

Human vs AI Service Recovery: The Role Of Empathy In Driving Customer Forgiveness

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ABSTRACT

Online complaint handling has become a critical aspect of digital service recovery as firms increasingly use artificial intelligence to manage customer communication. However, customers may evaluate AI-generated responses differently from humanized responses, particularly when service failures require empathy, sincerity, and relational repair. This study examines how response personalization and response type influence customer forgiveness in online complaint contexts and investigates whether perceived empathy mediates these relationships. A scenario-based experiment was conducted using a 2×2 between-subjects design that manipulated response personalization, consisting of humanized versus AI-generated responses, and response type, consisting of accommodative versus defensive responses. Data were collected from 342 participants and analyzed using partial least squares structural equation modeling. The results show that humanized responses generate higher perceived empathy than AI-generated responses, while accommodative responses produce higher perceived empathy than defensive responses. Perceived empathy significantly increases customer forgiveness and partially mediates the effects of response personalization and response type on forgiveness. These findings indicate that effective digital service recovery depends not only on what firms communicate but also on who is perceived to deliver the response. The study contributes to service recovery literature by demonstrating that empathy is a key psychological mechanism through which humanized and accommodative responses repair damaged customer relationships in increasingly automated service environments. The findings suggest that firms should balance the efficiency of AI-based complaint handling with the relational authenticity provided by human involvement.

KEYWORDS

Artificial intelligence
Customer forgiveness
Digital service recovery
Empathy
Service recovery

INTRODUCTION

Online complaint communication has become an increasingly important aspect of service recovery in contemporary service environments. Social media platforms and online review systems enable customers to publicly express dissatisfaction with service experiences and demand explanations or corrective action from firms (Dewayani & Loreño, 2025; Lu et al., 2025). Because such interactions

are visible to a wider audience, firms' responses to online complaints may influence not only the complaining customer but also other consumers observing the exchange. As a result, how organizations respond to online complaints has become a critical element of reputation management and relationship recovery in service industries (Einwiller & Steilen, 2015; Van Noort & Willemsen, 2012).

Prior research in service recovery highlights the importance of response strategies when firms address customer complaints. Scholars commonly distinguish between accommodative and defensive responses. Accommodative responses acknowledge the customer's concerns and often include apologies, explanations, or corrective actions aimed at resolving the problem. Defensive responses, in contrast, tend to deny responsibility or justify the firm's position. Empirical studies suggest that accommodative responses are generally perceived more favorably because they signal concern for the customer and a willingness to repair the relationship, whereas defensive responses may intensify dissatisfaction and weaken recovery efforts (Lee & Song, 2010; Min et al., 2015).

At the same time, advances in digital technologies have transformed how firms communicate with customers in service recovery contexts. Many organizations increasingly rely on artificial intelligence technologies, such as chatbots or automated customer service systems, to respond to online inquiries and complaints. These technologies allow firms to manage large volumes of interactions and provide quick responses to customers. However, AI-mediated communication may also raise concerns about impersonality, sincerity, and emotional understanding. This issue is particularly important in complaint situations because customers often expect firms to recognize their emotional distress, accept responsibility, and communicate genuine concern. In such contexts, AI-based responses may reduce perceived empathy if customers interpret them as standardized, procedural, or lacking human emotional involvement.

Although prior studies have examined complaint response strategies, service recovery justice, and online review management, less attention has been given to the perceived identity of the response source in AI-mediated service recovery. This represents an important theoretical gap. Service recovery theory explains how firms' corrective actions shape customer evaluations after service failures, while attribution theory explains how customers infer firm responsibility and motives from recovery responses. However, these perspectives have not fully explained how customers evaluate recovery attempts when the response appears to come from an artificial intelligence system rather than a human representative. In digital complaint settings, the identity of the communicator may function as a relational cue that shapes customers' judgments of sincerity, authenticity, and empathy.

Another important outcome in service recovery research is customer forgiveness. Customer forgiveness refers to customers' willingness to overcome negative emotions toward a firm following a service failure and to refrain from retaliatory behaviors. Forgiveness is considered a key relational mechanism that helps restore damaged relationships and enables continued interaction between customers and firms (Harrison-Walker, 2019). Unlike evaluative outcomes such as satisfaction or trust, which mainly capture cognitive assessments of service performance, forgiveness reflects a deeper emotional and motivational shift in which customers release resentment and become willing to reestablish relational continuity. This distinction is especially important in online complaint contexts, where unresolved dissatisfaction can escalate into public criticism and reputational damage.

Perceived empathy may explain why some complaint responses are more effective than others in restoring customer relationships. Empathy reflects customers' perception that the firm understands their feelings and acknowledges their concerns. In digital service recovery, empathy becomes especially important because online interactions often lack the interpersonal richness of

face-to-face communication. When a firm's response appears empathetic, customers may be more willing to reinterpret the service failure as a manageable incident rather than as evidence of organizational disregard. Therefore, empathy may serve as the key psychological mechanism linking response personalization and response type to customer forgiveness.

To address this gap, the present study examines how response personalization and response type influence customer forgiveness in online complaint situations. Specifically, the study compares humanized and AI-generated responses and investigates whether accommodative and defensive response strategies produce different customer reactions. In addition, the study proposes that perceived empathy mediates the relationship between complaint response strategies and customer forgiveness.

