ARTIFICIAL INTELLINGENCE BASED CONVERSATIONAL AGENTS IN SERVICE RECOVERY

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ABSTRACT

Artificial Intelligence-Based Conversational Agents in Service Recovery

This study focuses on artificial intelligence-based conversational agents in service recovery. The objective of this research is to investigate the factors that affect the service recovery satisfaction provided by AI-based conversational agents. Service recovery is an important topic that has been investigated for years. However, there are limited studies that emphasize the role of artificial intelligence-based conversational agents' role in solving and answering service failures. This study explores the factors that affect service recovery satisfaction provided by artificial intelligence-based conversational agents. The study uses an online survey as a data collection tool, and the sample size is n=250. Quantitative data analyses have been made by using regression and ANOVA. The regression analysis shows that anthropomorphism, the need for human interaction, distributive, procedural, interactional justice, apology, and compensation are positively related to service recovery satisfaction. The strongest relationship is between service recovery satisfaction and distributive justice. Extra analyses indicate that service recovery methods and perceived justice are related. Hence, service failure severity and the need for human interaction are more important for the ones who need to contact human employees because of getting an inadequate answer. This study has theoretical and managerial contributions by addressing the gap in literature. Firms should focus on the outcome since distributive justice is important for service recovery satisfaction

ÖZET

Yapay Zeka Tabanlı Konuşma Aracılarının Servis Hatası Çözümlemesi

Bu araştırma yapay zeka tabanlı konuşma aracılarının servis hatası çözümlemesini ele almaktadır. Araştırmanın hedefi yapay zeka tabanlı konuşma aracıları tarafından sağlanan servis hatası çözümlemesine etki eden faktörleri araştırmaktır. Servis hatası önemli ve yıllardır araştırılan bir konudur. Ancak, yapay zeka tabanlı konuşma aracılarının servis hatası çözümlemesini konu alan limitli sayıda araştırma vardır. Bu araştırma yapay zeka tabanlı konuşma aracılarının sağladığı servis çözümlemesindeki memnuniyete etki eden faktörleri araştırmayı hedeflemektedir. Bu araştırma veri toplama yöntemi olarak çevrimiçi anket kullanmaktadır ve örneklem büyüklüğü n=250'dir. Nicel veri analizi regresyon ve ANOVA ile yapılmıştır. Regresyon analiz sonuçları insan biçimcilik, insan ile etkileşime geçme isteği, dağıtım adaleti, etkileşimsel adalet, prosedür adaleti, özür dileme ve telafi etmenin servis hatası telafisi ile olumlu yönde ilişkisi olduğunu göstermektedir. En güçlü ilişki servis hatası telafisi memnuniyeti ve dağıtım adaleti arasındadır. Ek analizler servis hatası çözümleme metodu ve adalet yargısının ilişkili olduğunu göstermektedir. Ayrıca servis hatası büyüklüğü ve insan ile etkileşime geçme isteği, servis hatası çözümlemesinde yetersiz cevap alan kişiler için daha önemlidir. Araştırmanın literatürdeki boşluğu ele alarak hem teorik hem de yönetimsel açıdan önemli katkıları vardır. Firmalar servis hatası çözümlemede dağıtım adaleti önemli olduğu için sonuca odaklanmalıdır.

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CHAPTER 1

INTRODUCTION

Service failures are inevitable, this is a result of the characteristics of services. Services are intangible, heterogeneous, inseparable, and perishable (Goodwin & Ross, 1992). Service failure is when consumers find problems with their service outcomes (Palmer et al., 2000). Companies should compensate for these service failures to maintain a good reputation among customers. For more than thirty years, scholars have been researching service recovery (Goodwin & Ross, 1992). It is impossible to prevent service failures, although they can be recovered online and offline. (Singh & Crisafulli, 2016).

This study investigates the factors that affect the service recovery satisfaction provided by AI-based conversational agents. More specifically, it examines service recovery methods, justice perception, the need for human interaction, and anthropomorphism as factors influencing service recovery satisfaction.

Technology can be helpful in service recovery (Dong et al., 2008). Especially after COVID-19, firms started to recover from service failures through online methods. Agnihotri & Bhattacharya,(2023) stated artificial intelligence (AI-based)-based conversational agents can be helpful in online service recovery. AI-based conversational agents are voice or text-based agents that interact with consumers (Maedche et al. 2019). Currently, firms benefit from chatbots, online messengers, online chats, and voice-based assistants to recover from service failures and answer questions. In Turkey, especially in online retail, financial services, and telecommunication sectors, there are many examples of it (Albayrak et al., 2018).

These technologies benefit customer relationship management (CRM) by providing efficient service recovery and collecting precise customer data. Hence, we see the rise of avatars and robots that can contact customers, benefiting from natural language processing (NLP). These AI-based conversational agents help service firms identify and solve problems quickly. Firms benefit from AI-based conversational agents in many service areas due to speed, consistency, and different work capabilities (Leo & Huh, 2020). When automating and digitizing the service recovery process, firms should consider service recovery satisfaction. For chatbot service recovery satisfaction, 57% were neutral or satisfied with the service recovery. Moreover, 88% found it somewhat effective or very effective in solving service failures (Statista, 2022). By 2025, the chatbot market is expected to increase by 1250 million US dollars worldwide (Statista, 2022a). The top service areas that adopt chatbots are online retail, healthcare, telecommunication, and banking (Agnihotri & Bhattacharya, 2023); (Statista, 2022b). Thus, as consumer adoption of AI-based conversational agents increases, more research is needed (Eren, 2021).

There is a research gap in the literature regarding the effect of online service recovery methods on consumers (Singh & Crisafulli, 2016). Agnihotri & Bhattacharya, (2023) examined AI-based conversational agents in service recovery. However, their study was limited to consumer perceptions. Online service recovery is a topic that requires further exploration. In the literature, limited information related to service recovery is provided by AI-based conversational agents. As stated above, because AI-based conversational agents have become more popular, more research is needed on this topic. The primary objective of this research is to investigate the factors that affect the service recovery satisfaction provided by AI-based conversational agents. The study focuses on service recovery methods, justice

perception, the need for human interaction, service failure severity, and anthropomorphism as factors that affect service recovery satisfaction. The first eight hypotheses were formulated to test the factors that affect service recovery satisfaction. Except for service failure severity, the mentioned variables influence service recovery satisfaction. Thus, based on the literature review, the service recovery method and justice perception are related (Smith et al. 1999); (Mostafa et al. 2015). While apology is mainly related to procedural justice, compensation influences distributive justice the most. Therefore, some extra analyses were carried out. Hence, the different groups were compared to test the differences in service recovery perception. Groups that have different reasons for contacting a human service employee differ in need for human interaction and service failure severity perception. This research will contribute to both the academic and managerial environment.

CHAPTER 2

LITERATURE REVIEW

2.1 Service failure

Service failure is customers' dissatisfaction with the service outcome (Lewis & Spyrakopoulos, 2001). Furtherly, Maxham & Netemeyer, (2003) defined service failure as a service-related problem either experienced or perceived during a service encounter. Service failure happens when service delivery quality is lower than customer expectations (Zeithaml et al.,1993). When service deliveries fail, consumers often feel the inequality of service results (Weun et al.,2004). In the context of service failure, the literature covers two main topics: Dissatisfying experiences and service failures. Most studies categorize service failures into categories by considering their source, recovery types, and consumer responses to these failures (Fan et al., 2016). Service failures can be classified into four categories (Hoffman & Bateson, 2016). The failures in system delivery, the failures in satisfying customer needs and demands, employee actions that cause dissatisfaction, and customer failures. Service recovery methods can often resolve these issues. Service failure results from gaps in service quality (Parasuraman et al., 1988), (Zeithaml et al., 2017). The knowledge & perception gap between customers' expectations and service firms' perceptions. Standards and policy gap results from the variation between service firms' perceptions of customers' expectations and procedures. The delivery gap between service attributes and service delivery. The communication gap results from the variation between communication and service delivery. The delivery gap between service quality features and the outcome. The communication gap results from the variation between communication and outcome.

Hence, in addition to these four gaps resulting from the behaviors of service firms, there is a customer gap resulting from the difference between customer perceptions and expectations. The most common service failures, according to industries, are as follows: Banking: Problems with banking procedures, ignorant employees, functional or technical failures, long or unorganized queues, and problems with ATMs and payment (Lewis & Spyrakopoulos, 2001) (Shams et al., 2020). Retail & e-retail: Problems with the website, problems regarding delivery (not happening on time, missing items), issues regarding payment, security problems, overpriced products, technical problems, problems related to product quality, customer service failures (Holloway & Beatty, 2003), (Vakulenko et al., 2019).

2.2 Service recovery

Service recovery refers to a firm's actions against service failure (Gronroos, 1988). Service firms can't prevent service failures; they respond to them. This response refers to service recovery. Fornell & Wernerfelt (1988) explained that defensive marketing is a common approach to dealing with customer dissatisfaction. Service recovery includes all the activities related to recovering the loss after failure. Service recovery is used to regain customer trust (Weun et al., 2004). According to Johnston & Michel (2008), service recovery has three dimensions: Process, customer, and employee recovery. Most studies in the literature emphasize customer recovery to maximize service recovery satisfaction. Another study by Dong et al. (2015) focuses on two dimensions related to service recovery: Outcome & process. The outcome is the tangible part that focuses on tangible compensation. The process is the intangible part, focusing on interaction. Service failure can be related to outcomes and processes (Choi et al., 2021). Hence, service recovery's intangible and tangible

components affect customers' perceptions. In service marketing, the relationship is more important than the outcome (Clemmer & Schneider, 1996). Hence, service recovery influences customers who experience service failure. Customers who experience service failure tend to be more emotionally involved in service recovery (Berry & Parasuraman, 1991). Determining correct service recovery is essential. Wrong service recovery may lead to negative reviews (Bae et al., 2021).

2.3 Online service recovery

Internet and technology have changed the service delivery. It created new ways of customer-firm relationships. In addition to offline methods, service failures can be recovered online. (Singh & Crisafulli, 2016). Hence, online service recovery is crucial for solving problems. Online tools can increase fairness in service recovery (Singh & Crisafulli, 2016). Online service recovery differs from traditional services in which offline methods are used for service recovery. Instead of human interaction, technology has an essential impact on online services (Fan et al., 2010). Online and offline environments have differences in terms of service recovery. An apology, accompanied by compensation, can be effective in online settings. In offline situations, companies offer verbal apologies when service fails or customers complain. However, they can send e-mails and SMS or directly chat with consumers online. To compensate, in an offline environment, the company can replace it for free, but in an online environment, they can give away gift cards. Hence, they can make online explanations via social media, email, and blogs (Odoo et al., 2020). Consumers share their unpleasant experiences in online environments and spread them to different people. Service recovery should be managed effectively offline and online (Odoom et al.,2020).

2.4 AI-based conversational agents

Conversational agents can use AI-based algorithms and Natural Language Processing (NLP) technologies while interacting with humans (Kusal et al., 2022). They can either be task-orientated or non-task-orientated and used for fun and entertainment. When communicating with humans, these agents use speech or text (Hussain et al., 2019). The earliest forms of conversational agents are used in the 1960s. The first form uses keyword matching and context recognition. Nowadays, conversational agents are used in many areas. Conversational agents are a form of human-computer interaction. They are intelligent and can respond to consumers, learn their preferences, and engage with them (Ling et al. 2021). Customer service touchpoints are transitioning from human-based phone services to AI-based conversational agents. Many companies are starting to benefit from chatbots and messengers to solve service failures (Nguyen et al., 2022).

2.5 Anthropomorphism

Anthropomorphism refers to relating human-like traits and emotions with nonhuman objects (Waytz & Cacioppo, 2010). Anthropomorphism refers to associating humanlike characteristics, such as purposeful thinking, feelings, and behaviors, with nonhuman objects (van Pinxteren et al., 2019). Anthropomorphism states that non-human objects have mental characteristics similar to humans (Waytz et al., 2010). In other words, anthropomorphism is perceiving non-human objects as humans. Human service recovery usually includes the following methods: Apologizing to consumers, answering consumer questions, and offering refunds or compensation (Nikbin et al., 2015). On the other hand, AI-based service recovery depends on machines and technology (Lv et al., 2021). In literature, social robots, humanoid robots, and

conversational agents are differentiated, but they are all used in the context of anthropomorphism. Social robots are fully or partially automated machines that perform tasks, interact with humans, and create value with social functions (Čaić et al.,2019). Furthermore, service robots' perceived emotional and social abilities can be improved by robots' level of human-likeness. This maximizes consumers' willingness to interact (Breazeal, 2003). Consumers' perceptions of machines depend on human-like features. Hence, consumers associate personality traits with the human-like faces they see on computers (Qiu & Benbasat, 2009). Humanoid robots include human-like expressions (van Pinxteren et al., 2019). Humanized robots have five dimensions: anthropomorphism, likeability, animacy, safety, and perceived intelligence (Bartneck et al., 2009). Consumers expect more warmth from humanoid agents than non-humanoid agents (Choi et al., 2021). This fact dramatically affects their assessment of service failure and recovery. A high level of anthropomorphism can influence positive customer evaluations (Lu et al., 2019). Conversational agents are speech or text-based agents (Hussain et al.,2019). Previous research reveals that people evaluate anthropomorphic service agents more positively than non-anthropomorphic service agents (Aggarwal & McGill, 2007). Furthermore, consumers tend to apply social rules to anthropomorphic machines (Kim & McGill, 2011). The degree of anthropomorphism affects satisfaction in service failure (Shi et al., 2023).

