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AI Bias in Online Service Recovery

‘’AI or human? Exploring AI Bias in Perceived Ethical Concerns and Recovery Satisfaction During Online Complaint Handling’’

Name: Roel Laffra (s1063926)
Mentor: Dr. H.W.M. Joosten
Second reader: Dr. M. Hermans
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Radboud Universiteit

Preface

Writing this thesis has been a challenging yet rewarding journey, and I would like to express my appreciation to the people who supported me along the way.

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Abstract

As AI chatbots become increasingly common in online service recovery, concerns arise about how their use affects consumer perceptions. This study examines whether the awareness that a service agent is AI, as opposed to human, impacts perceptions of fairness, empathy, privacy, and recovery satisfaction, regardless of the quality of the recovery.

Using a 2x2 scenario-based experimental design (N = 125), participants were exposed to either a high or low-quality service recovery delivered by an AI chatbot or a human agent. Results show that AI agents are perceived as less empathic, less privacy-protective, and lower in interactional fairness. Privacy and interactional fairness were perceived less when the recovery was conducted by AI, regardless of the quality of the recovery. However, recovery satisfaction was not significantly impacted by agent type. Notably, the effect of agent type on empathy was moderated by recovery quality.

The study contributes to service recovery literature by incorporating AI bias into online service recoveries and highlighting that consumer perceptions are shaped not only by service quality but also by who or what delivers the service. Practical implications suggest organizations should humanize chatbot design and communicate transparently to build trust.

Keywords: AI-chatbot, online service recovery, ethical concerns, perceived fairness, perceived empathy, perceived privacy, recovery satisfaction & AI bias

Word count: 12986

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1. Introduction

´A late delivery´, ´the item you bought did not meet your expectations´, or ´certain items were missing´, many people have experienced some way of complaint when buying something online. These errors that lead to complaints affect the service recovery satisfaction a consumer experiences (Sahaf & Fazili, 2024). These errors are called 'service failures' and mean that the service performance from the organization does not meet the expectation of the customer (Hoffman & Bateson, 1997). Organizations need to handle complaints in a correct manner and rectify the loss customers have experienced to meet the desired expectation, which is referred to as 'service recovery' (Sahaf & Fazili, 2024). In 2019, half of the Dutch population who have bought something online, reported a complaint (CBS, 2019). This statistic keeps on growing as the number of e-shoppers also keeps on increasing because online shopping becomes more accessible and available. This excessive number of complaints, require a lot of service recovery, which also needs the attention of the customers themselves and especially the organization who has to recover the service.

Nowadays, to manage the growing volume of complaints efficiently, organizations make use of artificial intelligence like chatbots to handle customer complaints and to enhance customer experiences. The majority of organizations make use of a 'chatbot' in online service recovery, which is a form of artificial intelligence (AI) that virtually interacts in verbal communication with customers in complaint handling (Przegalinska et al., 2019). These chatbots significantly reduce interaction between customers and the service department of an organization as they can operate 24/7 and continually provide services regarding sales, support, errors, or other related questions (Collins et al., 2021). According to Karen Gilchrist, this reduction of interaction can potentially even reduce firm's annual costs by over 8 billion US dollars (2017).

Although, despite all the positive attributes and advantages of AI chatbots, consumers still prefer the human interaction with an actually human being. People experience some sort of discomfort and there could arise negative emotions while interacting with a chatbot, as studies have shown that even though AI chatbots increase 67% in sales, 87% of the consumers prefer to receive service from an actual human service actor (Press, 2019). One reason for this discrepancy lies in the ethical and emotional concerns customers have with AI. During service recovery, when emotions often run high, issues such as perceived fairness, privacy and empathy become especially salient (Hoffman & Bateson, 1997). AI-driven responses may lack the nuanced emotional intelligence that human agents naturally provide. In order to mitigate these concerns and for customers to be satisfied after the service recovery, organizations need to understand and optimize the chatbots to meet the desires expectations of the consumers. According to Agnihotri and Bhattacharya (2023) organizations can achieve consumers' satisfaction by making their chatbots anthropomorphic, which means creating chatbot with human attributes, so consumers perceive them as resembling humans that lower ethical concerns of fairness, privacy, and empathy.

However, these concerns can be lowered by improving and humanizing the chatbot as Agnihotri and Bhattacharya (2023) conclude, but there remains an underexplored issue: biases against AI chatbots. These biases are not just related to the chatbot's behaviour but to consumers' pre-existing negative attitudes or prejudices toward AI technologies. Xue et al., (2024) discuss there are still a lot of biases on the role of chatbots in the modern world, as people have negative feelings towards artificial intelligence regardless of the chatbot's functionality or quality. This study therefore extends the paper of Agnihotri and Bhattacharya (2023) and fills the gap related to biases on chatbots in existing literature, by investigating the role of biases on AI chatbots influencing perceived fairness, empathy, privacy, and recovery satisfaction.

1.1 Theoretical gap

Existing literature largely focuses on chatbot functionality, anthropomorphism, and ethical concerns during service recovery as previously discussed. However, the role of consumer bias, defined here as systematic negative attitudes or prejudices toward AI agents (Xue et al., 2024)., remains insufficiently examined. Specifically, there is limited research on how these biases influence perceived ethical concerns (e.g. fairness, empathy, and privacy) and recovery satisfaction when consumers know they are interacting with an AI versus a human. This forms a theoretical gap: the interaction between the type of agent, AI-related biases, and consumer perceptions in service recovery context is not well understood.

1.2 Research objective

The objective of this study is to gain a better understanding of the quality of the service recovery from an AI chatbot or human agent, influencing recovery satisfaction and perceived ethical concerns people have in online service recovery attributes, i.e., empathy, fairness, and privacy concerns. In addition, the role of biases on AI chatbots is investigated and tested by controlling the agent source awareness and the quality of the service recovery. Most research assumes that customer responses to service recovery depend primarily on the objective quality of the recovery (Wirtz & Mattila, 2004; Rio-Lanza et al., 2009). However, when the service agent is an AI chatbot, consumer biases may affect perceptions even when the service recovery is objectively high in quality (Dietvorst et al., 2015; Xue et al., 2024). This study aims to investigate how agent source awareness (knowing whether the service agent is human or AI) affects consumer´s perceived ethical concerns like; fairness, empathy and privacy, and recovery satisfaction. It particularly focusses on how AI biases, related to actual chatbot behaviour, moderate these perceptions. The goal is to assess whether identical service recovery responses are evaluated differently based only on agent type and not on quality/performance, and to identify the nature of biases that may influence this difference. By including both low and high recovery quality, we can isolate whether AI-related biases affect outcomes regardless of performance. This objective aims to combine and fill the gaps in the literature by answering the following research question;

To what extent do AI biases on the type of service agent play a role in the consumers' perceived ethical concerns and recovery satisfaction in AI chatbot-driven vs human-driven online service recovery?

To clarify, this study will look into AI biases in online service recovery by investigating if the customer's awareness of the source of the agent influences the relationship between the quality of service recovery and the ethical concerns and recovery satisfaction after the service recovery. This research contributes to the literature in the following ways:

- It extends the work of Agnihotri and Bhattacharya (2023) by incorporating the concept of AI biases as a moderating factor
- It explores consumer biases towards AI in real-world applications which adds to the paper of Xue et al. (2024).
- It provides practical implications for organizations aiming to design chatbots that minimize perceived ethical concerns and improve service recovery outcomes.

This paper proceeds as follows: It starts by reviewing the existing literature and forming the conceptual model with corresponding hypotheses. This is followed by the methodology and the analysis/results section. Finally, it concludes with a discussion, key findings, theoretical contributions, managerial implications, limitations and future research.

2. Literature review

In order to answer the research question we need to dive in the literature to understand and explain the various constructs that this study entails. This chapter addresses the various concepts by starting with online service failure and online service recovery. Next, AI chatbots is discussed by looking at the attributes and ethical concerns that come with it, like perceived fairness, privacy, and empathy. This is followed by consumers' perceived recovery satisfaction and lastly, the concept of AI biases is addressed.

2.1 Service failure

The main topic of this paper is online service recovery, however before a service needs to be recovered, a failure has to occur. As mentioned before, the number of people that buy something online is rapidly increasing. In 2021, more than 75% of the Dutch population, older than 12 years old, made a purchase in an online store, which was 9% more than the year before. From that group, 56% had a complaint about their order (CBS, 2021). Service failures occur when organizations, often through digital platforms or services, fail to deliver their expected performances, which results in frustrating the consumers.

Such failures can range from technical issues to customer service and can significantly impact user trust, satisfaction, and business reputation (Agnihotri & Bhattacharya, 2023). Online service failure can result in significant disruption for businesses and consumers, leading to financial losses, loss of reputation, and business operational challenges. This can be small, for instance you did not receive your money back after returning a package, or it can be big like the Barclays Bank IT outage on January 2025. Barclays experienced a three-day IT outage that led to over 50% of its payments failing. This incident affected millions of customers, some of whom were attempting to make tax payments to HM revenue & customs (Quinio, 2025).

There are two types of service failures, service failures can be process-oriented or outcome-oriented (Hoffman et al., 1995). Process-oriented failures relate to how a service is delivered, such as errors in the execution. Outcome-oriented failures occur when a company fails to provide the expected service, so what the customer receives (Gronroos, 1988). As process failures relate to errors in the delivery of the service, outcome failures reflect the inability of a business to fulfil its fundamental service promise (Jean Harrison-Walker, 2012). Service failures can harm a company by negatively influencing customer satisfaction (Lam et al., 2004), weakening customer trust, and generating negative word-of-mouth (Agnihotri & Bhattacharya, 2023).

2.2 Online service recovery

Now that we have discussed service failures that can occur within organizations, we now dive in to the process of how to deal with these failures. Due to the customers' dissatisfaction with the received service, the involved organization has the crucial task to address the failure and try to win back the customer in order to prevent or minimalize the loss of customer satisfaction (Lam et al., 2004; Agnihotri & Bhattacharya, 2023). So, after a service failure organizations need to rectify the loss customers have experienced in order to meet the desired expectation, which is referred to as 'service recovery' (Sahaf & Fazili, 2024). The recovery of service failures include the initiatives taken by an organization to "rectify, amend, and restore the loss experienced" by customers (Gronroos, 1988; Agnihotri & Bhattacharya, 2023). Another definition of service recovery is provided by Smith et al. (1999, p. 357), who defined service recovery as "a bundle of resources that an organization can employ in response to a failure."

In today´s digital age, people mainly rely on digital environments when buying products, make transactions, or ask for support. This also leads to the movement of complaining behaviour from offline to online as social media and review websites are open and accessible platforms for expressing dissatisfaction. Also online complaints are easy to make with minimal effort compared to traditional channels like a phone call or actually visiting a store. This illustrates the importance of handling complaints online (Istanbulluoglu, 2017).

The methods of handling service failures are often based on the framework of Justice Theory from Rawl (1971), which states that consumers assess recovery strategies through procedural justice, distributive justice, and interactional justice. This framework is used to understand an individual´s perception of fairness within organizational context (Kumar & Kumar, 2016). In the context of service recovery, this theory is used in assessing how customers evaluate the efforts to address service failures of an organization and is seen as an effective tool (Kim et al., 2012). The theory consists of three dimensions: procedural, distributive, and interactional justice. This theory will be discussed in the section on 'perceived fairness'. Overall, organizations want to score high on all three of the dimensions of Rawl (1971) for an optimal service recovery.

Existing research has provided multiple strategies for service recoveries, for example clear communication with customers, incorporating customer feedback, and providing explanations for service failures (Boshoff & Kelly, 2001). Also, apologizing and offering compensations for service failures are commonly used approaches. Studies suggest that sincere apologies and appropriate compensation can improve fairness perceptions and customer satisfaction, especially when the recovery is delivered with empathy (Swanson & Kelly, 2001; Rock & Kaiser, 2014). Overall, organizations need an active approach in service recovery, as taking the right strategies in handling complaints and create an effective service recovery plan can lead to customers coming back, increase the repurchase intentions, and increase the customer satisfaction (Wirtz & Matilla, 2004).

