

Article

Procedural and Distributive Unfairness in AI Interactions: Are People Less Satisfied with Unfairness from AI Compared to Humans?

Devon Johnson ^{1,*}, Sungyong Chun ², Sneha Pandey ³ and Gouher Ahmed ⁴¹ Feliciano School of Business, Montclair State University, Montclair, NJ 07043, USA² College of Business and Economics, Dankook University, Jukjeon Campus, Yongin 16890, Republic of Korea; sychun@dankook.ac.kr³ Jaipuria Institute of Management, Noida 201309, India; pandey.sneha1994@gmail.com⁴ Horizon University College, Ajman 5700, United Arab Emirates; gouher.ahmed@hu.ac.ae

* Correspondence: johnsonde@montclair.edu

Abstract

This study investigates consumer perceptions of procedural and distributive fairness/unfairness in service interactions involving AI versus human providers. It also examines how these perceptions are influenced by technology-related discomfort and the perceived responsibility of the service organization. A scenario-based online experiment was conducted using participants recruited through the Prolific research platform. Participants were asked to review a small business loan application process at a fictional digital bank where the application is processed either by an AI algorithm or a human loan officer. The study found that consumers experienced a higher level of satisfaction when they encountered procedural unfairness from humans compared to AI. The negative effect of procedural unfairness on satisfaction was amplified as algorithm discomfort and perceived company responsibility increased. The findings suggest that AI unfairness requires special attention to address differences in consumer reaction.

Keywords: AI; satisfaction; procedural fairness; unfairness; algorithm discomfort

1. Introduction

Artificial intelligence (AI) technologies—such as chatbots, virtual assistants, and machine learning systems—are transforming customer service by enabling both self-directed interactions and support for frontline employees. These technologies enhance service personalization through real-time data analysis, allowing businesses to interpret and respond dynamically to customer behavior [1,2]. Consumers increasingly value AI's capabilities, including its capacity for monitoring, self-correction, and delivering contextually relevant information, all of which help reduce cognitive effort in daily tasks. However, the full potential of AI to deliver customer value depends on addressing concerns related to information privacy and ethics. While AI tools are now embedded in everyday experiences—appearing as chatbots, automated transaction processors, and decision-making systems—some consumers find these encounters disconcerting due to the growing collaboration between humans and machines [1,3,4]. Of particular concern is algorithmic decision-making (ADM) or the use of AI technologies to make or inform decisions previously made by humans. ADM can assist consumers with complex purchasing journeys but may also expose them to biased outcomes [5–7]. For example, when a consumer applies for a bank loan and they



Academic Editors: Ashkan Ebadi and Mani Abedini

Received: 3 April 2026

Revised: 5 June 2026

Accepted: 9 June 2026

Published: 20 July 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

are told that processing decisions are made by AI, it raises questions in their mind about the thoroughness, objectivity and fairness of AI.

Research has revealed conflicting findings regarding how consumers view fairness in AI versus humans. Several factors suggest that consumers may have more confidence in certain types of decisions made by humans compared with AI. Recent studies have argued the opposite, noting that people regard AI as fairer than humans and have found support under certain conditions, e.g., [8]. People have greater confidence that AI will make better decisions in situations that lend themselves to algorithmic decision-making like scheduling service delivery. AI eliminates the fear that humans may introduce prejudices and create unfairness in service delivery. For example, ref. [9] manipulated unfairness in a hotel check-in interaction and found that subjects perceived higher levels of unfairness with humans compared to AI. The study examined unfairness involving customers overhearing preferential treatment to another customer. Since consumers think AI algorithms are absent of such initiated bias, they will trust AI more than humans for such utilitarian tasks.

However, consumer perception of fairness remains unclear for service delivery situations involving complex decision-making. For example, deciding to grant a loan or a mortgage to a customer may involve multiple levels of analysis and assessment of the personal disposition of the customer. Consumers are generally less familiar with AI service agents compared to their human counterparts [10]. While social expectations and norms for frontline employees are well established, the protocols for AI interactions are less known to consumers [11]. This may foster skepticism toward complex AI-mediated transactions. Research has found that consumers experience paradoxical emotions in response to technology, simultaneously feeling empowered and constrained, undermining customer satisfaction [12,13]. Further compounding this issue is the perception that AI is less adaptive than humans. While humans are seen as capable of learning and correcting their mistakes, AI is often viewed as more rigid and limited in responsiveness [14]. Consumer evaluations of AI are subject to bias, with service experiences receiving lower ratings when consumers are told they are interacting with a chatbot rather than a human agent [15]. Collectively, these factors suggest that consumer responses to unfairness from human and AI in complex service delivery situations are not well understood. The purpose of this study is to clarify our understanding of consumer response to unfair decision-making by AI versus humans.

This study examines consumer perceptions of two dimensions of fairness, namely, procedural and distributive. Procedural fairness refers to the perceived justice of the process, including whether customers are treated with respect, receive timely information, and are engaged in decisions that affect them [16,17]. In the AI context, this includes transparency, non-discrimination, and accountability [18,19]. Distributive fairness, on the other hand, concerns the perceived fairness of the outcome, specifically the value customers receive relative to what they give, such as price paid or effort exerted [20,21]. The present study also examines the moderators of the effects of fairness on customer satisfaction. Drawing from the theoretical perspective that consumer response to unfairness should be influenced by attitudinal and situational factors, the role of algorithm discomfort and perceived firm responsibility for the AI actions are examined as moderating consumer response to fairness experiences.

The present study makes significant contributions to emerging research and theory on AI fairness and the need to eliminate communication blind spots around AI transactions (see Table 1 for a summary of influential research). First, the study contributes to the extant literature by highlighting that perceived AI fairness is not monolithic. Prior research on AI fairness has often failed to make a distinction between different types of fairness. Moreover, when these studies examine different types of fairness such as procedural

and distributive fairness, they often do not manipulate distributive fairness but instead measure it as fairness of the overall outcome. This study manipulates both distributive and procedural unfairness to illustrate clear differences in the consumer response to different types of fairness. Whereas previous studies have argued that consumers prefer AI to humans, this study articulates an alternate perspective that consumers find unfairness from humans more tolerable than unfairness from AI. This arises from higher-quality communication opportunities in transactions between humans versus transactions between humans and AI.

Table 1. Influential Studies on Fairness and AI Algorithms.

Author(s)	Research Question	Research Methodology	Context	Key Finding(s)
[22]	Employee perception of human versus algorithm decisions	Online experiment	Intra-organizational	Algorithms perceived to be less trustworthy and fair for tasks considered better suited to humans
[23]	How (un)favorable outcomes affect perceived fairness	Online experiment	Intra-organizational	People rate algorithms as fairer when they predict in their favor
[24]	How decision agents' explanations affect decision-recipients' perceptions of justice (human vs. automation)	Experiment using healthcare professional subjects	Healthcare delivery	Perceptions of interpersonal justice are stronger for human agents. Human agents offer more voice, and automated agents are more consistent in decision-making
[25]	How much people extend "human-human interaction" rules (such as fairness) to artificial intelligence	Game theory experiment	Computer-mediated communication	People's self-perception of fairness influences their interactions with AI. Reputational systems used in online communities and virtual environments can significantly influence social behavior and fairness
[7]	How do individuals perceive the fairness of algorithmic decisions	Systematic literature review of 58 empirical studies	Multi-context	Perceived fairness varies highly within and across context
[26]	Can service robots use interactional justice as frontline employees do during service recovery?	Literature review	Service recovery and social robotics literature	Robots may approximate procedural or distributive justice, but interactional justice remains difficult to replicate due to limited perceived empathy and moral agency
[9]	How power distance belief differs in relation to fairness (procedural and distributive) perceptions towards humans and AI robots in service delivery	Qualitative and experiment	Multi-context and hospital	Robotic services are perceived to be fairer than human services. The effect is stronger for people with low power distance belief
This study	Are procedural and distributive fairness of human vs. AI perceived differently for complicated decisions.	Online experiment	Application for a bank loan	Consumers are less satisfied with procedural unfairness (but not distributive unfairness) from AI versus humans. Perceived company responsibility and algorithm discomfort moderate this effect

