Mitigating Service Failure Blame on Firms:

The Role of Perceived Controllability and Warmth in Service Robots

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Abstract

Service failures in hospitality can damage guest satisfaction and brand reputation, especially when blame shifts to the service firm. This paper develops a conceptual model to explain how guests attribute responsibility in robot-assisted service failures and proposes strategies to prevent firm-level blame. We argue that perceived controllability plays a key role—when robots are seen as competent and in control, guests are more likely to hold them accountable rather than the firm. Additionally, warmth-oriented robot design encourages internal attributions, prompting guests to blame themselves. Generative AI (GAI)-based robots further reinforce competence by enabling adaptive, real-time interactions, strengthening perceptions of robot responsibility. Since firm-directed blame carries significant reputational risks, strategically enhancing both warmth and competence offers a pathway to mitigating negative spillover effects. This study integrates insights from attribution theory, human-robot interaction, and service failure research to provide theoretical and managerial implications for effective service robot design.

Keywords: *Controllability*, *Service Robot*, *Competence*, *Warmth*, *GAI*

Track: *Technological Human-Centered Innovations*

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Introduction

The hospitality industry is a cornerstone of the global economy, encompassing accommodation, tourism, and food and beverage services. However, labor shortages have increasingly strained service delivery, raising concerns about maintaining service quality and operational efficiency (Kwok, 2022; Oliva & Sterman, 2001). In the European Union, for example, waiter shortages are widespread, with 17 out of 27 member states reporting labor deficits in this occupation, and nearly half of those experiencing severe shortages (European Labor Authority, 2024). To address these workforce challenges, businesses are integrating service robots into frontline operations as a potential solution (Morosan & Bowen, 2022). While service robots alleviate labor shortages, they also introduce new complexities, particularly in the realm of service failures. Like their human counterparts, robots inevitably make mistakes, leading to guest dissatisfaction and service disruptions (Liu et al. 2023). However, a key distinction lies in how guests attribute blame for these failures. Unlike service failures caused by human employees—where blame is often directed at the individual worker—failures involving service robots tend to shift responsibility toward the firm deploying them (Ryoo, et al. 2024). This firm-level blame attribution can have significant consequences, including negative reviews, reduced guest trust, and financial losses. Therefore, understanding how guests assign blame in robotic service failures is critical for service firms, as it can inform strategies to manage guest expectations, improve service recovery efforts, and mitigate negative brand perceptions.

Attribution theory provides a useful framework for analyzing service failures, as it explains how individuals assign responsibility for negative outcomes (Heider, 1958; Weiner, 1984). Within the hospitality field, service failure attributions are generally categorized into internal (guest-related) and external (non-guest-related) causes. While guests occasionally acknowledge their responsibility, research suggests they predominantly blame external factors, such as service providers (e.g., waiters and receptionists) or the service firms (e.g., restaurants and hotels) (see Van Vaerenbergh et al. 2014, for a review). However, there is limited research on whether guests differentiate between these two external attributions—whether they primarily hold the individual service provider accountable or extend their blame to the service firm. This distinction has important implications for hospitality management. Although service firms aim to minimize blame altogether, when guests do assign responsibility, it is preferable for them to direct it toward the immediate service provider—whether human or robotic—rather than the firm itself. When guests hold an individual service provider accountable, they may still trust the brand if the company effectively resolves the issue. Conversely, if guests attribute responsibility to the entire firm, the failure can result in widespread dissatisfaction, negative reviews, and loss of customer loyalty.

Building on attribution theory, we address two key research questions in this paper: (1) *Why do guests differ in their attribution tendencies when served by human employees versus service robots*? We propose that perceived controllability—defined as the extent to which a service provider is seen as influencing service outcomes (Weiner, 1984)—is central to this distinction. Specifically, we argue that service robots are generally perceived as having lower controllability than human employees, leading guests to shift blame from the robot to the firm responsible for deploying it. (2) *How can service firms mitigate guest blame in the incidences of service robot failures?* We propose that increasing robots' perceived controllability—through competence signalling in robot design and technological advancements like generative AI (GAI) and warmth—can systematically influence attribution patterns, ensuring that responsibility remains with the robot or the guests rather than the firm. This study advances the literature by integrating attribution theory with research on human-robot interaction, offering a conceptual model for understanding how robot design and GAI influence responsibility judgments in service settings.