This research contributes to the literature in three ways. First, it extends service recovery research by positioning customer forgiveness as a key relational outcome in online complaint handling. Second, it contributes to emerging research on AI-mediated service communication by showing how the perceived identity of the responder shapes customers' emotional evaluations of complaint responses. Third, it advances service recovery and attribution perspectives by identifying perceived empathy as the central mechanism through which response personalization and response type influence forgiveness. These insights offer theoretical and managerial implications for firms seeking to manage online complaints effectively while balancing automation efficiency with relational authenticity.

LITERATURE REVIEW

This study is grounded in service recovery theory and attribution theory, which together explain how customers evaluate firm responses following service failures and how these evaluations shape post-failure relational outcomes. Service recovery theory emphasizes that customers evaluate not only the failure itself but also the firm's response to that failure. Appropriate responses may mitigate negative emotions, restore relational perceptions, and influence subsequent behavioral outcomes (Gelbrich & Roschk, 2011). In digital environments where complaints are publicly visible, the nature of the firm's response becomes particularly important because it signals how the organization values its customers and manages service failures.

A central element in service recovery evaluation concerns the type of response provided by the firm. Prior research distinguishes between accommodative and defensive responses. Accommodative responses acknowledge the problem, express concern, and often offer corrective actions, thereby demonstrating a willingness to resolve the issue. Defensive responses, in contrast, attempt to justify the firm's actions or deny responsibility for the problem. According to attribution theory, customers interpret these responses as signals of the firm's intentions and responsibility for the service failure (Praharjo et al., 2025; Rifqi, 2025; Weiner, 2000). When firms provide accommodative responses, customers are more likely to attribute benevolent motives to the organization, whereas defensive responses may increase perceptions that the firm is unwilling to take responsibility.

Another important dimension concerns response personalization, particularly in the context of increasing use of artificial intelligence in customer service communication. Humanized responses that include identifiable representatives may signal authenticity and emotional engagement, whereas AI-generated responses may be perceived as procedural or impersonal. Because empathy is a critical component of service recovery evaluation, the perceived source of the response may influence how customers interpret the firm's concern for their situation (Gelbrich & Roschk, 2011).

Within this framework, perceived empathy functions as an important psychological mechanism that links communication strategies to relational outcomes. When customers perceive that the firm

understands their feelings and concerns, negative emotions may be reduced, and relational repair becomes more likely. One key relational outcome of successful recovery is customer forgiveness, which reflects a willingness to move beyond negative experiences and maintain the relationship with the firm (Harrison-Walker, 2019). Consequently, both response type and response personalization may influence forgiveness through their effects on perceived empathy.

Response Personalization and Perceived Empathy

In online service recovery contexts, customers evaluate not only the content of a firm's response but also the perceived characteristics of the communicator delivering the response (Asghar Ali et al., 2021). Response personalization refers to the extent to which a firm's reply appears to originate from an identifiable human representative rather than an automated system. The perceived identity of the responder may influence how customers interpret the sincerity, authenticity, and emotional engagement conveyed in the response. These perceptions are particularly important in complaint situations, where customers often expect firms to demonstrate concern and understanding of their dissatisfaction.

Social presence theory suggests that communication channels and communicators differ in their ability to convey a sense of human warmth and interpersonal connection (Parker et al., 1978). Messages that signal the presence of a real person tend to create stronger perceptions of interpersonal involvement and emotional understanding. In service interactions, higher perceived social presence can increase customers' perceptions that the firm is attentive and responsive to their needs. When complaint responses appear to be delivered by a human representative, customers may therefore interpret the response as more sincere and relationally oriented.

Service recovery research also highlights the importance of perceived empathy in restoring damaged customer relationships after service failures (Aji et al., 2023). Empathy reflects the extent to which customers believe that the firm understands their feelings and acknowledges their concerns. Perceptions of empathy are often influenced by cues that signal attentiveness, emotional awareness, and genuine concern for the customer's experience (Gelbrich & Roschk, 2011). Humanized responses that include identifiable representatives may provide stronger relational cues and emotional signals, thereby enhancing perceptions of empathy.

In contrast, responses generated by artificial intelligence systems may be interpreted as procedural or standardized communication. Although AI-based systems can provide efficient and timely responses, customers may perceive them as lacking emotional authenticity or personal concern. Automated replies may therefore reduce the perceived sincerity of the firm's response, which can weaken perceptions that the firm genuinely understands the customer's situation. Consequently, the degree of response personalization may shape how customers evaluate the emotional quality of a firm's complaint response.

Based on these theoretical considerations, responses that appear to come from human representatives are expected to communicate stronger social presence and emotional understanding than responses generated by automated systems. This increased perception of interpersonal engagement may enhance customers' perceptions of empathy during the service recovery process.

H1: Humanized responses generate higher perceived empathy than AI-generated responses in online complaint handling.

Response Type and Perceived Empathy

In service recovery contexts, the way firms respond to customer complaints plays a crucial role in shaping customers' emotional and cognitive evaluations of the interaction. Service recovery research commonly distinguishes between accommodative responses and defensive responses when organizations address customer dissatisfaction. These response strategies signal different levels of responsibility, concern, and willingness to resolve the problem, which may influence how customers interpret the firm's intentions during the recovery process.