2.6 Need for human interaction

Dabholkar (1999) defined the need for human interaction as the consumer's perception of human interaction in the service encounter. Satisfaction from non-human service recovery depends on the need for human interaction. The need for

interaction can also be described as a customer's preference to be involved in a more personalized service (Dabholkar, 1992). Human interaction is essential to service encounter evaluation (Gronroos, 1982). The need for human interaction affects consumers' control of the service process (Immonen et al., 2018). Consumers may have different levels of need for human interaction. Customers with a high need for human interaction prefer interacting with human service employees rather than non-human service employees. It can be important for some customers to interact with a human service employee during the service recovery (Hu et al., 2021). On the other hand, consumers with a low need for human interaction perceive technology-based services as nearly similar to those performed by service employees (Forman & Sriram, 1991). However, all customers do not necessarily prefer human interaction (Dabholkar, 1999)

2.7 Perceived justice

Service recovery satisfaction has cognitive aspects such as justice perception (Harris et al., 2006). Efficient service recovery helps improve customer satisfaction and loyalty. Hence, helpful in carrying out long-term relationships with customers (McCollough et al., 2000). In the literature, there is a limited study on how different dimensions of justice affect customers' complaint behavior. This is an important question that determines service recovery (Blodgett & Tax, 1997). Justice refers to the perception of fairness in exchange relationships (Maxham & Netemeyer, 2002). The roots of justice theory can be traced to social psychology theory (Smith et al., 1999). Perceived justice can be traced back to equity theory. It is the degree of treatment fairness during the service recovery (Maxham & Netemeyer, 2002). Distributive justice focuses on using tangible resources to compensate for service

failures. These tangible resources can be refunds or discounts. Distributive justice focuses on resource allocation and outcome fairness. Interactional justice focuses on customers' perceptions of employees' empathy, courtesy, and effort in solving a problem (del Río-Lanza et al.,2009). Interactional justice focuses on the way that outcomes are delivered. Hence, there are five elements of interactional justice: Explanation of the cause, effort, empathy, politeness, and honesty. Procedural justice emphasizes a firm's methods by considering timing& speed, process, and accessibility. Procedural justice focuses on the process and procedures. There are five elements of procedural justice: Flexibility, timing, control of decision, speed, and accessibility. These are important and affect procedural justice. Customer satisfaction with service failure is affected by three dimensions of justice, as stated above (Smith et al.1999). Distributive justice is related to outcome; interactional justice focuses on interactions and procedural justice is related to problem-solving processes (Tax et al.,1998). Customers emphasize distributive and procedural justice, such as compensation and responsible actions, when experiencing service failures (Smith et al.,1999). Distributive and interactional justice are important in service recovery (McCollough et al.,2000). The justice model is an important model that explains service recovery satisfaction. Jung & Seock (2017) focused on different types of service recovery perceptions and justice perceptions to investigate service recovery satisfaction. Customers' justice perceptions are affected by service recovery efforts (De Meyer et al., 2013). Using cognitive evaluation theory, Bagozzi et al. (1999) stated that consumers evaluate the condition that generates the emotions, not the condition itself. From this view of point, Schoefer & Ennew (2005) argue that perceived justice can be seen as a cognitive evaluative dimension. It affects emotions during service recovery.

2.8 Apology & compensation as service recovery methods

Apology and compensation are the most preferred methods in service recovery (Kaur et al., 2022). Human service recovery generally includes apology and compensation (Nikbin et al., 2015). Apology refers to the firm's kindness and empathy for the service failure. When firms express that they are sorry for a service failure, this response can lead to customer empathy and enhance their evaluation of service encounters (Harrison-Walker, 2019). Usually, compensation is the financial recovery that firms provide in the case of a service failure (Smith et al., 1999). Discounts and refunds are examples of compensation. Compensation is intended to overcome losses (Harrison-Walker, 2019). Apology and compensation reveal service providers' respect for their customers after a service failure (Kaur et al., 2022). Service failure can happen in economic loss (money time) or social loss (status, esteem). Firms try to recover from these failures with apology and compensation methods. The apology method makes up for social losses, and the compensation method makes up for economic losses. Service recovery and perceived justice are related, and perceived justice further influences satisfaction in service encounters (Smith et al. 1999).

2.9 Service failure severity

Service failure severity is perceived strength of a service problem or failure (Weun et al., 2004). When the exchange relationship becomes unbalanced and the severity of the problem increases, potential harm is likely to occur (Smith et al, 1999). Customers lose more when service failures become more severe and intense (Weun et al., 2004). Service failure can also be defined as customers' dissatisfaction with a service provider without depending on the causes (Lewis & Spyrakopoulos, 2001). Service failure occurs when customers have problems with the company (Maxham &

Netemeyer, 2003). Customer losses from failures can be either tangible(monetary) or intangible (time and energy) (Hart et al., 1990). Hence, service recovery is more complicated when the customer perceives service failure as more severe (Mattila, 1999). Therefore, understanding the service failure severity is important for finding a suitable service recovery strategy (Hart et al. 1990). The severity of service failure depends on consumers' perceptions (Mattila, 2001). Hence, firms may alter their service recovery strategies according to service failure severity (Smith et al., 1999).

2.10 Service recovery satisfaction

Satisfaction has various definitions in the literature. Satisfaction can be perceived as a consumer's fulfillment response (Oliver, 1997). Satisfaction with service recovery can be related to the perceived quality, expectations & disconfirmation, and fairness of the outcome (Andreassen,2000). Outcome and service-related attributes influence satisfaction in a service failure (Singh, 1991). Service recovery satisfaction is affected by many factors. Most of the models in the literature use service failure severity, service recovery method, and justice perception as determinants related to service recovery satisfaction. Harrison (2018) discussed that perceived justice and service failure severity are important for service recovery satisfaction. Shams et al. (2020) found that service failure severity influences service recovery satisfaction. Perceived justice and the severity of service failure affect satisfaction with service recovery (Sidhu et al.,2023). A high level of perceived justice can increase service recovery satisfaction even with high service failure severity. Consumers who go through more severe service failures and subsequently experience higher recovery tend to behave positively. Service failure severity also positively moderates the relationship between perceived justice and behavioral intention. Perceived justice

and service failure severity affect service recovery satisfaction (Nikbin & Hyun, 2015). Mostafa et al. (2015) pointed out that service recovery methods are related to service recovery satisfaction. Harrison & Walker (2018) stated that apology and compensation are related to service recovery outcomes. Hence, human interaction and anthropomorphism are important for service recovery satisfaction in AI-based conversational agents. Customers may want to contact an agent who can solve their problem in case of a service failure (Teodorescu et al., 2021).

CHAPTER 3

HYPOTHESIS DEVELOPMENT

3.1 Service recovery satisfaction & anthropomorphism

Crolic et al. (2022) stated that anthropomorphism may affect customers' expectations related to service. An increase in expectations can decrease customer satisfaction with service recovery. However, the effects of human vs non-human service encounters are still unknown and need to be discovered. Shi et al. (2023) stated that the degree of anthropomorphism may impact service recovery satisfaction. Huang & Dootson, (2022) identified that consumers respond positively to anthropomorphic service agents, although they respond negatively when anthropomorphism is too high. Choi et al. (2020) stated that anthropomorphic robots can reduce customer complaints and dissatisfaction from service failure. Consumers are more satisfied when a more anthropomorphic AI-based conversational agent interacts with them after a service failure (Adam et al., 2021). For example, when a chatbot asks questions, consumers find this attitude similar to human service employees. In addition, consumers may expect chatbots to examine their problems as human service employees, provide helpful information for service recovery, and deliver service recovery the same way as human service employees. According to the Computers Are Social Actors (CASA) theory, anthropomorphism can lead consumers to perceive AI-based conversational agents as warmer and able to solve their problems (Teodorescu et al., 2021). In addition, consumers may perceive AI-based conversational agents as similar to human service employees in resolving service failures.

Consumers are more likely to form closer relationships when agents are more human-like. (Lee & Choi, 2017). Consumers believe that AI-based agents also exhibit human-like characteristics during the service process. Consumers perceive AI-based agents as beneficial for service recovery (Adam et al., 2021). Consumers can view AI-based agents like humans (Qiu & Benbasat, 2009). Choi et al. (2021) discussed that human-like agents could effectively apologize and explain the cause of the increase in satisfaction. Anthropomorphic features can increase consumers' perception of social presence (Adam et al.,2021). Anthropomorphism and the need for human interaction impact service recovery satisfaction. Individuals' level of digital commitment impacts online service recovery satisfaction (Al-Jader, 2015). When robots behave more correspondingly to humans, more meaningful service interactions occur. Hence, robot-like emotions are perceived as more inauthentic (Wirtz et al., 2018). Prior research shows that robots can communicate feelings such as empathy with customers (de Kervenoael et al., 2020). The human-like attributes of non-human service agents can affect service recovery satisfaction (Liu, 2022). Therefore, hypothesis 1 is formulated as follows:

H1: Anthropomorphism positively influences service recovery satisfaction provided by AI-based conversational agents.

3.2 Service recovery satisfaction and need for human interaction

Consumers with a low need for human interaction perceive technological service encounters more positively than those with a high need for human interaction (Kelly et al., 2019). Consumers with a lower need for human interaction rated service recovery efforts provided by non-human beings as effective as service employees. They are less likely to question the sincerity of the apology offered by non-human

recovery (Hu et al.,2021). The need for human interaction is an important factor that affects service recovery satisfaction. Individuals with varying degrees of need for human interaction may consider online service recovery provided differently (Hu et al.,2021). Non-human service recovery can be more effective than human service efforts in identifying needs during service recovery (de Kervenoael et al., 2020). Hence, they provide personalized feedback (Dabholkar & Bagozzi, 2002). Consumers who seek novelty tend to use technology-based products more and are more motivated to try these new ways of service recovery (Hirschman 1980). Hence, hypothesis 2 is formulated as follows:

H2: The need for human interaction negatively influences service recovery satisfaction provided by AI-based conversational agents.

3.3 Service recovery satisfaction & perceived justice dimensions

Goodwin & Ross (1992) investigated the relationship between fairness perception & satisfaction and service recovery. They argue that procedural and interactional justice positively influences satisfaction. De Ruyter et al. (1998) argued that perceptions of justice and fairness in service recovery can affect service recovery satisfaction. Consumers seek procedural fairness in online services requiring less interpersonal contact (Jung & Seock 2017). For consumers in airline services, procedural justice and distributive justice are more dominant due to the need for final solutions and time constraints (Nikbin et al. 2015). Interactional justice is more important when the service outcome is uncertain, or the service has technical attributes. For example, consumers who have experienced a bank failure place greater emphasis on interactional justice (Maxham & Netemeyer 2002). In service recovery situations where time is limited and the final solution is needed, procedural and distributive

justice is more important than interactional justice (Lajante et al., 2023). Service robots can express interactional justice (Lajante et al., 2023). Service robots can recover a service through interactional justice and service recovery methods such as apology (Choi et al. 2021).

Therefore, hypotheses 3,4 & 5 are formulated as follows:

H3: Distributive justice perception positively influences service recovery satisfaction provided by AI-based conversational agents.

H4: Procedural justice perception positively influences service recovery satisfaction provided by AI-based conversational agents

H5: Interactional justice perception positively influences service recovery satisfaction provided by AI-based conversational agents.

3.4 Service recovery satisfaction and service recovery method

In the literature, many models have investigated service recovery in terms of perceived justice, service recovery efforts, and individual and situational factors that affect service recovery. Service recovery efforts may take different forms: Apology, compensation, and explanation (Liao, 2007), (Mostafa et al., 2014). Firms can use several strategies to recover from service failure. For example, explaining and apologizing for their losses (Mostafa et al., 2014). Recovery satisfaction is more significant in online service recovery than in offline services. Most studies have focused on symbolic recovery (mental & psychological) and utilitarian recovery (tangible recovery) to study the effects of service recovery. Symbolic service recovery is the verbal statement of service failure and provides social and psychological compensation to consumers. These compensatory behaviors can be an apology or a promise (Bagozzi, 1975). Apology is a primary recovery method when

a service failure occurs (Wang & Mattila, 2011). Utilitarian service compensation refers to tangible compensation to consumers. These actions include economic compensation or discounts (Smith et al., 1999). Compensation is one of the important service recovery methods (Odoom et al.,2020). Apology refers to service providers' kindness and empathy after a service failure. Apology is closely related to interactional fairness (Bae et al.,2020). According to social exchange and equity theories, an apology is a tool that redistributes social resources.

On the other hand, compensation focuses on restoring equity (Walster et al., 1973). It drives distributive justice and satisfaction with service recovery (Mostafa et al., 2015). Distributive justice mainly allocates compensation (discounts, free merchandise, refunds, coupons…). Customers generally expect to be fairly compensated while services are restored. Customers' familiarity with service recovery efforts can affect service recovery satisfaction. Service recovery is an important concept that affects customer satisfaction. Also, customers who face an effective service recovery may evaluate services more positively than the ones who did not experience service failure (McCollough & Bharadwaj, 1992).

Therefore, hypotheses 6 & 7 are formulated as follows:

H6: Apology positively influences service recovery satisfaction provided by AI-based conversational agents.

H7: Compensation positively influences service recovery satisfaction provided by AI-based conversational agents.

3.5 Service recovery satisfaction and service failure severity

The severity of service failure affects service failure assessment. According to prospect theory and mental accounting principles, service failure losses are more important than the gains in service recovery. Service recovery is more effective when failure severity is low. On the contrary, when service failure severity is higher, the service recovery effort is less effective. Hence, a severe service failure may lead to losses despite an adequate service recovery (Weun et al., 2004). When service failure is more severe, customers' zone of toleration tends to be narrower, resulting in customer dissatisfaction (Zeithaml et al.,1993). Service failure severity negatively influences service recovery satisfaction (Weun et al., 2004). Service failure and its severity depend on an individual's subjective perceptions (Smith et al., 1999). When customers perceive service failure as more severe, negative emotions and dissatisfaction increase, and the loss perceived by the customer is higher (Choi & Choi, 2014). A failure that is perceived to be very severe leads to customer dissatisfaction (Cho et al., 2017). Customer losses can be tangible or intangible (Hart et al., 1990). Hence, the severity of service failure affects customer loyalty. When service delivery is lower than customers' expectations, customers can perceive loss more. Efficient service recovery should compensate for service failure and increase customer satisfaction with service recovery (Wang et al., 2011). Hence, hypothesis 8 is formulated as follows:

H8: Service failure severity negatively influences service recovery satisfaction provided by AI-based conversational agents.

