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Master's Degree Program in
Data-Driven Marketing

Human or Smart Robot?

The effect of the type of employee on brand loyalty, negative word-of-mouth, and the moderator role of emotional engagement

Efstathia Styliagkatzi

Master Thesis

presented as a partial requirement for obtaining a Master's Degree in Data-Driven Marketing

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Master Thesis presented as a partial requirement for obtaining the Master's degree in Data-Driven Marketing, with a specialization in Marketing Intelligence

Supervised by

Diego Costa Pinto, Associate Dean for Research and Director at Nova Marketing Analytics Lab, Nova Information Management School

Joana Rita Martinho Nunes, Lab Manager, Teaching Assistant and Neuromarketing Consulting at Nova Marketing Analytics Lab, Nova Information Management School

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STATEMENT OF INTEGRITY

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ABSTRACT

This research examines the effectiveness of service recovery strategies implemented by human and smart robot agents in the aviation industry. The study aims to evaluate the differential impacts of these agents on customer perceptions of brand loyalty and negative word-of-mouth, with apology and courtesy serving as mediators and emotional engagement as a moderator. Two methods were employed to investigate this research model: the neuromarketing method, where FaceReader recorded the emotional expressions of participants watching videos of service recovery in lost luggage incidents handled by either a smart robot or a human agent, and the experimental method, where participants responded to questions after viewing the videos. This research found that although there were significant differences in perceived apology and courtesy between human and robot agents, these factors only partially mediated the impact on brand loyalty and negative word-of-mouth. Interestingly, participants interacting with smart robot agents exhibited slightly higher brand loyalty and a reduced tendency to share negative feedback compared to those served by human agents, possibly due to the innovative and engaging nature of robot-delivered services. Emotional engagement was a crucial factor, with smart robots leveraging higher attention and engagement levels, suggesting greater cognitive stimulation. Conversely, human-led service interactions were associated with higher confusion levels, indicating potential inconsistencies. In total, this study provides valuable insights into the differing impacts of human and smart robot agents in service recovery, contributing to a deeper understanding of customer service dynamics in the aviation industry and suggesting that AI can play a crucial role in enhancing service recovery outcomes and customer loyalty.

KEYWORDS

Service recovery; service failure; smart robots; aviation industry; brand loyalty; emotional engagement; negative word-of-mouth; service recovery strategies

Sustainable Development Goals (SDG):

8 DECENT WORK AND ECONOMIC GROWTH

9 INDUSTRY, INNOVATION AND INFRASTRUCTURE

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Nwom	Negative word-of-mouth

1. INTRODUCTION

In today's world, the prevalence of Artificial Intelligence (AI) applications is ubiquitous, and airport services are no exception (Gursoy et al., 2019; Hoyer et al., 2020; Lv et al., 2022). In particular, the deployment of smart service robots has become a vital component in enhancing customer service and optimizing operational efficiency. These robots, which are powered by artificial intelligence (AI), possess the ability to detect external stimuli, interpret environmental data, provide human-like responses, and continuously learn from their interactions with users (Bowen & Morosan, 2018). The aim of these robots is to enhance the overall travel experience for passengers (Hoyer et al., 2020; Rajapaksha & Jayasuriya, 2020).

To date, many airlines and airports around the world have employed and tested AI smart service robots. The primary applications in the literature are primarily focused on parking services, passenger services, luggage handling, outdoor transportation, and other services (Chen, 2022). Since this study focuses on smart service robots, it will reference some implementations of them at major international airports.

First, KLM Royal Dutch Airlines introduces an innovative solution to enhance the passenger experience at Schiphol airport by deploying a socially aware robot named Spencer (KLM Blog, 2016). This social robot addresses the challenges faced by air carriers and airport operators dealing with increased passenger volumes and resulting delays. Functioning as a helpful guide, Spencer assists passengers in navigating the airport smoothly, from scanning boarding passes to directing them to departure gates. One of Spencer's standout features is its ability to analyze social situations and recognize relationships between people, allowing it to interact with passengers in a human-friendly manner. The robot adapts its speed to match the pace of the group and provides real-time information about the remaining distance (Triebel et al., 2016). In a survey conducted across some of the world's busiest airports, the guiding robot received positive feedback from participants who found it "cute" and appreciated its design and basic functionalities (Joosse & Evers, 2017).

Additionally, KLM is testing Care-E, a self-driving trolley, at JFK and San Francisco International airports. It utilizes AI to adapt to real-time changes, such as gate reassignments. Specifically, it is a bright blue robot that communicates with travelers using nonverbal sounds. It can scan boarding passes and transport up to 85 pounds of luggage while moving at a speed of 3 miles per hour (Lilit Marcus, 2018).