2. Fairness in Algorithmic Decisions

Perceived fairness in decision-making—particularly regarding service delivery timing and customer billing—has long been recognized as a fundamental component of effective relationship management [27–32]. It is argued that recent technological advances will increase rather than decrease consumer concerns about fairness. Recent years have witnessed the integration of AI technologies—including machine learning, natural language processing, and computer vision—into customer-facing business operations. These

systems are widely adopted to streamline workflows, improve service quality, and personalize customer journeys. Empirical research affirms AI's effectiveness in service contexts, with some studies showing that chatbots can match or even surpass proficient human workers—especially when users are unaware that they are interacting with AI [15]. However, consumer responses are not universally positive as empathy levels may decrease when customers are told they are interacting with an AI agent. AI systems add value by anticipating customer dissatisfaction and implementing service recovery measures [33]. Consumers are vulnerable to a variety of adverse circumstances and actors that seek to take advantage of them in the marketplace. Adverse circumstances like illnesses, depression, and temporary financial constraints expose consumers to vulnerable circumstances where they have little control or options to determine outcomes [34,35]. AI can increase ethical risks due to its unprecedented ability to acquire customer data at negligible cost, observe customers and predict behavior, making corporate indiscretions exponentially more damaging to consumers [36–38]. AI's ability to muster people-related technologies and techniques such as ubiquitous surveillance, social engineering, and the real-time analysis of behavioral and mobile platform-based data suggests an exponential increase in dark-side persuasive attempts, dissemination of misinformation, behavioral modification and security compromise [4,36,38–42]. Consumers recognize the added risk of AI as research reveals a preference for the regulatory oversight of AI technology by government over corporate self-regulation [43]. These factors place consumer fairness perceptions at the center of AI transactions.

Research points out differences in consumer evaluation of trust and fairness in humans versus AI. Consumers often react more negatively to mistakes made by AI and robots than by humans, with a sharper decline in trust following errors [14,44]. This effect may be attributed to consumers' limited familiarity with algorithms, combined with their perception of algorithms as opaque "black box" systems [10,45]. Improving the perceived fairness of AI systems can involve enhancing specific features such as accuracy, transparency, and interpretability. For instance, ref. [46] found that even if algorithmic features increase outcome disparities, they may still be perceived as fair depending on how they are framed. Interpretability—especially the ability of AI to communicate the rationale behind its decisions—is key to enhancing procedural fairness [47]. Research shows that people rate accurate AI decisions as fairer and perceive decisions on simpler tasks as more just than those involving complex judgment [48]. This underscores the importance of timing in fairness assessments—users may need a more holistic view of the decision-making process before making accurate fairness judgments. In addition to system-level attributes, user characteristics significantly shape fairness perceptions. Individual self-concept plays a role as people aim to maintain a consistent self-perception of fairness, whether interacting with humans or AI [25]. These interpersonal norms carry over into AI interactions, suggesting that consumer fairness judgments may be compared across digital and human touchpoints. Finally, contextual appropriateness also influences fairness perceptions. Consumers deem AI decisions less fair in contexts they view as requiring human judgment—such as hiring or performance evaluation—highlighting a perceived mismatch between task type and AI suitability [22].

Consumers also consider AI to be fairer for calculative decisions. People regard AI as more objective than humans and are apparently less scrutinizing of AI decision-making on objective tasks. For example, consumers perceive demographic price discrimination as more fair when prices are determined by algorithms than by humans. The researchers in [8,9] examined calculative service delivery procedures and outcomes for robots versus humans in restaurant, hotel and medical service delivery and found instances of higher procedural and distributive fairness associated with robots than humans. However, studies

show that in situations involving more complex decision-making, humans are preferred for their ability to provide empathy and nuanced judgment [45]. For example, ref. [49] found that for service recovery tasks requiring feelings or empathic skills, consumers perceived AI as less customer-oriented than humans. On analytical tasks, however, humans were perceived as performing on par with AI.

Fairness in AI application is an essential component of corporate digital responsibility (CDR), along with the ethical and protective use of technology and customer data [37,38,50]. CDR is, in essence, a roadmap to sustainable competitive advantage for service businesses [38]. These businesses rely on data-driven insights from sustained customer interactions to deliver personalized and customized experiences [41,51]. It has been suggested that AI should be applied as an intervention to enhance consumer agency and autonomy in vulnerable transactions [34]. While there is consensus on the need for ethical AI, implementing enforceable and scalable global guidelines remains a pressing challenge. Against this background, fairness that entails impartiality, honesty, rule compliance, and service quality needs to be fully understood within the context of AI transactions.

3. Hypotheses

Distributive fairness, defined as the perceived fairness of the outcome relative to customer expectations, is unlikely to vary significantly between AI and human service channels. Both are generally capable of delivering value that meets expectations. In contrast, procedural fairness—the fairness of the process by which outcomes are delivered—may be evaluated differently for AI and human interactions, due to differences in perceived empathy, adaptability, and communication arising from limitations in AI's ability to deliver empathy and interactional justice (for a discussion, see [26]).

It is anticipated that consumers will respond less negatively to procedural unfairness experiences from humans compared to AI. This is because human interactions provide greater opportunities for dialogue and resolution than interactions with chatbots [24]. Theoretical support also comes from the notion of parametric reductionism [52], which refers to the tendency for AI algorithms to objectify consumers by placing them into reductionist categories that misrepresent or underrepresent the full complexity of their opinions. For example, a customer may expect to have a conversation with a service provider to communicate idiosyncratic perspectives relevant to a transaction decision. Should the transaction conclude without such an opportunity, the customer is likely to conclude that the AI made the decision with incomplete information. This is less likely to occur in interactions between people. Additionally, studies on perceptions of bots and computational systems suggest that AI is perceived as having limited emotional capacity, including reduced ability to feel, sense, or exercise self-control [50,53,54]. Finally, consumers respond less favorably to robot-led service recovery, particularly when emotional or relational repair is required, suggesting that competence-based rather than empathy-based recovery is more effective for AI agents [44]. Given these differences between perceptions of service delivered by humans and AI, consumers are likely to perceive less similarity and feel less empathy toward AI. This should amplify negative reactions to unfair treatment by AI compared to humans. It is anticipated that these differences will result in different levels of perceived fairness/unfairness and levels of customer satisfaction in response to fairness and unfairness experiences. In contrast, for heretofore mentioned reasons, similar responses are not anticipated for distributive fair/unfair experiences.

H1: *Consumers will perceive higher procedural fairness (lower unfairness) in interactions with humans compared to AI. No difference is expected for distributive unfairness.*

H2: *Procedural unfairness (fairness) will lead to lower (higher) customer satisfaction in interactions with AI compared to humans. No difference is expected for distributive unfairness.*

Moderators of Procedural and Distributive Unfairness

Figure 1 presents the conceptual model, which includes the proposed moderating relationships to be tested. The selection of moderators is based on the premise that the effects of AI-related unfairness are influenced by both consumer attitudes toward AI and their beliefs about the extent to which AI behavior reflects company policy. Accordingly, two moderators were examined: algorithm discomfort and perceived company responsibility. Consumers are often reticent to engage technology due to biases in their attitudes toward technology (e.g., [45]). The notion that firms have a responsibility to assure the integrity of transactions and protect customers, which is embodied by corporate digital responsibility (CDR), is well established [37,52]. According to [38], service firms weigh the benefits and costs of good CDR to determine their degree of conformance to its principles. Consistent with this reasoning, we argue that companies make decisions about their responsibility for AI conduct and that consumers make attributions about how AI performance reflects company policy.

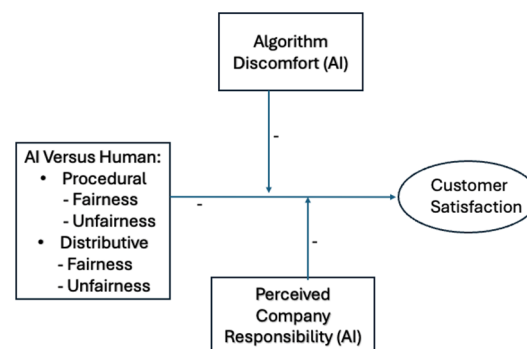


Figure 1. Human vs. AI Fairness and Moderators of AI Effect on Satisfaction.