We adopt a theoretical approach, given the evolving nature of GAI-based service robots and the complexity of attribution mechanisms in human-robot interactions. The literature on controllability and responsibility attribution remains fragmented, particularly for GAI-based service robots. Our conceptual model draws from social cognition, service management, and human-robot interaction, providing a foundation for future empirical work. Given the novelty of GAI-based robots, the psychological mechanisms shaping guest perceptions require clarification before testing. This paper structures key constructs and causal relationships, offering a basis for future experimental research. While we focus on responsibility attribution from the guest's perspective, legal liability lies beyond the scope of this paper.

The paper proceeds as follows. First, we review the literature on service failure attribution, followed by a discussion of attribution tendencies related to service robots, with a particular focus on controllability, design characteristics and GAI-based robots. We then present a conceptual model outlining the role of perceived controllability in service failure attributions. Finally, we discuss theoretical and managerial implications.

Literature Review

To address the first research question—why guests make different attributions when served by human employees versus service robots—we first examine attribution theory in service failures, focusing on how perceived controllability shapes blame assignment. We then review research on robot design and generative AI, highlighting their role in enhancing perceived competence and reducing blame on service firms. This provides the foundation for answering the second research question: how service firms can strategically design and implement robotic service providers to mitigate blame towards the firms.

Attribution Theory in Service Failures

Attribution theory, as conceptualized by Weiner (1984, 2010), posits that individuals seek explanations for unexpected events, particularly those that disrupt their expectations. In hospitality settings, guests anticipate seamless service, and deviations from this norm trigger a need to assign responsibility. Weiner (1984) proposed three key attribution dimensions: locus of causality, controllability, and stability. Within the hospitality field, research has predominantly focused on the first two dimensions: locus of causality and controllability (Van Vaerenbergh et al. 2014).

Locus of causality refers to whether an event is attributed to internal (self) or external (others) factors. Research suggests that warmth-oriented service providers encourage guests to take personal responsibility for service failures, leading to more internal attributions. Fiske, Cuddy and Glicket (2006) identified warmth and competence as fundamental dimensions of social perception. Warmth includes friendliness and sociability, signalling positive intentions, while competence reflects intelligence and efficiency, signalling the ability to achieve goals effectively. Previous studies show that when human service providers exhibit warmth through smiles, sincere apologies and empathetic communication, customers are more likely to blame themselves, reducing blame directed at the service provider or firm (e.g., Güntürkün, Haumann, & Mikolon, 2020; Huang, et al. 2020). This phenomenon extends to service robots as well. Warmth-oriented robots—characterized by human-like appearance, friendly communication, and expressive behaviors—elicit similar attribution patterns (Meyer et al. 2023; Chang et al. 2024). Therefore, design service robots with warmth-enhancing features offers a strategic approach to mitigate firm-level blame in service failures.

Regarding external attribution, it remains unclear whether guests primarily blame individual service providers or service firms. Some research suggests that guests blame service providers on some occasions and firms in others (McColl-Kennedy et al. 2011; Noone & Lee 2011). Noone and Lee (2011) found that when failures involve procedural fairness concerns—such as hotel overbooking—guests held the service firm responsible rather than any individual front desk employee. Similarly, McColl-Kennedy et al. (2011) found that guests attribute blame differently depending on the cause of the failure: they direct dissatisfaction toward frontline employees when failures result from poor responsiveness (e.g., slow service) but blame service firms when failures involve broader fairness issues (e.g., compensation disputes). These findings suggest that guests differentiate between service providers and firms depending on whether failures are seen as operational (performance-related where service providers have more control) or systemic (policy-related where service providers have less control). However, how these attribution patterns apply to service robots remain underexplored. If guests perceive robots as independent service providers, they may assign blame similarly to how they blame human employees. Conversely, if robots are viewed as extensions of the firm's technology and policies, blame may instead shift to the firm.

