AI Service Rejection and its Impact on Customer Satisfaction

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Abstract

Given the widespread use of artificial intelligence (AI) in the service sector, it is pertinent to examine whether service application rejection decisions made by AI, compared to those made by human agents, impact customer satisfaction. Findings show that consumers are generally less satisfied with AI rejections because they tend to blame AI more than human agents. However, this effect is moderated by the moral basis of the rejection. When rejections are seen as based on moral grounds, dissatisfaction levels are similar for both AI and human decisions. Additionally, the study highlights the importance of providing explanations: teleological explanations (i.e., explaining why a decision was made) are more effective than mechanistic ones (i.e., explaining how it was made) in reducing the negative impact of AI rejections. This study contributes to the ongoing debate on how consumers respond to decisions, especially unfavorable ones, made by AI.

Keywords

Service rejection, Artificial intelligence, Customer satisfaction

Introduction

Many commercial services, particularly in finance (e.g., loans, credit cards, mortgages), require customer applications subject to evaluation. Rejections are inevitable and often lead to dissatisfaction, alienating customers and prompting negative behaviors like complaints and negative word-of-mouth (Mittal 2016). With AI increasingly involved in decision-making and outcome delivery (Bigman and Gray 2018), these effects may worsen due to consumer aversion to AI (Dietvorst et al. 2018). Thus, understanding whether AI-driven rejections heighten dissatisfaction and how providers can mitigate this impact is crucial.

AI is widely used in customer service, acquisition, delivery, failure recovery, and application evaluation (Yoon and Lee 2021). Research highlights mixed consumer responses to AI. While AI is favored for personalized recommendations, it can evoke discomfort in more personal roles, such as service robots (Mende et al. 2019). Acceptance depends on situational factors (e.g., crowding, (Hou et al. 2021) and personal traits (e.g., self-efficacy, (Pozharliev et al. 2021). However, consumers may be particularly sensitive to AI in high-stakes, consequential decisions like service rejections.

Studies on consumer reactions to AI-driven decisions are limited. (Yu et al. 2024) found that AI rejections elicit fewer negative reactions than human rejections, while (Yalcin et al. 2022) reported that decision-maker type (AI vs. human) has little effect on reactions to rejections. However, these studies primarily focus on attitudes toward the company rather than consumer satisfaction. Notably, managers often predict lower satisfaction with AI decisions, especially rejections.

Customer satisfaction depends on decision outcomes and perceived agent qualities. Consumers often blame AI more, viewing it as less empathetic and unable to consider personal traits (Longoni et al. 2019). This perceived lack of human-like qualities diminishes satisfaction with AI-driven rejections. However, the perceived moral basis of rejections and

explanations can moderate these effects. In morally charged situations, in-group favoritism toward human agents diminishes (Marques et al. 2001), while AI's perceived objectivity increases its accountability (Kleinberg et al. 2018). Explanations enhance transparency, reducing dissatisfaction by fostering fairness and trust (Yu et al. 2024).

This research examines how service rejections by AI versus human agents impact customer satisfaction. It explores how rejection's moral basis and explanations moderate these effects, addressing gaps in prior research on AI's role in consumer decision-making.

Hypotheses Development

The impact of agent type on blame attribution and consumer satisfaction

When consumers face unfavorable service outcomes, they seek to assign blame, often attributing failure to external factors, a process known as blame attribution (Van Varrenbergh et al. 2014). This tendency is linked to self-serving bias, where success is credited to oneself, and failure to external agents (Campbell and Sedikides 1999). Research shows that blame extends not only to firms but also to service agents, whether human or AI (Jörling et al. 2019). AI, perceived as lacking empathy and adaptability, is often judged more harshly than human agents, who are seen as better at considering individual needs (Longoni et al. 2019).

In-group favoritism further drives this bias, as consumers prefer human agents who share commonalities (Chatman and von Hippel 2001). Human agents are viewed as more capable of nuanced evaluations, while AI's rigid processes can amplify dissatisfaction (Castelo et al. 2019). Additionally, human-like traits, such as empathy and inclusivity, are crucial for service agents, enhancing fairness and effectiveness (Lindsey-Hall et al. 2021). When these traits are absent, as with AI, consumers are more likely to blame the agent, lowering satisfaction (Oliver and DeSarbo 1988). Expectation-disconfirmation theory supports this, showing dissatisfaction arises when performance falls short of expectations. In

service rejections, AI's perceived inability to meet individual needs often leads to reduced satisfaction compared to human agents. Therefore, we hypothesize:

H1: Consumers experience lower satisfaction levels when the service rejection decision is made by an AI agent than when it is made by a human agent.