It is expected that consumer responses to procedural and distributive fairness from AI will vary depending on these moderators. Algorithm discomfort refers to a form of algorithm aversion characterized by negative emotional reactions when interacting with AI systems. It manifests as biased evaluations of algorithms, typically in comparison to human agents [55]. This discomfort may reduce technology self-efficacy by increasing users' doubts about their ability to effectively engage with AI. Prior research has shown that algorithm discomfort leads to a decline in trust in AI systems [45], which, in turn, heightens consumer uncertainty during digital transactions. To accurately evaluate fairness in AI-driven service interactions, users must have confidence in their ability to navigate the technology and a clear understanding of how AI decision-making works. In the absence of such self-efficacy, users may experience increased frustration, particularly when faced with perceived unfairness.

The literature on technology anxiety further supports this moderating role. Technology anxiety refers to a multi-dimensional emotional state that includes nervousness, fear, and uncertainty related to technology use [56]. Studies have shown that individuals with high technology anxiety demonstrate lower trust in technology, reduced privacy assurance, and more negative overall attitudes toward digital systems [56–58]. Based on this framework, it is hypothesized that algorithm discomfort will exacerbate the negative impact of both procedural and distributive unfairness in AI interactions.

H3a–b: *As algorithm discomfort increases, the negative effects of (a) procedural unfairness and (b) distributive unfairness on customer satisfaction will increase.*

As consumers are still in the early stages of engaging with AI-based services, they are actively forming experience-driven expectations. When interacting with AI touchpoints, consumers may attribute service procedures either to the inherent limitations of the technology or to deliberate company policies. In situations involving procedural unfairness, this ambiguity can complicate how consumers assign blame. For instance, a delay in processing may be perceived as stemming from the AI's inability to address a unique request—or, alternatively, as a strategic decision by the company to process certain transactions more slowly. Prior research shows that consumers attribute service failures by robots more to the firm and underlying system than to the agent itself, perceiving such failures as more stable and less easily corrected than human errors [59]. This finding suggests that unfair AI-driven experiences are likely to be attributed to company policy rather than to human service providers. As the perception of company or corporate responsibility increases, consumers are more likely to view instances of AI unfairness as systematic and controllable. According to attribution theory [60,61], the perceived controllability of a service failure intensifies its negative impact on customer satisfaction. If consumers interpret unfair treatment as the result of intentional company decisions, their dissatisfaction is likely to increase accordingly. Based on this reasoning, the following hypothesis is proposed:

H4a–b: *As perceived company responsibility for AI performance increases, the negative effects of (a) procedural unfairness and (b) distributive unfairness on customer satisfaction will increase.*

4. Methods

A scenario-based experiment was conducted in which participants were asked to review the loan application experience of a small business customer applying for a \$10,000 loan from a fictional digital bank and provide their opinion. The experiment employed a between-subjects design of 4 fairness conditions (procedural fairness, procedural unfairness, distributive fairness, distributive unfairness) X 2 provider conditions (human vs. AI). Rather than measure fairness and unfairness on a continuum, these were separately manipulated to understand differences in consumer reactions across human and AI service interactions. Participants were randomly assigned to one of these conditions.

All participants read the following:

For the purposes of this study, we ask that you set aside your thoughts and opinions about how bank loan decisions are made. Instead, we ask that you focus on a scenario where you are considering the experience of a local small business entrepreneur who has applied to a digital bank for a \$10,000 loan to finance the expansion of his/her business. The loan application is made via a digital portal involving the completion of an online application form and uploading requested documents. Applicants are informed of further requests and the loan approval decisions via email. Customers submit loan applications using a digital portal.

Following this, participants were randomly assigned to an AI or a human condition that identified their service provider as human or AI. All participants were informed that standard loan processing time was 24 hours, followed by an additional 8 hours for fund disbursement. The fairness manipulations are available in Appendix B. The experimental conditions were structured as follows. Procedural fairness: loans were processed within 24 h and deposited within 8 h. Procedural unfairness loans were processed and approved within 24 h, but funds were not deposited until five days later. The distributive fairness condition offered subjects a 3.5% interest rate. The distributive unfairness condition of-

ferred subjects a 6.0% interest rate. All participants received monetary compensation of \$13.54 per hour with a median time of 5.19 min to complete their response.

Data were collected from 306 adult participants in the United States via the Prolific research platform. The target sample size was determined by the recommendation of at least 30 participants per experimental condition in between-subjects designs. The final sample consisted of 306 participants, resulting in more than 30 participants in each of the eight experimental cells. In addition, a post hoc sensitivity analysis conducted using G*Power 3.1 indicated that the sample provided excellent statistical power (greater than 0.95) to detect medium-sized effects at $\alpha = 0.05$.

All participants were 18 years or older, with an average age of 40 years. Subjects were 44.4% female, and 68.3% reported an annual household income of between \$40,000 and \$150,000. Procedural fairness and distributive fairness were measured using the same four-item scales. In addition, algorithm discomfort (7-point Likert scale, $\alpha = 0.892$), perceived company responsibility (7-point Likert scale, $\alpha = 0.702$), and customer satisfaction (9-point Likert scale, $\alpha = 0.773$) were measured using scales detailed in Appendix A.

5. Results

Manipulation checks confirmed the effectiveness of the experimental conditions (see Appendix A for measures of fairness). A single procedural fairness scale was used to measure procedural fairness for both the procedural fairness and procedural unfairness conditions, and similarly for the distributive fairness/unfairness conditions. To verify the procedural fairness manipulation, an independent-samples *t*-test was conducted. Results indicated that participants in the procedural fairness condition rated their experience as significantly fairer than those in the procedural unfairness condition ($M_{\text{procedural fair}} = 5.38$, $SD = 1.05$ vs. $M_{\text{procedural unfair}} = 4.65$, $SD = 1.27$; $t(148) = 3.76$, $p < 0.001$, two-tailed Cohen's $d = 0.62$, power > 0.95), confirming the success of the manipulation. A similar pattern was found for distributive fairness. An independent-samples *t*-test revealed that participants in the distributive fairness condition rated their experience as significantly fairer than those in the distributive unfairness condition ($M_{\text{distributive fair}} = 5.49$, $SD = 0.98$ vs. $M_{\text{distributive unfair}} = 4.33$, $SD = 1.60$; $t(125.70) = 5.42$, $p < 0.001$, two-tailed Cohen's $d = 0.87$, power > 0.95), confirming the success of the manipulation.

The results comparing fairness perceptions across AI and human service providers, are presented in Tables 2 and 3. They indicate that perceived procedural fairness does not differ between human and AI service providers under the procedural fairness condition ($M_{\text{Human}} = 5.3542$ vs. $M_{\text{AI}} = 5.3971$, $p = 0.866$). However, under the procedural unfairness condition, there is a significant difference at the $p < 0.10$ level, with perceived procedural fairness being higher for humans than for AI, providing partial support for Hypothesis 1 ($M_{\text{Human}} = 4.8618$ vs. $M_{\text{AI}} = 4.4643$, $p = 0.08$). In addition, no significant differences in perceived distributive fairness were observed between human and AI service providers, both under the distributive fairness condition ($M_{\text{Human}} = 5.47$ vs. $M_{\text{AI}} = 5.51$, $p = 0.866$) and the distributive unfairness condition ($M_{\text{Human}} = 4.49$ vs. $M_{\text{AI}} = 4.41$, $p = 0.349$; see Table 3).

Hypothesis 2 was supported in the procedural unfairness condition, with subjects reporting significantly lower levels of customer satisfaction in interactions with AI compared to humans (see Table 4; $M_{\text{Human}} = 5.9737$ vs. $M_{\text{AI}} = 4.9841$, $p = 0.037$). No difference was found in customer satisfaction between human and AI conditions under distributive unfairness (see Table 5). In summary, when experiencing procedural unfairness, consumers report lower satisfaction with AI than with human service providers.

Table 2. Perceived Procedural Fairness under Procedural Fairness/Unfairness Conditions (AI vs. Human).

Fairness Condition	N	Perceived Procedural Fairness (1—Low to 7—High)	Std. Deviation	Std. Error Mean
Procedural fairness condition				
Human	36	5.35	1.147	0.191
AI	34	5.40	0.958	0.164
Difference ($p = 0.866$)				
Procedural unfairness condition				
Human	38	4.86	1.474	0.239
AI	42	4.46	1.032	0.159
Difference Significant ($p = 0.08$)				

Table 3. Perceived Distributive Fairness under Distributive Fairness/Unfairness Conditions (AI vs. Human).