Service Robots and Perceived Controllability

Despite the growing adoption of service robots in hospitality, research has yet to fully explore the cognitive mechanisms driving guests' attribution tendencies toward service robots versus service firms. While people often interact with service robots as if they were humans (Sheridan, 2016), robots are typically perceived as less autonomous and less capable of independent decision-making (Arikan et al. 2023; Shi et al. 2023). This distinction has important implications for blame attribution. Existing studies suggest that guests blame human employees directly for failures but shift blame to the service firm when failures involve robots (Ryoo et al. 2024). However, the underlying mechanism explaining this shift remains unclear.

One potential explanation is perceived *controllability*, which refers to the extent to which an event could have been prevented through volitional action (Weiner, 1984). When guests perceive a service provider as having high controllability, they are more likely to hold that provider accountable for failures (Folkes et al. 1987; see Liu et al. 2023 for a review). Conversely, when controllability is perceived as low, blame often shifts to the service firm. Ryoo et al. (2024) provide empirical support for this tendency, showing that guests assigned blame differently depending on whether a human employee or a service robot provided the service. Participants read a frontline service failure scenario and were asked to list potential causes. The findings revealed six main attribution targets: service provider, service firm, robot programmer, guests themselves, external authorities (e.g., government), and no one. When human employees caused failures, guests primarily blamed them. However, when service robots were responsible, blame shifted toward the service firm, suggesting that guests viewed robots as lacking sufficient control over the service outcomes.

Our study builds on Ryoo et al.'s findings by investigating the role of perceived controllability as the key mechanism shaping these attributions. Robots are perceived as having lower controllability than human employees due to their pre-programmed nature and limited adaptability (Park & Lehto, 2022). For instance, a human receptionist can adjust greetings based on guest cues, whereas a service robot follows scripted interactions (Boelens, 2013). These differences in flexibility and decision-making may lead guests to see human employees as directly responsible for failures, while viewing robots as mere extensions of the firm.

In summary, to answer our first research question—how do guests make different attributions when served by human employees versus service robots?—we propose that warmth affects attributions similarly across both provider types. Warmth appears to have a similar effect regardless of whether the service provider is a human or a robot—warm-oriented service providers tend to elicit self-attributions, meaning guests are more likely to blame themselves for service failures rather than external parties (Mozafari et al. 2022). Consequently, both warm-oriented human employees and service robots reduce firm-level blame. However, a key difference between human employees and service robots lies in perceived controllability. Because human employees are generally seen as having greater control over service outcomes, guests are more likely to hold them directly accountable for failures. In contrast, service robots, often perceived as pre-programmed and less autonomous, do not bear the same level of responsibility in guests' eyes. Instead, when service failures occur with robots, blame is more likely to shift toward the firm that deployed them.

If blame systematically shifts from robots to firms, it poses risks for brand perception, guest trust, and customer retention. To mitigate this negative spillover effect, we propose enhancing robot design to increase perceived controllability, ensuring that responsibility for service failures remains with the service provider rather than transferring to the service firm. The next section explores how competence signaling—through appearance, behavior, and responsiveness—can reinforce perceived controllability and address our second research question.

Robot Design: Enhancing Perceived Controllability to Reduce Blame Spillover

The competence of a service robot plays a crucial role in shaping external blame attributions. In social cognition, competence reflects intelligence and efficiency, signaling an entity's ability to control outcomes (Fiske et al. 2006). Applied to service robots, competence enhances perceived controllability, making the robot the primary target for blame when failures occur. Robots demonstrating professional communication, efficient task execution, and responsiveness are more likely to be perceived as autonomous decision-makers and held accountable for failures (Horstmann & Krämer, 2022). Conversely, when robots exhibit mechanical delays, awkward interactions, or inconsistent responses, guests may struggle to see them as independent actors, shifting blame to the firm (Ryoo et al. 2024; Tuncer et al. 2024).