2.3 The role of AI in service recovery and ethical concerns

Artificial Intelligence (AI) is transforming service recovery by enabling businesses to address customer complaints more efficiently and effectively. AI-based chatbots, predictive analytics, and automated decision-making systems allow companies to provide instant responses, analyse customer complaints, and personalize recovery efforts. These advancements improve response time sand reduce operational costs, which has led to service interfaces now are dominated by technology (Wang et al., 2022; Castillo et al., 2021). AI chatbots possess unique characteristics that set them apart from human employees. They continuously improve through machine learning algorithms and retain unlimited memory. Unlike humans, whose performance is influenced by individual backgrounds and learning speeds, chatbots can process and update information almost instantly (Wirtz et al., 2018).

Even though chatbots have significantly advantages, research have shown that the use of chatbots also has an impact on various marketing outcomes, including customer engagement, loyalty, and purchase intention (Mostafa & Kasamani, 2022). Also, the way people have to interact with the chatbot (free text vs button-based) influences customer experiences, while the quality of the of communication shapes the outcome of service delivery (Haugeland et al., 2022). In existing research these effects are explained by using theories like the Justice theory (Xing et al., 2022).

With the rise of AI chatbots, ethical concerns also come into play. People are often reluctant to engage with chatbots due to the lack of a personal touch compared to human service agents. During service failures, customers who experience economic or non-economic losses often seek empathy and anthropomorphism, which human agents typically can provide more effectively than an AI chatbot (Nguyen et al., 2022). This has led to some companies being hesitant to fully implement chatbot technology (Press, 2019). Customers experience ethical concerns such as the fairness of the service recovery, the perceived empathy of the service agent (Nguyen et al., 2022), and the privacy risks of the service (Kopalle et al., 2022), which are concerns that make people reluctant to interact with chatbots as it impacts customers' trust and loyalty (Rapp et al., 2021; Agnihotri & Bhattacharya, 2023). These ethical concerns are more discussed in detail in the next sections.

2.3.1 Perceived fairness

Perceived fairness plays an important role in online service recovery, it can influence customer satisfaction, trust, and loyalty (Agnihotri & Bhattacharya, 2023). When customers experience service failures, their evaluation of a company's recovery efforts depends on the fairness of the response. The Justice theory of Rawl (1971) identifies three key dimensions of fairness in service recovery: distributive justice, procedural justice, and interactional justice (Tax et al., 1998; Smith et al., 1999).

Distributive justice refers to the perceived fairness of the outcome received by the customer, such as compensation, refunds, or discounts. Customers expect recovery efforts to align with the severity of the service failure and asses if the outcome is acceptable (Gelbrich & Roschk, 2011). Second, procedural justice focuses on the fairness of the process, including response time, transparency, and timeliness of complaint handling (Davidow, 2003). Customers prefer recovery processes that are efficient and consistent. Third, interactional justice involves the manner in which customers are treated during the recovery process, including respect, politeness, and personalized responses (Kumar & Kumar, 2016; Kim et al., 2012).

In online service recovery, the use of AI chatbots bring ethical risks with it, related to perceived fairness. While automation enhances efficiency, AI-driven responses may lack empathy and personalization, reducing interactional justice (Wirtz et al., 2018). Algorithmic bias in AI decision-making can also lead to unfair outcomes, affecting distributive and procedural justice (Chaturvedi & Verma, 2023). Ensuring fairness in AI-driven service recovery requires transparency, bias mitigation, and a balance between automation and human oversight.

2.3.2 Perceived empathy

The second ethical concern that is discussed is perceived empathy. Empathy is defined as the act depicting another person's emotional experience (Plank et al., 1996), or to simplify; understanding and sharing someone else's feelings. Perceived empathy is an ethical concern in AI-driven service recovery, as customers expect emotional understanding and genuine concern when experiencing a service failure. As human agents can express empathy naturally through tone, language, and emotional intelligence, AI chatbots often struggle to do the same, which leads to interactional justice concerns (Gelbrich & Roschk, 2011; Wirtz et al., 2018). A lack of perceived empathy may lead to customers feeling unheard or undervalued, reducing trust in AI-driven service recovery (Kumar & Kumar, 2016).

AI chatbots are limited in emotional intelligence, as they rely on pre-programmed responses and sentiment analysis, which may not always interpreted customer emotions (Schuetzler, 2020). Also, excessive personalization in chatbot responses intended to copy empathy from a human, can feel inauthentic or intrusive, causing discomfort (Ashktorab, 2019). This creates a conflict and an ethical dilemma, as companies must balance efficiency with meaningful emotional engagement.

To address these concerns, firms should improve chatbot design by integrating human-like/anthropomorphic elements, providing transparency about AI limitations and allowing customers to choose between AI and human support can improve perceptions of empathy in online service recovery (Huang & Rust, 2021).

2.3.3 Privacy concerns

The third ethical issue customers can have with an AI chatbot providing service recovery is the use or misuse of the customer's privacy. Privacy concerns refer to "the degree to which a consumer is worried about the potential invasion of the right to prevent the disclosure of personal information to others" (Baek & Morimoto, 2012, p. 63).

AI chatbots rely on customer data to personalize interactions and improve the responses they give. However, customers may feel uncomfortable about how their personal information is collected, stored, and used, which affects their trust in AI-based service recovery systems (Beldad et al., 2016; Aguirre et al., 2015).

Privacy concerns in AI service recovery primarily come from three factors: data collection, transparency, and control. Customers often lack clarity on what data is gathered and how it is processed, raising issues of procedural fairness (Martin et al., 2017). Additionally, customers may feel a loss of autonomy when they have limited control over their data, further increasing their privacy concerns (Acquisti et al., 2015). This relates to the relatively newness of AI and the recent data privacy scandal of Facebook, which increases the privacy concerns on technology (Hinds et al., 2020).

Companies must address these ethical risks by ensuring data transparency, clear communication about data practices and offering customers control over their information can help build trust in AI-driven service recovery while mitigating privacy concerns (Culnan & Bies, 2003).

Existing studies often address fairness (Gelbrich & Roschk, 2011), empathy (Wirtz et al., 2018), and privacy (Baek & Morimoto, 2012), as separate constructs, yet customer reactions to agents frequently cluster around these three concerns. This study therefore defines perceived ethical risks as the consumer's concern that the AI chatbot fails to uphold moral norms and humanistic values in its recovery process (Rapp et al., 2021). This integrative conceptualization is justified by firstly the shared roots that all the three concepts are rooted in Justice Theory and influence recovery satisfaction (Kim et al., 2012; Rio-Lanza et al., 2009). Secondly, studies show that these concerns co-occur when humans interact with AI, particularly under stress which means observed clustering in consumer behaviour (Nguyen et al., 2022; Kopalle et al., 2022).

2.4 Recovery satisfaction

Now that we have discussed the ethical concerns that people can have from receiving online service recovery by a service actor, we will now dive into the customer satisfaction of the service recovery strategies. When a service failure occurs, organizations aim to recover the service and mitigate the influence on brand image as a failure can lead to customers being dissatisfied of the actor's service recovery (Agnihotri & Bhattacharya, 2023).

The perceived satisfaction of a customer after a service recovery depends of the performance of the service agent in resolving the complaint. Satisfaction consists of various factors that include the ability of the agent to provide timely, correct, and fair solutions (Huang & Rust, 2021;Yim, 2024). If a complaint is resolved in time, in a correct and fair manner, customers are likely to experience a good time are more likely to be satisfied. If the agent fails to provide a helpful solution, frustration increases and negative brand perception can arise.

One of the key drivers in satisfaction is perceived competence, which refers to customers believing that the agent is able to understand and fix their issue (Schuetzler et al., 2020). Empathy and fairness also play a part, as AI does not have human feelings, chatbots that use empathy with natural language and fair compensation can increase customer satisfaction (Wirtz et al., 2018; Yim, 2024). Perceived fairness is highly integrated with the degree a customer is satisfied with the service recovery. This relationship is investigated by looking at the three dimension of the Justice theory from Rawl (1971); procedural, distributive, and interactional justice. The article of Rio Lanza et al. (2009) concluded that all of the three justice dimensions affect satisfaction in the recovery process. The most important dimension is procedural justice, then distributive justice, and lastly interactional justice. These three dimensions relate to each other, as customers have to interact with a company in order to voice their complaint (interactional justice), the company processes the complaint (procedural justice), and an outcome (distributive justice) follows (Agnihotri & Bhattacharya, 2023).

In addition, reaction time also matters because quick or instant respond time by chatbots raise satisfaction, while delays lead to disappointment (Al-Shafei, 2025). However, an AI-driven chatbot also has negative attributes as mentioned before. Customers are not likely to experience personality or emotional remoteness from a chatbot, especially in sensitive or complex scenarios (Jiang, 2023).

Organizations need to develop AI chatbots that are transparent, fair, and sensitive to emotions when handling a complaint.

2.5 AI biases

As AI chatbots in service recovery are being used in practice more often these days, there are still flaws that have negative impact on ethical concerns and the outcome of satisfaction of the recovery as we now know. One of the largest issues that companies overlook are AI biases that people have, which can influence ethical concerns and negatively impact customer satisfaction (Xue et al., 2024). These biases are rooted in pre-existed attitudes about automation, perceived humanness, and trust in technology (Eiband et al., 2018; de Visser et al., 2016). People can form AI biases when chatbots provide unfair or inconsistent resolutions based on biased data or algorithms. This can lead to a decrease in recovery satisfaction and an increase in ethical problems, like perceived unfairness, privacy concerns, and lack of empathy (Wirtz et al., 2018; Yim, 2024; Agnihotri & Bhattacharya, 2023). Customers often assume that AI lacks the capacity of emotional intelligence or ethical reasoning, which are important for perceiving fairness and empathy (Yim, 2024). This algorithm aversion is often evaluated stronger than human-driven recoveries (Dietvorst, Simmons, & Massey, 2015).

Perceived fairness is one of the initial causes in forming AI bias. If a chatbot gives unequal compensation for the same issues or offers special treatment to some consumers but not all, customers will feel inequal and cheated. This undermines distributive and procedural justice and will affect satisfaction which could lead to customers seeking for services elsewhere (Al-Shafei, 2025; Wirtz et al, 2018). So, when this image of unequal compensation by AI agents is spread over customers, people will take over this prejudice on AI agents. This is grounded in Justice Theory (Rawls, 1971), which highlights fairness as a critical dimension of service recovery evaluation (Tax et al., 1998). AI agents are often seen as less capable of making fair decisions due to perceived inflexibility or their reliance on biased data (Al-Shafei, 2025; Wirtz et al., 2018). When customers know the agent is AI, they may judge its actions as less just/fair even when the service recovery is good or successful. Therefore the following hypothesis is formulated:

H1: Consumers will perceive the service recovery as less fair when they are aware that the agent is AI than when they think that the agent is human, regardless of the quality of the recovery.

The lack of perceived empathy of the chatbot is another main concern. Chatbots are designed to mimic human interaction, but when they fail accordingly the specific case, it causes them to provide responses that seem uncaring and impersonal, customers will eventually feel undervalued. This will have a negative impact on customer satisfaction, and the service recovery will consequently seem impersonal, and also perceived as ineffective (Huang & Rust, 2021). Empathy is essential in emotionally charged situations like service failures, as Wirtz et al. (2018) stated. Despite programmed emotional expressions, AI agents are often seen as incapable of genuine empathy. Algorithm aversion leads to consumers interpreting chatbots responses as inauthentic or robotic, leading to reducing perceived emotional sensitivity (Huang & Rust; 2021; Yim, 2024). So, when customers assume that the AI chatbot lacks the capacity for emotional intelligence or ethical reasoning, even when the chatbot provides consistent and compassionate responses, it can influence their perceptions of empathy (Huang & Rust, 2021). Therefore the following hypothesis is formulated:

H2: Consumers will perceive the service recovery as less empathic when they are aware that the agent is AI than when they think that the agent is human, regardless of the quality of the recovery.

