-service kiosk, the screen on the service robot [receptionist] showed the content as follows:

[No apology]

"I am not able to find your room reservation. Please key in the reservation information for the room check-in."

You follow the service robot's [receptionist's] instructions and key in the reservation information, including your name, e-mail address, type of room, date of check-in and check-out, as well as the payment information. Then, the robot [receptionist] asks you to scan your ID. After this, the robot [receptionist] issues you the keys.

[Apology]

"I am sorry that I am not able to find your room reservation. Let me see what I can do to solve this problem. Please key in the reservation information for the room check-in."

You follow the service robot's instructions and key in the reservation information, including your name, e-mail address, type of room, date of check-in and check-out, as well as the payment information. Then, the robot asks you to scan your ID. After this, the robot issues you the keys. Meanwhile, the screen on the service robot showed the content as follows:

"I understand that check-in took a little longer than you may have expected. I promise something like this will not happen again."