Accommodative responses typically acknowledge the customer's concern and express a willingness to address the problem (Zhou et al., 2025). Such responses often include elements such as apologies, explanations, or corrective actions aimed at resolving the issue and restoring the relationship. By recognizing the customer's dissatisfaction and demonstrating accountability, accommodative responses signal that the firm values the customer and takes the complaint seriously. Prior research suggests that these responses can help mitigate negative emotions and improve customer evaluations of the firm following service failures (Gelbrich & Roschk, 2011; Lee & Song, 2010).

In contrast, defensive responses attempt to justify the firm's actions or deny responsibility for the problem (Zhou et al., 2025). Defensive communication may emphasize policies, rules, or explanations that shift responsibility away from the organization. While such responses may aim to protect the firm's reputation or clarify the situation, they can also be interpreted as dismissive or insensitive to the customer's experience. When firms appear unwilling to acknowledge the customer's concerns, customers may perceive a lack of emotional understanding and relational concern (Liu-Thompkins et al., 2022).

Attribution theory provides a useful framework for explaining these responses. According to this theory, individuals interpret events by assigning responsibility and evaluating the intentions of others involved in the situation (Kelley & Michela, 1980). When firms provide accommodative responses, customers may attribute benevolent motives to the organization, interpreting the response as evidence that the firm understands and cares about the customer's experience. In contrast, defensive responses may lead customers to attribute self-protective motives to the firm, which can reduce perceptions of empathy and relational concern.

Because accommodative responses acknowledge the customer's perspective and signal a willingness to repair the relationship, they are more likely to convey emotional understanding and attentiveness to the customer's feelings. These relational cues can enhance customers' perceptions that the firm empathizes with their dissatisfaction. Therefore, accommodative responses are expected to generate stronger perceptions of empathy than defensive responses in online complaint situations.

H2: Accommodative responses generate higher perceived empathy than defensive responses in online complaint situations.

Perceived Empathy and Customer Forgiveness

Perceived empathy plays an important role in shaping customers' emotional and relational responses following service failures. In service recovery contexts, empathy refers to the extent to which customers believe that a firm understands their feelings and acknowledges their dissatisfaction (Wieseke et al., 2012). When firms demonstrate empathy during complaint handling, customers may perceive that their concerns are taken seriously and that the organization genuinely cares about their

experience. These perceptions can significantly influence how customers evaluate the firm after a service failure.

From the perspective of service recovery literature, empathetic communication can help mitigate negative emotional reactions that arise after service failures. Customers who experience dissatisfaction often develop feelings such as frustration, anger, or resentment toward the firm (Huang & Lo, 2025). Empathetic responses may help reduce these negative emotions by validating the customer's experience and demonstrating that the firm recognizes the impact of the failure. As a result, empathy may play a key role in emotional regulation during service recovery interactions (Mu et al., 2025).

Relationship repair theory also suggests that empathy is a critical mechanism for restoring damaged relationships between firms and customers (Schoofs et al., 2019). When customers perceive that the firm understands their feelings and expresses genuine concern, they may interpret the response as a signal of relational commitment. These signals can help rebuild trust and reduce the desire for retaliation following negative experiences. In this sense, empathy functions as a relational cue that encourages customers to reconsider their negative evaluations of the firm.

One important relational outcome that may emerge from empathetic service recovery is customer forgiveness. Customer forgiveness refers to the willingness of customers to move beyond negative emotions toward the firm and refrain from retaliatory behaviors after a service failure. Forgiveness enables customers to maintain the relationship despite the negative experience and may contribute to long-term relationship continuity (Wei et al., 2025). When customers perceive empathy in the firm's response, they may be more inclined to reinterpret the service failure as a resolvable incident rather than a reflection of the firm's lack of concern.

Consequently, perceived empathy may reduce customers' negative emotional responses and encourage more positive relational evaluations following a complaint interaction. By signaling emotional understanding and concern, empathetic responses may facilitate forgiveness and promote relationship repair after service failures.

H3: Perceived empathy positively influences customer forgiveness following online complaint responses.

Direct Effects of Response Strategies on Customer Forgiveness

In addition to influencing customer evaluations through perceived empathy, response strategies may also exert direct effects on customer forgiveness. Service recovery research suggests that customers often evaluate a firm's response strategy when determining whether the organization has adequately addressed a service failure (Ozuem et al., 2021). These evaluations may influence relational outcomes independently of the emotional mechanisms involved in the recovery process.

One important aspect concerns the type of response adopted by the firm. Accommodative responses, which acknowledge the customer's concern and demonstrate a willingness to resolve the issue, may directly influence customers' willingness to forgive the firm (Zhou et al., 2025). By recognizing the problem and offering corrective actions or apologies, accommodative responses may signal accountability and relational commitment. Such signals can reduce perceptions of harm associated with the service failure and encourage customers to adopt more positive evaluations of the firm. In contrast, defensive responses that deny responsibility or justify the firm's position may reinforce customers' negative perceptions and make forgiveness less likely (Gelbrich & Roschk, 2011; Lee & Song, 2010).

Response personalization may also directly influence customer forgiveness. When complaint responses appear to be delivered by a human representative, customers may perceive greater sincerity and authenticity in the communication. Humanized responses may therefore signal that the firm is genuinely engaged in resolving the issue and values the customer relationship. These relational cues may strengthen customers' willingness to forgive the firm after a negative experience. Conversely, responses perceived as automated or generated by artificial intelligence may appear less personal and may weaken perceptions of sincerity, which could reduce the likelihood of forgiveness. Taken together, these considerations suggest that response strategies may influence customer forgiveness both directly and indirectly. While perceived empathy represents an important mechanism through which communication strategies affect relational outcomes, customers may also evaluate the firm's response strategy itself when deciding whether to forgive the service failure. Consequently, response personalization and response type may exert direct effects on forgiveness in addition to their indirect effects through perceived empathy.