Third, privacy concerns can rise when AI systems are making decisions from biased data, which questions how customer data is collected and used. Overall, these negative outcomes influence the word-of-mouth regarding AI driven service recoveries which enhances AI biases (Gnewuch et al., 2022). Similarly, privacy concerns are likely to increase when customers know that an AI is managing the interaction. Customers tend to associate AI systems with surveillance, data collection, and algorithmic profiling (Rapp et al., 2021; Bhuiyan, 2024). Even if the chatbot complies with data protection standards or privacy regulations, customers will likely perceive the exchange as more intrusive due to their suspicion of digital surveillance and algorithmic profiling (Rapp et al., 2021; Bhuiyan, 2024). So, simply knowing that the agent is not human can trigger suspicion about how personal data is collected, processed, and used, regardless of the performance or outcome of the service recovery. Therefore the following hypothesis is formulated:

H3: Consumers will perceive less privacy protection when they are aware that the agent is AI than when they think that the agent is human, regardless of the quality of the recovery.

Fourth, source awareness may also influence recovery satisfaction. Customers may interpret the same recovery efforts less favourably when it is performed by an AI, due to a perceived lack of authenticity or human attributes (Nguyen et al., 2022; Bhuiyan, 2024). This perception of reduced social presence diminishes feelings or trust and personal commitment, which are key drivers of satisfaction, and it can suppress satisfaction even when the service outcome is objectively positive (Gnewuch et al., 2017). Furthermore, consumers may attribute a lack of personal investment or care to the organization when it is delegating about complaint to AI, which signals to the customer that the issue is not worth a human response. This can result in lowered expectations of organizational commitment, regardless of the quality of the service recovery, reducing the overall recovery satisfaction (Bhuiyan, 2024; Agnihotri & Bhattacharya, 2023). Therefore the following hypothesis is formulated:

H4: Consumers will report lower recovery satisfaction when they are aware that the agent is AI than when they think that the agent is human, regardless of the quality of the recovery.

To summarize, while high-quality service recovery typically leads to positive outcomes, the effectiveness of the recovery may also depend on who the customer believes the agent is, AI or human. Research shows that consumers tend to evaluate AI agents more critically than humans, even when the service outcome is identical (Dietvorst et al., 2015). This phenomenon, known as algorithm aversion, is driven by a lack of trust in automation and the belief that AI lacks human qualities like empathy, fairness, and ethical judgment like privacy (Eiband et al., 2018; Xue et al., 2024).

2.6 Conceptual model with hypothesis

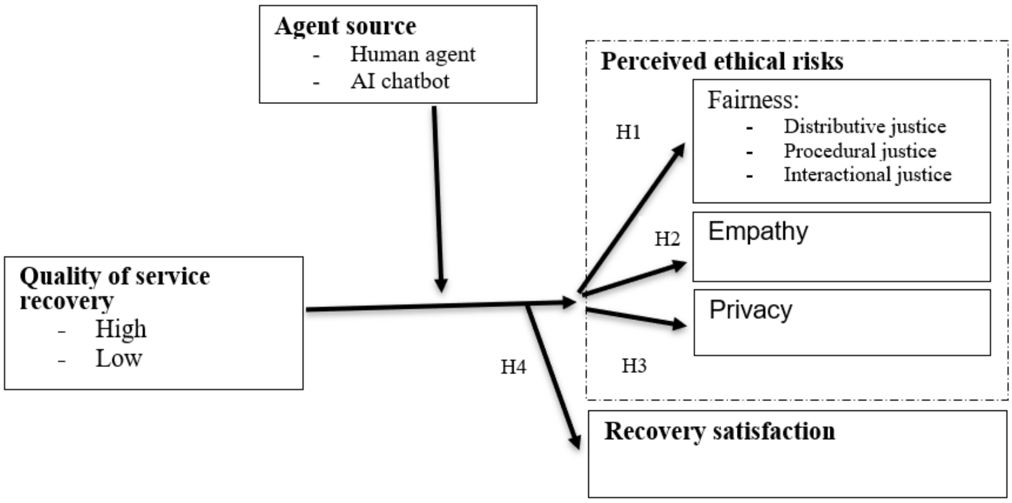
After reviewing the existing literature, hypothesises can be formed. In order to answer the research question, the following hypothesises are tested in this study:

H1: Consumers will perceive the service recovery as less fair when they are aware that the agent is AI than when they think that the agent is human, regardless of the quality of the recovery.

H2: Consumers will perceive the service recovery as less empathic when they are aware that the agent is AI than when they think that the agent is human, regardless of the quality of the recovery.

H3: Consumers will perceive less privacy protection when they are aware that the agent is AI than when they think that the agent is human, regardless of the quality of the recovery.

H4: Consumers will report lower recovery satisfaction when they are aware that the agent is AI than when they think that the agent is human, regardless of the quality of the recovery.



3. Methodology

This chapter outlines the design and execution of the research. It covers the research design, scenario, sample, procedure, operationalizations, pre-test, data analysis, the considerations of validity and reliability, and lastly the research ethics.

3.1 Research design

This study aims to investigate if people have different and potential negative feelings and prejudices on AI chatbot driven service recoveries, even if the service recovery of the chatbot does not differ with an actual human-driven service recovery actor. In a form of a scenario-based experiment, these prejudices are investigated by using both high and low quality service recovery scenarios to compare the corresponding perceptions and to isolate the quality of the service recovery. Respondents will be provided with either a high quality service recovery that resonates with a human-driven service recovery as Agnihotri and Bhattacharya (2023) stated, by also controlling the ethical concerns people have with AI chatbots in order to best resemble a human-driven service recovery, or with a low quality service recovery that does not meet the criteria of a desired service recovery. By doing this, the impact of quality can be isolated as we can compare the effects of AI-driven and human-driven service recoveries of both high and low quality on perceived fairness, empathy, privacy and satisfaction. These service recoveries will be labelled as AI-generated or human-generated, but the recovery itself will stay the same as high or low quality. Half of the respondents will be given the ‘’good’’ or ‘’bad’’ service recovery that is labelled as a human-driven while the other half will receive an either high or low quality service recovery from an AI service agent. In this way the effect of different service agents on ethical concerns and satisfaction can be tested, as well as the role of biases can be evaluated.

In order to answer the research question, a quantitative research approach is used, as this method is based on reproducibility, which is known for improving the reliability and robustness of the data analysis and also reduces the likelihood of disagreement (Fields, 2018). In terms of statistical analysis, a quantitative approach uses mathematical and statistical tool to identify patterns, relationships, and trends within data, which this research requires as it studies relationships between constructs. This method is known for its' comparability, generalizability, and subjective interpretations facilitating an easy-to-understand presentation of the data and findings (Field, 2018).

This research makes uses of an online scenario-based experimental approach, which means that the participants of this study are given a hypothetical scenario as if they experience it in real-life, followed by answering questions related to that scenario. This experimental design is appropriate for this study as it allows for manipulating a variable, to look for possible effects on other variables (Field, 2018). Scenario-based experiments are commonly used in service recovery research because they provide controlled and realistic settings, enabling a deeper examination of how service recovery strategies influence ethical concerns and recovery satisfaction (Sparks & McColl-Kennedy, 2001).

Participants are presented with one of four scenarios that vary based on two manipulated elements: the quality of the service recovery (high vs low) and the type of service agent (human vs AI-chatbot). While the content of each recovery is consistent within quality levels, the only difference between scenarios is the perceived source of the response. In other words, the low-quality recovery is identical regardless of whether it comes from a human or AI agent, and the same applies to the high-quality version. This results in a 2x2 between-subjects experimental design, where each participant is exposed to only one scenario, and their responses are compared across the four groups (Charness et al., 2012).

The scenario-based experiment is tested by making use of a questionnaire through Qualtrics, using self-administered questionnaires, where participants filled out the questionnaire on their own. This method has several benefits, like the flexibility for participants to complete the questionnaire in their own time at their convenience, which could lead to a larger sample size (De Leeuw, 2008). Additionally, the lack of an interviewer provides a more comfortable environment, limiting concerns about judgment and promoting honest responses (De Leeuw, 2008).

3.2 Scenario

In the scenario, the respondent is confronted with a service failure in the form of a package that was not delivered which had a guarantee in delivery the next day. Frustrated, the customer contacts the company's service platform for assistance, where he/she will receive a response from either an AI-chatbot or an actual human service agent. The story the participants encounter is identical in content but is either of high or low quality. So, the participants will be divided into four groups where they will receive the same service recovery of high or low quality, provided by an AI-chatbot or actual human agent. This will be explicitly mentioned in the beginning of the recovery by showing a picture of the agent and a short statement of ‘’response given by an AI-chatbot’’ or ‘’response given by (name of service agent)’’. In this way the differences in perceived fairness, empathy, privacy and recovery satisfaction per agent can be tested and the influence of performance/quality been isolated. The scenarios can be seen in appendix A.

3.3 Sample

This experiment was carried out among Dutch consumers aged 18 and older. Due to time and resource constraints, a non-probability sampling method was applied, which means not everyone in the population had an equal chance of being selected (Vennix, 2017). Firstly, a convenience sample was used, in which participants were chosen based on their easy accessibility and availability (Taherdoost, 2016). A key limitation of this approach is the presence of selection bias, as the sample may not accurately reflect the broader population (Taherdoost, 2016). Additionally, snowball sampling was employed, which is defined as a non-random technique where existing participants are encouraged to refer others to take part in the study (Taherdoost, 2016). In order to obtain more respondents and to stimulate them to fully and seriously complete the questionnaire, respondents could win a 20-euro Bol.com gift card by leaving their email address to join the giveaway. However, only respondents who completed the questionnaire had a chance of winning the lottery.

The questionnaire is posted on various social media platforms, including Instagram, Facebook, Snapchat, and WhatsApp. The two sampling methods are used to obtain enough statistical power to recruit a minimum number of participants needed (Hair et al., 2019). Lastly, participants in each condition need to be statistically viable, which means the research will need at least 120 participants for meaningful results. But more participants are better in the interest of statistical power (Hair et al., 2019). To ensure the adequacy of this research, a minimum of 20/30 participants per scenario are considered statistically robust (Hair et al., 2019). The participants are then randomly allocated to either of the four scenarios using the Qualtrics tool in order to eliminate selection bias and ensure even distribution.

3.4 Procedure

The experiment consists of a number of stages.

Introduction- Before it starts, participants are sent a thank-you note for their interest and are informed of the topic of service recovery and of the goal of the study. In addition, an introduction page provides details on the study, the experimental process, and the research ethics.
Also, participants are informed of the voluntarily participation in the research. If they are willing to carry on, they must provide explicit consent to allow their responses to be used for research.

Situation- Following consent, the participants will be shown a situation of a service failure of a package with guaranteed next day delivery which was not delivered (see appendix A). The participants are asked to image themselves in the given situation. Next the participants are allocated to one of the following four experimental conditions at random:

Scenario 1: High quality service recovery received from an AI-chatbot

Scenario 2: High quality service recovery received from a human service agent

Scenario 3: Low quality service recovery received from an AI-chatbot

Scenario 4: Low quality service recovery received from a human service agent

Perceived fairness- After reading the situation and scenario, the respondents respond to a series of 3 items per dimension (distributive, procedural, and interactional justice) related to how they perceived the service recovery as fair. The dependent variables are measured through multiple items directly after been exposed to the scenario, when vividness is as it highest.

Perceived empathy- The same applies for this dependent variable, 3 items were used to measure the perceived empathic behaviour.

Perceived privacy- Again, 3 items are used for the third ethical concern to measure the perceived consideration of the customer's privacy

Recovery satisfaction- Next, the respondents will be asked about how satisfied they were with the delivered service recovery. 4 items are used to measure the dependent variable.

Manipulation check- The items regarding the dependent variables are followed by 2 manipulation checks which aim to ensure that "participants perceive, comprehend, and/or react as expected to the portion of the manipulation of interest contained within the independent variable" (Hoewe, 2017, p1).

Realism check- Additionally, a realism check is conducted to check whether the participants had received the stimulus provided to them to be authentic. It involves two questions with a 5-point Likert scale, designed to assess whether the scenarios reflect believable, real-life situations. This ensures that participants' responses genuinely reflect how they might react in reality, thereby providing accurate insight into their perception.

Lastly, the participants are asked about their age, gender and education for an additional descriptive analysis, as age, gender, and education could reveal potential moderating effects which are not apparent from the primary analysis. The survey ends by thanking the respondents for their participation and the insurance of the stimulus material being used for scientific reasons only. Optionally, the respondents could leave their email address if they would like to win a 20-euro bol.com gift card.