Another example is "Josie Pepper" a humanoid robot in Terminal 2 at Munich Airport and Lufthansa, equipped with AI to assist passengers by answering questions and providing directions. Unlike conventional robots, Josie Pepper can learn and adapt, enabling it to offer personalized responses to individual inquiries (Munich Airport, 2018). Moreover, AI is widely adopted for automated customer service chatbots, such as those used at Vienna Airport, AirAsia, and Ford Airport, providing customers with useful information automatically (Biswas et al., 2020).

As robotics-related technologies continue to advance, the aviation industry is increasingly adopting robot technology to meet the growing demand for convenient, efficient, and humanized airport services (Chen, 2022). However, notwithstanding the fact that their deployment is aimed at enriching the travel experience for passengers (Hoyer et al., 2020; Rajapaksha & Jayasuriya, 2020), the performance of these robotic systems, when compared to human assistance, is not always satisfactory (Hwang et al., 2023; Xiao & Kumar, 2021).

Research on the comparative analysis of service quality or performance offered by smart services and humans has been inconclusive. While some studies have highlighted the potential benefits of service robots in terms of operational efficiency and consistency (Huang & Rust, 2021; Ivanov et al., 2020; Ling & Weiguo, 2021), concerns remain regarding their ability to replicate the personalized touch and emotional intelligence that are inherent in human interactions (Choi et al., 2020; Zhang et al., 2022). In the tourism industry, empathy, flexibility, and intimacy are deemed critical (Prentice et al., 2020; Reis et al., 2020), hence, the adequacy of smart service robots in the event of service failure in comparison to human service may be questionable.

This research paper tries to contribute to this conflict and aims to shed light on what customers feel about when facing a service failure, such as lost luggage, and they must be assisted by a smart service robot versus a human. To accomplish this, the study will use face reader analysis to detect the emotions of the customers (Lewinski et al., 2014). Additionally, the study will explore the effect of robot recovery service versus human intervention on brand loyalty and negative word-of-mouth, which remains unknown (Shuqair et al., 2021), while considering the mediating roles of apology and courtesy. The objective is to provide useful insights that can guide decision-making in the aviation industry. Insights will be based on customer emotions and thoughts to determine the most effective agent type that can improve brand loyalty and prevent negative word-of-mouth.

2. LITERATURE REVIEW

2.1. Service failure

Service failures are a common problem in the aviation industry and are primarily attributed to the intricate nature of the service processes involved in providing air travel experiences (Steyn et al., 2011;Chou, 2015). As the airline industry continues to expand, a rise in dissatisfaction with services is inevitable. Service failure examples in the airline sector are mentioned in the survey of Steyn et al. (2011) and include flight delays, inadequate service provision, and mishandling of luggage.

Passengers often harbor specific expectations before their scheduled flights (Coye, 2004). Nevertheless, service failures create a noticeable gap between anticipated and actual travel experiences. Such failures occur when the delivered service falls short of customers' expectations (Chahal & Devi, 2015), encompassing outcome failures such as poor service and billing errors, or process failures such as unresponsive or impolite service employees (Harrison-Walker, 2019). Customers perceive severe service failures to be highly inconvenient and aggravating, causing them to feel like victims and seek amends to restore balance to the relationship (El-Manstrly et al., 2021).

Given the inevitability of disappointment with the service stemming from its unique characteristics and recognizing that companies cannot completely eliminate all disappointments, it is imperative for companies to explore solutions that effectively cope with service failures (Blodgett et al., 1997). In instances where failure recovery is ignored, service failures can have a detrimental impact on customers' continuous purchase intentions (Y. Zhu et al., 2023), escalating dissatisfaction, fostering switching intentions (Keaveney, 1995; Robertson, 2012), declining customer satisfaction, and triggering negative word-of-mouth (H. H. Lin et al., 2011). The repercussions of air service failures can be severe, burdening airline operators with significant financial losses (Chang & Chang, 2010), customer attrition, and the potential erosion of corporate reputation (H. H. Lin et al., 2011). As noted by Magnini et al. (2007) and Ngai et al. (2007), the aftermath of service failures can forge a mutually beneficial symbiotic relationship between customers and organizations through effective service recovery measures. Therefore, in order to mitigate the negative impact on the airline brand, it is imperative to investigate the service recovery.