Hypotheses are formulated based on the literature reviews and summarized in Table 1.

Table 1. Hypothesis Summary Table

Hypothesis	
H1	Anthropomorphism positively influences service recovery satisfaction provided by AI-based conversational agents.
H2	The need for human interaction negatively influences service recovery satisfaction provided by AI-based conversational agents
H3	Distributive justice perception positively influences service recovery satisfaction provided by AI-based conversational agents.
H4	Procedural justice perception positively influences service recovery satisfaction provided by AI-based conversational agents
H5	Interactional justice perception positively influences service recovery satisfaction provided by AI-based conversational agents.
H6	Apology positively influences service recovery satisfaction provided by AI-based conversational agents.
H7	Compensation positively influences service recovery satisfaction provided by AI-based conversational agents
H8	Service failure severity negatively influences service recovery satisfaction provided by AI-based conversational agents.

CHAPTER 4

METHODOLOGY

4.1 Research design

A descriptive study was conducted. An online English questionnaire was chosen as the data collection method. Questions can be found in Appendix A. All the statistical analyses are carried out in SPSS 29. The questionnaire scales are reliable and valid and were taken from the literature. Details are provided in the following section. A summary of scale reliability scores is provided in Table 2.

Table 2. Scales Reliability Summary Table

Scale	Cronbach's Alpha
Anthropomorphism	0.86
Need For Human Interaction	0.84
Distributive Justice	0.95
Procedural Justice	0.93
Interactional Justice	0.80
Apology	0.94
Compensation	0.97
Service Failure Severity	0.78
Service Recovery Satisfaction	0.70

4.2 Measures

The constructs were measured using a seven-item Likert Scale. Therefore, the original scales had high reliability and were chosen because they were suitable for this study. The reliability and validity of the scales were measured using SPSS 29 and Pallant's (2016) guidelines. All the scales have high reliability and validity scores. According to exploratory factor analysis, no item needed to be deleted.

4.2.1 Anthropomorphism

The original scale is used in (Kim & Mcgill, 2011). Reliability analysis of the original scale is as follows: Cronbach's alpha=0.83. Hence, the scale's validity was assessed by a manipulation check, which showed that it was valid. Wan, Kulow & Cowan (2022) used this scale and found that Cronbach's alpha equals 0.88. (Huang, 2023) used this scale in a study on health. The scale has Cronbach's alpha equal to 0.92 with mean = 4.62, standard deviation =1.50). In this study, the scale is reliable with Cronbach's alpha of 0.86, mean of 2.87, standard deviation=4.23)

4.2.2 Need for human interaction

The original scale was used (Dabholkar, 1996). Reliability analysis of the original scale is as follows: Cronbach's alpha=0.83. Later, the scale Dabholkar & Bagozzi (2002) used had three items. One of the items was dropped as a result of confirmatory factor analysis. (Meuter et al. 2005) used this scale in the banking context to measure the need for human interaction. They reported 0.70 Cronbach's alpha in their pretest. In this study scale is reliable with Cronbach's alpha 0.84, mean=5.15, standard deviation=4.27)

4.2.3 Distributive justice

The original scale was used by (Maxham & Neteyemer, 2002). The reliability analysis of the original scale is as follows: Cronbach's alpha =0.90. Hence, validity analysis is conducted, and the model has a good fit and discriminant validity. In this study, the scale is used in the banking sector. Later, the scale is used by Maxham & Neteyemer (2003) in electronic goods, and Cronbach's alpha =0.90 is determined. Hence, the scale is valid due to confirmatory factor analysis, discriminant, and

convergent validity. In this study scale is reliable with Cronbach's alpha 0.95, mean=4.06, standard deviation=6.00)

4.2.4 Interactional justice

The original scale was used by (Maxham & Neteyemer, 2002). The reliability analysis of the original scale is as follows: Cronbach's alpha = 0.93 and 0.94 (Study 1 vs Study 2). The scale fits the model and has discriminant validity. Later, Maxham & Neteyemer (2003) used this scale and found 0.93 Cronbach's alpha. Hence, convergent and discriminant validity tests are conducted. In this study scale is reliable with Cronbach's alpha 0.80, mean=4.33, and standard deviation=4.94)

4.2.5 Procedural justice

The original scale was used by (Maxham & Neteyemer, 2002). The reliability analysis of the original scale is as follows: Cronbach's alpha = 0.91. Hence, the model fits well with discriminant validity. Later, Maxham & Neteyemer (2003) also determined 0.91 Cronbach's alpha. The scale has convergent and discriminant validity according to confirmatory factor analysis. In this study scale is reliable with Cronbach's alpha 0.93, mean=4.29, standard deviation=6.00)

4.2.6 Apology

The original scale was used in (Liao, 2007). The reliability analysis of the original scale is as follows: Mean=4.08, Standard Deviation =1.97, Cronbach's alpha=0.94. Later, Mostafa et al. (2015) used this scale in a service recovery context and found that Cronbach's alpha equals 0.98 with a composite reliability of 0.97. In this study,

the reliability of the scale is Cronbach's alpha 0.94, mean=3.85, standard deviation=6.87)

4.2.7 Compensation

The original scale is used in (Valenzuela & Llanos, 2008). Reliability analysis of the original scale is as follows: Later, Mostafa et al. (2015) used this scale in service recovery and found that composite reliability (CR) is 0.98 with an average variance error (AVE) of 0.91. Later, Odoom et al. (2019) used this scale and derived Cronbach's alpha of 0.94 and CR(composite reliability) of 0.94. In this study, the reliability of the scale is Cronbach's alpha 0.97, mean=3.35, standard deviation=8.59)

4.2.8 Service failure severity

The original scale was used (Weun, Betty & Jones, 2004). The reliability analysis of the original scale is as follows: CR=0.93. Wang et al. (2011) used this scale and determined that Cronbach's alpha is equal to 0.87. In this study, the reliability of the scale is Cronbach's alpha 0.78, mean=4.87, standard deviation=3.24.

4.2.9 Service recovery satisfaction

The original scale was used by (Maxham & Neteyemer, 2002). Reliability analysis of the original scale is as follows: Cronbach's alpha = 0.93, 0.97 (Failure 1 vs failure 2). Later, the scale was used by Albrecht et al. (2019). Cronbach's alpha was determined to be 0.94, indicating the scale has high structural reliability and validity. In this study, the reliability of the scale is Cronbach's alpha 0.70, mean=4.12, standard deviation=3.90)

4.3 Factor analysis

Before conducting factor analysis, presumptions were checked. The KMO(Kaiser-Meyer-Olkin) value should be greater than the threshold value of 0.60 to perform factor analysis. Hence, at a 95% confidence interval, Bartlett's Test should have a p-value less than 0.05 to be significant. The relationship between the variables was linear, and there were no outlier values in data screening. This assumption holds for all scales. All the items in the scales were loaded on a single factor. Based on the sample size, minimum factor loading should be 0.35 (Hair et al. 2019). This is true for all scales. Hence, the explained variance ratio was more than 0.60 for all scales (Hair et al., 2019). Details can be found in Appendix B.

4.4 Sampling and data collection

The study uses a survey to collect data, distributed via Google Forms to the respondents. The convenience sampling method is used for the data collection because it is less time-consuming (Malhotra,2019). Most of the population consists of adults in Turkey, mainly aged 18-44. Before data collection, the ethics committee's approval was obtained. The approval can be found in Appendix C. Data is collected between 13 December 2023 and 31 January 2024. A total of 347 participants completed the survey voluntarily. The target population of this study is Turkish consumers above the age of 18 who encountered AI-based conversational agents in the context of service failure or problems. According to TUİK (2023), the approximate adult population is 57 million. The minimum required sample size is 150 for conducting meaningful analyses (Hair et al. 2019). The first question was the screening question in the survey. Ninety-seven respondents selected no for previously interacting with AI-based conversational agents, and these respondents

did not see further questions in the survey. Survey questions can be found in Appendix A. Hence, the final sample size was 250 after eliminating the responses who said no to the screening question.

4.5 Sample characteristics

Among 250 respondents, 126 respondents (50.4%) are male, 118 respondents (47.2%) are female, and six respondents (2.4%) prefer not to say. Most participants belong to the 25-34 age group, with (66.8%) of the total participants. (21.2%) participants belong to the 18-24 age group. Hence, (74%) of the participants are university graduates. (82.4%) of the participants are full-time employed, (40%) of the participants earn more than 45,000₺ individual monthly household income. In addition to these demographic questions, some questions about AI-based conversational agents are asked. (37.6%) participants use call centers, (35.2%) contact customer representatives, and (25.2%) use a website as a second source of information in case of a service failure. The majority of the respondents' experience was new with AI-based conversational agents. (75.6%) respondents encountered an AI-based conversational agent within one or two months ago, (15.2%) participants encountered within three or four months ago. Respondents used AI-based conversational agents in different contexts. (47.6%) respondents use AI-based conversational agents to solve service failures in the online retail sector, (26.8%) in online financial services, and (19.6%) in telecommunication services. The industries that the respondents select are as follows: Online retail, online financial services, telecommunication services, electric supply services, online food delivery services, software services, online education, and transportation. Hence, most service failure was related to delivery problems (48.8%). This is followed by technical and

procedural problems (28.8%) and payment problems (15.6%); after contacting an AI-based conversational agent (95.6%), the participants needed to contact a human service employee. The main reasons for contacting human service employees are as follows: (47.6%) lack of understanding of the problem, (42%) inadequate answer, and (4%) lack of empathy and emotions. Sample characteristics are detailed and presented in Appendix D. Characteristics of the majority are summarized in Table 3.

Table 3. Demographics of the Majority

Majority of the Sample		n	%
Gender	Male	126	50.4
Age	25-34	167	66.8
Education Status	University Graduate	185	74
Employment Condition	Full-time employed	206	82.4
Income	More than 45000₺	100	40
Second source of reference for failure	Call center	94	37.6
Last time contact with AI-based conversational agent	1 or 2 months ago	189	75.6
Service Context	Online Retail	119	47.6
Need for getting contact with human agent	Lack of understanding of the problem	119	47.6
Type of failure/question	Delivery Problems	122	48.8

4.6 Survey design and pre-test

The pretest was conducted with eight people aged 18-44 who had submitted the survey. Based on the comments and feedback, the survey questions were organized more appropriately. Adapted scale items can be found in Table 4 below. The online English Questionnaire can be found in Appendix A.

Table 4. Adapted Scale Items

Construct	Item	Item Detail	Reference
Anthropomorphism	ANTH1	It looks like a person.	Kim and McGill 2011
	ANTH2	It seems almost as if it has free will.	
	ANTH3	It seems as if it has intentions.	
Need for Human Interaction	NHI1	Human contact in providing services makes the process enjoyable for the consumer	Dabholkar (1996)
	NHI2	I like interacting with the person who provides the service	
	NHI3	It bothers me to use a machine when I could talk to a person instead.	
Distributive Justice	DIST1	Although this event caused me problems, (Firm x) effort to fix it resulted in a very positive outcome for me.	Maxham & Neteyemer (2002)
	DIST2	The final outcome I received from (Firm x) was fair, given the time and hassle.	
	DIST3	Given the inconvenience caused by the problem, the outcome I received from (Firm x) was fair	
	DIST4	The service recovery outcome that I received in response to the problem was more than fair.	
Procedural Justice	PRO1	Despite the hassle caused by the problem, (Firm x) responded fairly and quickly	Maxham & Neteyemer (2002)
	PRO2	I feel (Firm x) responded in a timely fashion to the problem	
	PRO3	I believe (Firm x) has fair policies and practices to handle problems.	
	PRO4	With respect to its policies and procedures, (Firm x) handled the problem in a fair manner	
Interactional Justice	INT1	In dealing with my problem, (Firm x)'s AI based conversational agent treated me in a courteous manner.	Maxham & Neteyemer (2002)
	INT2	During their effort to fix my problem, (Firm x)'s AI based conversational agent showed a real interest in trying to be fair.	
	INT3	(Firm x)'s AI based conversational agent got input from me before handling the problem.	
	INT4	While attempting to fix my problem, (Firm x)'s AI based conversational agent considered my views.	
Apology	APOL1	The company apologized to me for what had happened	Liao (2007)
	APOL2	The company expressed regret for the mistake that occurred	
	APOL3	The company apologized for the inconvenience the problem had brought to me	
	APOL4	The company apologized for what I have suffered because of the problem	
Compensation	COM1	The compensation the company gave me for the loss incurred is good	Valenzuela & Llanos (2008)
	COM2	The compensation the company gave me for all the time I spent dealing with the complaint is good	
	COM3	The compensation the company provided me to cover my financial losses is good	
	COM4	The compensation the company gave me for all the hard times I had due to the complaint is good	
	COM 5	The compensation the company provided me for the inconvenience I went through due to the complaint is good	
Service Failure Severity	SEVER1	If this problem were really happening to me, I would consider the problem to be: severe	Weun, Beatty & Jones (2004)
	SEVER2	If this problem were really happening to me, it would make me feel: angry	
	SEVER3	If this problem were really happening, it would be unpleasant to me	
Service Recovery Satisfaction	SAT1	In my opinion, [firm x] provided a satisfactory resolution to my problem on this particular occasion	Maxham & Neteyemer (2002)
	SAT2	I am not satisfied with [firm x]'s handling of this particular problem(r*)	
	SAT3	Regarding this particular event (most recent service problem), I am satisfied with [firm x].	

r* stands for reverse-coded item

CHAPTER 5

ANALYSES AND RESULTS

5.1 Missing value, outliers & assumption check

There were no system-missing values since all the questions in the survey were mandatory to answer. There were no univariate outliers according to Z scores between -4 and +4 (Hair et al., 2019). Therefore, no multivariate outliers exist according to the Mahalanobis distance between -3 and +3 (Hair et al., 2019). Scatter plots were drawn to detect whether there were outliers. No outliers were detected in the study.