H2: Blame attribution mediates the effect of agent type on consumer satisfaction.

The moderating role of moral bias

We propose that the moral basis of a rejection moderates the impact of agent type on blame attribution. AI-driven rejections evoke stronger negative reactions when based on non-moral grounds, while morally biased rejections elicit similar dissatisfaction for both AI and human agents. Consumers attribute moral rejections to human agents due to their perceived higher agency and to AI agents because of their expected impartiality. Service rejection, viewed as social exclusion, provokes stronger negative reactions when perceived as unfair, especially in cases involving bias related to group membership (Richman and Leary 2009).

In-group favoritism toward human agents diminishes when moral violations tarnish the group's positive image (Marques et al. 2001). Humans are held more accountable for moral lapses due to their perceived capacity for intentionality and autonomous judgment (Gray and Wegner 2012). Although AI agents are viewed as less capable of moral reasoning, their perceived objectivity sets high expectations for fairness (Mullainathan 2019). Consequently, morally biased rejections by AI can trigger backlash, as consumers expect AI to deliver unbiased outcomes (Bigman and Gray 2018). Thus, both agent types face significant blame for moral rejections, driven by fairness expectations. Therefore, we hypothesize:

H3: Morally biased (vs. non morally biased) rejection moderates the effect of agent type (AI vs. human) on blame attribution to the agent. Specifically, the negative

effect of AI-initiated rejection is decreased when rejections are morally biased (vs. non morally biased).

The moderating role of explanation

The effect of service rejection by AI versus human agents may depend on whether an explanation is provided (Querci et al. 2022). Explanations clarify decisions, making them more understandable and justifiable, which can improve applicants' satisfaction (Shaw et al. 2003). Companies like JPMorgan Chase and Deutsche Bank have invested in AI explainability research to enhance transparency.

Explainable AI (XAI) can reduce the disadvantage of AI in service rejections by addressing its perceived lack of empathy and adaptability, narrowing the perceived gap between human and AI agents. By providing clear reasoning, XAI diminishes out-group bias, reduces blame, and enhances satisfaction with AI-driven services.

H4: The negative effect of agent type (AI vs. human) on blame attribution to the agent is weaker when an explanation (vs. no explanation) for the decision is offered.

H5: Blame attribution mediates the negative effect of agent type (AI vs. human) on consumer satisfaction when an explanation (vs. no explanation) for the decision is offered.

Empirical Studies

Study 1

Method. We recruited one hundred and seventy Prolific participants (M_{age} = 41.55; 55.1% female) and randomly assigned them to one of two conditions in an AI vs human agent type between-subjects experimental design. Participants read that they were applying for a personal loan and as part of the application, they were required to submit their details through a bank's online application form. They were also told that their application will be evaluated

by a specialist credit risk artificial intelligence (AI) algorithm deployed by [analyst of] the company, who will make a decision. Then, we told them that their application was rejected. We used four items adapted from (Li et al. 2019) to measure customer satisfaction towards the service ($\alpha = .90$) and measured the extent they attribute blame to the agent using measurement adapted from (Leo and Huh 2020).

Results. An independent samples t-test (agent type: AI vs. human) on customer satisfaction revealed that participants in the AI condition showed a greater tendency to be dissatisfied with the provided service ($M_{AI} = 1.99$) than participants in the human condition ($M_{human} = 2.42$; $t(97) = -2.11$, $p < .05$), validating H1. An independent samples t-test (agent type: AI vs. human) on blame further revealed that participants in the AI condition attribute more blame to the service evaluator in the ai condition ($M_{AI} = 4.67$) than participants in the human condition $M_{human} = 3.90$; $t(97) = 2.40$, $p < .05$).

Mediation analysis. We conducted a regression analysis to investigate our prediction that the blame attribution mediates the effect of agent type on customer satisfaction. The results indicate that agent type is a significant predictor of blame attribution to the agent (b = .77, SE = .32, 95% CI [.1329, 1.4099]), and blame attribution to the agent is a significant predictor of customer satisfaction (b = -.24, SE = .06, 95% CI [-.3639, -1.1257]). Agent type is no longer a significant predictor of customer satisfaction after we control for blame attribution to the agent (b = -.24, SE = 19.55, 95% CI [-.6307, -.1453]), consistent with full mediation. The test for the indirect effect, using a bootstrap estimation approach with 5,000 samples (Hayes, 2022 PROCESS Model 4), indicates a significant indirect coefficient (b = -.19, SE =.09, 95% CI [-.3811, -.0320]).