Fairness Condition	N	Perceived Distributive Fairness (1—Low to 7—High)	Std. Deviation	Std. Error Mean
Distributive fair Condition				
Human	40	5.47	1.000	0.158
AI	39	5.51	0.979	0.157
Difference ($p = 0.866$)				
Distributive unfair Condition				
Human	42	4.49	1.530	0.236
AI	35	4.14	1.683	0.284
Difference ($p = 0.349$)				

Table 4. Customer Satisfaction under Procedural Fairness/Unfairness Conditions (AI vs. Human).

Fairness Condition	N	Perceived Satisfaction (1—Low to 9—High)	Std. Deviation	Std. Error Mean
Procedural fair condition				
Human	36	6.66	1.840	0.307
AI	34	6.95	1.696	0.291
Difference ($p = 0.491$)				
Procedural unfair condition				
Human	38	5.97	1.944	0.315
AI	42	4.98	2.195	0.339
Difference Significant ($p = 0.037$)				

A moderated regression analysis using Hayes' PROCESS macro (Model 1) for SPSS Version 4.1 was used to test Hypotheses 3 and 4. The independent variables—procedural unfairness and distributive unfairness—were measured using the previously described fairness scale, which was reverse-coded so that higher values indicated greater unfairness. The results are presented in Tables 6–9.

Table 5. Customer Satisfaction under Distributive Fairness/Unfairness Conditions (AI vs. Human).

Fairness Condition	N	Perceived Satisfaction (1—Low to 9—High)	Std. Deviation	Std. Error Mean
Distributive fair condition				
Human	40	6.84	1.619	0.256
AI	39	6.38	2.096	0.336
Difference ($p = 0.272$)				
Distributive unfair condition				
Human	42	5.32	2.334	0.360
AI	35	4.86	1.992	0.337
Difference ($p = 0.360$)				

Hypothesis 3a was supported, while Hypothesis 3b was not. A significant moderating effect of algorithm discomfort was found in the relationship between procedural unfairness and customer satisfaction. Specifically, as algorithm discomfort increased, the negative impact of procedural unfairness on customer satisfaction also increased ($\beta = -0.3254$, $p = 0.042$; see Table 6). This interaction is illustrated in Figure 2. The effect of procedural unfairness was not significant at low levels of algorithm discomfort ($\beta = -0.2262$, $p = 0.2238$) but became significant at medium and high levels ($\beta = -0.8421$, $p < 0.001$). In contrast, no significant moderating effect of algorithm discomfort was found for distributive unfairness (see Table 7). This suggests that consumer discomfort with AI does not intensify dissatisfaction stemming from financial outcomes. Instead, algorithm discomfort appears to primarily influence evaluations of process-related fairness.

Table 6. Algorithm Discomfort Moderating the Effect of Procedural Unfairness on Customer Satisfaction.

	Coefficient	SE	t-Value	p-Value	LLCI	d
Dependent Variable: Customer Satisfaction						
Constant	−0.4656	0.1361	−3.4210	0.0015	−0.7412	−0.1901
Procedural unfairness	−0.5569	0.1424	−3.9104	0.0004	−0.8452	−0.2686
Algorithm discomfort	−0.3231	0.1586	−2.0367	0.0487	−0.6442	−0.0019
Procedural unfairness × Algorithm discomfort	−0.3254	0.1546	−2.1051	0.0420 *	−0.6384	−0.0125

Table 7. Algorithm Discomfort Moderating the Effect of Distributive Unfairness on Customer Satisfaction.

	Coefficient	SE	t-Value	p-Value	LLCI	ULCI
Constant	0.0198	0.0599	0.3310	0.7411	−0.0985	0.1382
Distributive unfairness	−0.6662	0.0667	−9.9928	<0.0001	−0.7979	−0.5344
Algorithm discomfort	−0.1839	0.0620	−2.9666	0.0035	−0.3064	−0.0614
Distributive unfairness × Algorithm discomfort	0.0805	0.0544	1.4788	0.1413	−0.0271	0.1881

Hypotheses 4a and 4b were supported. Specifically, higher levels of perceived company responsibility increased the negative effect of both procedural unfairness on customer

satisfaction ($\beta = -0.3399$, $p < 0.01$; see Table 8) and distributive unfairness on customer satisfaction ($\beta = -0.1525$, $p < 0.01$; see Table 9). These effects are illustrated in Figures 3 and 4. The negative effect of procedural unfairness became non-significant at low levels of perceived company responsibility ($\beta = -0.1499$, $p = 0.3941$), but was significant at both medium and high levels ($\beta = -0.8296$, $p < 0.001$), indicating that consumers are more sensitive to process-based unfairness when they believe the company is responsible. Additionally, perceived company responsibility demonstrated a robust moderating effect on the relationship between distributive unfairness and satisfaction. This effect was statistically significant at low, medium, and high levels of perceived responsibility (all p -values < 0.001 ; see Figure 4). A Johnson–Neyman analysis indicated that the interaction was significant across more than 96% of the perceived responsibility distribution, highlighting the widespread influence of perceived company responsibility on fairness evaluations. These findings suggest that when consumers attribute unfair AI outcomes to company policy or intent, the negative consequences for satisfaction and trust are significantly amplified.