3.5 Operationalizations

Data for this study is collected using an online questionnaire based on an experimental study. The structured questionnaire is developed based on the theoretical framework, research question/objective, and already existing research. Standard measurement scales developed from earlier studies are used to construct the questionnaire. The opinions of participants on various statements are assessed on a 5-point Likert scale from '1= Strongly disagree to' to '5= Strongly agree'. Since the experiment is being carried out in the Netherlands, it is specified in Dutch to make it understandable and not ambiguous. As a result, the measurement scales used within the research are translated into Dutch.

Perceived distributive justice: The construct fairness in service recovery is tested in separate dimensions, as this provides more specific insights on the construct of fairness. Three items are used to increase validity, which are adapted from Tax et al. (1998) and Smith et al. (1999).

Perceived procedural justice: 3 items are used, adapted from Tax et al. (1998) and Smith et al. (1999).

Perceived interactional justice: 3 items are used, adapted from Tax et al. (1998) and Smith et al. (1999).

Perceived privacy: This construct is also measured with three items, obtained from Malhotra et al. (2004) and Balapour et al. (2020).

Perceived empathy: Again, three items are used to measure this construct, Adapted from the SERVQUAL model of Parasuraman et al. (1988).

Recovery satisfaction: This construct is measured with four items, obtained from Maxham and Netemeyer (2002). All four items obtained from this study are found equally important, that is why all four items were used instead of three items.

Manipulation check: The manipulation check consists of the following two multiple choice questions; ‘Was the service recovery either conducted by an AI chatbot or Mike the human service agent?’ and ‘was the service recovery of high or low quality?’. Failing the manipulation check, so providing the wrong answer corresponding to a specific scenario, will lead to exclusion of the dataset.

Realism check: Realism will be measured through two items, which are based on the studies of Maxham (2001) and Goodwin & Ross (1992). These items consist of ‘the described situation could occur in my own life’ and ‘ the described situation is realistic’. Again, a 5-point Likert scale from ‘1= Strongly disagree to’ to ‘5= Strongly agree’ is used.

Gender: The gender of the participant is determined through the following multiple-choice question: What is your gender? The response options include: ‘male’, ‘female’, ‘non-binary/ third gender’, and ‘I would rather not tell’.

Age: To find out the age of the participants, they are asked to fill in their age in an open-ended question.

Educational level: To measure the educational level of the respondents, the following question is asked: ‘’What is you highest completed level of education?’’. Participants could select one of the following response options: ‘primary school’, ‘secondary school’, ‘MBO’, ‘HBO’, and ‘WO’.

3.6 Pre-test

There is a pre-test on a sample of participants in order to try out the experiment’s clarity and verify and check the efficiency of manipulation. A small group of around 10 people are included in this phase, reviewing the experiment, providing comments, and providing feedback. Participants are asked to complete the questionnaire through Qualtrics and request any questions or concerns they may have. It is very important in this scenario-based experiment to make sure participants understand the scenario well. Others may view the scenario as unreal or don’t understand the scenario, therefore it is important to test its perceived truthfulness and understanding before going any further. This test was successfully executed as all 10 people passed the manipulation checks.

3.7 Data analysis

To examine data, the data set is exported from Qualtrics as an SPSS file and examined using IBM SPSS Statistics version 29. The data are cleaned before analysis, eliminating unwanted variables, missing values, and incomplete responses. Reliability is conducted, followed by reporting descriptive statistics, and correlation analysis. A randomization check is also performed to ensure group validity.

In order to compare differences between multiple group and experimental conditions, MANOVA is used as the primary research tool.

Because this study includes multiple related dependent variables, namely perceived fairness, empathy, privacy, and recovery satisfaction, a MANOVA (Multivariate Analysis of Variance) was conducted. MANOVA is preferred over separate ANOVAs as it accounts for potential correlations between the dependent variables and reduces the risk of Type I errors (Hair et al., 2019). This approach allows for a more holistic understanding of how the independent variables (service agent type and recovery quality) affect the combined ethical and satisfaction-related outcomes of the service recovery process. As the experimental design used here is 2x2, varying on both the service agent type (AI vs. human) and service recovery quality (high vs. low), MANOVA allows testing for main effects and interaction effects (Hair et al., 2019). This is to determine whether perceived distributive, procedural and interactional justice, empathy, privacy, and recovery satisfaction with recovery differ significantly between the conditions of the agent source awareness, regardless of the quality of the recovery.

3.8 Validity & reliability

When conducting research, the concepts of validity and reliability are important for ensuring the credibility of study findings. These concepts serve as the foundation upon which the quality of the research is built, assuring that the methods and measurements are accurately and consistently capturing the phenomena under investigation (Cohen et al., 2017).

Validity refers to the extent to which a research study or measurement tool measures what it is intended to measure (Field, 2018). The three dimensions; distributive, procedural, and interactional justice, which measure the concept of fairness are validated by prior research (Tax et al., 1998; Smith et al., 1999). The same applies for the concepts of privacy (Malhotra et al., 2004; Balapour et al., 2020)., empathy (Parasuraman et al., 1988), and recovery satisfaction (Maxham & Netemeyer, 2002).

Reliability, on the other hand, concerns the consistency of the measurement tool. This means the extent to which the measurements of the characteristics give the same results when the study would be repeated under the same conditions (Field, 2018). This is measured by using of the Cronbach's alpha, which has a desired value of > 0.70 and every value below 0.60 will be considered as problematic (Field, 2018). This is the case for distributive justice (α=0. 886), procedural justice (α= 0.809), and interactional justice (α= 0.878), deleting an item would not significantly increase the Cronbach's alpha. The other dependent variables; privacy (α=0.927), empathy (α= 0.835), and recovery satisfaction (α= 0.948), also exceed the threshold of Cronbach's alpha of 0.7. Again, deleting items would not lead to an significant increase of the Cronbach's alpha. It can be concluded that all constructs are reliable. All the relevant SPSS output can be found in Appendix B.

3.9 Research ethics

This research addresses ethical guidelines, providing voluntary participation and informed consent for data use. Participants are free to withdraw at any time, and their answers are kept anonymous to ensure privacy.

Before the study begins, participants are given a clear explanation of the topic, intention and the goal of the research. The data that will be retrieved will only be utilized for the purpose of this study and is erased after analysis, with access limited to the researcher for confidentially maintenance.

Participants are randomly allocated via Qualtrics and asked to engage with pre-constructed scenarios. Participants are informed about the possibility of encountering sensitive content and are advised that they may experience discomfort. To ensure their well-being throughout the study, they are encouraged to report any concerns or negative emotions that may arise.

4. Analysis & Results

4.1 Descriptive analysis

This study had a total of 158 participants, however only 125 responses (79.1%) were useful, with as main reason that many people did not complete the whole questionnaire. This has led to a total amount of 30 people that have been removed. Additionally, 3 participants did not pass the manipulation checks as they answered the manipulation questions about the service agent awareness and quality of the recovery wrong. They were removed to ensure validity, which is more explained in 4.2. The participants are according Hair et al. (2019) acceptably distributed over the four scenarios as all scenarios exceed the threshold of 20/30 participants (see table 1). Scenario 1 involved a good/high quality recovery from an AI-chatbot (N=33). Secondly, scenario 2 involved also a good/high quality recovery but from a human service agent (N=29). Third, scenario 3 involved a bad/low quality recovery from an AI chatbot (N=36). Lastly, scenario 4 involved again a bad/low quality recovery but from Mike the human service agent (N=27).

		Quality of service recovery		
		High quality	**Low quality**	Total
Service agent	**AI-chatbot**	33 (scenario 1)	36 (scenario 3)	69
	Human service agent	29 (scenario 2)	27 (scenario 4)	56
Total		62	63	125

Table 1-*Distribution of respondents on scenarios*

Of the total sample size; 61.6 % were male, 36.8 % female, and 1.6 % would rather not say their gender. The average age of the respondents was 33.03, with a rage from 19 to 71 years old. Additionally, 44.0 % of the participants have a WO education, followed by the second largest group 38.4 % of the respondents have a HBO education.

Variable	**Scenario 1** N= 33	**Scenario 2** N= 29	**Scenario 3** N= 36	**Scenario 4** N= 27
Fairness (Distributive justice)	M= 3.44 SD= 0.67	M= 3.61 SD= 0.69	M= 1.85 SD= 0.71	M= 1.90 SD= 0.54
Fairness (Procedural justice)	M= 3.67 SD= 0.51	M= 3.83 SD= 0.38	M= 2.12 SD= 0.65	M= 2.17 SD= 0.57
Fairness (Interactional justice)	M= 3.51 SD= 0.65	M= 4.18 SD= 0.52	M= 2.27 SD= 0.89	M= 2.75 SD= 0.77
Privacy	M= 3.02 SD= 0.93	M= 3.78 SD= 0.47	M= 2.96 SD 0.89	M= 3.68 SD= 0.53
Empathy	M= 3.19 SD= 0.60	M= 4.03 SD= 0.47	M= 2.24 SD= 0.77	M= 2.57 SD= 0.71
Satisfaction	M= 3.70 SD= 0.50	M= 4.01 SD= 0.50	M= 1.90 SD= 0.64	M= 1.87 SD= 0.51

Table 2- *Descriptive statistics dependent variables*

Table 2 indicates that scenario 1 and scenario 2 have the highest means for most of the dependent variables, which indicates that high quality service recovery leads to overall higher perceived fairness (on all three dimensions) empathy and recovery satisfaction, as we derived from existing literature in chapter 3. Privacy is an exception as it has relatively high means in all four scenarios, especially scenario 2 and 4 indicating high perceived privacy considerations when the recovery is conducted by a human agent. Also noticeable, is that scenarios 1 and 3 have relatively lower means for all the variables except satisfaction, indicating an AI-driven service recovery leads to lower perceived fairness (including all 3 dimensions), privacy and empathy. Satisfaction is an exception, which could mean that perceived recovery satisfaction is not affected by the type of agent. So, it can be concluded that the means between different types conditions of agent source awareness and service recovery quality.

4.2 Manipulation check

In the end of the questionnaire, two questions were asked to check if whether the manipulations worked and caused the desired situation. Two manipulation checks were conducted to test the agent source awareness and the quality of the service recovery.

The first manipulation check is to see if the participants have noticed if they encountered an AI-chatbot or a human service agent. Of the 128 participants that were included in the research, 58 participants saw a scenario of a service recovery from a human, however 1 participant did not answer this question correctly (see appendix C table 1). Therefore this participant was removed from the sample. All the 70 participants who encountered the AI-chatbot, answered the question correctly. It can be concluded that the AI-chatbot and the human service agent were easy to distinguish.

The second manipulation check is to see if the participants have noticed if they encountered a high or low quality service recovery. Of the 128 participants, all 64 participants who encountered a low quality service recovery did noticed the service recovery was of low quality. However, of the 64 participants who encountered a high quality service recovery, a total of 2 participants did not notice that the service recovery they saw was of high quality (see appendix C table 2). These two participants were removed. Again, it can be concluded that two types of service recovery were easy to notice.

After removing these 3 participants from the sample, the total sample size consisted of 125 participants (see table 1).

4.3. Realism check

In order to test the realism of the situation and the scenarios, two items were given to the participants to measure realism on a 5-point Likert scale, ranging from'' totally disagree'' to'' totally agree''. These two items have a Cronbach's alpha of 0,923 and this would not increase by deleting one item. With an overall mean of 3.876, it can be concluded that the scenarios were experienced by the participants as relatively realistic. The SPSS output can be found in Appendix C.

4.4 Assumptions

Before running the analysis, there are several assumptions that need to be met according to Hair et al. 2018). We start with the first assumption; independence (Hair et al., 2018, p. 399). Because participants completed the questionnaire individually in their own personal setting, there input is likely not to be influenced.

Secondly, the assumption of homogeneity of the variance-covariance metrics is tested (Hair et al., 2028, p399). By conducting a Box's M test, we can look at differential differences in the amount of variances between groups (Hair et al., 2018). A significance level of $p < 0.001$ is set as criterion for indicating serious violations of the assumption of equal covariances matrices. There is no violation as the Box's M test (=97.246) had a significance of 0.019 which means this assumption is met (see appendix D, table 1).