Study 2

Method. We recruited one hundred and seventy participants ($M_{age} = 29.60$, 52.2% female) from Prolific. We randomly assigned participants to one of four conditions in a 2 (rejection

type: morally biased vs. control) × 2 (agent type: AI vs. human) between-subjects experimental design. Similar to Study 1, participants read that they were applying for a personal loan from a bank and their application was evaluated by a human or an AI agent who specializes in credit risk assessment. Then, they were told that their applications were rejected. To manipulate the types of rejection, participants read that they talked to some friends who have the same demographic and socio-economic background about their recent application. Those in the morally biased [control] condition then read: "The only reason you believe their application was successful while yours was not, was because of gender differences" ["However, their application was successful while yours was not"]. We used the same items as in Study 1 to measure customer satisfaction towards the service experience (α = .93) and the extent they attribute blame to the agent.

Customer satisfaction. We conducted a 2 (rejection type: morally biased vs. control) × 2 (agent type: AI vs. human) between-subject ANOVA on customer satisfaction. The results reveal main effects of agent type was not significant (M_{human} = 2.82; M_{AI} = 2.54, F(1,157) = 2.29, p = .132) but the main effect of rejection type was significant (M_{moral} = 2.48; $M_{control}$ = 2.90, F(1,157) = 4.21, p = .042, η^2_p =.026). Moreover, the interaction effect was significant (F(1,157) = 7.78, p = .006, η^2_p =.047). Simple analysis further revealed that for the morally biased rejection, satisfaction did not differ between human and AI conditions (M_{human} = 3.34; M_{AI} = 2.46, F(1,157) = .86, p = .355). While in the control condition, participants rejected by an AI (M_{AI} = 2.61) still reported higher dissatisfaction than those in human condition (M_{human} = 2.35; F(1,157) = 8.77, p = .004, η^2_p =.053).

Blame attribution. We then conducted a 2 (rejection types: morally biased vs. control) × 2 (agent type: AI vs. human) ANOVA on blame attribution. The results reveal main effects of agent type was not significant (M human = 4.88, SD = 1.48; M AI = 5.16, SD = 1.29, F(1,157) = 2.05, p = .154), but the main effect of rejection type was significant (M moral =

5.25, SD = 1.30; M control = 4.76, SD = 1.45, F(1,157) = 5.12, p = .025, η2p =.032). Moreover, the interaction effect was significant (F(1,157) = 4.03, p = .046, η2p =.025). Simple analysis further revealed that for the morally biased rejection, participants attribute blame to human and AI agent equivalently (M human = 5.31, SD = 1.33; M AI = 5.19, SD = 1.28, F(1,157) = 0.18, p = .675). While in the control condition, participants attribute more blame to AI (M AI = 5.13, SD = 1.32) than human agent (M human = 4.39, SD = 1.50; F(1,157) = 5.61, p = .019, η^2_p =.034).

Mediation analysis. We then performed a moderated mediation analysis (PROCESS Model 8, 5000 bootstrapped sample; Hayes, 2022) with customer satisfaction as dependent variable, agent type (0 = human, 1 = AI) as independent variable, rejection type as moderator, and blame attribution as mediator. We found a significant moderated mediation effect (b = .29, SE = .17, 95% CI [.0152, .7086]). For the control condition, the indirect effect of the agent type through blame attribution was significant (b = -.25, SE = .14, 95% CI [-.5800, -.0314]), suggesting the effect that participants had lower satisfaction when rejected by AI than human was caused by higher level of blame attribution. For the morally biased rejection condition, however, the corresponding indirect effect was not significant (b = .04, SE = .10, 95% CI [-.1524, .2291]).

Study 3

Method. We recruited two-hundred twenty-four Prolific participants (M_{age} = 41.54; 54.1% female) and randomly assigned them to one of six conditions in a 2 (agent type: AI vs. human) × 3 (explanation: control vs mechanistic vs teleological) between-subjects experimental design. Similarly to Studies 1 and 2, participants read that they were applying for a loan from a bank and were exposed to the same manipulation for agent type (i.e., their application was evaluated by a(n) AI [human] agent of the bank who specializes in credit risk assessment). To manipulate the explanation type, we provided participants with either a

mechanistic or a teleological explanation for their rejection decision. In specific, in the mechanistic explanation condition, we told participants that as explanation for the decision, they were informed that the rejection was based on an evaluation process that included analyzing their personal details, employment history, monthly income, and credit score. In the teleological explanation condition, we told participants that as explanation for the decision, they were informed that the rejection was based on an evaluation aimed at ensuring their financial capability to repay the loan and protecting the bank's financial viability. In the control condition, we only provided the agent's decision. Then, we used the same measures as in previous studies to measure customer satisfaction towards the service experience (α = .94) and blame attribution to the agent.