2.2. Aviation Service Agents: Human vs. Smart Robots

Recognizing the inevitable nature of service failures in such a complex industry (Steyn et al., 2011), such failures can have a significant impact on brand loyalty and can lead to negative word-of-mouth from dissatisfied customers (Blodgett et al., 1997; Z. Zhu et al., 2013). To address these challenges and to enrich the customer experience, airlines use different service agents, such as human staff and smart service robots (West et al., 2018). This study aims to investigate the effects of service agent types on brand loyalty and negative word-of-mouth in the aviation sector.

Upon reviewing the literature, it has come to light that there are varying perceptions and evaluations of service robots among customers. For instance, customers tend to exhibit higher brand satisfaction with robotic servers as opposed to human servers (Hwang et al., 2021). On the other side, other surveys reveal that customers do not find robotic servers as satisfying as human servers (Paluch et al., 2020; Wirtz et al., 2018). Therefore, it is imperative to delve further into the literature review to gain a comprehensive understanding of the matter.

Starting with the positive aspects of service robots, in the context of frontline service, they can be seen as social robots that interact with customers to create value (Caic et al., 2019; Wirtz et al., 2018). Service robots with professional abilities are considered to be an improvement over human service, enhancing service performance (Ivanov et al., 2020; Huang & Rust, 2021; Ling & Weiguo, 2021) and improving customers' service experiences (Qiu et al., 2020). When customer value is combined with a positive experience, studies have shown that it can lead to increased brand loyalty (Mostert et al., 2009; Steyn et al., 2011; Hu et al., 2013). At the same time, effective service recovery measures can boost customers' trust and loyalty, ultimately increasing their likelihood of repurchasing in the future (Hu et al., 2013). Therefore, if robot service can lead to effective service recovery, it has the potential to drive brand loyalty and decrease negative word-of-mouth. Even though there is no research to approve this hypothesis, multiple studies (Blodgett et al., 1997; Boshoff & Leong, 1998; Smith et al., 1999;Weber & Sparks, 2009) have demonstrated that effective service recovery measures can result in customer satisfaction, positive word-of-mouth, repeat purchases, and loyalty.

Additionally, it is vital to note the significance of service robots' entertainment value for service outcomes (Morita et al., 2018). The novel and captivating ways in which robots provide service often evoke a sense of enjoyment and pleasure among customers, setting them apart from traditional human service (H. Lin et al., 2020). As a result, service robots possessing professional abilities and unique value can enhance service performance (Ivanov et al., 2020;Huang & Rust, 2021; Ling & Weiguo, 2021).

Adding another note in the positive aspect, smart service robots have become increasingly popular due to their ability to work efficiently and accurately for extended periods (Ivanov et al., 2020; Vatan & Dogan, 2021). Customers perceive more reliable service robots over human staff, particularly in repetitive and potentially risky tasks (Zhang et al., 2022). This has led to higher customer satisfaction levels, as they provide faster service speeds and higher quality services (Ivanov et al., 2020; Vatan & Dogan, 2021).However, despite their excellence in performing repetitive tasks and ensuring procedural accuracy, they may lack the emotional intelligence and personalized touch inherent in human interactions (Choi et al., 2020).

In general, the utilization of service robots offers various benefits such as improved operational efficiency, consistency, and contactless service delivery (Ivanov et al., 2020; Wirtz et al., 2018). Although service robots have been identified by scholars and practitioners as having the potential to enhance customer service, customer satisfaction, and sales revenue (Lu et al., 2020; Schatsky & Arora, n.d., 2017), a significant percentage of customers, up to 61%, still feel uncomfortable with the idea of interacting with robots (West et al., 2018).

In this way, the other side is coming to light where several surveys have shown that service robots do not perform as successfully as human staff. More specifically, the Service Robot Deployment model (Paluch, 2020; Wirtz & Zeithaml, 2018) states that while service robots are capable of carrying out service tasks with almost any degree of cognitive complexity, are limited in their ability to handle tasks that require high emotional/social complexity. According to a survey conducted by X. Zhang et al. (2022), human employees are deemed to be more responsive and empathetic than service robots, implying that robots currently lack the human touch necessary for certain interactions. Ivanov et al. (2020) also found that customers perceive a higher level of social skills and emotional intelligence when humans provide services as opposed to robots. As empathy, flexibility, and intimacy are crucial in tourism and hospitality services (Prentice et al., 2020; Reis et al., 2020), human recovery might be more suitable compared to smart service.