The third assumption is normality, which means that the dependent measurements must have a multivariate normal distribution (Hair et al., 2018, p. 400). To test this, a normality test is conducted for all the dependent variables, in which we look at the skewness and kurtosis values, and the histograms are assed. Table 3 shows the results of the normality tests and the histograms can be found in Appendix D (figure 1-6). Skewness and kurtosis values should fall between -2 and +2 to be considered acceptable values for assuming normality in multivariate analysis like MANOVA (Hair et al., 2018). All the dependent variables meet this criteria which means that the linearity assumption is met.

Variable	**Skewness**	**Kurtosis**
Distributive justice	0.034	-1.268
Procedural justice	-0.237	-1.202
Interactional justice	-0.296	-0.758
Privacy	-0.721	-0.442
Empathy	-0.159	-0.683
Recovery satisfaction	-0.087	-1.370

Table 3*- Normality test of dependent variables (Skewness & Kurtosis)*

The fourth assumption is linearity. Linearity was assessed by using scatterplot matrices of the dependent variables. Because differences per scenario are expected, linearity was assed per scenario. The plots show mixed linear relationships between variables, with some higher and lower linear relationships. Overall, this assumption of linearity is met. The plots can be found in Appendix D (Figures 7-10).

The last assumption the multicollinearity. Between the dependent variables there are no multicollinearities as all the variables correlate < 0.90, indicating no multicollinearity (Hair et al., 2018). This can be found in Appendix D table 10. Additionally, the tolerance values are all above 0.1 and the VIF values all are below 10 (see Appendix D, table 11), which indicates no multicollinearity and satisfying this assumption.

4.5 Analysis

4.5.1 Hypothesis 1

In order to test whether consumers perceive the service recovery as less fair when they are aware that the service agent is AI than when they think that the agent is human, regardless of the quality of the recovery, a MANOVA analysis is conducted. Based on the descriptive statistics in table 4, we see that distributive justice scores lower when people are aware the recovery is from an AI than of a human regardless of the quality, as it has lower means for both qualities from the AI-chatbot (3.444, 1.852 vs 3.610, 1.877). Procedural justice also has lower means when the recovery is done by AI rather than human for both quality levels (3.667, 2.120 vs 3.828, 2.173). This also applies for interactional justice (3.505, 2.269 vs 4.184, 2.753). So, based on these descriptive statistics, people perceive service recovery from an AI as less fair than from a human, regardless of the quality of the recovery. This supports hypothesis 1. The SPSS output is found in Appendix E, table 12.

Agent	**N**	**Quality**	**Distributive Justice (mean | SD)**		**Procedural Justice (Mean | SD)**		**Interactional Justice (Mean | SD)**	
AI-chatbot	33	High	3.444	0.670	3.667	0.514	3.505	0.652
	36	Low	1.852	0.715	2.120	0.641	2.269	0.894
Human	29	High	3.610	0.690	3.828	0.384	4.184	0.516
	27	Low	1.877	0.540	2.173	0.565	2.753	0.771
Total	125							

Table 4- *Descriptive statistics of MANOVA (Fairness)*

However, descriptive statistics alone do not tell whether the difference are statistics significant. Therefore we also look at the multivariate result (Appendix E, table 13) which show the overall effect of independent variables (agent type, quality, and their interaction) on the dependent variables. With a Wilks Lambda value of 0.712 and an $\alpha < 0.001$, it can be concluded that the type of agent (AI vs human) has a statistically significant multivariate effect on perceived fairness across the combined variables of justice (the SPSS output can be found in Appendix E, table 13).

Additionally, we look at the test of between-subjects effects (Appendix E, table 14), where we check which specific justice perceptions are influenced by the ''agent'' factor. This table shows that distributive justice (F=0.630, α= 0.0429) and procedural justice (F=1.195, α=0.277) are not significantly affected by whether the agent is AI or human. Interactional justice (F=19.602, α= <0.001) does shows a significant effect from the type of agent.

Lastly, the interaction between agent type and recovery quality is measured. This multivariate effect is not significant for distributive justice (F= 0.344, α= 0.558), procedural justice (F=0.309, α=0.580), and interactional justice (F=0.547, α= 0.461) which supports that quality does not matter in the perception of fairness of a service recovery by an AI-chatbot or human agent.

To conclude, hypothesis 1 is partially supported as the type of agent does not fully affect fairness perceptions, but only interactional justice. The effect is however independent of recovery quality, which matches H1.

4.5.2 Hypothesis 2

Hypothesis 2 tests whether consumers perceive service recovery as less empathic when they are aware that the agent is AI than when they think that the agent is human, regardless of the quality of the recovery. First, we look again at the descriptive statistics (see table 5), which shows that empathy has lower means when the service recovery is done by an AI-chatbot (3.192, 2.241) rather by a human agent (4.035, 2.568) for both qualities. So, based on these descriptive statistics hypothesis 2 is supported.

Agent	**N**	**Quality**	**Empathy (mean | SD)**	
AI-chatbot	33	High	3.192	0.601
	36	Low	2.241	0.767
Human	29	High	4.035	0.466
	27	Low	2.568	0.703

Table 5- *Descriptive statistics of MANOVA (Empathy)*

Secondly, we already assed that the type of agent (AI vs human) has a statistically significant multivariate effect on the dependent variables, in this case empathy, with a Wilks Lambda value of 0.712 and a α <0.001 (Appendix E, table 12).

Third, from the test of between-subjects effects (Appendix E, table 14) we see that perceived empathy is significantly affected (F=25.015, α <0.001) by the type of agent (AI vs human). This is however dependent on the quality of the recovery as the interaction between agent type and recovery quality is significant (F= 4.857, α= 0.0.29), which does not supports H2 and that quality does matter in the perception of empathy of a service recovery by an AI-chatbot or human agent. Even though, the descriptive statistics support H2, the effect of the type of agent delivering the recovery does lead to lower perceived empathy, but not regardless of the quality. H2 not supported.

4.5.3 Hypothesis 3

The third hypothesis tests whether consumers perceive less privacy protection when they are aware that the agent is AI than when they think that the agent is human, regardless of the quality of the recovery. The descriptive statistics support this hypothesis as perceived privacy has lower means when the service recovery is done by an AI-chatbot (3.020, 2.963) rather by a human agent (3.782, 3.680) for both qualities (see table 6). So, based on these descriptive statistics hypothesis 3 is supported.

Agent	**N**	**Quality**	**Privacy (mean**	**SD)**
AI-chatbot	33	High	3.020	0.935
	36	Low	2.963	0.894
Human	29	High	3.782	0.474
	27	Low	3.680	0.527

Table 6- *Descriptive statistics of MANOVA (Privacy)*

Secondly, we look again at the between-subjects effects (Appendix E, table 14), which indicate that perceived privacy is significantly affected ($F=29.350$, $\alpha <0.001$) by the type of agent (AI vs human). This effect is independent on the quality of the recovery as the interaction between agent type and recovery quality is not significant ($F= 0.028$, $\alpha= 0.868$), which does supports H3 and that quality does not matter in the perception of privacy of a service recovery by an AI-chatbot or human agent. To conclude, the descriptive statistics and the insignificant interaction effect of agent type and quality illustrate that the effect of the type of agent delivering the recovery does lead to lower perceived privacy, regardless of the quality. H3 is supported.

4.5.4 Hypothesis 4

Lastly, H4 tests whether consumers report lower recovery satisfaction when they are aware that the agent is AI than when they think that the agent is human, regardless of the quality of the recovery. The descriptive statistics in table 7, partially supports this. Recovery satisfaction scores lower on means for high quality recovery when it is done by an AI-chatbot (3.697) than by a human agent (4.009). However when the service recovery is of low quality, recovery satisfaction has a lower mean score when it is done by a human agent (1.870) than by an AI-chatbot (1.896). This is however a very small difference, so based on these statistics is H4 partially supported.

Agent	N	Quality	Recovery satisfaction (mean | SD)	
AI-chatbot	33	High	3.697	0.499
	36	Low	1.896	0.636
Human	29	High	4.009	0.498
	27	Low	1.870	0.511

***Table 7**- Descriptive statistics of MANOVA (Recovery satisfaction)*

Secondly, we will again look at the tests in between-subjects effects (Appendix E, table 14). These results indicate that the type of agent does not have a significant effect (F= 2.132, α= 0.147) on recovery satisfaction. The interaction effect between agent type and quality on satisfaction is also insignificant (F=2.958, α= 0.088). Therefore we can conclude that the type of agent (human vs AI) has no significant effect on recovery satisfaction, even when it is independent of quality. H4 is not supported.

5. Discussion

5.1 Conclusion

This study investigated how consumers perceive service recovery when delivered by either an AI chatbot or a human agent, focusing on perceived fairness, empathy, privacy concerns, and recovery satisfaction. The central aim was to examine whether biases against AI influence ethical concerns and satisfaction, independent of the quality of the recovery. Through a 2x2 scenario-based experimental design, participants were exposed to either a high or low-quality service recovery, delivered by either an AI chatbot or a human agent.

The results offer diverse insights. First, the analysis showed that perceived fairness, particularly interactional justice, was significantly lower when participants believed the agent was AI rather than human, supporting the idea that agent source influences perceptions, regardless of actual performance. Similarly, participants perceived less empathy and less privacy protection from AI agents compared to human agents. However, the interaction effect for empathy was significant, suggesting that the empathy perceived in AI-driven recoveries is influenced by the quality of the recovery, meaning H2 was not fully supported. Interestingly, the hypothesis predicting lower recovery satisfaction for AI agents was not supported, indicating that satisfaction may rely more on the objective quality of recovery than the agent's identity.

These findings contribute to the theoretical understanding of AI biases in service recovery contexts by showing that ethical concerns such as fairness, empathy, and privacy are impacted by agent identity, even when the quality is controlled. Practically, this means that companies must not only focus on chatbot performance but also address user biases through design improvements, transparency, and hybrid service models. As organizations increasingly adopt AI tools, understanding and mitigating these biases becomes essential for maintaining consumer trust and delivering ethically acceptable digital service recoveries.

5.2 Theoretical contributions

This study contributes to the theoretical understanding of online service recovery by integrating the concept of AI bias into perceptions of ethical concerns (fairness, empathy, and privacy) and recovery satisfaction. While pervious research has focused on chatbot functionality, anthropomorphism and perceived effectiveness (Agnihotri & Bhattacharya, 2023; Wirtz et al., 2018), this thesis extends the literature by highlighting that negative consumer perceptions may arise purely from the awareness that the service agent is AI, regardless of performance quality (Xue et al., 2024; Dietvorst et al., 2015).

In contrast to existing literature that primarily attribute perceptions to objective service performance (Wirtz & Mattila, 2004; Rio-Lanza et al., 2009), this research reveals that agent source awareness can independently shape ethical evaluations. Specifically, it shows that perceptions of empathy and privacy are significantly lower for AI agents, while the effect on fairness is primarily driven by the interactional dimension (Kim et al., 2012). Notably, recovery satisfaction was not significantly affected by the agent source, which suggests that satisfaction may be more resilient to source-related bias than ethical concerns.

Additionally, this research provides empirical support for the idea that algorithm aversion influences consumer judgments in emotionally sensitive contexts like service failure, therefore it enriches the literature on trust and emotional response in AI-human interaction (Dietvorst et al., 2015; Huang & Rust, 2021).

5.3 Practical contributions

This study highlights the importance for organizations to acknowledge and address consumer biases toward AI in online service recovery. Even when the quality of the service is high, customers may still perceive AI agents as less fair, empathic, or ethical in consideration privacy. To mitigate these concerns, companies should consider designing chatbots with more human-like attributes, such as emotionally intelligent language and personalized interaction (Agnihotri & Bhattacharya, 2023).

Additionally, offering users the option to choose between AI and human support can improve trust and satisfaction. Transparent communication about how AI handles data and fairness can also reduce ethical concerns. Ultimately, firms should balance efficiency with emotional intelligence to maintain customer trust in digital interactions.