Thus, enhancing a robot's perceived competence is a strategic way to minimize blame spillover to the service firm. By incorporating human-like appearance, adaptive behaviors, and precise task execution (Meyer et al. 2022; Mozafari et al. 2022), service firms can reinforce the perception that robots, rather than firms, control service outcomes. This targeted design approach can help mitigate firm-level blame attribution, ensuring that responsibility remains with the service robot.

Beyond physical and behavioral design, Generative AI (GAI) can further reinforce competence by enabling robots to engage in more adaptive and contextually aware interactions. The next section explores how GAI enhances service robots' ability to process guest inputs, generate natural responses, and personalize interactions, potentially strengthening competence and further reducing the likelihood of firm-level blame attribution.

Controllability in Generative AI-based Service Robots

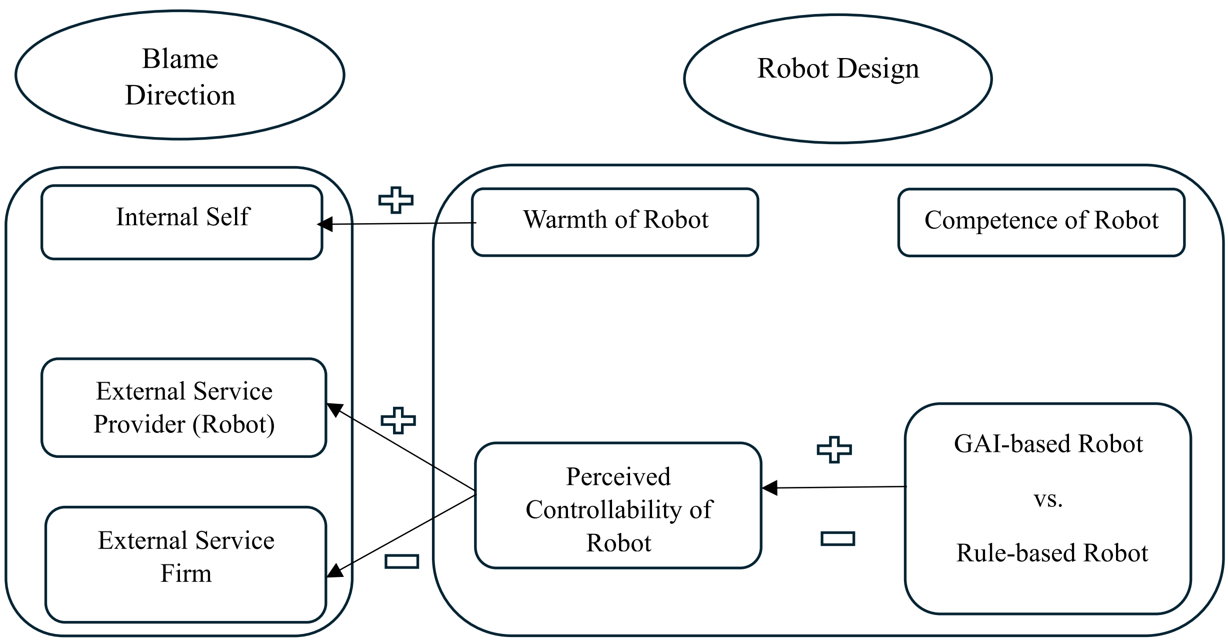
The integration of generative AI (GAI) into service robots is reshaping how guests perceive control and assign responsibility in service encounters. Unlike traditional pre-programmed robots, which are often seen as mere extensions of the service firm, GAI-based robots—such as those equipped with ChatGPT—generate dynamic responses, adapt to situational cues, and engage in human-like interactions (Ye et al. 2023). This adaptability enhances perceived controllability, making guests more likely to attribute responsibility for service failures to the robot rather than the firm (Choi & Mattila, 2008).