H4: Humanized responses positively influence customer forgiveness.

H5: Accommodative responses positively influence customer forgiveness.

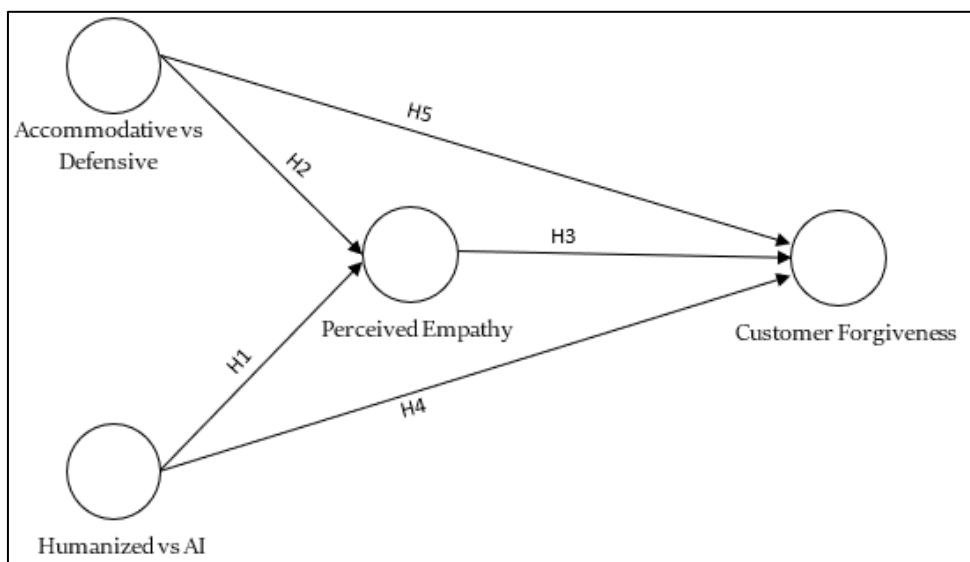


Figure 1. Research Framework

RESEARCH METHOD

This study employed a scenario-based experimental design to examine how response personalization and response type influence perceived empathy and customer forgiveness in online complaint contexts. A 2×2 between-subjects design was used, with response personalization, consisting of humanized versus AI-generated responses, and response type, consisting of accommodative versus defensive responses, as the two manipulated factors. This design produced four experimental conditions and enabled the study to isolate the effects of response source and response content in a controlled service recovery setting.

The experimental stimulus described an online complaint interaction in a hospitality context. Participants were asked to imagine that a customer booked a hotel room through an online promotion advertised on social media, but later discovered upon arrival that the promotional price

did not apply. The customer then posted a complaint under the hotel's social media post. The firm's response to the complaint was manipulated according to the assigned experimental condition. In the humanized condition, the response was presented as originating from a named customer service representative and included a personal name and job title. In the AI-generated condition, the response was presented as originating from an automated AI customer service system. For response type, the accommodative response acknowledged the issue, expressed an apology, and indicated willingness to resolve the problem, whereas the defensive response emphasized company policy and shifted responsibility away from the firm.

Before the main data collection, the scenario and response manipulations were pretested with 30 participants. The purpose of the pretest was to assess whether the scenario was clear, realistic, and appropriate for representing a typical online complaint situation. The pretest also examined whether participants could distinguish the response source and response type as intended. Feedback from the pretest indicated that the scenario was understandable and realistic. Minor wording adjustments were made to improve clarity and strengthen the plausibility of the response messages before the main experiment.

Participants in the main study were randomly assigned to one of the four experimental conditions. After reading the assigned scenario and firm response, they completed manipulation check items, followed by questionnaire items measuring perceived empathy and customer forgiveness. Manipulation checks were included immediately after the scenario to verify whether participants correctly perceived the response as humanized or AI-generated and whether the response was accommodative or defensive. Attention check questions were also included to improve data quality.

The survey was fielded online via Qualtrics from March through May 2025. Rather than drawing a probability sample, the study relied on a convenience sampling strategy, recruiting participants through online consumer panels and social media outlets. This sampling choice was justified by the study's aim of testing causal relationships within an experimental design, as opposed to generating population-level estimates. Eligibility was restricted to adults aged 18 and older who had some prior experience with brands, online reviews, or brand-related content on social media, ensuring the sample matched the study's focus.

Table 1. Measurement Scales

Construct	Item Code	Measurement Items	Source
Perceived Empathy	EMP1	The firm understands the customer's feelings.	Adapted from Lajante & Tojib (2025).
	EMP2	The firm shows genuine concern for the customer's situation.	
	EMP3	The firm acknowledges the customer's problem in a caring manner.	
Customer Forgiveness	FOR1	I would forgive this company for the problem.	Adapted from Christodoulides et al. (2023)
	FOR2	I am willing to move on from this negative experience.	
	FOR3	I would not hold this problem against the company.	
	FOR4	I would be willing to continue my relationship with this company despite the issue.	

Data collection yielded 368 responses initially. Removing incomplete submissions and those that did not pass attention checks left a final analytic sample of 342 responses, distributed fairly evenly across the study's four experimental conditions. Respondents were 53.2% women and 46.8% men, with a mean age of 31.6 years. The majority indicated regular use of social media for reading reviews and engaging with brands, supporting the sample's fit for studying digital consumer behavior in the context of online complaints.