By extension, human-robot interaction plays a crucial role in shaping the customer experience (Choi et al., 2020; Fuentes-Moraleda et al., 2020). Service robots that are limited by their technology may not be able to provide efficient human-robot interactions, which can leave customers feeling dissatisfied and isolated (Xiao & Kumar, 2021). The perceived lack of emotional intelligence and the impersonal nature of interactions with smart service robots can worsen dissatisfaction and increase the likelihood of negative word-of-mouth (Choi et al., 2020). Consequently, service failures and inadequate service recovery may lead to dissatisfied customers sharing their grievances with others, resulting in negative word-of-mouth (H. H. Lin et al., 2011).

Buttle & Burton (2002) have contended that human service recovery can effectively reduce the likelihood of negative word-of-mouth by addressing customer concerns with empathy and personalized assistance. Recent research conducted by Boubker & Naoui (2022) has demonstrated that service quality and customer satisfaction can significantly enhance brand loyalty and generate positive word-of-mouth engagement. Moreover, human interaction is not only approved to be more effective in providing assistance and guidance than service robots (Hwang et al., 2023) but also can ensure adequate service quality compared to them (Yu & Ngan, 2019). This can also contribute to the fact that customers are not yet familiar with service robots, which makes them perceive the efficiency and convenience of robot service as relatively low (Lee & Kim, 2022).

There is disagreement on whether smart service robots or human staff are more effective employees. However, there is limited research on how the type of employee affects brand loyalty and word of mouth, especially in the aviation industry. Therefore, there is a need to investigate the following hypothesis:

H1a. The type of service agent (human versus smart robot) has a significant effect on brand loyalty after service failure.

H1b. The type of service agent (human versus smart robot) significantly affects negative word-of-mouth after a service failure.

2.3. Service Recovery Strategies

Effective service recovery management is a crucial element in service management, which involves implementing service recovery strategies. These strategies are meticulously designed to mitigate the negative consequences of service failures, not only by restoring customers to their pre-failure state but also by exceeding their expectations and providing complete satisfaction (Danaher & Mattsson, 1994; Davidow, 2003).

Implementing effective service recovery after service failures does not necessarily have adverse effects (K.-C. Hu et al., 2013). Even if organizations cannot entirely eliminate service failures (Steyn et al., 2011), they can still implement service recovery efforts to handle these failures effectively and maintain, or even improve, customer satisfaction and loyalty (Chou, 2015). Effective service recovery can lead to a mutually beneficial situation for both the customer and the organization, mitigating the potential negative consequences of service failures (Magnini et al., 2007;Ngai et al., 2007). Many researchers have also suggested that organizations can recover from service failures by using various strategies (Harrison-Walker, 2019; Liao, 2007; Mostafa et al., 2015; Smith et al., 1999), however in this paper will focus on apology (Boshoff & Leong, 1998; Chou, 2015; Mostert et al., 2009; van Hooijdonk & Liebrecht, 2021), and courteous and respectful behavior toward the complaining customer (Liao, 2007; Mostafa et al., 2015).

2.3.1. Apology

Expressing remorse for negative events and taking responsibility for them is the definition of apology ((Liao, 2007). This is significant when addressing customer complaints, as it demonstrates the company's acceptance of responsibility for the service failure and apology for the inconvenience caused to the customer. Offering an apology to a customer who has experienced a problem can be an effective way to reduce their anxiety and demonstrate that the company values their services and their well-being. Additionally, when a customer is complaining, they may be upset or angry, so offering an apology can help to defuse their emotions and prevent negative word-of-mouth from spreading (Boshoff & Leong, 1998). For instance, airlines that offer apologies to customers who have had negative experiences and complaints on social media platforms like Twitter can not only help to protect the airline's reputation but also prevent negative reviews from being shared widely (van Hooijdonk & Liebrecht, 2021).

Additionally, apologizing for a service failure can demonstrate politeness, courtesy, concern, effort, and empathy toward customers, which can improve their assessment of the encounter even in the case of a service failure (Chou, 2015; Smith et al., 1999; Hart et al., 1990). Research has shown that customers are more satisfied when an apology is given after a service failure (Conlon & Murray, 1996; Smith et al., 1999; Tax et al., 1998). By extension, satisfied customers tend to develop a fondness for the brand and are more likely to exhibit loyalty. Moreover, brand-loyal customers have the potential to become loyal and engage in positive word-of-mouth (Boubker & Naoui, 2022). Hence, apologies can mitigate the adverse effects of service failures and foster customer loyalty (Chou, 2015).