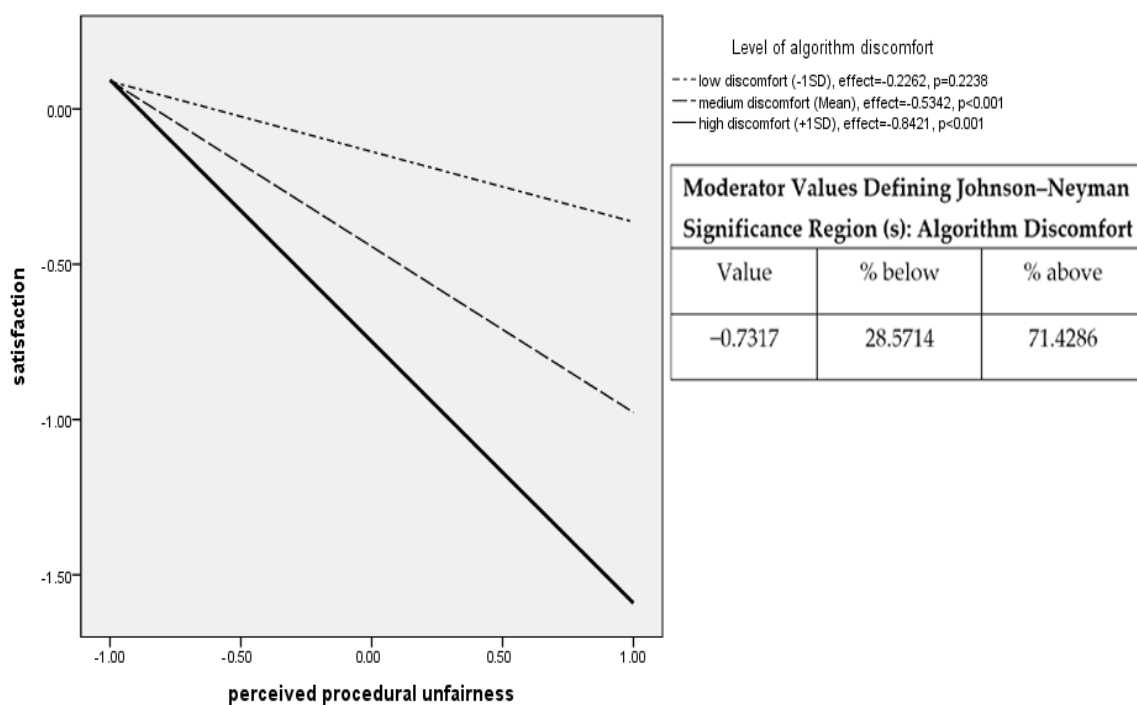


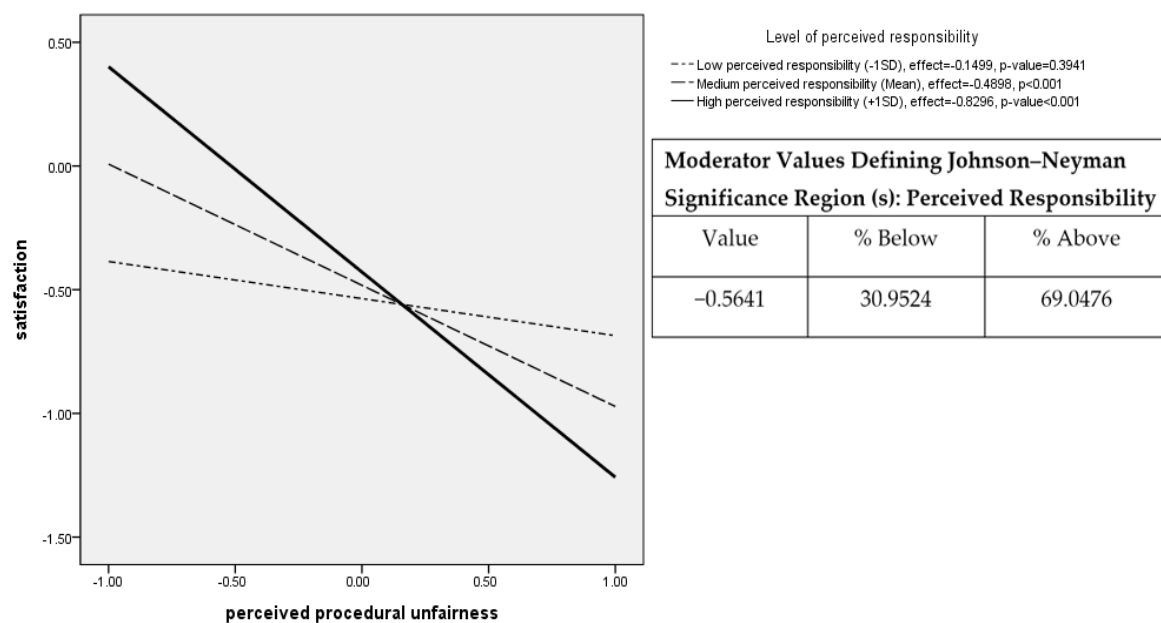
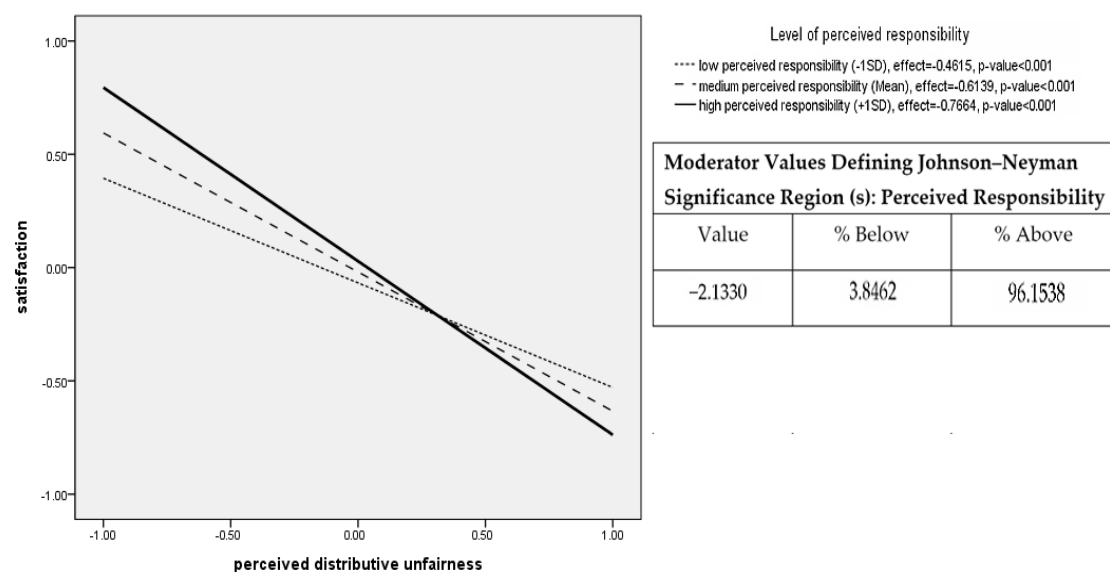
Figure 2. The Main Effect of Procedural Unfairness on Customer Satisfaction at Levels of Algorithm Discomfort.

Table 8. Perceived Company Responsibility Moderating the Effect of Perceived Procedural Unfairness on Customer Satisfaction.

	Coefficient	SE	t-Value	p-Value	LLCI	ULCI
Constant	−0.4822	0.1309	−3.6829		−0.7472	−0.2171
Procedural unfairness	−0.4898	0.1326	−3.6946	0.0007	−0.7581	−0.2214
Perceived company responsibility	0.0537	0.1333	0.4029	0.6893	−0.2161	0.3235
Procedural unfairness × Perceived company responsibility	−0.3399	0.1111	−3.0586	0.0041 *	−0.5648	−0.1149

Table 9. Results: Perceived Company Responsibility Moderating the Effect of Perceived Distributive Unfairness on Customer Satisfaction.

	Coefficient	SE	t-Value	p-Value	LLCI	ULCI
Constant	−0.0196	0.0599	−0.3271	0.7440	−0.1379	0.0987
Distributive unfairness	−0.6139	0.0619	−9.9223	<0.0001	−0.7362	−0.4917
Perceived company responsibility	0.0479	0.0607	0.7892	0.4312	−0.0720	0.1677
Distributive unfairness × Perceived company responsibility	−0.1525	0.0557	−2.7397	0.0069 *	−0.2624	−0.0425

**Figure 3.** The Main Effect of Procedural Unfairness on Customer Satisfaction at Levels of Perceived Company Responsibility.**Figure 4.** The Main Effect of Distributive Unfairness on Customer Satisfaction at levels of Perceived Company Responsibility.

6. Discussion

This study contributes to emerging theory on consumer perceptions of fairness in AI versus human service interactions. Participants perceived higher procedural unfairness and lower satisfaction when interacting with AI compared to human agents. This difference was not found for distributive fairness evaluations. Whereas prior research found that, for scheduling decisions, consumers regard AI as more fair than humans [9], this study found that for more complex decisions such as a loan approval, consumers are more satisfied with unfairness from humans than from AI. People value the flexibility, empathy and responsiveness of humans when service delivery involves complex decision-making.

This study introduces key moderators that shape the implications of unfairness. Algorithm discomfort—defined as negative emotional reactions to AI—was found to significantly increase the negative impact of procedural unfairness on customer satisfaction. This aligns with prior findings suggesting that discomfort with algorithmic systems erodes trust and increases evaluation ambiguity [45]. This moderating effect was not found for distributive unfairness, indicating that distributive unfairness involves an objective assessment of value received that is not influenced by consumers attitudes to AI or service delivery technology. Additionally, perceived company responsibility intensified the negative effects of both procedural and distributive unfairness. When consumers interpret service failures as intentional outcomes of company policy rather than technological limitations, their dissatisfaction is amplified. These findings are consistent with attribution theory [61], which emphasizes the role of controllability and intentionality in shaping reactions to service failure.

The study also positions procedural fairness as a key domain for meaningful collaboration between humans and AI. While AI excels in analytical and mechanical tasks [33], humans bring intuition, empathy, and emotional intelligence—qualities that help ensure the process feels fair to the consumer. These findings suggest that perceived procedural unfairness in AI interactions could be mitigated through human intervention, particularly during early or emotionally sensitive stages of service delivery. Lastly, the study reinforces the idea that consumer evaluations of AI are not based on holistic impressions but are shaped by specific features of the interaction. This supports prior work suggesting that people judge AI systems not in general terms, but through distinct cues related to transparency, adaptability, and emotional resonance [46]. Overall, this research advances a more detailed understanding of how consumers experience and evaluate fairness in hybrid human–AI service systems and highlights the cognitive and emotional mechanisms that shape these perceptions.

7. Future Research and Conclusions

The findings of this study open several avenues for future research. The study findings suggest the possibility that procedurally fair scenarios may hold low motivational relevance for consumers, whereas procedural unfairness creates cognitive dissonance and may trigger stronger emotional or behavioral responses. Understanding how consumers resolve this dissonance—particularly when AI is involved—warrants further investigation. One important direction for future research involves examining how consumers respond to AI versus human-led service recovery efforts following perceived unfairness. The current study also highlights the moderating role of perceived company responsibility, suggesting that broader organizational factors can significantly influence consumer perceptions of AI. This invites further exploration into how elements such as brand image, reputation, and corporate positioning may shape consumer trust and fairness judgments in AI-mediated interactions, which is an area largely overlooked in existing AI research. Additionally, scholars have pointed out that current AI systems often lack the intuition and empathy

that characterize effective human–service interactions. Although emerging technologies enable AI to detect emotional cues through voice and facial expression, the present study was limited to text-based interactions, which may not fully capture the nuances of emotional response to procedural unfairness. This limitation offers fertile ground for future research. Studies could investigate the extent to which emotionally responsive AI, capable of interpreting vocal intonation, facial expressions, or affective language, can improve service recovery outcomes. Research in this area could help identify the conditions under which AI can approximate human-like emotional intelligence and repair perceived unfairness effectively.