5.2 Hypothesis testing

First, pre-assumption tests were conducted to perform regression analysis. Data had a normal distribution with skewness and kurtosis values in the threshold range. Hence, standard probability plots (p-p) did not significantly deviate from the diagonal line. Thus, data is normally distributed, and parametric analysis can be carried out (Hair et al. 2019). Scatter plots demonstrated linearity between dependent and independent variables in H1-H8. In addition, Pearson Correlation tests showed that the variables are positively correlated, and the p-value is smaller than 0.01 and significant. The data's Multicollinearity was checked. There was no correlation between multiple independent variables (Hair et al. 2019). None of the tolerance and variation inflation factors (VIF) exceeded the threshold value of 5 (Kline, 1988).

5.2.1 Analysis for Hypothesis 1

The regression summary for Hypothesis 1 is shown in Table 5. Results are significant with the following values. ($F(1,248) = 5.03$, $p < 0.001$) with $R^2 = 0.02$. In the model, anthropomorphism explained %2 of the variance in service recovery satisfaction.

Table 5. Regression Summary Anthropomorphism and Service Recovery Satisfaction

Model Summary[b]				
Hypo	R	R^2	Adjusted R^2	Standard Error
1	.141[a]	.020	.016	3.87143
a.Independent Variable ANTH				
b.Dependent Variable SAT				

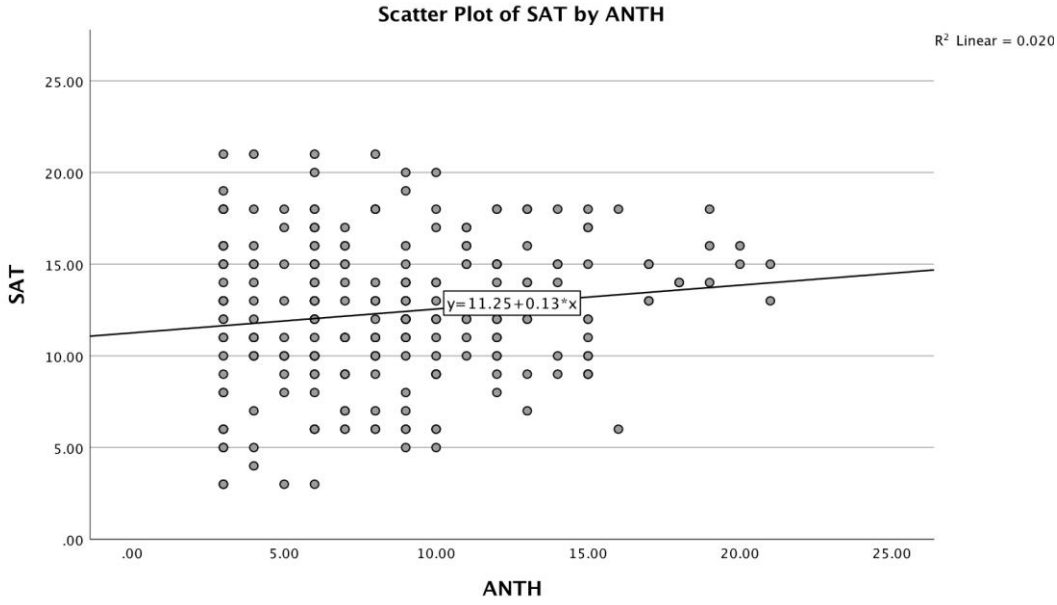

Figure 1. Scatter Plot for Hypothesis 1

The relationship can also be observed in Figure 1. Therefore, we can conclude that the hypothesis is supported.

5.2.2 Analysis for Hypothesis 2

The regression summary for hypothesis 2 is depicted in Table 6. Results are significant with the following values. ($F(1,248) = 4.52$, $p < 0.001$) with $R^2 = 0.018$. In the model, the need for human interaction explained %1.8 of the variance in service recovery satisfaction.

Table 6. Regression Summary for Need for Human Interaction and Service Recovery Satisfaction

Model Summary[b]				
Hypo	R	R^2	Adjusted R^2	Standard Error
2	.134[a]	.018	.014	3.87531
a.Independent Variable NH				
b.Dependent Variable SAT				

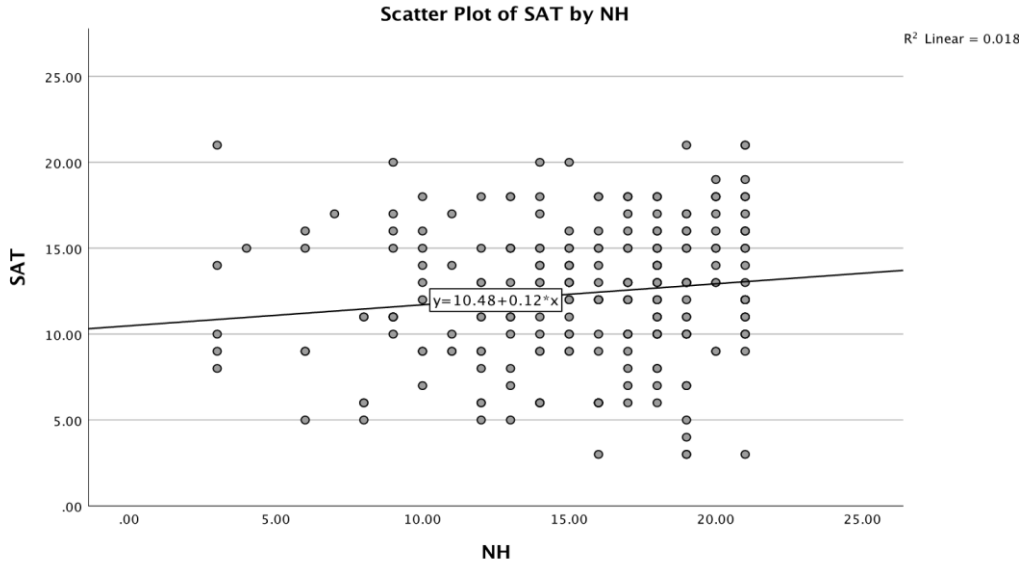

Figure 2. Scatter Plot for Hypothesis 2

The relationship can also be observed in Figure 2. Therefore, we can conclude that the hypothesis is significant, but the relationship is positive, not negative, as expected.

5.2.3 Analysis for Hypothesis 3

The regression summary for hypothesis 3 is depicted in Table 7. Results are significant with the following values. ($F(1,248) = 314.59$, $p < 0.001$) with $R^2 = 0.559$. In the model, distributive justice explained %55.9 of the variance in service recovery satisfaction.

Table 7. Regression Summary for Service Recovery Satisfaction and Distributive Justice

Model Summary[b]				
Hypo	R	R^2	Adjusted R^2	Standard Error
3	.748[a]	.559	.557	2.59635
a.Independent Variable DIST				
b.Dependent Variable SAT				

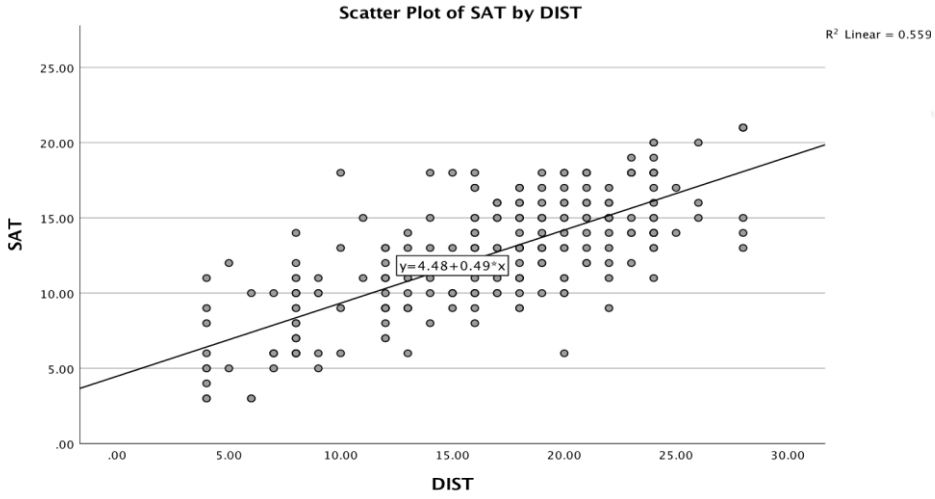

Figure 3. Scatter Plot for Hypothesis 3

Figure 3 also shows the relationship. Therefore, we can conclude that the hypothesis is supported.

5.2.4 Analysis for Hypothesis 4

The regression summary for hypothesis 4 is depicted in Table 8. Results are significant with the following values. ($F(1,248) = 217.94$, $p < 0.001$) with $R^2 = 0.468$. In the model, procedural justice explained %46.8 of the variance in service recovery satisfaction.

Table 8. Regression Summary for Procedural Justice and Service Recovery Satisfaction

Model Summary[b]				
Hypo	R	R^2	Adjusted R^2	Standard Error
4	.684[a]	.468	.466	2.85293
a.Independent Variable PRO				
b.Dependent Variable SAT				

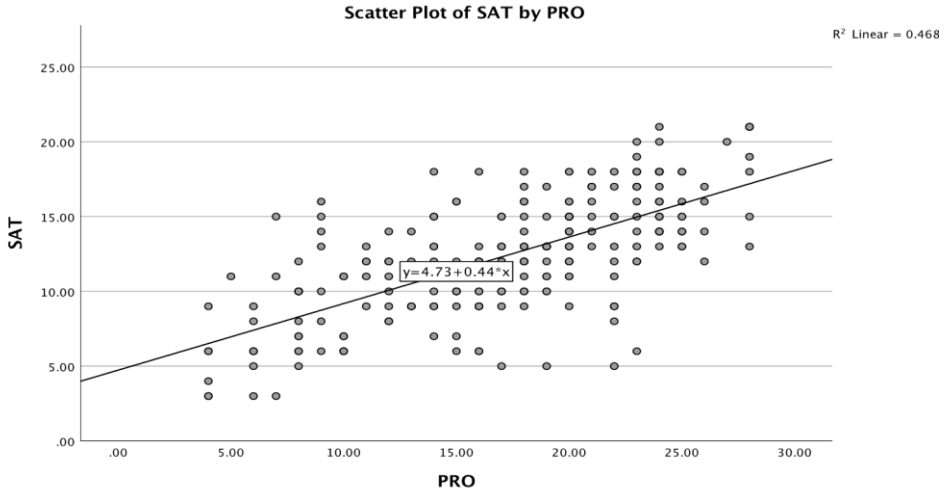

Figure 4. Scatter Plot for Hypothesis 4

Figure 4 also shows the relationship. Therefore, we can conclude that the hypothesis is supported.

5.2.5 Analysis for Hypothesis 5

The regression summary for hypothesis 5 is depicted in Table 9. Results are significant with the following values. ($F(1,248) = 31.64$, $p < 0.001$) with $R^2 = 0.113$. In the model, interactional justice explained %11.3 of the variance in service recovery satisfaction.

Table 9. Regression Summary for Interactional Justice and Service Recovery Satisfaction

Model Summary[b]				
Hypo	R	R^2	Adjusted R^2	Standard Error
5	.336[a]	.113	.110	3.68266
a.Independent Variable INT				
b.Dependent Variable SAT				

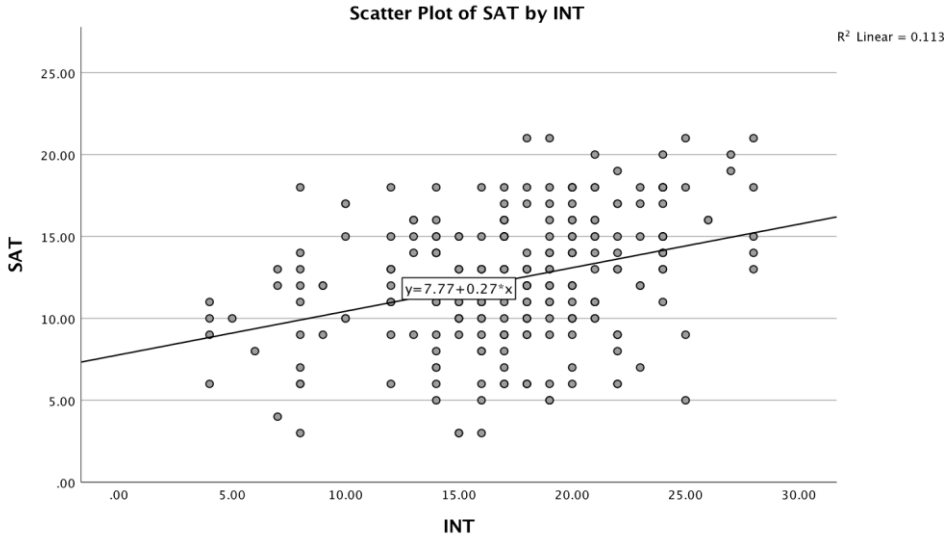

Figure 5. Scatter Plot for Hypothesis 5

The relationship can also be observed in Figure 5. Therefore, we can conclude that the hypothesis is supported.

5.2.6 Analysis for Hypothesis 6

The regression summary for hypothesis 6 is depicted in Table 10. Results are significant with the following values. (F (1,248) = 27.50, p < 0.001) with R^2= 0.100. In the model, apology explained %10 of the variance in service recovery satisfaction.