Each construct was assessed with multi-item scales drawn from prior published research, using seven-point Likert responses (1 = strongly disagree to 7 = strongly agree). While the wording of these instruments was adjusted to suit the experimental setting, their underlying conceptual content was retained. Perceived empathy was captured through three items adapted from Lajante and Tojib (2025), reflecting participants' sense that the firm recognized and validated their emotional experience. Customer forgiveness was assessed with four items adapted from Christodoulides et al. (2023), reflecting participants' readiness to let go of the negative encounter and continue the relationship with the firm. The full set of measurement items appears in Table 1.

Hypothesized relationships were tested through partial least squares structural equation modeling (PLS-SEM) in SmartPLS. Despite using a 2×2 experimental design, the study adopted PLS-SEM because the underlying model incorporated latent constructs alongside mediation pathways. This technique permits joint evaluation of measurement properties and structural paths while correcting for measurement error, and it is well suited to testing indirect effects—here, specifically, whether perceived empathy mediates the relationship between response personalization and response type on the one hand and customer forgiveness on the other. The experimental manipulations served as predictor variables, while perceived empathy and customer forgiveness were treated as latent constructs.

Analysis proceeded in two stages. The first stage assessed the measurement model, examining indicator reliability, internal consistency, convergent validity, and discriminant validity. The second stage tested the structural model, evaluating both the hypothesized direct paths and the indirect (mediated) relationships. Path coefficients and mediation effects were tested for significance using bootstrapping with 5,000 resamples. Model explanatory and predictive power were further assessed via the coefficient of determination and measures of predictive relevance.

RESULTS

Manipulation Check

To confirm that the experimental conditions were perceived as designed, manipulation checks were carried out using two items presented directly after each scenario. One item gauged perceived personalization ("The response appears to come from a human representative"), while the other gauged perceived response type ("The response is apologetic and shows willingness to resolve the problem"). Both were rated on a seven-point scale from 1 (strongly disagree) to 7 (strongly agree).

Because each manipulation compared two distinct experimental groups, independent-samples *t*-tests were the appropriate analytic choice. The personalization check compared the humanized-response group against the AI-generated-response group, while the response-type check compared the accommodative-response group against the defensive-response group. Cohen's *d* was computed alongside each test to gauge effect magnitude.

The personalization manipulation worked as intended: participants in the humanized condition perceived substantially greater human presence ($M = 5.82$, $SD = 0.89$) than those in the AI-generated condition ($M = 2.41$, $SD = 1.02$), $t = 31.47$, $p < .001$, with a very large effect size ($d = 3.56$)

indicating a clear perceptual distinction between the two response types. The response-type manipulation was similarly effective. Participants exposed to the accommodative response rated it as more apologetic and resolution-focused ($M = 5.96$, $SD = 0.84$) than those exposed to the defensive response ($M = 2.87$, $SD = 1.10$), $t = 29.63$, $p < .001$, again with a very large effect size ($d = 3.18$) reflecting a strong perceived contrast between the two conditions.

Together, these results demonstrate that both manipulations were perceived by participants as intended. The large effect sizes indicate clear differentiation across scenario conditions, lending support to the internal validity of the experimental design. With the manipulation checks confirmed, the analysis moved on to evaluating the measurement and structural models.

Table 2. Manipulation Check Results

Manipulation Check	Condition	Mean	SD	t value	p value	Cohen's d
Perceived human presence	Humanized response	5.82	0.89	31.47	< .001	3.56
	AI-generated response	2.41	1.02			
Perceived accommodative tone	Accommodative response	5.96	0.84	29.63	< .001	3.18
	Defensive response	2.87	1.10			

Measurement Model Assessment

Before testing relationships among the study's constructs, the measurement model was assessed to confirm that the latent variables demonstrated sufficient reliability and validity. In line with recommended practice for PLS-SEM (Hair et al., 2021), this evaluation covered indicator reliability, internal consistency reliability, convergent validity, and discriminant validity.

Indicator reliability was examined via the outer loadings linking each item to its respective construct, with loadings at or above 0.70 signaling that an indicator accounts for a meaningful share of the construct's variance. All items in the study met this benchmark, with loadings falling between 0.80 and 0.91, confirming satisfactory indicator reliability.

Table 3. Measurement Model Results

Construct	Item	Loading	Cronbach's Alpha	CR	AVE
Perceived Empathy	EMP1	0.84	0.86	0.91	0.76
	EMP2	0.89			
	EMP3	0.87			
Customer Forgiveness	FOR1	0.88	0.89	0.92	0.74
	FOR2	0.91			
	FOR3	0.80			
	FOR4	0.86			

Internal consistency was gauged using Cronbach's alpha and composite reliability (CR), both of which surpassed the 0.70 benchmark across constructs—evidence that items within each construct reliably tap the same underlying concept.

Convergent validity was evaluated through Average Variance Extracted (AVE), where values exceeding 0.50 indicate that a construct accounts for more than half the variance in its indicators. As reported in Table 3, every construct exceeded this threshold, supporting adequate convergent validity.

Discriminant validity was tested using the Fornell–Larcker criterion, which requires comparing each construct's square root of AVE against its correlations with other constructs; validity is supported when this square root exceeds the corresponding inter-construct correlations.