Author Contributions: The contributions of the authors are as follows: D.J.: conceptualization, research design, investigation, writing, funding; S.C.: conceptualization, research design, investigation, data analysis, review, funding; S.P.: conceptualization, investigation; G.A.: investigation, review. All authors have read and agreed to the published version of the manuscript.

Funding: This research received funding from Montclair State University.

Institutional Review Board Statement: Institutional Review Board approval was obtained from Montclair State University IRB-FY21-22-2306.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author(s).

Conflicts of Interest: The authors declare no conflicts of interest. Data collection was funded by the authors.

Appendix A. Measurement Items

Procedural fairness ($\alpha = 0.877$) [23,32]	1. The timeliness of processing of the loan application was fair to the applicant.
	2. The bank kept the customer appropriately informed throughout the process.
	3. The bank considered all the information provided by the applicant.
	4. The applicant was treated the same as others in terms of processing of the loan.
Distributive fairness ($\alpha = 0.881$) [23,32]	1. The approved loan offer treats the applicant equally as other customers.
	2. The interest and charges offered to the applicant are equal to what others receive.
	3. The terms of the approved loan to the applicant are financially reasonable.
	4. The interest rate offered to the applicant is reasonable.
Algorithm discomfort ($\alpha = 0.883$) [40]	1. Algorithms that can perform this kind of task better than humans make me uncomfortable.
	2. Algorithms that can perform this kind of task go against what I believe computers should be used for.
	3. Algorithms that can perform this kind of task are unsettling

Perceived Company Responsibility ($\alpha = 0.730$)	To what extent do you think the bank is responsible for this situation experienced by the applicant? 1. Not responsible at all (1) ... Extremely responsible (7) 2. Not caused by the bank's policy (1) ... Directly caused by the bank's policy (7)
Satisfaction ($\alpha = 0.768$) [62]	Overall, how do you feel about the service received by the loan applicant? 1. Displeased (1) ... Pleased (9) 2. Discontented (1) ... Contented (9) 3. Dissatisfied (1) ... Satisfied (9)

Appendix B.

Manipulations

Procedural Fairness Condition

Application for Bank Loan (All participants across all conditions).

For the purposes of this study, we ask that you set aside your thoughts and opinions about how bank loan decisions are made. Instead, we ask that you focus on a scenario where you are considering the experience of a local small business entrepreneur who has applied to a digital bank for a \$10,000 loan to finance the expansion of his/her business.

The loan application is made via a digital portal involving the completion of an online application form and uploading requested documents. Applicants are informed of further requests and the loan approval decisions via email. Customers submit loan applications using a digital portal.

Human Conditions:

The applications are reviewed and approved by a Loans Officer who is an employee of the bank.

Having review the application, the Loans Officer may request further information before making a decision or inform the applicant of his/her decision via email. All communications from the bank to the applicant is initiated by the loans officer.

AI Conditions:

The applications are reviewed and approved by an AI (artificial intelligence) algorithm decision-making system. An AI algorithm is a computer program that can perform tasks done by humans without human intervention. The AI algorithm reviews applications and makes decisions independently of human input. Having review the application, the AI may request further information before making a decision or inform the applicant of its decision via email. All communications from the bank to the applicant are initiated by the AI Algorithm.

The Bank's Service Policy (All participants across all conditions)

Applicants are informed of a yes/no decision within 24 h of applying. The Bank's policy is to make the first substantive response to the applicant within ten (10) to twelve (12) hours of receiving the application. The bank aims to achieve an interest rate of 3.5% for all loan applicants. Once the loan is approved, the applicant is sent direct message (DM) informing him/her of the decision. Once the applicant accepts the offer of the loan, the deposit of the loan to the customer's account is triggered automatically. At the end of each transaction, the bank shares the average loan processing time with the customer.

Actual Experience of the Applicant: Direct Message responses from the bank

The small business entrepreneur submitted a completed application for a loan of \$10,000 on the Bank's Web Site. After the initial confirmation of the application, twelve (12) hours later the applicant received the following direct message.

“Dear applicant,

Thank you for your application. We are confirming that your application is being processed. We are requesting additional information, which we have listed in your account. Please log into your account and respond to the following.

1. Upload the title for your 2015 Honda Accord listed as an asset in your application. [Upload document slot]
2. Our due diligence revealed that you are owing \$5000 in back taxes for 2020. Please confirm that the amount is owing. [Yes/No]

If you have already paid this bill, please provide the date of payment. [mm/dd/yy]

Failure to provide this information could result in a denial of your application or a higher interest rate being charged on your loan. ”

The applicant responded one (1) hour later by uploading the title and confirming that the tax bill had already been paid. Seven (7) hours later the applicant received the following direct message:

“Dear applicant,

Thank you for providing the requested information, which has been considered in making your loan decision. We are happy to advise you that your loan application has been approved at our standard interest rate (average for all applicants). Your loan amount will be deposited to your account as soon as you accept our offer. Thank you for using our bank for your financial needs.”

Your loan processing time was 20 h.

Average 5-day loan processing time is 20 h.

Procedural Unfairness Condition

Actual Experience of the Applicant: Email responses from the bank

The small business entrepreneur submitted a completed application for a loan of \$10,000. After submitting the application, twenty (20) hours later the entrepreneur received the first direct message with the following.

“Dear applicant,

Thank you for your application. We are confirming that your application is being processed. We are requesting additional information, which we have listed in your account. Please log into your account and respond to the following.

1. Upload the title for your 2015 Honda Accord listed as an asset in your application. [Upload document slot]
2. Our due diligence revealed that you are owing \$5000 in back taxes for 2020.

Please confirm that the amount is owing. [Yes/No]

If you have already paid this bill, please provide the date of payment. [mm/dd/yy]

Failure to provide this information could result in a denial of your application or a higher interest rate being charged on your loan. ”

The applicant responded within one (1) hour by uploading the title and confirming that the tax bill had already been paid. Three (3) hours later the applicant received the following direct message:

“Dear applicant,

We regret to inform you that the additional information we requested was not submitted on time and was not considered in making your loan decision. Despite this, we have approved your loan application at our general interest rate. Your loan amount will be deposited to your account as soon as you accept our offer. Thank you for using our bank for your financial needs.”

Your loan processing time was 24 h.

Average 5-day loan processing time is 15 h.

Despite hearing that the loan was approved, the applicant felt disappointed with the banks handling of the application.

Distributive Fairness Condition

Actual Experience of the Applicant: Direct Message responses from the bank

The small business entrepreneur (applicant) submitted a completed application for a loan of \$10,000. The applicant listed the last tax bill of \$8000 from the Internal Revenue Service (IRS) as paid in the application. However, the applicant had mailed the check to the Internal Revenue Service only two days before and had not yet see it deposited against the bill. The applicant was worried that without verification of the tax payment by the bank, the loan application would be approved at a higher interest rate of 6 to 8% listed on the Bank's web site for high-risk customers. The applicant was also worried that the application would be adversely affected by late payments on a previously held bank loan.

After the initial application confirmation, the first direct message was received from the bank twelve (12) hours after submitting the application:

"Dear applicant,

After reviewing your loan application, we are happy to inform you that your application for a loan of \$10,000 has been approved. The interest rate on your loan is 3.5%. The average interest rate for applicants with a similar risk profile is 3.5%. We are waving your \$100.00 loan application processing fee as we do for all clients having a similar risk profile.

Your loan will be deposited to your account as soon as you accept our offer. Thank you for using our bank for your financial needs."

Our customer service tracker indicates the following 5-day averages for all customers:

Average interest rate on loans: 3.5%

Customers receiving loan application fee waivers: 50%

Distributive Unfairness Condition

Actual Experience of the Applicant: Direct message responses from the bank

The small business entrepreneur (applicant) submitted a completed application for a loan of \$10,000 on the Bank's Web Site. The applicant listed the last tax bill of \$8000 from the Internal Revenue Service (IRS) as paid in the application. The payment was made 24 h before by bank transfer. The bank can verify that the payment has been made using its big data IT system.