Table 10. Regression Summary for Apology and Service Recovery Satisfaction

Model Summary[b]				
Hypo	R	R^2	Adjusted R^2	Standard Error
6	.316[a]	.100	.096	3.71017
a.Independent Variable APOL				
b.Dependent Variable SAT				

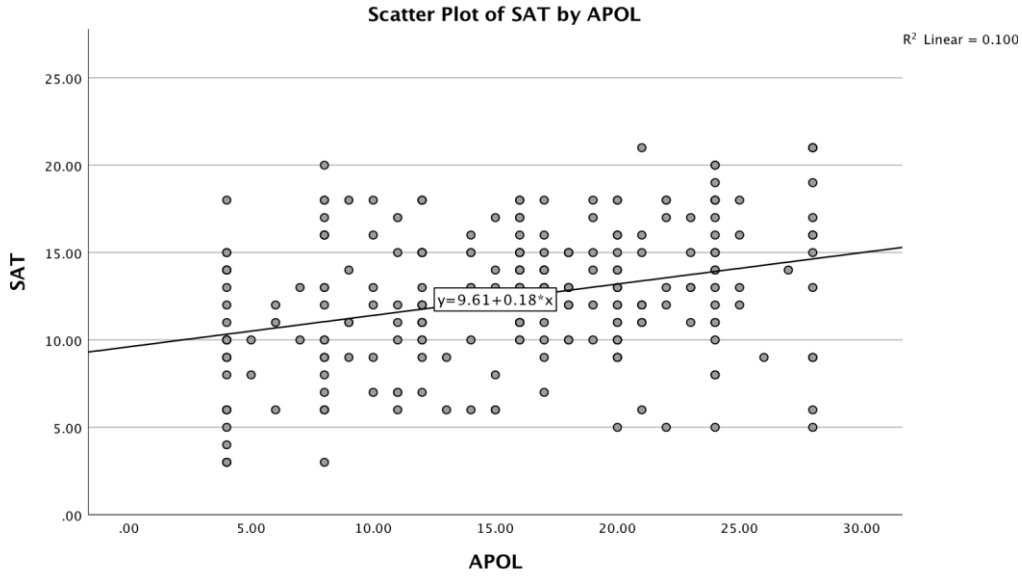

Figure 6. Scatter Plot for Hypothesis 6

Figure 6 also shows the relationship. Therefore, we can conclude that the hypothesis is supported.

5.2.7 Analysis for Hypothesis 7

The regression summary for hypothesis 7 is depicted in Table 11. Results are significant with the following values. ($F(1,248) = 130.82$, $p < 0.001$) with $R^2 = 0.345$. In the model, compensation explained %34.5 of the variance in service recovery satisfaction.

Table 11. Regression Summary for Compensation and Service Recovery Satisfaction

Model Summary[b]				
Hypo	R	R^2	Adjusted R^2	Standard Error
7	.588[a]	.345	.343	3.16405
a.Independent Variable COM				
b.Dependent Variable SAT				

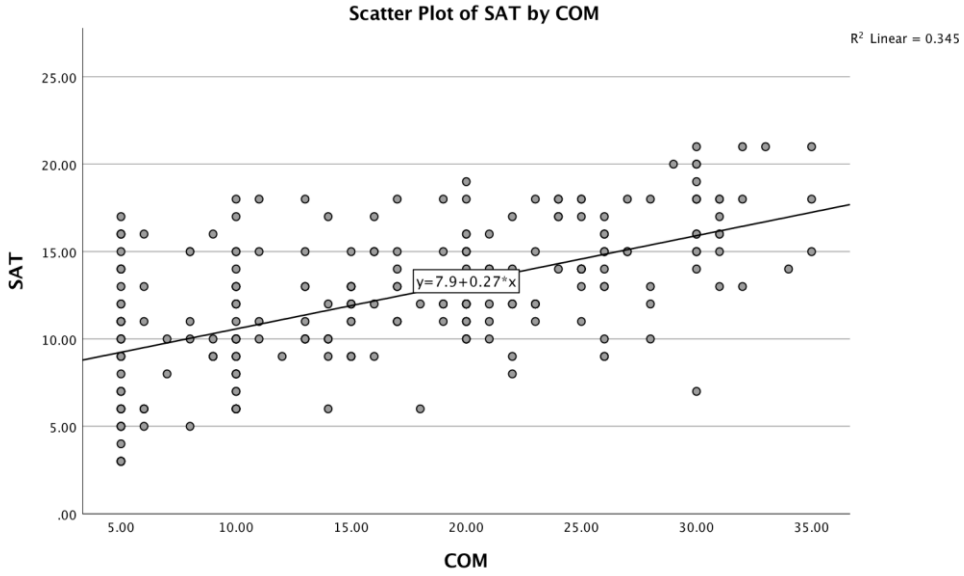

Figure 7. Scatter Plot for Hypothesis 7

Figure 7 also shows the relationship. Therefore, we can conclude that the hypothesis is supported.

5.2.8 Analysis for Hypothesis 8

The regression summary for hypothesis 8 is depicted in Table 12. Results are not significant with the following values. (F (1,248) = 0.41, p =0.521) with R^2= 0.002.

Table 12. Regression Summary for Service Failure Severity and Service Recovery Satisfaction

Model Summary[b]				
Hypo	R	R^2	Adjusted R^2	Standard Error
8	.041[a]	.002	-.002	3.90724
a.Independent Variable SEVER				
b.Dependent Variable SAT				

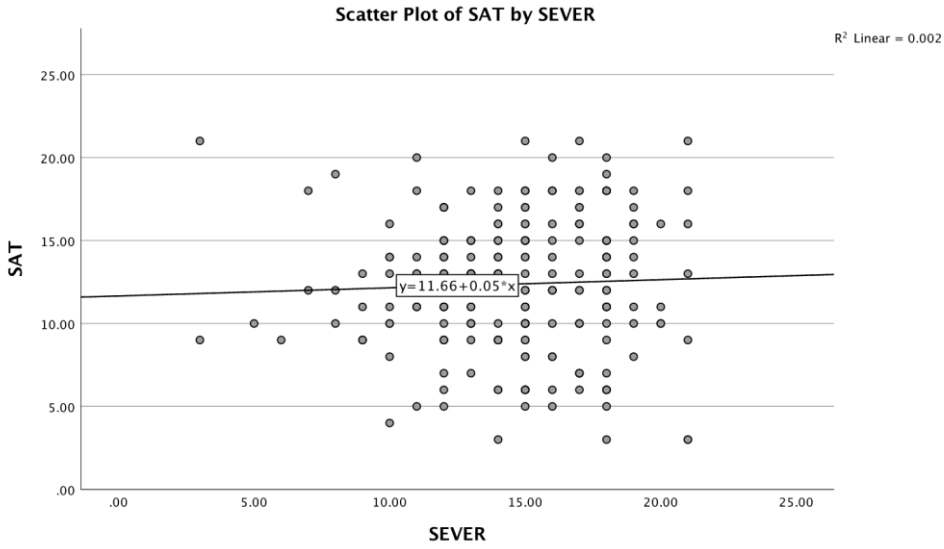

Figure 8. Scatter Plot for Hypothesis 8

As we can see in Figure 8 and Table 12, the hypothesis is not supported. All the results of Hypothesis 1-8 can be found in Appendix E. A Summary of the hypothesis is provided in Table 13.

Table 13. Hypotheses Summary

Hypothesis	R^2	Hypothesis	Status
1	0.02	Anthropomorphism positively influences service recovery satisfaction provided by AI-based conversational agents.	Supported
2	0.02	The need for human interaction negatively influences service recovery satisfaction provided by AI-based conversational agents	Not supported(Relationship is positive)
3	0.56	Distributive justice perception positively influences service recovery satisfaction provided by AI-based conversational agents.	Supported
4	0.47	Procedural justice perception positively influences service recovery satisfaction provided by AI-based conversational agents	Supported
5	0.11	Interactional justice perception positively influences service recovery satisfaction provided by AI-based conversational agents.	Supported
6	0.1	Apology positively influences service recovery satisfaction provided by AI-based conversational agents.	Supported
7	0.35	Compensation positively influences service recovery satisfaction provided by AI-based conversational agents	Supported
8	0.002	Service failure severity negatively influences service recovery satisfaction provided by AI-based conversational agents.	Not supported

5.2.9 Extra Analyses

After all assumptions had been examined, additional analyses were performed to investigate further findings. Literature states that service recovery methods can be closely related to perceived justice (Smith et al. 1999), (Mostafa et al. 2015). According to the literature review, simple linear regression was carried out for variables that can be related to each other. Hence, different groups were compared in terms of mean scores with ANOVA analysis to see the differences. The findings are consistent with the literature. Hypothesis Extra 1: Apology positively influences distributive justice by service recovery provided by AI-based conversational agents.

A summary is depicted in Table 14. Results are significant with the following values. (F (1,248) = 28.30, p < 0.001) with R^2= 0.102. In the model, apology explained 10.2% of the variance in distributive justice.

Table 14. Regression Summary for Apology and Distributive Justice

Model Summary[b]				
Hypo	R	R^2	Adjusted R	Standard Error
9	.320[a]	.102	.099	5.70406
a.Independent Variable APOL				
b.Dependent Variable DIST				

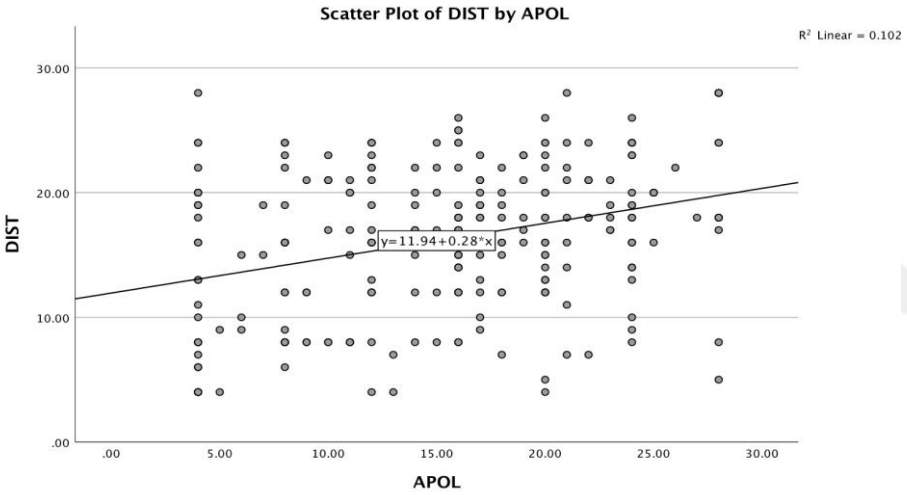

Figure 9. Scatter Plot for Apology and Distributive justice

The relationship can also be observed in Figure 9. Therefore, we can conclude that the hypothesis is supported.

Hypothesis Extra 2: Apology positively influences interactional justice in service recovery provided by AI-based conversational agents. A summary is depicted in Table 15. Results are significant with the following values. (F (1,248) = 20.56, p < 0.001) with R^2= 0.077. In the model, apology explained 7.7% of the variance in interactional justice.

Table 15. Regression Summary for Apology and Interactional Justice

Model Summary[b]				
Hypo	R	R^2	Adjusted R^2	Standard Error
10	.277[a]	.077	.073	4.75510
a.Independent Variable APOL				
b.Dependent Variable INT				

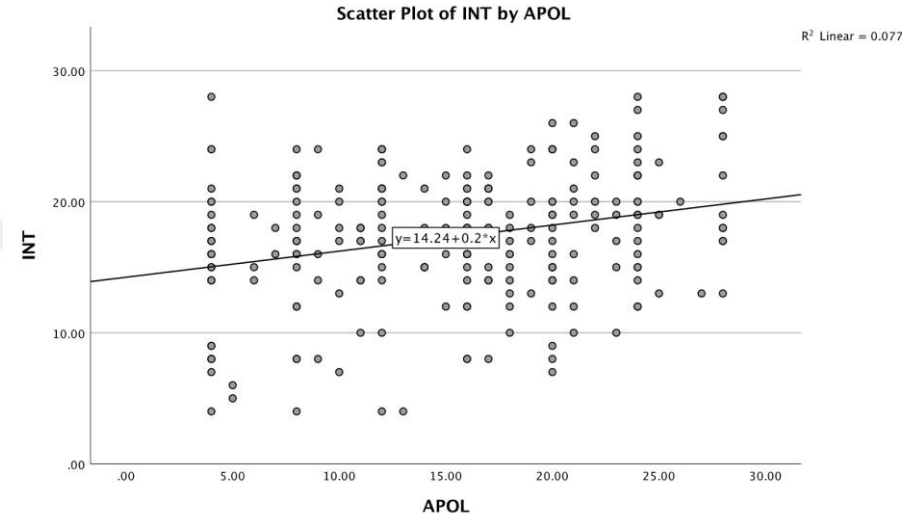

Figure 10. Scatter Plot for Apology and Interactional justice

The relationship can also be observed in Figure 10. Therefore, we can conclude that the hypothesis is supported.

Hypothesis Extra 3: Apology positively influences procedural justice in service recovery provided by AI-based conversational agents. A summary is depicted in Table 16. Results are significant with the following values. ($F(1,248) = 49.92$, $p < 0.001$) with $R^2 = 0.168$. In the model, apology explained 16.8% of the variance in procedural justice.

Table 16. Regression Summary for Apology and Procedural Justice

Model Summary[b]				
Hypo	R	R^2	Adjusted R^2	Standard Error
11	.409[a]	.168	.164	5.48495
a.Independent Variable APOL				
b.Dependent Variable PRO				

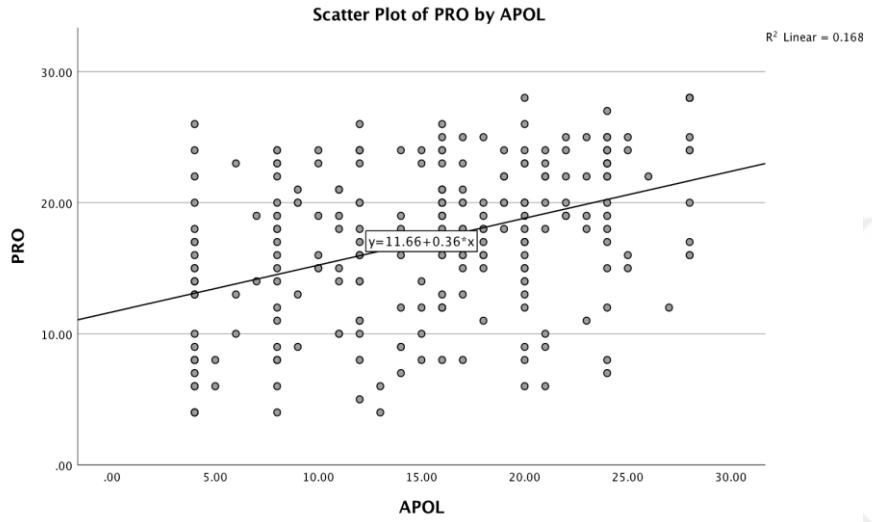

Figure 11. Scatter Plot for Apology and Procedural justice

Figure 11 also shows the relationship. Therefore, we can conclude that the hypothesis is supported.