5.4 Limitations & Future research

While this study offers valuable insights into consumer perceptions of AI versus human service recovery agents, there are some limitations to be mentioned. First, the research was conducted using a scenario-based experimental design, which, is effective in isolating variables, it also may not fully capture the complexity of real-life service recovery experiences. Respondents may behave differently in actual customer service interactions where emotions and stakes are higher (Sparks & McColl-Kennedy, 2001). Future research could include field experiments or real-time service interactions to enhance ecological validity.

Second, the sample was drawn primarily from Dutch consumers using convenience and snowball sampling, which may limit the generalizability of the results to broader or international populations. Cultural attitudes toward AI and service expectations may vary, and future studies could benefit from cross-cultural comparisons to assess whether AI-related biases are universal or context-specific. Additionally, this study only incorporated participants of 18 years of older. Younger people between 15 and 18 for example, also purchase a lot online. This group could have different interpretations of a AI service recovery, leading to a research opportunity in the future.

Third, this study did not assess participants' prior experience with AI or their pre-existing attitudes toward technology, which could strongly influence how they interpret chatbot interactions. Research shows that trust in AI, familiarity, and tech-savviness can shape consumer bias, with those that are more comfortable with AI reacting more positively, and those more sceptical showing stronger resistance (Dietvorst et al., 2015; Xue et al., 2024). Future studies should include measures of AI familiarity, trust, or tech resilience as potential moderating variables. This would allow researchers to understand who is most biased against AI and tailor chatbot design or communication strategies accordingly.

Lastly, the use of all three fairness dimensions (distributive, procedural, interactional) as separate variables, which aligned with the Justice Theory of Rawl (1971), did increase the complexity of the model. Some conceptual overlap emerged, particularly between interactional justice and perceived empathy, as both involve respectful and personalized treatment. Additionally, distributive justice may correlate with satisfaction, as both relate to outcome evaluations. Although MANOVA was used to control for Type I error, the inclusion of multiple dependent variables may still complicate interpretation. Future research may consider consolidating variables or testing for discriminant validity to ensure clear differentiation between constructs.

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Appendices

Appendix A. Experiment

Beste deelnemer,
Hartelijk dank voor uw bereidheid om deel te nemen aan dit onderzoek! Mijn naam is Roel Laffra en ik ben masterstudent aan de Radboud Universiteit Nijmegen. Voor mijn scriptie, onder begeleiding van Dr. Herm Joosten, doe ik onderzoek naar online klachtafhandeling.
In deze vragenlijst krijgt u een korte verzonnen scenario te zien over een online klachtafhandeling van een bedrijf waarin u wordt gevraagd uzelf in de rol van de klant te verplaatsen alsof u het echt zou meemaken. Vervolgens beantwoord u een aantal vragen over hoe jij deze situatie hebt ervaren. Er zijn geen goede of foute antwoorden, ik ben enkel geïnteresseerd in uw mening.
Deelname aan dit onderzoek is volledig vrijwillig en u kunt op elk moment stoppen zonder opgave van reden. Alle antwoorden worden volledig anoniem verwerkt en uitsluitend gebruikt voor dit onderzoek.
Let op: Onder alle deelnemers die deze vragenlijst volledig invullen wordt een €20 Bol.com bon verloot. Het invullen duurt ongeveer 5 minuten. Heb je vragen over het onderzoek? Neem dan gerust contact op via het volgende e-mailadres: Roel.laffra@ru.nl
Door verder te gaan, verklaart u dat:

- U de bovenste informatie hebt gelezen en begrepen
- U 18 jaar of ouder bent
- U toestemming geeft voor het gebruik van uw antwoorden in dit onderzoek.

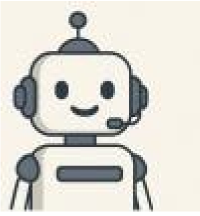
0 Ja, ik ga akkoord
0 Nee, sluit het venster
Alvast bedankt voor je deelname!
Vriendelijke Groet, Roel Laffra

Servicefout voor alle scenario's:
U krijgt nu een situatie te zien met een bijbehorend scenario. Lees de volgende situatie over de service fout goed door en beantwoord hierna de vragen:

"U hebt online een Iphone besteld bij een bedrijf met gegarandeerde levering de volgende dag. Er zijn echter twee dagen verstreken en het pakket is nog steeds niet geleverd. Gefrustreerd neemt u via de livechat contact op met de klantenservice van het bedrijf om een klacht in te dienen."

U krijgt de volgende reactie terug van het bedrijf:

SCENARIO 1: Goede serviceherstel – AI-chatbot



“Directe reactie reactie gegenereerd door een AI-chatbot”

"Hallo, ik ben onze virtuele assistent. Het spijt me zeer om te horen dat uw pakket niet op tijd is geleverd. Ik begrijp uw frustratie volledig en waardeer het dat u dit aan ons meldt.

Ik heb uw bestelling nagekeken en kan bevestigen dat er sprake is van vertraging. We vergoeden de verzendkosten en bieden u 15% korting op uw volgende bestelling aan. Uw pakket krijgt nu prioriteit en wordt morgen bezorgd.

Dank voor uw geduld, en nogmaals onze oprechte excuses."

SCENARIO 2: Goede serviceherstel – Menselijke servicemedewerker

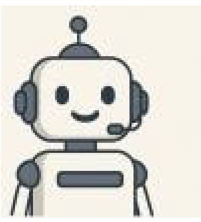
“Reactie binnen één dag van Mike, een menselijke servicemedewerker”

"Hallo, ik ben Mike. Het spijt me zeer om te horen dat uw pakket niet op tijd is geleverd. Ik begrijp uw frustratie volledig en waardeer het dat u dit aan ons meldt.

Ik heb uw bestelling nagekeken en kan bevestigen dat er sprake is van vertraging. We vergoeden de verzendkosten en bieden u 15% korting op uw volgende bestelling aan. Uw pakket krijgt nu prioriteit en wordt morgen bezorgd.

Dank voor uw geduld, en nogmaals onze oprechte excuses."

SCENARIO 3: Slecht serviceherstel – AI-chatbot



“Directe reactie gegenereerd door een AI-chatbot”

"Hallo, ik ben onze virtuele assistent. Jammer om te horen dat uw pakket nog niet is aangekomen. Soms gebeuren er vertragingen. Helaas kan ik er niet veel aan doen.

U kunt uw track & trace blijven volgen, het pakket komt uiteindelijk wel. Excuses voor het ongemak."

SCENARIO 4: Slecht serviceherstel – Menselijke service medewerker

“Reactie na 1–2 dagen van Mike, een menselijke servicemedewerker”

"Hallo, ik ben Mike. Jammer om te horen dat uw pakket nog niet is aangekomen. Soms gebeuren er vertragingen. Helaas kan ik er niet veel aan doen.

U kunt uw track & trace blijven volgen, het pakket komt uiteindelijk wel. Excuses voor het ongemak."

Vragenlijst
Beantwoord nu de vragen:
(1= ‘’helemaal oneens’’, 5= ‘’helemaal eens’’)

Waargenomen eerlijkheid (Distributieve rechtvaardigheid)
In hoeverre bent u het eens met de volgende stellingen over de eerlijkheid van de uitkomst van de klachtbehandeling?
1. “Het resultaat dat ik heb ontvangen was eerlijk.”
2. “Ik heb gekregen wat ik verdiende.”
3. “Bij het oplossen van het probleem gaf dit bedrijf me wat ik nodig had.”

(Procedurele rechtvaardigheid)
In hoeverre bent u het eens met de volgende stellingen over de manier waarop de klacht is behandeld?
1. “De procedures die werden gebruikt om mijn probleem op te lossen waren eerlijk.”
2. “De tijd die nodig was om mijn probleem op te lossen was noodzakelijk.”
3. “Het bedrijf toonde voldoende flexibiliteit bij het omgaan met mijn probleem.”

(Interactionele rechtvaardigheid)
In hoeverre bent u het eens met de volgende stellingen over de manier waarop de service agent met u communiceerde?
1. “De medewerker toonde gepaste betrokkenheid bij mijn probleem.”
2. “De medewerker deed zijn best om mijn probleem op te lossen.”
3. “De communicatie van de medewerker met mij was gepast.”

---

2. Waargenomen privacy
In hoeverre bent u het eens met de volgende stellingen over uw gevoel van privacy tijdens de interactie met de service agent?
1. “Ik geloof dat het bedrijf verantwoordelijk omgaat met mijn persoonlijke gegevens.”
2. “Ik heb vertrouwen dat mijn gegevens beschermd zijn tijdens interactie met deze service.”
3. “Ik vertrouw erop dat mijn persoonlijke gegevens niet worden misbruikt door het bedrijf.”

---

3. Waargenomen empathie
In hoeverre bent u het eens met de volgende stellingen over de empathie van de service agent tijdens de klachtbehandeling?
1. “De servicemedewerker begreep mijn specifieke behoeften.”
2. “Ik had het gevoel dat de servicemedewerker echt begaan was met mijn situatie.”
3. “De servicemedewerker toonde empathie tijdens onze interactie.”

---

4. Tevredenheid over serviceherstel
"Hoe tevreden was u over de manier waarop uw klacht werd afgehandeld?"
1. “Ik ben tevreden met de manier waarop mijn probleem is afgehandeld.”
2. “De serviceherstel voldeed aan mijn verwachtingen.”
3. “Ik ben tevreden met de algehele service-ervaring.”
4. “Ik zou in de toekomst opnieuw gebruikmaken van deze service.”

Manipulatie check
Wie behandelde het service herstel?
1. AI-chatbot
2. Mike de service medewerker

Realism check
Hoe realistisch is dit scenario?
1. De omschreven situatie kan in mijn eigen leven voorkomen
2. De omschreven situatie is realistisch

Demographics
1. Wat is uw geslacht?
- Man
- Vrouw
- Anders

2. Wat is uw leeftijd?

….

3. Wat is uw hoogst genoten opleidingsniveau?

- Basisonderwijs
- Voortgezet onderwijs
- MBO
- HBO
- WO

Slotwoord
Bedankt voor het invullen van de vragenlijst, uw antwoorden zijn opgeslagen!
Om kans te maken op de Bol.com cadeaubon vul dan hieronder uw e-mail adres in.
…..

Appendix B- Reliability analysis

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,886	,886	3

Inter-Item Correlation Matrix

	In hoeverre bent u het eens met de volgende stellingen: - "De oplossing die ik heb ontvangen was eerlijk."	In hoeverre bent u het eens met de volgende stellingen: - "Ik heb gekregen wat ik verdiende."	In hoeverre bent u het eens met de volgende stellingen: - "Bij het oplossen van de klacht gaf dit bedrijf me wat ik nodig had."
In hoeverre bent u het eens met de volgende stellingen: - "De oplossing die ik heb ontvangen was eerlijk."	1,000	,739	,702
In hoeverre bent u het eens met de volgende stellingen: - "Ik heb gekregen wat ik verdiende."	,739	1,000	,726
In hoeverre bent u het eens met de volgende stellingen: - "Bij het oplossen van de klacht gaf dit bedrijf me wat ik nodig had."	,702	,726	1,000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
In hoeverre bent u het eens met de volgende stellingen: - "De oplossing die ik heb ontvangen was eerlijk."	5,02	4,653	,776	,604	,841
In hoeverre bent u het eens met de volgende stellingen: - "Ik heb gekregen wat ik verdiende."	5,52	4,735	,794	,630	,825
In hoeverre bent u het eens met de volgende stellingen: - "Bij het oplossen van de klacht gaf dit bedrijf me wat ik nodig had."	5,57	4,893	,765	,587	,850