Customer satisfaction. We conducted a 3 (explanation types: mechanistic vs. teleological vs. control) × 2 (agent type: AI vs. human) between-subject ANOVA on customer satisfaction. The results reveal that the main effects of agent type was significant (M_{human} = 3.92; M_{AI} = 3.57, $F(1,207) = 7.79$, $p < .01$, η^2_p =.036) as was the main effect of explanation type ($M_{mechanistic}$ = 3.96; $M_{teleological}$ = 4.53; $M_{control}$ = 2.75, $F(2,207) = 41.23$, $p < .001$, η^2_p =.285). Moreover, the interaction effect was significant ($F(2,207) = 3.39$, $p = .036$, η^2_p =.032). Simple analysis further revealed that when a teleological explanation was offered, customer satisfaction did not differ between human and AI conditions (M_{human} = 4.46; M_{AI} = 4.58, $F(1,207) = .18$, $p = .67$). While when a mechanistic explanation was offered, participants rejected by an AI (M_{AI} = 3.64) reported lower satisfaction than those in human condition (M_{human} = 4.28; $F(1,207) = 4.49$, $p < .05$, $\eta^2_p = .021$). This effect was more prominent when no explanation was offered (M_{AI} = 2.28; M_{human} = 3.17; $F(1,207) = 9.93$, $p < .01$, $\eta^2_p = .046$).

Blame. We then conducted a 3 (explanation types: mechanistic vs. teleological vs. control) × 2 (agent type: AI vs. human) between-subject ANOVA on blame. The results reveal that the main effects of agent type was significant (M_{human} = 3.44; M_{AI} = 3.83, $F(1,207)$ =

7.79, $p < .05$, $\eta^2_p = .027$) as was the main effect of explanation type ($M_{mechanistic} = 3.73$; $M_{teleological} = 2.45$; $M_{control} = 4.73$, $F(2,207) = 32.95$, $p < .001$, $\eta^2_p = .241$). Moreover, the interaction effect was significant ($F(2,207) = 3.32$, $p = .038$, $\eta^2_p = .031$). When a teleological explanation was offered, blame attribution did not differ between human and AI conditions ($M_{human} = 2.61$; $M_{AI} = 2.33$, $F(1,207) = .48$, $p = .49$). While when a mechanistic explanation was offered, participants rejected by an AI ($M_{AI} = 4.18$) blamed the agent less than those in human condition ($M_{human} = 4.25$; $F(1,207) = 4.73$, $p < .05$, $\eta^2_p = .022$). This effect was more prominent when no explanation was offered ($M_{AI} = 5.29$; $M_{human} = 4.23$; $F(1,207) = 7.13$, $p < .01$, $\eta^2_p = .033$).

Mediation analysis. We then performed a moderated mediation analysis (PROCESS Model 8, 5000 bootstrapped sample; Hayes, 2022) with satisfaction as dependent variable, agent type (0 = human, 1 = AI) as independent variable, explanation type as a multi-categorical moderator, and blame attribution as mediator. We found that the provision of a teleological explanation significantly moderates the mediation effect of blame (b = .49, SE = .17, 95% CI [.1203, .7876]). For the control condition, the indirect effect of the agent type through blame attribution was significant (b = -.35, SE = .12, 95% CI [-.6016, -.1305]), suggesting the effect that participants were less satisfied when rejected by AI than human agent was caused by higher blame attribution. For the teleological explanation condition, the indirect effect of the agent type through blame attribution was not significant (b = -.09, SE = .12, 95% CI [-.1511, .3357]). The moderation effect of a mechanistic explanation on the mediating effect of blame was not significant (b = .05, SE = .20, 95% CI [-.3766, .4352]).

Discussion

Our study makes several contributions to the present literature. Firstly, we contribute to the service literature by examining consumer responses to decisions made by human versus AI agents. Our study thus contributes to the existing literature by examining how consumers

respond to unfavorable decision-making by humans versus AI in a service context. Secondly, we contribute to the AI rejection literature. Our study contributes to this body of literature by investigating consumer satisfaction in response to AI versus human application rejections. Third, the present study contributes to the understanding of consumers' perceptions of AI versus human capabilities, which influence their subsequent blame attribution. Across four studies, we found that consumers have more negative responses toward AI (vs. human) after rejection, which is due to a higher attribution of blame towards AI (vs. humans). Our findings thus provide additional evidence for AI aversion and support the notion that AI agent is more blameworthy compared to a human agent. Fourth, our research revealed that the adverse effect of AI service rejection is observed only for rejections made on non-moral grounds and not for rejections based on moral grounds. Finally, our research finds that the presence of an explanation positively influences customers' satisfaction with their service experience in service application decision, and further influences the effect of agent type

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