Hypothesis Extra 4: Compensation positively influences distributive justice in service recovery provided by AI-based conversational agents. The summary is depicted in Table 17. Results are significant with the following values. ($F(1,248) = 145.73$, $p < 0.001$) with $R^2 = 0.370$. In the model, compensation explained 37% of the variance in distributive justice.

Table 17. Regression Summary for Compensation and Distributive Justice

Model Summary[b]				
Hypo	R	R^2	Adjusted R^2	Standard Error
12	.608[a]	.370	.368	4.77829
a.Independent Variable COM				
b.Dependent Variable DIST				

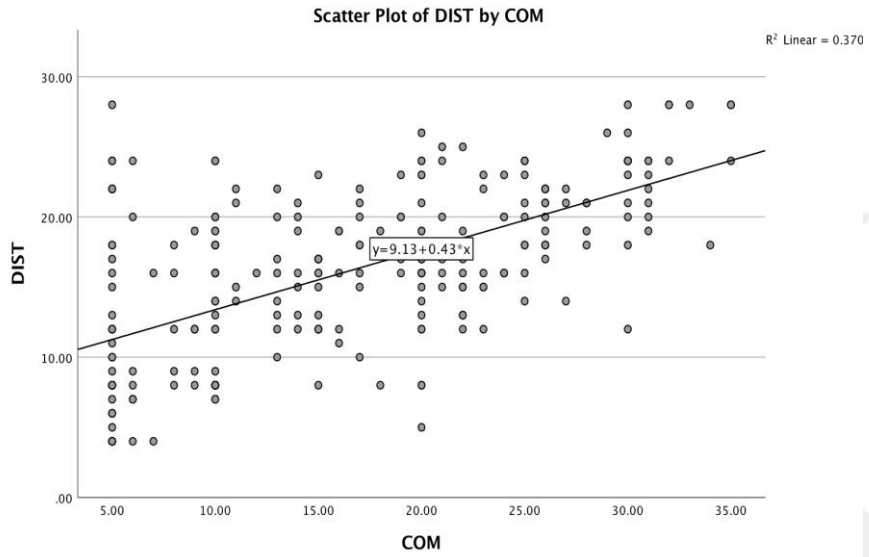

Figure 12. Scatter Plot for Compensation and Distributive justice

The relationship can also be observed in Figure 12. Therefore, we can conclude that the hypothesis is supported.

Hypothesis Extra 5: Compensation positively influences interactional justice in service recovery provided by AI-based conversational agents. The summary is depicted in Table 18. Results are significant with the following values. ($F(1,248) = 23.98$, $p < 0.001$) with $R^2 = 0.088$. In the model, compensation explained 8.8% of the variance in interactional justice.

Table 18. Regression Summary for Compensation and Interactional Justice

Model Summary[b]				
Hypo	R	R^2	Adjusted R^2	Standard Error
13	.297[a]	.088	.084	4.72513
a.Independent Variable COM				
b.Dependent Variable INT				

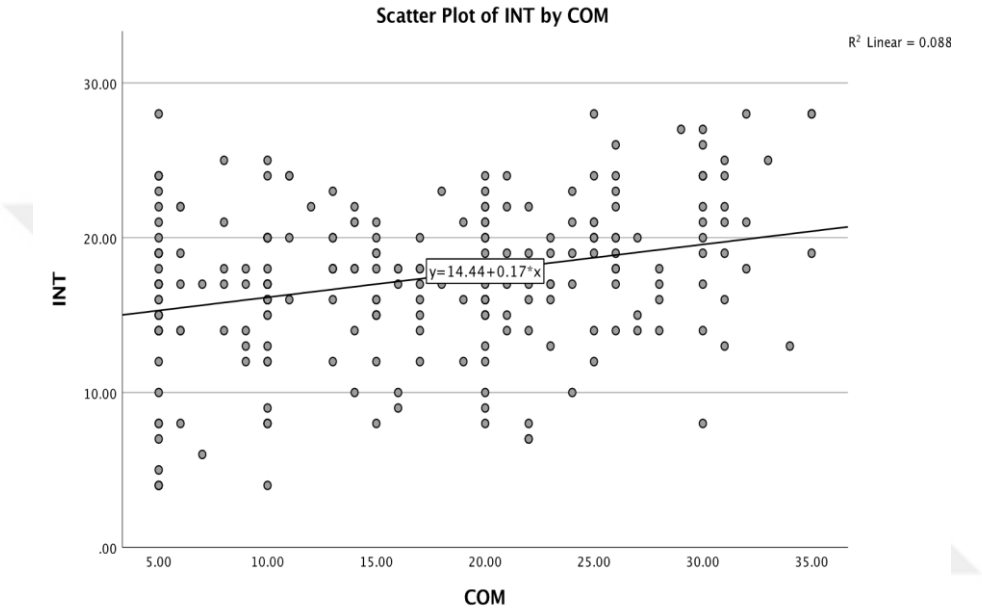

Figure 13. Scatter Plot for Compensation and Interactional justice

Figure 13 also shows the relationship. Therefore, we can conclude that the hypothesis is supported.

Hypothesis Extra 6: Compensation positively influences procedural justice in service recovery provided by AI-based conversational agents. The summary is depicted in Table 19. Results are significant with the following values. ($F(1,248) = 86.25$, $p < 0.001$) with $R^2 = 0.258$. In the model, compensation explained 25.8% of the variance in procedural justice.

Table 19. Regression Summary for Compensation and Procedural Justice

Model Summary[b]				
Hypo	R	R^2	Adjusted R^2	Standard Error
14	.508[a]	.258	.255	5.17831
a.Independent Variable COM				
b.Dependent Variable PRO				

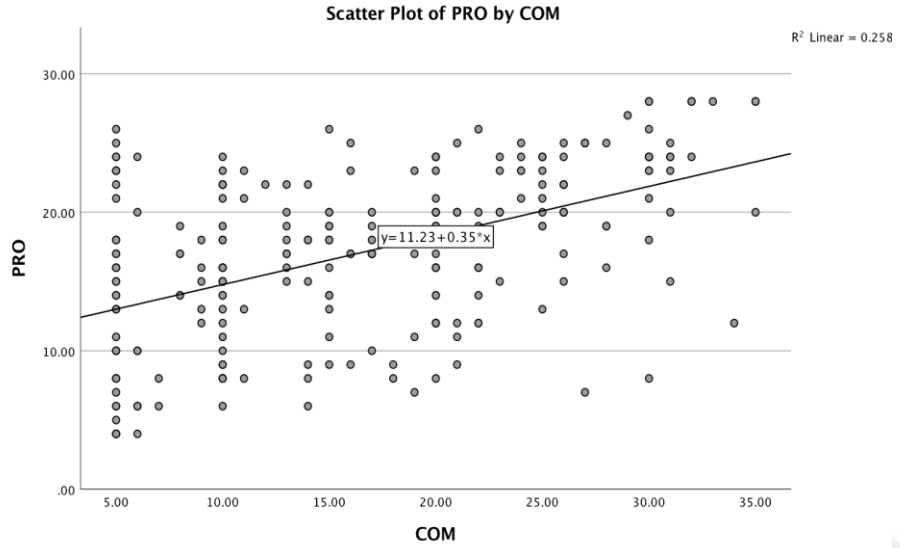

Figure 14. Scatter Plot for Compensation and Procedural justice

Figure 14 also shows the relationship. Therefore, we can conclude that the hypothesis is supported.

Hypothesis Extra 7: There is a significant difference in the human interaction needs of different groups. These different groups are people who have different reasons for contacting human service employees. This hypothesis is tested with One-Way ANOVA. First, assumptions are checked. Levene's Significance Value > 0.05, as shown in Table 20; therefore, it did not violate the assumption.

Table 20. Levene's Test

Tests of Homogeneity					
		Levene Statistic	df1	df2	Significance
NH	For Mean	1.365	4	245	.247
	For Median	.801	4	245	.526
	For Median and with adjusted df	.801	4	203.189	.526
	For trimmed mean	1.320	4	245	.263

Afterward, descriptives were checked. Table 21 demonstrates the descriptives of the one-way ANOVA test.

Table 21. One-way ANOVA Reason for Contacting with Human Service Employee & Need for Human Interaction

Descriptives								
NH								
	N	Mean	Standard Deviation	Standard Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Limit	Upper Limit		
Getting an inadequate answer	105	15.6762	4.02992	.39328	14.8963	16.4561	4.00	21.00
Lack of understanding of the stated problem	119	15.7815	4.04877	.37115	15.0465	16.5165	3.00	21.00
Lack of empathy and emotions	10	13.9000	4.99889	1.58079	10.3240	17.4760	3.00	18.00
No, I did not need to contact	11	11.5455	5.93908	1.79070	7.5555	15.5354	3.00	21.00
Other	5	14.8000	5.71839	2.55734	7.6997	21.9003	6.00	19.00
Total	250	15.4560	4.27189	.27018	14.9239	15.9881	3.00	21.00

The ANOVA test is significant; the p-value is less than 0.05, as shown in Table 22.

Table 22. One-way ANOVA Sum of Squares

ANOVA					
NH					
	Sum of Squares	Degrees of Freedom	Mean Square	F	Significance
Between Groups	212.279	4	53.070	3.002	.019
Within Groups	4331.737	245	17.681		
Total	4544.016	249			

Table 23 shows which groups differ in terms of mean scores. There is a difference in the need for human interaction between different groups (Getting an inadequate answer vs. no need to contact).

Table 23. One-Way ANOVA Multiple Comparisons Table

Multiple Comparisons Table						
Dependent Variable: NH						
Tukey HSD						
(I) Need to contact human service employee	(J) Need to contact human service employee	Mean Difference (I-J)	Standard Error	Significance	95% Confidence Interval	
					Lower Limit	Upper Limit
Getting an inadequate answer	Lack of understanding of the stated problem	-.10532	.56299	1.000	-1.6525	1.4419
	Lack of empathy and emotions	1.77619	1.39156	.706	-2.0481	5.6005
	No, I did not need to contact	4.13074*	1.33256	.018	.4686	7.7929
	Other	.87619	1.92471	.991	-4.4133	6.1657
Lack of understanding of the stated problem	Getting an inadequate answer	.10532	.56299	1.000	-1.4419	1.6525
	Lack of empathy and emotions	1.88151	1.38442	.654	-1.9232	5.6862
	No, I did not need to contact	4.23606*	1.32510	.014	.5944	7.8777
	Other	.98151	1.91955	.986	-4.2938	6.2568
Lack of empathy and emotions	Getting an inadequate answer	-1.77619	1.39156	.706	-5.6005	2.0481
	Lack of understanding of the stated problem	-1.88151	1.38442	.654	-5.6862	1.9232
	No, I did not need to contact	2.35455	1.83722	.703	-2.6945	7.4036
	Other	-.90000	2.30308	.995	-7.2293	5.4293
No, I did not need to contact	Getting an inadequate answer	-4.13074*	1.33256	.018	-7.7929	-.4686
	Lack of understanding of the stated problem	-4.23606*	1.32510	.014	-7.8777	-.5944
	Lack of empathy and emotions	-2.35455	1.83722	.703	-7.4036	2.6945
	Other	-3.25455	2.26791	.606	-9.4872	2.9781
Other	Getting an inadequate answer	-.87619	1.92471	.991	-6.1657	4.4133
	Lack of understanding of the stated problem	-.98151	1.91955	.986	-6.2568	4.2938
	Lack of empathy and emotions	.90000	2.30308	.995	-5.4293	7.2293
	No, I did not need to contact	3.25455	2.26791	.606	-2.9781	9.4872
*. The mean difference is significant at the 0.05 level.						

Hypothesis Extra 8: There is a significant difference in service failure severity for different groups. These different groups are people who have different

reasons for contacting human service employees. This hypothesis is tested with One-Way ANOVA. First, assumptions are checked. Levene's Significance Value > 0.05, as shown in Table 24; therefore, it did not violate the assumption.

Table 24. Levene's Test

Tests of Homogeneity					
		Levene Statistic	df1	df2	Significance
SEVER	For Mean	.209	4	245	.933
	For Median	.232	4	245	.920
	For Median and with adjusted df	.232	4	214.539	.920
	For trimmed mean	.216	4	245	.930

Afterward, descriptives were checked. Table 25 demonstrates the descriptives of the one-way ANOVA test.

Table 25. One-way ANOVA Reason for Contacting with Human Service Employee & Service Failure Severity

Descriptives								
SEVER								
					95% Confidence Interval for Mean			
	N	Mean	Standard Deviation	Standard Error	Lower Limit	Upper Limit	Minimum	Maximum
Getting an inadequate answer	105	14.7429	3.21065	.31333	14.1215	15.3642	6.00	21.00
Lack of understanding of the stated problem	119	14.6723	3.11124	.28521	14.1075	15.2371	3.00	21.00
Lack of empathy and emotions	10	13.8000	3.52136	1.11355	11.2810	16.3190	5.00	18.00
No, I did not need to contact	11	15.0909	3.41920	1.03093	12.7939	17.3880	9.00	21.00
Other	5	10.2000	4.08656	1.82757	5.1259	15.2741	3.00	13.00
Total	250	14.5960	3.24266	.20508	14.1921	14.9999	3.00	21.00

ANOVA test is significant. p-value is less than 0.05, as we can see in Table 26.