After the initial application confirmation, the first direct message response was received twelve (12) hours after submitting the completed application:

"Dear applicant,

After reviewing your loan application, we are happy to inform you that your application for a loan of \$10,000 has been approved. The interest rate on your loan is 8.0%. The average interest rate for applicants with a similar risk profile is 3.5%. You will be charged a \$100.00 loan processing fee.

Your loan will be deposited to your account as soon as you accept our offer. Thank you for using our bank for your financial needs."

Our customer service tracker indicates the following 10-day averages for all customers:

Average interest rate on loans: 3.5%

Customers receiving loan application fee waivers: 80%

Although the applicant felt fortunate to have gotten the loan, he/she felt disappointed about the high interest rate and having to pay the application fee.

References

1. Peltier, J.W.; Dahl, A.J.; Schibrowsky, J.A. Artificial Intelligence in Interactive Marketing: A Conceptual Framework and Research Agenda. *J. Res. Interact. Mark.* **2023**, *18*, 54–90. [\[CrossRef\]](#)
2. Swan, E.L.; Peltier, J.W.; Dahl, A.J. Artificial Intelligence in Healthcare: The Value Co-Creation Process and Influence of Other Digital Health Transformations. *J. Res. Interact. Mark.* **2023**, *18*, 109–126. [\[CrossRef\]](#)
3. Barnes, S.; de Ruyter, K. Guest Editorial: Artificial Intelligence as a Market-Facing Technology: Getting Closer to the Consumer through Innovation and Insight. *Eur. J. Mark.* **2022**, *56*, 1585–1589. [\[CrossRef\]](#)
4. Puntoni, S.; Reczek, R.W.; Giesler, M.; Botti, S. Consumers and Artificial Intelligence: An Experiential Perspective. *J. Mark.* **2021**, *85*, 131–151. [\[CrossRef\]](#)
5. Longoni, C.; Cian, L. Artificial Intelligence in Utilitarian vs. Hedonic Contexts: The “Word-of-Machine” Effect. *J. Mark.* **2020**, *86*, 91–108.
6. Williams, B.A.; Brooks, C.F.; Shmargad, Y. How Algorithms Discriminate Based on Data They Lack: Challenges, Solutions, and Policy Implications. *J. Inf. Policy* **2018**, *8*, 78–115. [\[CrossRef\]](#)
7. Starke, C.; Baleis, J.; Marcinkowski, F. Fairness Perceptions of Algorithmic Decision-Making: A Systematic Review of the Empirical Literature. *Big Data Soc.* **2022**, *9*, 20539517221115189. [\[CrossRef\]](#)
8. Duani, N.; Barasch, A.; Morwitz, V. Demographic Pricing in the Digital Age: Assessing Fairness Perceptions in Algorithmic versus Human-Based Price Discrimination. *J. Assoc. Consum. Res.* **2024**, *9*, 257–268. [\[CrossRef\]](#) [\[PubMed\]](#)
9. Wu, X.; Li, S.; Guo, Y.; Fang, S. Human or AI Robot? Who Is Fairer on the Service Organizational Frontline. *J. Bus. Res.* **2024**, *181*, 114730. [\[CrossRef\]](#)
10. Berger, B.; Adam, M.; Rühr, A.; Benlian, A. Watch Me Improve—Algorithm Aversion and Demonstrating the Ability to Learn. *Bus. Inf. Syst. Eng.* **2021**, *63*, 55–68. [\[CrossRef\]](#)
11. Ou, M.; Zheng, H.; Li, B.; Luo, C. The Dark Side of Algorithms: How Ethical and Privacy Considerations Affect Individuals’ Engagement with Health Information on Social Media? *Int. J. Commun.* **2026**, *20*, 24. [\[CrossRef\]](#)
12. Mick, D.G.; Fournier, S. Paradoxes of Technology: Consumer Cognizance, Emotions, and Coping Strategies. *J. Consum. Res.* **1998**, *25*, 123–143. [\[CrossRef\]](#)
13. Johnson, D.; Bardhi, F.; Dunn, D.T. Understanding How Technology Paradoxes Affect Customer Satisfaction with Self-Service Technology: The Role of Performance Ambiguity and Trust in Technology. *Psychol. Mark.* **2008**, *25*, 416–443. [\[CrossRef\]](#)
14. Dietvorst, B.J.; Simmons, J.P.; Massey, C. Algorithm Aversion: People Erroneously Avoid Algorithms after Seeing Them Err. *J. Exp. Psychol. Gen.* **2015**, *144*, 114–126. [\[CrossRef\]](#) [\[PubMed\]](#)
15. Luo, X.; Tong, S.; Fang, Z.; Qu, Z. Machines vs. Humans: The Impact of Artificial Intelligence Chatbot Disclosure on Customer Purchases. *Mark. Sci.* **2019**, *38*, 937–947. [\[CrossRef\]](#)
16. Colquitt, J.A.; Conlon, D.E.; Wesson, M.J.; Porter, O.L.H.; Ng, Y.K. Justice at the Millennium: A Meta-Analytic Review of the Last 25 Years of Organizational Justice Research. *J. Appl. Psychol.* **2001**, *86*, 425–445. [\[CrossRef\]](#) [\[PubMed\]](#)
17. Smith, A.K.; Bolton, R.N.; Wagner, J. A Model of Customer Satisfaction with Service Encounters Involving Failure and Recovery. *J. Mark. Res.* **1999**, *36*, 356–372. [\[CrossRef\]](#)
18. Giovanola, B.; Tiribelli, S. Beyond Bias and Discrimination: Redefining the AI Ethics Principle of Fairness in Healthcare Machine-Learning Algorithms. *AI Soc.* **2023**, *38*, 549–563. [\[CrossRef\]](#) [\[PubMed\]](#)
19. Shin, D.; Park, J. Role of Fairness, Accountability, and Transparency in Algorithmic Affordance. *Comput. Hum. Behav.* **2019**, *98*, 277–284. [\[CrossRef\]](#)
20. Anderson, W.D.; Patterson, M.L. Effects of Social Value Orientations on Fairness Judgments. *J. Soc. Psychol.* **2008**, *148*, 223–245. [\[CrossRef\]](#) [\[PubMed\]](#)
21. Hamilton, R.W. When the Means Justify the Ends: Effects of Observability on the Procedural Fairness and Distributive Fairness of Resource Allocations. *J. Behav. Decis. Mak.* **2006**, *19*, 303–320. [\[CrossRef\]](#)
22. Lee, M.K. Understanding Perception of Algorithmic Decisions: Fairness, Trust, and Emotion in Response to Algorithmic Management. *Big Data Soc.* **2018**, *5*, 2053951718756684. [\[CrossRef\]](#)
23. Wang, Y. Artificial Intelligence in Educational Leadership: A Symbiotic Role of Human-Artificial Intelligence Decision-Making. *J. Educ. Adm.* **2021**, *59*, 256–270. [\[CrossRef\]](#)
24. Schlicker, N.; Langer, M.; Ötting, S.K.; Baum, K.; König, C.J.; Wallach, D. What to Expect from Opening up Black Boxes? Comparing Perceptions of Justice between Human and Automated Agents. *Comput. Hum. Behav.* **2021**, *122*, 106837. [\[CrossRef\]](#)
25. Russo, P.A.; Duradoni, M.; Guazzini, A. How Self-Perceived Reputation Affects Fairness towards Humans and Artificial Intelligence. *Comput. Hum. Behav.* **2021**, *124*, 106920. [\[CrossRef\]](#)
26. Lajante, M.; Remisch, D.; Dorofeev, N. Can Robots Recover a Service Using Interactional Justice as Employees Do? A Literature Review-Based Assessment. *Serv. Bus.* **2023**, *17*, 315–357. [\[CrossRef\]](#)
27. Bhatt, K. Measuring Service Fairness and Its Impact on Service Quality and Satisfaction: A Study of Indian Banking Services. *J. Financ. Serv. Mark.* **2020**, *25*, 35–44. [\[CrossRef\]](#)