GAI enables service robots to generate human-like responses. GAI-based service robots can comprehend and interpret complex guest inquiries through advanced natural language processing capabilities (Ahuja, et al. 2023). This allows robots to understand context, nuances, and intent more effectively, leading to more accurate and relevant responses. Moreover, GAI empowers robots to tailor interactions based on individual guest preferences and behaviors. By analyzing guest data and prior interactions, robots can offer personalized recommendations and services, enhancing the overall guest experience. This level of personalization contributes to a perception of the robot as an intelligent, autonomous entity capable of independent decision-making (Ferraro, et al. 2024). Furthermore, unlike traditional rule-based service robots, which require manual updates to improve performance, GAI-based robots can continuously learn from interactions and refine their responses over time. Machine learning models integrated into service robots allow them to adapt to evolving guest preferences and industry trends. Research has shown that AI systems capable of iterative learning are perceived as more competent and intelligent than static rule-based systems (Glikson & Woolley, 2020). By integrating these advanced capabilities, GAI-based service robots can strengthen guests' perception of their competence and control over service outcomes. As a result, guests are more likely to attribute service failures to the robot itself rather than shifting blame to the firm, ultimately reducing the negative spillover effect on the business. Building on these insights, we present a conceptual model in the next section.

Conceptual Model

Our conceptual model explains how guests attribute responsibility in service failures (see Figure 1) and how service firms can mitigate blame when deploying service robots. Guests can assign blame internally (to themselves) or externally (to the robot or service firm). Warm-oriented robots, like warm human employees, encourage internal attributions, making guests more likely to see themselves as partially responsible for failures, reducing external blame (Mozafari et al., 2022). Among external attributions, perceived controllability determines whether guests blame the robot or the firm. Competent robots with high perceived controllability are more likely to be held accountable, reducing firm-level blame, while low-competence robots lacking control shift blame to the firm (Ryoo et al., 2024). Generative AI (GAI) enhances perceived controllability and competence by enabling real-time adaptation, personalized interactions, and dynamic decision-making (Ye et al., 2023), reinforcing the perception that robots—not firms—are responsible for service failures. By strategically balancing warmth and competence, firms can minimize negative spillover effects and maintain guest trust.

Figure 1. Conceptual model: Guest blame towards themselves, robot and service firm depending on the warmth and perceived controllability of the robot (GAI-based vs. Rule-based).



Conclusion

This study advances the understanding of responsibility attribution in service failures by integrating attribution theory (Weiner, 1984; 2010) with the warmth-competence framework (Fiske et al. 2006). Our conceptual model extends prior research (Ryoo et al. 2024) by demonstrating how guests differentiate between blaming service providers (human employees vs. service robots) and service firms based on perceived controllability.

We contribute to social cognition research in human-robot interactions by showing that warmth and competence play distinct roles in shaping guest attributions. Warmth fosters social bonding and encourages internal attribution, reducing the likelihood of external blame. In contrast, competence signals controllability and decision-making capability, reinforcing the perception that the robot is responsible for service outcomes (Mozafari et al. 2022). Moreover, competence-enhancing features, such as generative AI (GAI), further strengthen perceived controllability, ensuring that guests hold the robot accountable rather than the service firm.

This study also offers practical insights for firms deploying service robots, emphasizing the importance of designing robots to minimize negative spillover effects. Increasing warmth through human-like features (e.g., facial expressions, empathetic language) can encourage guests to internalize service failures, while enhancing perceived competence—through responsive interactions and efficient task execution—ensures that responsibility remains with the robot. GAI-based robots, such as those utilizing ChatGPT, further reinforce controllability by generating real-time, context-aware responses, reducing firm-level blame. By strategically balancing warmth and competence in robot design, firms can mitigate reputational risks, maintain guest trust, and optimize service recovery strategies.

This paper presents a conceptual model explaining how guests attribute blame in service failures involving service robots. We propose that increasing a robot's warmth and perceived controllability mitigates blame spillover to the firm, ensuring that service failures do not erode brand trust and customer loyalty.

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