Table 4 shows that the diagonal values (square roots of AVE) consistently exceed the off-diagonal inter-construct correlations, confirming that each construct is empirically distinct from the others and that the measurement model achieves satisfactory discriminant validity.

Table 4. Discriminant Validity (Fornell–Larcker Criterion)

Construct	Perceived Empathy	Customer Forgiveness
Perceived Empathy	0.87	
Customer Forgiveness	0.63	0.86

Note: Diagonal elements represent the square root of AVE.

Prior to examining the structural paths among constructs, collinearity diagnostics were performed to rule out problematic multicollinearity among the predictor variables. High collinearity between predictors can inflate standard errors and bias path coefficient estimates within structural equation modeling, making it essential to verify that the independent variables retain sufficient distinctiveness when predicting endogenous constructs.

Multicollinearity was evaluated through variance inflation factor (VIF) values for each predictor in the structural model. Conventional guidelines treat VIF values under 5.0 as indicating no serious collinearity concern, though more stringent benchmarks recommend values ideally under 3.3 (Hair et al., 2021).

Table 5. Collinearity Assessment (VIF Values)

Endogenous Construct	Predictor	VIF
Perceived Empathy	Response Personalization	1.42
	Response Type	1.47
Customer Forgiveness	Response Personalization	1.36
	Response Type	1.55
	Perceived Empathy	1.49

The results indicate that all VIF values fall well below the recommended threshold, suggesting that collinearity among the predictor constructs is not problematic. Specifically, the VIF values for the predictors of perceived empathy range from 1.42 to 1.47, while the predictors of customer forgiveness exhibit VIF values ranging from 1.36 to 1.55. These values indicate that the independent variables do not exhibit excessive overlap in explaining the endogenous constructs.

Hypothesis Testing

After confirming the adequacy of the measurement model and the absence of problematic multicollinearity, the structural model was evaluated to test the proposed hypotheses. The hypothesized relationships were assessed using bootstrapping with 5,000 resamples in SmartPLS. This procedure provides robust estimates of path coefficients and allows the significance of direct and indirect effects to be examined.

Table 6. Structural Model Results

Hypothesis	Path	β	t	p	Result
H1	Response Personalization $\rightarrow$ Perceived Empathy	0.38	7.24	< .001	Supported
H2	Response Type $\rightarrow$ Perceived Empathy	0.41	8.16	< .001	Supported
H3	Perceived Empathy $\rightarrow$ Customer Forgiveness	0.52	11.37	< .001	Supported
H4	Response Personalization $\rightarrow$ Customer Forgiveness	0.17	3.28	.001	Supported
H5	Response Type $\rightarrow$ Customer Forgiveness	0.21	4.02	< .001	Supported

The results show that response personalization has a positive and significant effect on perceived empathy ($\beta = 0.38$, $t = 7.24$, $p < .001$), supporting H1. This indicates that humanized responses generate stronger perceptions of empathy than AI-generated responses. The magnitude of the effect suggests that the perceived identity of the responder is an important relational cue in online complaint handling.

Response type also has a positive and significant effect on perceived empathy ($\beta = 0.41$, $t = 8.16$, $p < .001$), supporting H2. The coefficient is slightly larger than the effect of response personalization, indicating that the content and tone of the response are marginally more influential than responder identity in shaping perceived empathy. This suggests that customers are especially sensitive to whether the firm acknowledges the problem, apologizes, and expresses willingness to resolve the issue.

Perceived empathy has the strongest effect on customer forgiveness ($\beta = 0.52$, $t = 11.37$, $p < .001$), supporting H3. This result indicates that customers are more likely to forgive a firm when they perceive that the firm understands their feelings and responds with genuine concern. Among all predictors in the model, perceived empathy has the largest coefficient, highlighting its central role as the main relational mechanism through which digital service recovery responses influence forgiveness.

The direct effect of response personalization on customer forgiveness is positive and significant ($\beta = 0.17$, $t = 3.28$, $p = .001$), supporting H4. However, this effect is smaller than the effect of perceived empathy. This suggests that humanized responses may directly encourage forgiveness, but their influence is stronger when they also generate perceptions of empathy.

Finally, response type has a positive and significant direct effect on customer forgiveness ($\beta = 0.21$, $t = 4.02$, $p < .001$), supporting H5. This effect is also smaller than the effect of perceived empathy but slightly stronger than the direct effect of response personalization. The result indicates that accommodative responses can directly increase forgiveness because they signal accountability and willingness to repair the relationship.

Overall, the structural model shows that all hypotheses are supported. More importantly, the relative size of the path coefficients indicates that perceived empathy is the most influential predictor of customer forgiveness. Response personalization and response type matter, but their effects are partly explained by the extent to which they make customers feel understood and emotionally acknowledged.

Mediation Analysis

To examine whether perceived empathy mediates the effects of response personalization and response type on customer forgiveness, indirect effects were tested using bootstrapping with 5,000 resamples in SmartPLS. This procedure is appropriate for mediation analysis because it estimates the significance of indirect effects without assuming a normal sampling distribution.

The indirect effect of response personalization on customer forgiveness through perceived empathy is positive and significant ($\beta = 0.20$, $t = 5.94$, $p < .001$). This result indicates that humanized responses increase customer forgiveness partly because they enhance the perception that the firm understands and cares about the customer's situation. In other words, the human identity of the responder becomes meaningful when it is interpreted as a signal of empathy.