28. Carr, L.C. The FAIRSERV Model: Consumer Reactions to Services Based on a Multidimensional Evaluation of Service Fairness. *Decis. Sci.* **2007**, *38*, 107–130. [\[CrossRef\]](#)
29. Devlin, J.; Kumar, S.; Sekhon, H. Perceptions of Fair Treatment in Financial Services. *Eur. J. Mark.* **2014**, *48*, 7–8. [\[CrossRef\]](#)
30. Seiders, K.; Berry, L.L. Service Fairness: What It Is and Why It Matters. *Acad. Manag. Exec.* **1998**, *12*, 8–20. [\[CrossRef\]](#)
31. Worthington, S.; Devlin, J.F. Fairness and Financial Services in Australia and the United Kingdom. *Int. J. Bank. Mark.* **2013**, *31*, 289–304. [\[CrossRef\]](#)
32. Zhu, Y.; Chen, H. Service Fairness and Customer Satisfaction in Internet Banking. *Internet Res.* **2012**, *22*, 482–498. [\[CrossRef\]](#)
33. Huang, M.-H.; Rust, R.T. A Framework for Collaborative Artificial Intelligence in Marketing. *J. Retail.* **2022**, *98*, 209–223. [\[CrossRef\]](#)
34. Hermann, E.; Puntoni, S. Artificial Intelligence and Consumer Behavior: From Predictive to Generative AI. *J. Bus. Res.* **2024**, *180*, 114720. [\[CrossRef\]](#)
35. Hill, P.H.; Sharma, E. Consumer Vulnerability. *J. Consum. Psychol.* **2020**, *30*, 551–570. [\[CrossRef\]](#)
36. Bock, D.E.; Wolter, J.S.; Ferrell, O.C. Artificial Intelligence: Disrupting What We Know about Services. *J. Serv. Mark.* **2020**, *34*, 317–334. [\[CrossRef\]](#)
37. Lobschat, L.; Mueller, B.; Eggers, F.; Brandimarte, L.; Diefenbach, S.; Kroschke, M.; Wirtz, J. Corporate Digital Responsibility. *J. Bus. Res.* **2021**, *122*, 875–888. [\[CrossRef\]](#)
38. Wirtz, J.; Kunz, W.H.; Hartley, N.; Tarbit, J. Corporate Digital Responsibility in Service Firms and Their Ecosystems. *J. Serv. Res.* **2023**, *26*, 173–190. [\[CrossRef\]](#)
39. Belk, R. Ethical Issues in Service Robotics and Artificial Intelligence. *Serv. Ind. J.* **2021**, *41*, 860–876. [\[CrossRef\]](#)
40. Grub, M.F.; Humprecht, E. Generative AI and Disinformation | Defining the Role(s) of AI in Disinformation Research—A Systematic Review. *Int. J. Commun.* **2025**, *19*, 25.
41. Rangaswamy, A.; Moch, N.; Felten, C.; Van Bruggen, G.; Wieringa, J.E.; Wirtz, J. The Role of Marketing in Digital Business Platforms. *J. Interact. Mark.* **2020**, *51*, 72–90. [\[CrossRef\]](#)
42. Zuboff, S. Big Other: Surveillance Capitalism and the Prospects of an Information Civilization. *J. Inf. Technol.* **2015**, *30*, 75–89. [\[CrossRef\]](#)
43. Yoganathan, V.; Osburg, V.S.; Janakiraman, N. Lending Legitimacy to Corporate Digital Responsibility: Trust in Firm versus Government Regulation of Artificial Intelligence Services. *J. Serv. Res.* **2026**, *29*, 313–333. [\[CrossRef\]](#)
44. Choi, S.; Mattila, A.S.; Bolton, L.E. To Err Is Human(-Oid): How Do Consumers React to Robot Service Failure and Recovery? *J. Serv. Res.* **2021**, *24*, 354–371. [\[CrossRef\]](#)
45. Castelo, N.; Bos, M.W.; Lehmann, D.R. Task-Dependent Algorithm Aversion. *J. Mark. Res.* **2019**, *56*, 809–825. [\[CrossRef\]](#)
46. Grgić-Hlača, N.; Redmiles, E.M.; Gummadi, K.P.; Weller, A. Human Perceptions of Fairness in Algorithmic Decision Making: A Case Study of Criminal Risk Prediction. In *Proceedings of the AAAI Conference on Artificial Intelligence, Lyon, France, 23–27 April 2018*; ACM: New York, NY, USA, 2018; Volume 32. [\[CrossRef\]](#)
47. Doshi-Velez, F.; Kim, B. Towards a Rigorous Science of Interpretable Machine Learning. *arXiv* **2017**, arXiv:1702.08608. [\[CrossRef\]](#)
48. Hsu, S.; Li, T.W.; Zhang, Z. Attitudes Surrounding an Imperfect AI Autograder. In *Proceeding of the CHI '21: CHI Conference on Human Factors in Computing Systems, Yokohama, Japan, 8–13 May 2021*; Association for Computing Machinery: New York, NY, USA, 2021; pp. 1–15. [\[CrossRef\]](#)
49. Carrilho, M.G.; Wagner, R.; Pinto, D.C.; Gonzalez-Jimenez, H.; Akdim, K. The Feeling Skills Gap: The Role of Empathy in Voice-Driven AI for Service Recovery. *J. Bus. Res.* **2025**, *201*, 115703. [\[CrossRef\]](#)
50. Mihale-Wilson, C.; Hinz, O.; van der Aalst, W.; Weinhardt, C. Corporate Digital Responsibility. *Bus. Inf. Syst. Eng.* **2022**, *64*, 127–132. [\[CrossRef\]](#)
51. Cukier, K. Commentary: How AI Shapes Consumer Experiences and Expectations. *J. Mark.* **2021**, *85*, 152–155. [\[CrossRef\]](#)
52. Valenzuela, A.; Puntoni, S.; Hoffman, D.; Castelo, N.; De Freitas, J.; Dietvorst, B.; Hildebrand, C.; Huh, Y.E.; Meyer, R.; Sweeney, M.E.; et al. How Artificial Intelligence Constrains the Human Experience. *J. Assoc. Consum. Res.* **2024**, *9*, 241–256. [\[CrossRef\]](#) [\[PubMed\]](#)
53. Gray, H.M.; Gray, K.; Wegner, D.M. Dimensions of Mind Perception. *Science* **2007**, *315*, 619. [\[CrossRef\]](#) [\[PubMed\]](#)
54. Gray, K.; Wegner, D.M. Feeling Robots and Human Zombies: Mind Perception and the Uncanny Valley. *Cognition* **2012**, *125*, 125–130. [\[CrossRef\]](#) [\[PubMed\]](#)
55. Jussupow, E.; Benbasat, I.; Heinzl, A. Why Are We Averse towards Algorithms? A Comprehensive Literature Review on Algorithm Aversion. In *Proceedings of the 28th European Conference on Information Systems (ECIS), Online, 15–17 June 2020*. Available online: https://aisel.aisnet.org/ecis2020_rp/168 (accessed on 8 June 2026).
56. Troisi, O.; Fenza, G.; Grimaldi, M.; Loia, F. COVID-19 Sentiments in Smart Cities: The Role of Technology Anxiety before and during the Pandemic. *Comput. Hum. Behav.* **2021**, *126*, 106986. [\[CrossRef\]](#) [\[PubMed\]](#)
57. Compeau, D.; Higgins, C.A.; Huff, S. Social Cognitive Theory and Individual Reactions to Computing Technology: A Longitudinal Study. *MIS Q.* **1999**, *23*, 145–158. [\[CrossRef\]](#)

58. Washizu, A.; Nakano, S.; Ishii, H.; Hayashi, Y. Willingness to Pay for Home Energy Management Systems: A Survey in New York and Tokyo. *Sustainability* **2019**, *11*, 4790. [[CrossRef](#)]
59. Belanche, D.; Casaló, L.V.; Flavián, C.; Schepers, J. Robots or Frontline Employees? Exploring Customers' Attributions of Responsibility and Stability after Service Failure or Success. *J. Serv. Manag.* **2020**, *31*, 267–289. [[CrossRef](#)]
60. Bitner, M.J. Evaluating Service Encounters: The Effects of Physical Surroundings and Employee Responses. *J. Mark.* **1990**, *54*, 69–82. [[CrossRef](#)]
61. Weiner, B. Attributional Thoughts about Consumer Behavior. *J. Consum. Res.* **2000**, *27*, 382–387. [[CrossRef](#)] [[PubMed](#)]
62. Ganesan, S. Determinants of Long-Term Orientation in Buyer-Seller Relationships. *J. Mark.* **1994**, *58*, 1–19. [[CrossRef](#)] [[PubMed](#)]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.