Table 26. One-way ANOVA Sum of Squares

ANOVA					
SEVER					
	Sum of Squares	df	Mean Square	F	Signficance
Between Groups	108.611	4	27.153	2.651	.034
Within Groups	2509.585	245	10.243		
Total	2618.196	249			

Multiple comparisons table, Table 27 shows which groups differ from each other. There is a difference in the need for human interaction between different groups (Getting an inadequate answer vs other reasons).

Table 27. One-Way ANOVA Multiple Comparisons Table

Multiple Comparisons Table						
Dependent Variable: SEVER						
Tukey HSD						
(I) Need to contact human service employee	(J) Need to contact human service employee	Mean Difference (I-J)	Standad Error	Significance	95% Confidence Interval	
					Lower Limit	Upper Limit
Getting an inadequate answer	Lack of understanding of the stated problem	.07059	.42852	1.000	-1.1071	1.2483
	Lack of empathy and emotions	.94286	1.05919	.900	-1.9680	3.8537
	No, I did not need to contact	-.34805	1.01428	.997	-3.1355	2.4394
	Other	4.54286*	1.46499	.018	.5168	8.5689
Lack of understanding of the stated problem	Getting an inadequate answer	-.07059	.42852	1.000	-1.2483	1.1071
	Lack of empathy and emotions	.87227	1.05375	.922	-2.0237	3.7682
	No, I did not need to contact	-.41864	1.00860	.994	-3.1905	2.3532
	Other	4.47227*	1.46107	.021	.4570	8.4876
Lack of empathy and emotions	Getting an inadequate answer	-.94286	1.05919	.900	-3.8537	1.9680
	Lack of understanding of the stated problem	-.87227	1.05375	.922	-3.7682	2.0237
	No, I did not need to contact	-1.29091	1.39840	.888	-5.1340	2.5522
	Other	3.60000	1.75299	.244	-1.2176	8.4176
No, I did not need to contact	Getting an inadequate answer	.34805	1.01428	.997	-2.4394	3.1355
	Lack of understanding of the stated problem	.41864	1.00860	.994	-2.3532	3.1905
	Lack of empathy and emotions	1.29091	1.39840	.888	-2.5522	5.1340
	Other	4.89091*	1.72622	.040	.1469	9.6349
Other	Getting an inadequate answer	-4.54286*	1.46499	.018	-8.5689	-.5168
	Lack of understanding of the stated problem	-4.47227*	1.46107	.021	-8.4876	-.4570
	Lack of empathy and emotions	-3.60000	1.75299	.244	-8.4176	1.2176
	No, I did not need to contact	-4.89091*	1.72622	.040	-9.6349	-.1469
*. The mean difference is significant at the 0.05 level.						

A summary of the extra analysis can be found in Appendix F and G. Hence, the status of the additional analysis is provided in Table 28

Table 28. Summary of Extra Analyses

Hypothesis	Status
Extra 1	Supported
Extra 2	Supported
Extra 3	Supported
Extra 4	Supported
Extra 5	Supported
Extra 6	Supported
Extra 7	Supported
Extra 8	Supported

CHAPTER 6

CONCLUSION AND DISCUSSION

6.1 Discussion

Service failure is when the final service outcome has problems (Palmer et al. 2000). Firms should recover from these failures to maintain good customer relationships. Nowadays, firms have started to use online methods for service recovery. This study examines the factors that affect service recovery satisfaction provided by AI-based conversational agents. There are limited studies on this topic in literature, and research about AI-based conversational agents is new. The studies mentioned in the literature review mainly focus on one factor for service recovery satisfaction. Especially in Turkey nearly, there are no studies about service recovery provided by AI-based conversational agents. Therefore, the study's contributions are essential for academic and managerial environments.

Results of H1-H8 indicate that service recovery method, perceived justice, need for human interaction and anthropomorphism, and service recovery satisfaction are positively related. Among these factors, distributive justice, procedural justice, and compensation influence service recovery satisfaction the most. This indicates that consumers are more outcome-focused. Hence, among the dimensions of perceived justice, distributive justice has the strongest relationship with service recovery satisfaction. The result shows that people focus more on outcomes while considering the perceived justice of AI-based conversational agents. Only the eighth hypothesis, which is about service failure severity and service recovery satisfaction, was not significant. This can be attributed to the research design. In this research, the questions were not about a specific industry. Therefore, service failure severity may be perceived differently for different industries. Overall, the findings support the

discussion in the literature review. The weakest relationship is between the need for human interaction and service recovery satisfaction. Hence, the relationship is in the opposite direction than what is stated in the hypothesis formulation. The literature states that when consumers highly need human interaction, service recovery satisfaction decreases in non-human service recovery. However, the findings state that when AI-based conversational agents provide service recovery, the need for human interaction is less important. In addition, some interesting findings are derived. According to regression analysis, the need for human interaction and anthropomorphism tends to have a negligible effect on service recovery satisfaction. This can be attributed to chatbot service recovery being a new concept in Turkey. Most of the respondents selected agree or strongly agree for questions about the need for human interaction. 51 % of the responses to these questions are chosen as agree or strongly agree. This signifies that most people must interact with humans during service encounters. Most respondents selected strongly disagree, disagree, and somewhat disagree with the anthropomorphism question.67 % of the responses to these questions are chosen as somewhat disagree, disagree, or strongly disagree. This signifies that people do not perceive AI-based conversational agents as similar to humans, though they have human-like characteristics. Hence, as stated above, using AI-based conversational agents is a new topic in Turkey. It is rare for consumers to interact with these types of agents. (Eren, 2021). Also, no visual or example was given to prevent prejudice or bias while asking about anthropomorphism. As stated in the literature, consumers tend to contact service agents capable of resolving problems (Teodorescu et al., 2021).

The literature also states that service recovery methods may affect perceived justice dimensions (Smith et al. 1999), (Mostafa et al. 2015). Therefore, some extra

analyses were conducted. A summary of extra analysis can be found in Appendix F and G. Extra analyses are conducted to see more detailed findings. Apology is positively related to interactional, distributive, and procedural justice. However, the relationship between apology and procedural justice is strongest between these three justice dimensions. This is an interesting contribution. Literature argues that apology is mainly related to interactional justice (Bae et al. 2020). However, the findings show that apology primarily affects procedural justice in AI-based conversational agents. This can be attributed to the fact that in the context of AI-based conversational agents, the apology is mainly related to procedural justice due to differences in the service encounter process. Compensation is positively associated with interactional, distributive, and procedural justice. However, the relationship between compensation and distributive justice is strongest between these three dimensions. This result matches the findings in the literature review. Compensation is mainly related to distributive justice in literature (Smith et al. 1999), (Mostafa et al. 2015). Previous research has examined perceived justice's impact on service recovery satisfaction. The contribution of this study is to explore service recovery satisfaction by considering perceived justice, service recovery method (apology vs. compensation), service failure severity, need for human interaction, and anthropomorphism by considering research gaps in the literature. Especially in Turkey, nearly there are no studies in this area. As survey results show, AI-based conversational agents are used in online retail, financial, and telecommunication services. Hence, these agents are used in new areas such as online food delivery, software service, and online education services. The major improvement areas in AI-based conversational agents are providing a more adequate answer and a better

understanding of the service problem. The majority of the respondents (89.6%) need to have contact with human service employees for these reasons.

Furthermore, the strongest relationship is between the justice dimension and satisfaction with service recovery. This suggests that justice aspects are also important in AI-based conversational agent service recovery and there is a need for anthropomorphism and human interaction. Most studies do not consider perceived justice dimensions in service recovery provided by AI-based conversational agents. More research is needed to be carried out in this area (Crolic et al., 2022). Therefore, this study's major conclusion is that in the context of AI-based conversational agents, attributes of the agent (anthropomorphism), consumer trait (need for human interaction), perceived justice, and attributes related to service context (service recovery method) affect service recovery satisfaction. Hence, the effect of perceived justice is important for service recovery satisfaction.

6.2 Theoretical and managerial contributions

This study has both theoretical and managerial implications. The study emphasizes social justice and service recovery theory by considering AI-based conversational agents. In the literature, there are limited studies about AI-based conversational agents, though the popularity of these agents has risen. The literature states that firms must provide efficient service recovery to solve service failures. Study confirms that AI-based conversational agents can be an effective tool for solving service recovery. Firms need to design AI-based conversational agents to manage service recovery effectively. Service recovery is crucial for customer retention. (Singh & Crisafulli, 2016).

Firms should design AI-based conversational agents that are more similar to humans to provide better service recovery (Agnihotri & Bhattacharya,2023). The study investigates service recovery provided by AI-based conversational agents.

Results show that the strongest relationship is between distributive justice and service recovery satisfaction in service recovery provided by AI-based conversational agents. This indicates that consumers focus on the outcome rather than the service recovery process regarding justice perception. The second strongest relationship is between procedural justice and satisfaction with service recovery. We can observe that the strongest two relationships are between the perceived justice dimension and service recovery satisfaction. This finding is helpful for companies because justice is important for AI-based conversational agents. The third strongest relationship is between compensation and satisfaction with service recovery. Consumers expect compensation from firms rather than an apology. Most respondents need help with service failure in online retail and financial services, especially regarding delivery and technical and procedural problems. Hence, firms should provide a service recovery focusing on service failure compensation. Other key findings were identified in additional analyses. Groups that need to interact with humans for different reasons differ regarding service failure severity and the need for human interaction. Service failure severity and the need for human interaction are more important for the ones who need to contact a human service agent because of getting an inadequate answer.

As predicted, the relationship between compensation and distributive justice is strongest compared to interactional and procedural justice. In addition, the relationship between apology and procedural justice is strongest compared to interactional and distributive justice. As stated in the literature, distributive justice is

more important in the service context where there is a time constraint and a final solution (Lajante et al., 2023). Therefore, companies may choose compensation as a service recovery method. On the other hand, firms may choose apology as a service recovery method for service contexts such as financial services where interaction plays an important role. While answering the survey questions, most respondents selected that they encountered service failure in online retail and online financial service contexts. Therefore, firms may use a strategy depending on the sector. Apologies and compensation are important for service recovery provided by AI-based conversational agents. Hence, research shows that compensation significantly impacts service recovery satisfaction more than apology.

6.3 Limitations and further research

The sample and data collection tools limit the study. First, it only focuses on service recovery provided by AI-based Conversational Agents. Future studies may also consider physical robots and research different service encounter situations. This study asked more general questions about service. A specific sector can be chosen in upcoming studies, and questions can be more sector-related. Hence, questions can be related to the attributes of AI-based Conversational Agents. Service recovery may change depending on the characteristics of these agents.

Secondly, there can be other factors that influence service recovery satisfaction. Further research may investigate the relationship between privacy concerns and satisfaction with service recovery. Consumers can worry about AI-based agents keeping personal information confidential (Wu et al. 2012). Hence, trust in AI-based conversational agents may have an important role closely related to privacy concerns (Agnihotri & Bhattacharya, 2023). In the context of service failure, consumers can be anxious about whether the information, like banking information,

will be processed safely (Agnihotri & Bhattacharya, 2023). Future studies may also investigate the relationship between customer forgiveness and service recovery satisfaction. Customer forgiveness can influence service recovery satisfaction (Yagil and Luria, 2016). When consumers are more likely to forgive in the case of a service failure, their satisfaction with service recovery can increase. In addition to these traits closely related to consumers, some attributes related to AI-based conversational agents may affect service recovery satisfaction. One of these factors is personalization. AI-based conversational agents can trigger a sense of personalization (Adam et al., 2021). While providing a service recovery, AI-based conversational agents can be more customized according to the situation. Different types of service recovery methods have different effects on service recovery satisfaction. (Kron et al., 2023). Finally, this study is limited to one sample in Turkey. Further studies can be replicated in other samples and countries, and cross-cultural study results can be compared.

APPENDIX A

ONLINE QUESTIONNAIRE IN ENGLISH

BOĞAZİÇİ UNIVERSITY

Institutional Review Board in Social Sciences and Humanities (SBINAREK)

Participant Information and Consent Form

Institute: Boğaziçi University

Thesis Title: Artificial Intelligence Based Conversational Agents in Service Recovery

Student Name: Zeynep Karakartal

Thesis Advisor: Assoc. Prof. Ali Coşkun

Service failures are inevitable, although firms can recover from these failures through service recovery efforts. Nowadays with the help of new technological advancements firms can use online methods to recover service failures. Using AI-based conversational agents is one of these methods. This study will try to investigate the factors and their relationship with service recovery satisfaction in the context of AI-based conversational agents. The research method will be an online survey and it will be distributed via Google Forms. The sample will include 18+ aged adults who are majorly in Turkey.

This study is part of Zeynep Karakartal's Master's thesis and investigates service recovery provided by AI-based conversational agents. The aim of the study is to investigate the factors that affect service recovery satisfaction provided by AI-based conversational agents. In order to participate in the study, you will be asked 5 demographic questions, 6 questions regarding your experience with an AI-based conversational agent, and 9 questions about service recovery satisfaction provided by

an AI-based conversational agent. You can support this research by spending approximately 15 minutes of your time. The responses will remain totally anonymous. Only the researcher and the thesis advisor will have access to the survey data for educational research purposes. No one who forwards the link to you will have access to data. No personally identifiable data (Id, Name & Surname, ID number, email, IP address, etc.) is collected from the respondents therefore responses cannot be matched with the respondents. Data which is collected will be confidential and will not be shared with any other third party. Participation in this survey is voluntary and you will not receive any payment or reward. You can exit from the survey at any time you want without facing any penalty. The responses will not be saved or used if you exit or withdraw. There are no known risks of participating in this survey. The study will try to benefit the academic environment and business by investigating the factors that affect service recovery satisfaction in the context of AI-based conversational agents. If you have any questions about this research, please contact researcher Zeynep Karakartal and thesis advisor Assoc. Prof. Ali Coşkun. If you have any questions about your rights as a research participant, you may contact Boğaziçi University Social and Human Sciences Human Research Ethics Committee Thanks for your time and participation.