Table 7. Indirect Effect Results

Indirect Path				β	t	p	Type
Response Personalization	→	Perceived Empathy	→	0.20	5.94	< .001	Partial mediation
Response Type	→	Perceived Empathy	→	0.21	6.47	.002	Partial mediation

The indirect effect of response type on customer forgiveness through perceived empathy is also positive and significant ($\beta = 0.21$, $t = 6.47$, $p = .002$). This finding shows that accommodative responses promote forgiveness partly by making the firm appear more empathetic. When the response acknowledges the problem, apologizes, and expresses willingness to resolve the issue, customers are more likely to perceive emotional understanding, which then increases forgiveness. Because the direct effects of response personalization and response type on customer forgiveness remained significant, the mediation pattern can be interpreted as partial mediation. This means that perceived empathy explains an important part of the influence of response strategies on forgiveness, but not the entire effect. Customers may also forgive the firm because humanized and accommodative responses directly signal sincerity, accountability, and relational commitment. Thus, the findings support the view that empathy is a central mechanism in digital service recovery while also showing that response source and response content have independent relational value.

Determination and Predictive Power

The structural model's explanatory power was assessed via the coefficient of determination (R^2) for each endogenous construct, representing the share of variance in a dependent construct accounted for by its predictors. In PLS-SEM, R^2 values around 0.25, 0.50, and 0.75 are conventionally interpreted as weak, moderate, and substantial explanatory power, respectively (Hair et al., 2021). As Table 7 indicates, the model accounts for a moderate share of variance in perceived empathy ($R^2 = 0.46$), meaning response personalization and response type jointly explain roughly 46% of variation in how customers perceive empathy during online complaint handling. This suggests the experimental manipulations meaningfully shape customers' emotional assessments of the firm's response.

Table 8. Coefficient of Determination (R^2)

Endogenous Construct	R^2	Interpretation
Perceived Empathy	0.46	Moderate explanatory power
Customer Forgiveness	0.58	Moderate to strong explanatory power

For customer forgiveness, the model yields an R^2 of 0.58, reflecting moderate-to-strong explanatory power. This indicates that response personalization, response type, and perceived empathy together account for a substantial share of the variance in customers' willingness to forgive the firm after a service failure.

DISCUSSION

The purpose of this study is to examine how response personalization and response type influence customer forgiveness in online complaint contexts, and to investigate perceived empathy as the mediating mechanism in this relationship. The findings extend service recovery literature by showing that customers evaluate complaint responses not only based on what firms communicate, but also based on who is perceived to deliver the message. This distinction is especially important in digital service environments where firms increasingly use AI-based systems to manage complaint interactions.

First, the results indicate that response personalization significantly influences perceived empathy, with humanized responses generating higher levels of empathy than AI-generated responses. This finding advances social presence theory by showing that the perceived source of communication functions as a relational cue in service recovery contexts. While prior research has emphasized the role of message content, the present study demonstrates that communicator identity also shapes emotional evaluation. From a theoretical perspective, this suggests that service recovery effectiveness depends not only on informational adequacy but also on the perceived authenticity and relational quality of the interaction (Chang & Hung, 2018). Humanized responses may signal that the firm is emotionally present, attentive, and willing to engage with the customer as a person. By contrast, AI-generated responses may be perceived as more procedural and less emotionally involved, even when they contain appropriate recovery language. This finding highlights a structural limitation of AI-mediated communication, namely its weaker ability to convey the socioemotional signals that customers associate with genuine understanding. This interpretation is consistent with research on artificial empathy, which emphasizes the difficulty of replicating human-like emotional interaction in AI systems (Walsh et al., 2025).

Second, the findings show that response type exerts a slightly stronger influence on perceived empathy than response personalization. This indicates that although responder identity matters, the substance of the response remains central in shaping customer perceptions. Accommodative responses, which acknowledge the problem and demonstrate corrective intent, appear to activate more favorable attributions regarding the firm's motives. Defensive responses, in contrast, may lead customers to interpret the firm as self-protective and less willing to accept responsibility (Zhou et al., 2025). This result refines attribution theory by suggesting that customers pay close attention to signals of responsibility, accountability, and concern when evaluating service recovery attempts. It also reinforces prior service recovery research showing that apology and corrective action are central elements of relational repair (Witvliet et al., 2020). Thus, empathy in online complaint handling is shaped by both the perceived source of the response and the extent to which the response communicates accountability.

Third, the results confirm that perceived empathy is the strongest predictor of customer forgiveness. Compared to the direct effects of response personalization and response type, the empathy and forgiveness relationship is substantially stronger. This finding highlights perceived empathy as the central relational mechanism in digital service recovery. Customers are more likely to forgive a firm when they believe that the firm understands their feelings and takes their dissatisfaction seriously. Theoretically, this finding contributes to service recovery literature by integrating emotional and attributional perspectives. Recovery strategies are effective not merely because they provide information or corrective action, but because they help customers reinterpret the service failure as a recoverable incident rather than as evidence of organizational disregard. In this sense, empathy functions as a bridge between firm response strategies and relationship repair (Harrison-Walker, 2019; Xu et al., 2022).