***Table 1-** Reliability analysis for Distributive justice (Fairness)*

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,809	,810	3

Inter-Item Correlation Matrix

	In hoeverre bent u het eens met de volgende stellingen: - “De procedures die werden gebruikt om mijn klacht op te lossen waren eerlijk.”	In hoeverre bent u het eens met de volgende stellingen: - “De tijd die nodig was om mijn klacht op te lossen was noodzakelijk.”	In hoeverre bent u het eens met de volgende stellingen: - “Het bedrijf toonde voldoende flexibiliteit bij het omgaan met mijn klacht.”
In hoeverre bent u het eens met de volgende stellingen: - “De procedures die werden gebruikt om mijn klacht op te lossen waren eerlijk.”	1,000	,524	,669
In hoeverre bent u het eens met de volgende stellingen: - “De tijd die nodig was om mijn klacht op te lossen was noodzakelijk.”	,524	1,000	,568
In hoeverre bent u het eens met de volgende stellingen: - “Het bedrijf toonde voldoende flexibiliteit bij het omgaan met mijn klacht.”	,669	,568	1,000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
In hoeverre bent u het eens met de volgende stellingen: - “De procedures die werden gebruikt om mijn klacht op te lossen waren eerlijk.”	5,74	4,273	,680	,478	,719
In hoeverre bent u het eens met de volgende stellingen: - “De tijd die nodig was om mijn klacht op te lossen was noodzakelijk.”	5,89	4,520	,600	,361	,795
In hoeverre bent u het eens met de volgende stellingen: - “Het bedrijf toonde voldoende flexibiliteit bij het omgaan met mijn klacht.”	5,98	3,500	,708	,513	,688

***Table 2**- Reliability analysis for Procedural justice (Fairness)*

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,878	,881	3

Inter-Item Correlation Matrix

	In hoeverre bent u het eens met de volgende stellingen: - “De medewerker toonde gepaste betrokkenheid bij mijn klacht.”	In hoeverre bent u het eens met de volgende stellingen: - “De medewerker deed zijn best om mijn klacht op te lossen.”	In hoeverre bent u het eens met de volgende stellingen: - “De communicatie van de medewerker met mij was gepast.”
In hoeverre bent u het eens met de volgende stellingen: - “De medewerker toonde gepaste betrokkenheid bij mijn klacht.”	1,000	,791	,685
In hoeverre bent u het eens met de volgende stellingen: - “De medewerker deed zijn best om mijn klacht op te lossen.”	,791	1,000	,657
In hoeverre bent u het eens met de volgende stellingen: - “De communicatie van de medewerker met mij was gepast.”	,685	,657	1,000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
In hoeverre bent u het eens met de volgende stellingen: - “De medewerker toonde gepaste betrokkenheid bij mijn klacht.”	6,41	4,163	,817	,673	,778
In hoeverre bent u het eens met de volgende stellingen: - “De medewerker deed zijn best om mijn klacht op te lossen.”	6,52	3,994	,795	,650	,804
In hoeverre bent u het eens met de volgende stellingen: - “De communicatie van de medewerker met mij was gepast.”	5,94	5,383	,709	,505	,882

Table 3- *Reliability analysis for interactional justice (Fairness)*

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,927	,927	3

Inter-Item Correlation Matrix

	In hoeverre bent u het eens met de volgende stellingen: - "Ik geloof dat het bedrijf verantwoordelijk omgaat met mijn persoonlijke gegevens."	In hoeverre bent u het eens met de volgende stellingen: - "Ik heb vertrouwen dat mijn gegevens beschermd zijn tijdens interactie met deze service."	In hoeverre bent u het eens met de volgende stellingen: - "Ik vertrouw erop dat mijn persoonlijke gegevens niet worden misbruikt door het bedrijf."
In hoeverre bent u het eens met de volgende stellingen: - "Ik geloof dat het bedrijf verantwoordelijk omgaat met mijn persoonlijke gegevens."	1,000	,811	,784
In hoeverre bent u het eens met de volgende stellingen: - "Ik heb vertrouwen dat mijn gegevens beschermd zijn tijdens interactie met deze service."	,811	1,000	,831
In hoeverre bent u het eens met de volgende stellingen: - "Ik vertrouw erop dat mijn persoonlijke gegevens niet worden misbruikt door het bedrijf."	,784	,831	1,000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
In hoeverre bent u het eens met de volgende stellingen: - "Ik geloof dat het bedrijf verantwoordelijk omgaat met mijn persoonlijke gegevens."	6,66	2,969	,834	,697	,908
In hoeverre bent u het eens met de volgende stellingen: - "Ik heb vertrouwen dat mijn gegevens beschermd zijn tijdens interactie met deze service."	6,65	2,859	,870	,757	,879
In hoeverre bent u het eens met de volgende stellingen: - "Ik vertrouw erop dat mijn persoonlijke gegevens niet worden misbruikt door het bedrijf."	6,63	2,863	,849	,726	,896

Table 4- Reliability analysis for Privacy

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,835	,834	3

Inter-Item Correlation Matrix

	In hoeverre bent u het eens met de volgende stellingen: - “De servicemedewerker begreep mijn specifieke behoeften.”	In hoeverre bent u het eens met de volgende stellingen: - “Ik had het gevoel dat de servicemedewerker echt begaan was met mijn situatie.”	In hoeverre bent u het eens met de volgende stellingen: - “De servicemedewerker toonde empathie tijdens onze interactie.”
In hoeverre bent u het eens met de volgende stellingen: - “De servicemedewerker begreep mijn specifieke behoeften.”	1,000	,642	,506
In hoeverre bent u het eens met de volgende stellingen: - “Ik had het gevoel dat de servicemedewerker echt begaan was met mijn situatie.”	,642	1,000	,732
In hoeverre bent u het eens met de volgende stellingen: - “De servicemedewerker toonde empathie tijdens onze interactie.”	,506	,732	1,000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
In hoeverre bent u het eens met de volgende stellingen: - “De servicemedewerker begreep mijn specifieke behoeften.”	5,87	4,403	,619	,415	,845
In hoeverre bent u het eens met de volgende stellingen: - “Ik had het gevoel dat de servicemedewerker echt begaan was met mijn situatie.”	6,22	3,267	,795	,635	,669
In hoeverre bent u het eens met de volgende stellingen: - “De servicemedewerker toonde empathie tijdens onze interactie.”	5,78	3,751	,693	,538	,776

Table 5- Reliability analysis for empathy

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,948	,948	4

Inter-Item Correlation Matrix

	In hoeverre bent u het eens met de volgende stellingen: - "Ik ben tevreden met de manier waarop mijn klacht is afgehandeld."	In hoeverre bent u het eens met de volgende stellingen: - "De klachtafhandeling voldeed aan mijn verwachtingen."	In hoeverre bent u het eens met de volgende stellingen: - "Ik ben tevreden met de algehele service-ervaring."	In hoeverre bent u het eens met de volgende stellingen: - "Ik zou in de toekomst opnieuw gebruikmaken van deze service."
In hoeverre bent u het eens met de volgende stellingen: - "Ik ben tevreden met de manier waarop mijn klacht is afgehandeld."	1,000	,879	,882	,798
In hoeverre bent u het eens met de volgende stellingen: - "De klachtafhandeling voldeed aan mijn verwachtingen."	,879	1,000	,827	,724
In hoeverre bent u het eens met de volgende stellingen: - "Ik ben tevreden met de algehele service-ervaring."	,882	,827	1,000	,807
In hoeverre bent u het eens met de volgende stellingen: - "Ik zou in de toekomst opnieuw gebruikmaken van deze service."	,798	,724	,807	1,000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
In hoeverre bent u het eens met de volgende stellingen: - "Ik ben tevreden met de manier waarop mijn klacht is afgehandeld."	8,59	11,098	,922	,859	,916
In hoeverre bent u het eens met de volgende stellingen: - "De klachtafhandeling voldeed aan mijn verwachtingen."	8,68	11,510	,862	,785	,936
In hoeverre bent u het eens met de volgende stellingen: - "Ik ben tevreden met de algehele service-ervaring."	8,50	11,494	,900	,815	,924
In hoeverre bent u het eens met de volgende stellingen: - "Ik zou in de toekomst opnieuw gebruikmaken van deze service."	8,50	12,317	,814	,685	,950

Table 6. *Reliability analysis for satisfaction*

Appendix C- Manipulation analysis

Wie behandelde het service herstel? * Agent Crosstabulation

Count

		Agent		Total
		1,00	2,00	
Wie behandelde het service herstel?	AI-Chatbot	70	1	71
	Mike de service mederwerker	0	57	57
Total		70	58	128

Tabel 7*- Manipulation check: Agent check with actual shown agent (1= AI & 2= Human agent)*

De klachtafhandeling was van: * Quality Crosstabulation

Count

		Quality		Total
		1,00	2,00	
De klachtafhandeling was van:	Hoge kwaliteit	62	0	62
	Lage kwaliteit	2	64	66
Total		64	64	128

***Table 8**- Manipulation check: Service recovery quality check with actual shown service recovery quality(1= High quality & 2= Low quality)*

Appendix D- Assumptions

Assumption 2:

Box's Test of Equality of Covariance Matrices[a]

Box's M	97,246
F	1,403
df1	63
df2	31450,255
Sig.	,019

Tests the null hypothesis that the observed covariance matrices of the dependent variables are equal across groups.

a. Design: Intercept + Agent + Quality + Agent * Quality

***Table 9**- Homogeneity of variance*

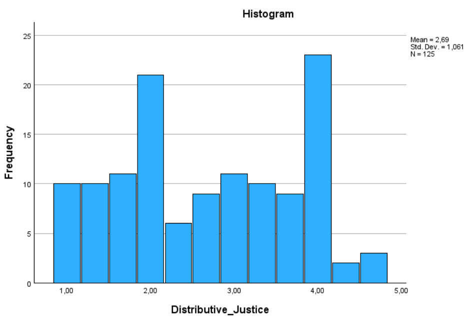


***Figure 1**- Histogram distributive justice*

Assumption 3:

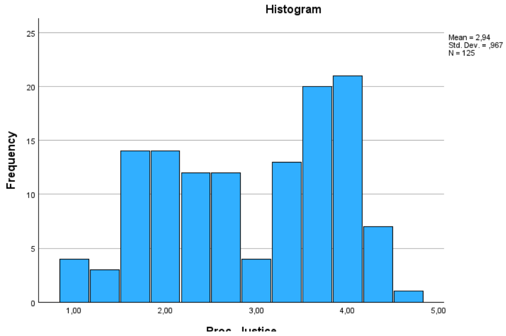


Figure 2*- Histogram Procedural justice*

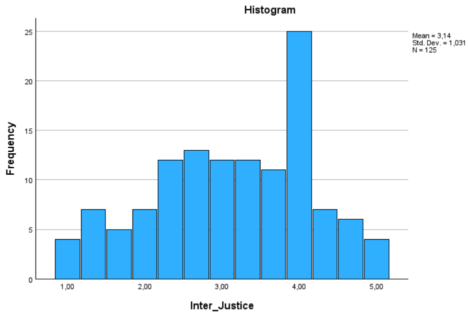


Figure 3*- Histogram Interactional justice*

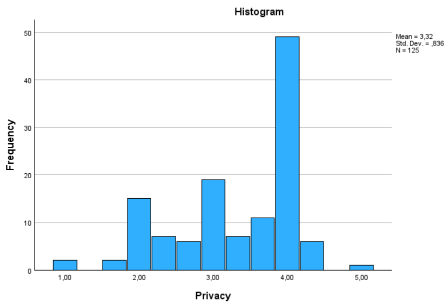


Figure 4- *Histogram Privacy*

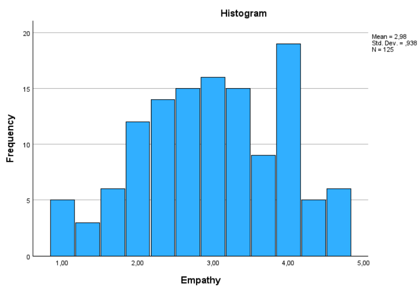


Figure 5- *Histogram Empathy*

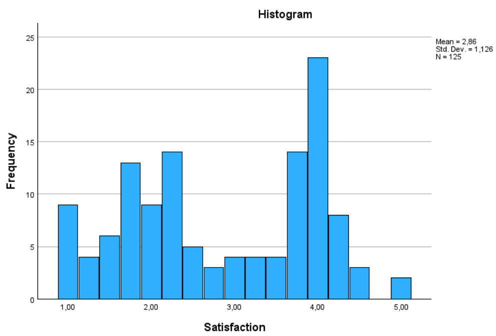


Figure 6*- Histogram Recovery satisfaction*

Assumption 4:

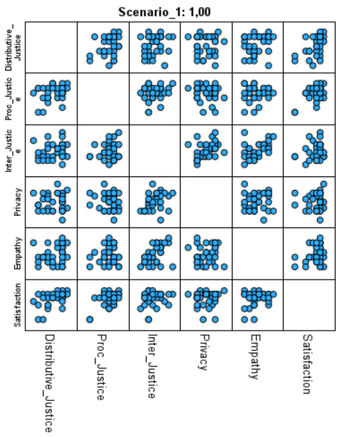


***Figure 7**- Linearity scenario 1*

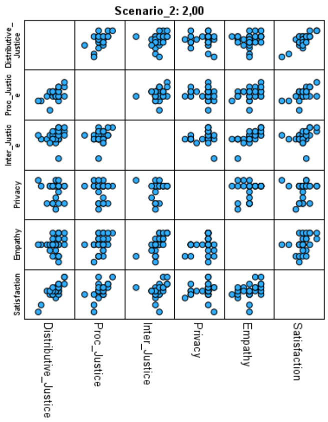


***Figure 8**- Linearity scenario 2*

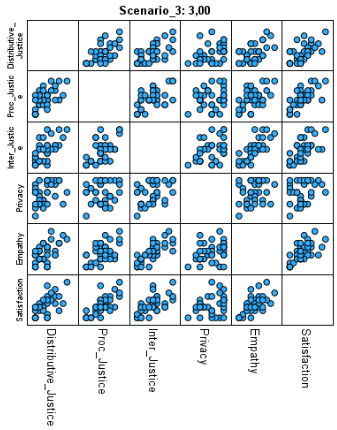


***Figure 9-** Linearity scenario 3*

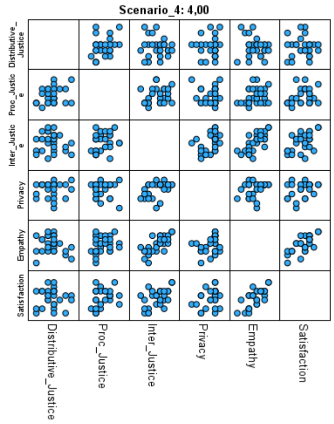


***Figure 10**- Linearity scenario 4*

Assumption 5:

Correlations

		Distributive_Justice	Proc_Justice	Inter_Justice	Privacy	Empathy	Satisfaction
Distributive_Justice	Pearson Correlation	1	,806**	,662**	,150	,632**	,847**
	Sig. (2-tailed)		<,001	<,001	,096	<,001	<,001
	Sum of Squares and Cross-products	139,623	102,483	89,886	16,469	77,939	125,419
	Covariance	1,126	,826	,725	,133	,629	1,011
	N	125	125	125	125	125	125
Proc_Justice	Pearson Correlation	,806**	1	,702**	,068	,680**	,877**
	Sig. (2-tailed)	<,001		<,001	,452	<,001	<,001
	Sum of Squares and Cross-products	102,483	115,932	86,819	6,804	76,496	118,431
	Covariance	,826	,935	,700	,055	,617	,955
	N	125	125	125	125	125	125
Inter_Justice	Pearson Correlation	,662**	,702**	1	,401**	,845**	,754**
	Sig. (2-tailed)	<,001	<,001		<,001	<,001	<,001
	Sum of Squares and Cross-products	89,886	86,819	131,852	42,859	101,384	108,592
	Covariance	,725	,700	1,063	,346	,818	,876
	N	125	125	125	125	125	125
Privacy	Pearson Correlation	,150	,068	,401**	1	,308**	,162
	Sig. (2-tailed)	,096	,452	<,001		<,001	,071
	Sum of Squares and Cross-products	16,469	6,804	42,859	86,652	29,972	18,891
	Covariance	,133	,055	,346	,699	,242	,152
	N	125	125	125	125	125	125
Empathy	Pearson Correlation	,632**	,680**	,845**	,308**	1	,765**
	Sig. (2-tailed)	<,001	<,001	<,001	<,001		<,001
	Sum of Squares and Cross-products	77,939	76,496	101,384	29,972	109,054	100,116
	Covariance	,629	,617	,818	,242	,879	,807
	N	125	125	125	125	125	125
Satisfaction	Pearson Correlation	,847**	,877**	,754**	,162	,765**	1
	Sig. (2-tailed)	<,001	<,001	<,001	,071	<,001	
	Sum of Squares and Cross-products	125,419	118,431	108,592	18,891	100,116	157,158
	Covariance	1,011	,955	,876	,152	,807	1,267
	N	125	125	125	125	125	125

**. Correlation is significant at the 0.01 level (2-tailed).

***Table 20**- Correlations between dependent variables*

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	-,487	,195		-2,492	,014		
	Distributive_Justice	,353	,063	,332	5,595	<,001	,331	3,021
	Proc_Justice	,489	,077	,420	6,382	<,001	,269	3,713
	Inter_Justice	,048	,080	,044	,602	,548	,218	4,591
	Privacy	-,008	,053	-,006	-,154	,878	,747	1,339
	Empathy	,280	,079	,233	3,548	<,001	,270	3,707

a. Dependent Variable: Satisfaction

***Table 11**- Collinearity statistics of the dependent variables*

Appendix E- Hypotheses

Descriptive Statistics

	Agent	Quality	Mean	Std. Deviation	N
Distributive_Justice	1,00	1,00	3,4444	,67013	33
		2,00	1,8519	,71467	36
		Total	2,6135	1,05661	69
	2,00	1,00	3,6092	,69046	29
		2,00	1,8765	,54024	27
		Total	2,7738	1,06952	56
	Total	1,00	3,5215	,67917	62
		2,00	1,8624	,64100	63
		Total	2,6853	1,06113	125
Proc_Justice	1,00	1,00	3,6667	,51370	33
		2,00	2,1204	,64809	36
		Total	2,8599	,97251	69
	2,00	1,00	3,8276	,38443	29
		2,00	2,1728	,56516	27
		Total	3,0298	,96038	56
	Total	1,00	3,7419	,46133	62
		2,00	2,1429	,60970	63
		Total	2,9360	,96692	125
Inter_Justice	1,00	1,00	3,5051	,65150	33
		2,00	2,2685	,89379	36
		Total	2,8599	,99903	69
	2,00	1,00	4,1839	,51629	29
		2,00	2,7531	,77124	27
		Total	3,4940	,96816	56
	Total	1,00	3,8226	,67943	62
		2,00	2,4762	,87111	63
		Total	3,1440	1,03118	125
Privacy	1,00	1,00	3,0202	,93519	33
		2,00	2,9630	,89364	36
		Total	2,9903	,90743	69
	2,00	1,00	3,7816	,47372	29
		2,00	3,6790	,52690	27
		Total	3,7321	,49816	56
	Total	1,00	3,3763	,84173	62
		2,00	3,2698	,83356	63
		Total	3,3227	,83595	125
Empathy	1,00	1,00	3,1919	,60110	33
		2,00	2,2407	,76682	36
		Total	2,6957	,83771	69
	2,00	1,00	4,0345	,46586	29
		2,00	2,5679	,70295	27
		Total	3,3274	,94386	56
	Total	1,00	3,5860	,68469	62
		2,00	2,3810	,75219	63
		Total	2,9787	,93780	125
Satisfaction	1,00	1,00	3,6970	,49905	33
		2,00	1,8958	,63633	36
		Total	2,7572	1,07098	69
	2,00	1,00	4,0086	,49769	29
		2,00	1,8704	,51127	27
		Total	2,9777	1,18827	56
	Total	1,00	3,8427	,51858	62
		2,00	1,8849	,58169	63
		Total	2,8560	1,12579	125

Table 12- *Descriptive analysis MANOVA*

Multivariate Tests[a]

Effect		Value	F	Hypothesis df	Error df	Sig.
Intercept	Pillai's Trace	,983	1109,391[b]	6,000	116,000	<,001
	Wilks' Lambda	,017	1109,391[b]	6,000	116,000	<,001
	Hotelling's Trace	57,382	1109,391[b]	6,000	116,000	<,001
	Roy's Largest Root	57,382	1109,391[b]	6,000	116,000	<,001
Agent	Pillai's Trace	,288	7,804[b]	6,000	116,000	<,001
	Wilks' Lambda	,712	7,804[b]	6,000	116,000	<,001
	Hotelling's Trace	,404	7,804[b]	6,000	116,000	<,001
	Roy's Largest Root	,404	7,804[b]	6,000	116,000	<,001
Quality	Pillai's Trace	,791	72,977[b]	6,000	116,000	<,001
	Wilks' Lambda	,209	72,977[b]	6,000	116,000	<,001
	Hotelling's Trace	3,775	72,977[b]	6,000	116,000	<,001
	Roy's Largest Root	3,775	72,977[b]	6,000	116,000	<,001
Agent * Quality	Pillai's Trace	,054	1,111[b]	6,000	116,000	,360
	Wilks' Lambda	,946	1,111[b]	6,000	116,000	,360
	Hotelling's Trace	,057	1,111[b]	6,000	116,000	,360
	Roy's Largest Root	,057	1,111[b]	6,000	116,000	,360

a. Design: Intercept + Agent + Quality + Agent * Quality

b. Exact statistic

***Table 13-** Multivariate test MANOVA*

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	Distributive_Justice	86,439[a]	3	28,813	65,553	<,001
	Proc_Justice	80,345[b]	3	26,782	91,059	<,001
	Inter_Justice	67,381[c]	3	22,460	42,154	<,001
	Privacy	17,214[d]	3	5,738	9,999	<,001
	Empathy	57,987[e]	3	19,329	45,799	<,001
	Satisfaction	121,285[f]	3	40,428	136,364	<,001
Intercept	Distributive_Justice	897,004	1	897,004	2040,790	<,001
	Proc_Justice	1072,096	1	1072,096	3645,199	<,001
	Inter_Justice	1246,587	1	1246,587	2339,611	<,001
	Privacy	1394,557	1	1394,557	2430,074	<,001
	Empathy	1117,605	1	1117,605	2648,099	<,001
	Satisfaction	1015,443	1	1015,443	3425,080	<,001
Agent	Distributive_Justice	,277	1	,277	,630	,429
	Proc_Justice	,351	1	,351	1,195	,277
	Inter_Justice	10,444	1	10,444	19,602	<,001
	Privacy	16,843	1	16,843	29,350	<,001
	Empathy	10,557	1	10,557	25,015	<,001
	Satisfaction	,632	1	,632	2,132	,147
Quality	Distributive_Justice	85,318	1	85,318	194,108	<,001
	Proc_Justice	79,063	1	79,063	268,821	<,001
	Inter_Justice	54,898	1	54,898	103,033	<,001
	Privacy	,197	1	,197	,343	,559
	Empathy	45,104	1	45,104	106,872	<,001
	Satisfaction	119,743	1	119,743	403,892	<,001
Agent * Quality	Distributive_Justice	,151	1	,151	,344	,558
	Proc_Justice	,091	1	,091	,309	,580
	Inter_Justice	,291	1	,291	,547	,461
	Privacy	,016	1	,016	,028	,868
	Empathy	2,050	1	2,050	4,857	,029
	Satisfaction	,877	1	,877	2,958	,088
Error	Distributive_Justice	53,184	121	,440		
	Proc_Justice	35,588	121	,294		
	Inter_Justice	64,471	121	,533		
	Privacy	69,439	121	,574		
	Empathy	51,067	121	,422		
	Satisfaction	35,873	121	,296		
Total	Distributive_Justice	1041,000	125			
	Proc_Justice	1193,444	125			
	Inter_Justice	1367,444	125			
	Privacy	1466,667	125			
	Empathy	1218,111	125			
	Satisfaction	1176,750	125			
Corrected Total	Distributive_Justice	139,623	124			
	Proc_Justice	115,932	124			
	Inter_Justice	131,852	124			
	Privacy	86,652	124			
	Empathy	109,054	124			
	Satisfaction	157,158	124			

a. R Squared = ,619 (Adjusted R Squared = ,610)

b. R Squared = ,693 (Adjusted R Squared = ,685)

c. R Squared = ,511 (Adjusted R Squared = ,499)

d. R Squared = ,199 (Adjusted R Squared = ,179)

e. R Squared = ,532 (Adjusted R Squared = ,520)

f. R Squared = ,772 (Adjusted R Squared = ,766)

***Table 14-** Test of between-subjects effects MANOVA*