(*All questions are mandatory and only one response can be selected) When you complete the survey, please do not forget to press the "Send" button.

AI(Artificial Intelligence) based conversational agent refers to chatbots, messengers, and voice-based assistants that interact with people.

1) Have you ever contacted with AI-based conversational agent?

( )Yes

( )No (survey will terminate here)

2) What is your second source of reference other than an AI-based conversational agent to solve a service failure? (Service failure may include any problems or questions that you face about online retail, financial services, telecommunication services…)

( )Call center

( )Website

( )Directly communicating with customer representative

( )Other(please state)

3) What is the last time you remember that you contacted with AI-based conversational agent in case of a service failure? (Service failure may include any problems or questions that you face about online retail, financial services, telecommunication services…)

( )One or two months ago

( )Three or four months ago

( )Five or six months ago

( )More than six months

4) What was the service context that you last contacted with an AI-based conversational agent for service failure? (Service failure may include any problems

or questions you face about online retail, financial services, telecommunication services…)

( ) Online financial services

( ) Online retail

( ) Telecommunication services

( ) Other(Please State)

5) Why did you need to get in contact with a human service employee after encountering with AI-based conversational agent in this experience?

( ) Getting an inadequate answer

( ) Lack of understanding of the stated problem

( ) Lack of empathy and emotions

( ) Other (please state)

( ) No, I did not need to contact

6) What type of failure/question made you contact with AI-based conversational agent?

( ) Delivery problems (missing item, delay in delivery, incorrect delivery, damaged delivery…)

( ) Payment problems

( ) Security problems

( ) Technical & procedural problems(incomprehensible statements, long queues, ignorant employees, slow procedures…)

( ) Other (please state)

7) The following statements are intended to measure the service recovery effort provided by the company in the context of an AI-based conversational agent. Please select the answer that best fits you by considering the last experience you had.

Items	1=Strongly Disagree	2=Disagree	3=Somewhat Disagree	4=Neither Agree or Nor Disagree	5=Somewhat Agree	6=Agree	7=Strongly Agree
The company apologized to me for what had happened							
The company expressed regret for the mistake that occurred							
The company apologized for the inconvenience the problem had brought to me							
The company apologized for what I have suffered because of the problem							

8)

Items	1=Strongly Disagree	2=Disagree	3=Somewhat Disagree	4=Neither Agree or Nor Disagree	5=Somewhat Agree	6=Agree	7=Strongly Agree
The compensation the company gave me for the loss incurred is good							
The compensation the company gave me for all the time I spent dealing with the complaint is good							
The compensation the company provided me to cover my financial losses is good							
The compensation the company gave me for all the hard times I had due to the complaint is good							
The compensation the company provided me for the inconvenience I went through due to the complaint is good							

9) The following statements are intended to measure the perceived justice of the service recovery in the context of an AI-based conversational agent. Please select the answer that best fits you by considering the last experience you had.

Items	1=Strongly Disagree	2=Disagree	3=Somewhat Disagree	4=Neither Agree or Nor Disagree	5=Somewhat Agree	6=Agree	7=Strongly Agree
Despite the hassle caused by the problem, (Firm x) responded fairly and quickly.							
I feel (Firm x) responded in a timely fashion to the problem.							
I believe (Firm x) has fair policies and practices to handle problems.							
With respect to its policies and procedures, (Firm x) handled the problem in a fair manner.							

10)

Items	1=Strongly Disagree	2=Disagree	3=Somewhat Disagree	4=Neither Agree or Nor Disagree	5=Somewhat Agree	6=Agree	7=Strongly Agree
In dealing with my problem, (Firm x)'s AI based conversational agent treated me in a courteous manner.							
During their effort to fix my problem, (Firm x)'s AI based conversational agent showed a real interest in trying to be fair.							
(Firm x)'s AI based conversational agent got input from me before handling the problem.							
While attempting to fix my problem, (Firm x)'s AI based conversational agent considered my views.							

11)

Items	1=Strongly Disagree	2=Disagree	3=Somewhat Disagree	4=Neither Agree or Nor Disagree	5=Somewhat Agree	6=Agree	7=Strongly Agree
Although this event caused me problems, (Firm x) effort to fix it resulted in a very positive outcome for me.							
The final outcome I received from (Firm x) was fair, given the time and hassle.							
Given the inconvenience caused by the problem, the outcome I received from (Firm x) was fair.							
The service recovery outcome that I received in response to the problem was more than fair.							

12) The following statements are intended to measure the need for interacting with human service employees. Please select the answer that best fits you by considering the last experience you had.

Items	1=Strongly Disagree	2=Disagree	3=Somewhat Disagree	4=Neither Agree or Nor Disagree	5=Somewhat Agree	6=Agree	7=Strongly Agree
Human contact in providing services makes the process enjoyable for the consumer.							
I like interacting with the person who provides the service.							
It bothers me to use a machine when I could talk to a person instead.							

13) The following statements are intended to measure the anthropomorphizing(perceiving AI-based conversational agents as human-like). Human-like characteristics include(language, features, and physical appearance if available) Please select the answer that best fits you by considering the last experience you had.

Items	1=Strongly Disagree	2=Disagree	3=Somewhat Disagree	4=Neither Agree or Nor Disagree	5=Somewhat Agree	6=Agree	7=Strongly Agree
It looks like a person.							
It seems almost as if it has free will.							
It seems as if it has intentions.							

14) The following statements are intended to measure the service failure severity of the problem or question encountered which leads to using an AI-based conversational agent for service recovery. Please select the answer that best fits you by considering the last experience you had.

Items	1=Strongly Disagree	2=Disagree	3=Somewhat Disagree	4=Neither Agree or Nor Disagree	5=Somewhat Agree	6=Agree	7=Strongly Agree
If this problem were really happening to me, I would consider the problem to be: severe							
If this problem were really happening to me, it would make me feel: angry							
If this problem were really happening, it would be unpleasant to me							

15) The following statements are intended to measure the service recovery satisfaction in the context of AI-based conversational agent service recovery. Please select the answer that best fits you by considering the last experience you had.

Items	1=Strongly Disagree	2=Disagree	3=Somewhat Disagree	4=Neither Agree or Nor Disagree	5=Somewhat Agree	6=Agree	7=Strongly Agree
In my opinion, [firm x] provided a satisfactory resolution to my problem on this particular occasion.							
I am not satisfied with [firm x]'s handling of this particular problem							
Regarding this particular event (most recent service problem), I am satisfied with [firm x].							

DEMOGRAPHIC QUESTIONS

16) What is your gender? (open-ended)----------

17) What is your monthly income?

( ) Less than 15000 TL

( ) 15000-25000 TL

( ) 25001-35000TL

( ) 35001-45000TL

( ) More than 45000TL

18) What is your education level?(Please select the highest level of education that you obtained)

( ) High school graduate

( ) University graduate

( ) Master’s graduate

( ) Ph.D. graduate

19) What is your age?

( ) Under 18

( ) 18-24

( ) 25-34

( ) 35-44

( ) Above 44

20) What is your current employment condition?

( ) Unemployed

( ) Full-time Employed

( ) Part-time Employed

( ) Other (please state)

APPENDIX B

FACTOR ANALYSIS

(1/2)

Construct	Item	Factor Loading
Anthropomorphism	ANTH1	0.835
	ANTH2	0.897
	ANTH3	0.869
Need for Human Interaction	NHI1	0.866
	NHI2	0.886
	NHI3	0.812
Distributive Justice	DIST1	0.645
	DIST2	0.698
	DIST3	0.642
	DIST4	0.678
Procedural Justice	PRO1	0.835
	PRO2	0.843
	PRO3	0.819
	PRO4	0.834
Interactional Justice	INT1	0.767
	INT2	0.706
	INT3	0.805
	INT4	0.581

APPENDIX B

FACTOR ANALYSIS

(2/2)

Construct	Item	Factor Loading
Apology	APOL1	0.868
	APOL2	0.871
	APOL3	0.884
	APOL4	0.814
Compensation	COM1	0.851
	COM2	0.877
	COM3	0.858
	COM4	0.861
	COM 5	0.855
Service Failure Severity	SEVER1	0.790
	SEVER2	0.815
	SEVER3	0.849

APPENDIX C

ETHICS COMMITTEE APPROVAL

T.C.
BOĞAZİÇİ ÜNİVERSİTESİ REKTÖRLÜĞÜ
Sosyal ve Beşeri Bilimler İnsan Araştırmaları Etik Kurulu (Sbinarek)

Sayı : E-84391427-050.01.04-157151 12.12.2023
Konu : 2023-22T Kayıt Numaralı Başvurunuz Hakkında

Sayın Doç. Dr. Ali ÇOŞKUN

Tez danışmanlığını yürüttüğünüz öğrenciniz Zeynep Karakartal'ın "Artificial Intelligence Based Conversational Agents in Service Recovery" başlıklı projesi ile Boğaziçi Üniversitesi Sosyal ve Beşeri Bilimler İnsan Araştırmaları Etik Kurulu (SBİNAREK)'e yaptığınız 2023-22T kayıt numaralı başvuru 20.11.2023 tarih ve 2023/09 sayılı kurul toplantısında incelenmiş ve projeye etik onay verilmesi uygun bulunmuştur.

Bu karar tüm üyelerin toplantıya on-line olarak katılımıyla ve oybirliği ile alınmıştır. Onay mektubu tüm üyeler adına Komisyon Başkanı tarafından e-imzalanmıştır. Bilgilerinizi rica ederiz.

Saygılarımızla,

Dr. Öğr. Üyesi Işıl ERDUYAN
Kurul Başkanı

Bu belge, güvenli elektronik imza ile imzalanmıştır.
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APPENDIX D

SAMPLE CHARACTERISTICS

(1/2)

	Variable	n	%
Gender	Male	126	50.4
	Female	118	47.2
	Prefer not to say	6	2.4
Age	18-24	53	21.2
	25-34	167	66.8
	35-44	24	9.6
	Above 44	6	2.4
Education Status	High school graduate	13	5.2
	University graduate	185	74
	Master's graduate	48	19.2
	PhD graduate	4	1.6
Employment Condition	Unemployed	14	5.6
	Full-time employed	206	82.4
	Part-time employed	24	9.6
	Other	6	2.4
Income	Less than 15000₺	24	9.6
	15000-25000₺	22	8.8
	25001-35000₺	49	19.6
	35001-45000₺	55	22
	More than 45000₺	100	40
Second source of reference for failure	Call center	94	37.6
	Website	63	25.2
	Customer representative	88	35.2
	Other	5	2

n=250, %100

APPENDIX D

SAMPLE CHARACTERISTICS

(2/2)

	Variable	n	%
Last time contact with AI-based conversational agent	1 or 2 months ago	189	75.6
	3 or 4 months ago	38	15.2
	5 or 6 months ago	6	2.4
	More than 6 months	17	6.8
Service Context	Online financial services	67	26.8
	Online retail	119	47.6
	Telecommunication services	49	19.6
	Other	15	6
Need for getting contact with human service agent	Inadequate answer	105	42
	Lack of understanding of problem	119	47.6
	Lack of empathy & emotions	10	4
	Other	5	2
	No need to contact	11	4.4
Type of failure/question	Delivery problems	122	48.8
	Payment problems	39	15.6
	Security problems	8	3.2
	Technical & procedural problems	72	28.8
	Other	9	3.6

n=250. %=100

APPENDIX E

REGRESSION SUMMARY

Model Summary[b]					
	Model	R	R^2	Adjusted R^2	Standard Error
a.Independent variable, ANTH b. Dependent variable: SAT	1	0.141[a]	0.02	0.016	3.87
a. Independent variable, NH b. Dependent variable: SAT	2	0.134[a]	0.02	0.01	3.88
a. Independent variable, DIST b. Dependent variable: SAT	3	0.748[a]	0.56	0.56	2.6
a. Independent variable, PRO b. Dependent variable: SAT	4	0.336[a]	0.47	0.47	3.68
a. Independent variable, INT b. Dependent variable: SAT	5	0.684[a]	0.11	0.11	2.85
a. Independent variable, APOL b. Dependent variable: SAT	6	0.316[a]	0.1	0.096	3.71
a. Independent variable, COM b. Dependent variable: SAT	7	0.59[a]	0.35	0.34	3.16
a. Independent variable, SEVER b. Dependent variable: SAT	8	0.04[a]	0.002	-0.002	3.91

APPENDIX F

SUMMARY OF EXTRA ANALYSES REGRESSION

Model Summary[b]					
	Model	R	R^2	Adjusted R^2	Standard Error
a. Independent variable, APOL b. Dependent variable: DIST	9	.320[a]	0.102	0.099	5.70406
a. Independent variable, APOL b. Dependent variable: INT	10	.277[a]	0.077	0.073	4.7551
a. Independent variable, APOL b. Dependent variable: PRO	11	.409[a]	0.168	0.164	5.48495
a. Independent variable, COM b. Dependent variable: DIST	12	.608[a]	0.37	0.368	4.77829
a. Independent variable, COM b. Dependent variable: INT	13	.297[a]	0.088	0.084	4.72513
a. Independent variable, COM b. Dependent variable: PRO	14	.508[a]	0.258	0.255	5.17831

APPENDIX G

SUMMARY OF EXTRA ANALYSES ANOVA

ANOVA Summary		
Hypothesis	Status	Tukey-HSD Test
There is significant difference in need for human interaction for groups who have different reasons for contacting with human service employee.	Supported Significant F(4,245)=3.0 p-value=0.02	Getting an inadequate answer Mean=15.67 / Standard Deviation=4.03 No, I did not need to contact Mean=11.55/ Standard Deviation=5.94
There is a significant difference in service failure severity for groups who have different reasons for contacting with human service employee.	Supported Significant F(4,245)=2.65 p-value=0.03	Getting an inadequate answer Mean=14.74 / Standard Deviation=3.21 Other reasons Mean= 10.20 / Standard Deviation= 4.09

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