In addition to these mediated relationships, response personalization and response type also exert direct effects on customer forgiveness, although these effects are comparatively modest. This suggests that perceived empathy explains an important part of the relationship between response strategies and forgiveness, but not the entire effect. Customers may also rely on visible cues when judging whether a firm deserves forgiveness. A humanized response may directly signal sincerity and personal attention, while an accommodative response may directly communicate accountability and willingness to resolve the problem. These findings are consistent with prior studies indicating that customers evaluate both the tone and content of service recovery responses when deciding whether to maintain the relationship with a firm (Gao et al., 2022; S et al., 2019).

The findings also point to several boundary conditions that may shape the effectiveness of humanized and AI-generated responses. The advantage of humanized responses may be stronger in high severity failures, where customers experience anger, disappointment, or perceived unfairness. In such situations, human cues may become more important because customers expect personal attention and moral accountability. In contrast, for low severity or routine service failures, customers may prioritize speed, convenience, and problem resolution over human presence. Similarly, the effectiveness of AI-generated responses may depend on whether the system can produce context-sensitive and emotionally appropriate language. As AI systems become more sophisticated, the perceived gap between human and automated responses may become smaller, suggesting that the difference between humanized and AI-generated responses is not fixed but may evolve with technological advancement (Zhai et al., 2024).

From a broader service management perspective, the findings reveal a tension between automation efficiency and relational authenticity. AI-based systems can help firms respond quickly, consistently, and at scale. However, the results suggest that efficiency alone is insufficient in emotionally sensitive complaint situations. When customers seek recognition, apology, and emotional understanding, AI-generated responses may weaken the relational signals needed for forgiveness. This concern is consistent with digital service research that highlights the trade-off between operational efficiency and human connection in AI-mediated interactions (Al-Oraini, 2025). Therefore, AI should not be understood as a complete replacement for human interaction in service recovery. Rather, it should be integrated as a complementary tool that supports routine complaint handling while allowing human representatives to manage emotionally complex or reputationally sensitive cases.

Overall, this study contributes to the literature by demonstrating that effective service recovery in digital environments requires the alignment of response content, communicator identity, and emotional signaling. By highlighting perceived empathy as the main pathway through which humanized and accommodative responses promote forgiveness, the study provides a more nuanced understanding of customer relationship repair in AI-mediated service contexts. The findings show that the future of digital service recovery depends not only on faster and more scalable technologies, but also on firms' ability to preserve empathy, authenticity, and relational sensitivity in customer interactions.

CONCLUSION

This study examines how response personalization and response type influence customer forgiveness in online complaint contexts, with perceived empathy positioned as the mediating mechanism. The findings show that humanized responses and accommodative responses increase perceived empathy, which in turn strengthens customer forgiveness. The results also show that

response personalization and response type have direct effects on forgiveness, although perceived empathy remains the strongest predictor.

The study contributes to service recovery literature by demonstrating that digital complaint handling is shaped by both response content and responder identity. In AI-mediated service environments, customers do not evaluate recovery messages only as information. They also interpret them as signals of sincerity, accountability, and emotional understanding. By positioning perceived empathy as the central mechanism linking response strategies to customer forgiveness, this study extends service recovery and attribution perspectives into increasingly automated customer service contexts.

Overall, the findings suggest that effective digital service recovery requires more than fast and standardized responses. Firms must also ensure that complaint responses convey empathy, authenticity, and willingness to repair the customer relationship. The theoretical contribution of this study lies in showing that forgiveness in digital service recovery depends on the interaction between technological mediation and relational communication.

MANAGERIAL IMPLICATION

The findings offer several practical implications for firms managing online complaints. First, firms should avoid relying entirely on AI-generated responses in emotionally sensitive complaint situations. Although AI can improve response speed and operational efficiency, customers may perceive automated responses as less empathetic than humanized responses. Human representatives should therefore be involved when complaints involve anger, disappointment, perceived unfairness, or reputational risk.

Second, firms should prioritize accommodative responses over defensive responses. Effective complaint responses should acknowledge the customer's concern, express regret, clarify the problem, and offer a clear resolution pathway. Defensive responses that emphasize policy or shift responsibility may reduce perceived empathy and weaken customer forgiveness.

Third, firms using AI in complaint handling should design automated responses that include empathetic language and contextual sensitivity. However, empathy should not be treated as a simple script. Managers should regularly monitor AI-generated responses to ensure that they sound sincere, relevant, and appropriate to the customer's situation.

Finally, firms should adopt a hybrid recovery system. AI can be used for routine complaints, initial classification, and simple information requests, while human staff should handle complex, emotional, or high-risk cases. This approach allows firms to balance efficiency with relational authenticity in digital service recovery.

LIMITATIONS AND FUTURE RESEARCH

This study has several limitations that provide opportunities for future research. First, the study used a scenario-based experiment in a hospitality context. Although this design strengthens internal validity, future research could examine real complaint interactions across different service industries to improve ecological validity. Second, the study focused on a specific comparison between humanized and AI-generated responses. Future studies could examine different levels of AI transparency, chatbot anthropomorphism, and generative AI sophistication to understand how customers evaluate automated recovery communication. Third, this study

examined perceived empathy as the primary mediating mechanism. Future research may include other psychological mechanisms, such as perceived sincerity, trust repair, perceived justice, or emotional reassurance. Fourth, cultural differences may influence how customers interpret AI responses and empathetic communication. Cross-cultural research would therefore be valuable for understanding whether the role of empathy differs across markets with different expectations of interpersonal service. Finally, longitudinal studies could examine whether customer forgiveness remains stable over time and whether initial recovery responses influence long-term loyalty, repurchase intention, or negative word of mouth.

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