2.3.2. COURTESY

Customer service employees' demeanor, which includes politeness, friendliness, respect, and patience, is the foundation of being courteous while interacting with customers (Liao, 2007). Previous studies have shown that handling a customer's complaint with politeness can de-escalate the issue in the customer's mind (Tax et al., 1998). Blodgett et al. (1997) claimed that employees who behave rudely when dealing with customer complaints can lead to disastrous results, such as negative word-of-mouth. Although, it has not been examined explicitly in prior studies, being service provider courteous may act as a mediating mechanism through which courteous behaviors influence brand loyalty and decrease negative word-of-mouth. Brand loyalty and positive word-of-mouth are fostered when individuals feel they are treated with respect, dignity, and sensitivity (Boubker & Naoui, 2022).

The attribute of courtesy has emerged as a crucial characteristic of airline service quality (Tsaur et al., 2002) and customer satisfaction (Parasuraman et al., 1988). Recent research by Boubker & Naoui (2022)has demonstrated that service quality and customer satisfaction can significantly enhance brand loyalty and lead to positive word-of-mouth engagement. Notably, the correlation between customer satisfaction and loyalty is particularly robust among customers who perceive high levels of service quality (Kuo et al., 2013).This correlation emphasizes that customers, when treated courteously, are more inclined to exhibit repurchase behavior and are less likely to propagate negative word-of-mouth sentiments (Blodgett et al., 1997).

2.3.3. APOLOGY AND COURTESY MEDIATION ROLE

As T. (Terry) Kim et al. (2009) suggest, airlines must adopt a responsive approach toward any service failure by demonstrating empathy, attentiveness, and courteous and respectful behavior toward their customers. This can result in customer satisfaction and increase the likelihood of repeat purchases (Liao, 2007). Considering the criticality of apology and courtesy in such situations, a hypothesis is proposed as follows:

H2a. Apology mediates the effect of the type of agent on brand loyalty and negative word-of-mouth.

H2b. Being courteous mediates the effect of the type of agent on brand loyalty and negative word-of-mouth.

2.4. THE MODERATOR ROLE OF EMOTIONAL ENGAGEMENT

The repercussions of service failures prove to be detrimental to customer satisfaction and can evoke negative emotions that can overshadow positive experiences (Wen & Geng-qing Chi, 2013). Service failures are among the most significant causes of negative emotions in customers, and airline service failures can have a profound impact on them. Instances such as lost luggage can cause customers to experience stress and anxiety about their lost belongings, thereby diminishing their positive emotions (J. S. C. Lin & Liang, 2011). As a result, when service failures occur, customers are more likely to feel negative emotions such as frustration, annoyance, and anger (Wallin Andreassen, 2001).

There are various studies that demonstrate the significant impact of a customer's emotions on brand loyalty and negative word-of-mouth (Dewitt & Brady, 2003; Keaveney, 1995; N. Y. Kim & Park, 2016; Liljander & Strandvik, 1997; Stephens & Gwinner, 1998). In particular, if customers experience negative emotions following a service failure, this can have adverse effects on the company. Negative emotions have a greater negative influence on customer satisfaction, loyalty, and word-of-mouth recommendations compared to positive emotions (Liljander & Strandvik, 1997).

For instance, it has been extensively studied how anger affects individuals, and it has been found that when individuals feel angry, they tend to verbally and/or non-verbally attack the target (Deffenbacher et al., 2002; McColl-Kennedy & Smith, 2006) .This can lead to non-confrontational behaviors, such as exit, boycott, negative word of mouth, and complaints to third parties, all of which negatively impact the organization (Dewitt & Brady, 2003; Keaveney, 1995; Stephens & Gwinner, 1998). That is why the front-line employee(s) play a crucial role in handling customers' negative emotions (McColl-Kennedy & Smith, 2006; Valentini et al., 2020; van Dolen et al., 2004; Xu et al., 2019).

There is currently no significant research on how customers perceive the assistance provided by a smart service robot versus a human in the airline industry after experiencing a service failure. However, studies conducted in the hospitality industry indicate that people tend to enjoy and have positive emotions (such as happiness, felicity, great pleasure and delight) interacting with robots when dealing with simple tasks (Filieri et al., 2022). According to (Wirtz et al., 2021), robots may have an advantage in the tourism and hospitality industry by providing consistent information without affecting people's emotions.

On the other side, service robots have been identified by scholars and professionals as having the potential to enhance customer service, satisfaction, and revenue (Lacity & Willcocks, 2016; Lu et al., 2020), a significant percentage of customers, up to 61%, still feel uncomfortable interacting with robots (West, 2018). This is because, when it comes to complex information and emotionally challenging tasks, human employees are better equipped to provide customer service than robots (Xiao & Kumar, 2021). For instance, research conducted by Filieri et al. (2022) demonstrated that while 60% of customers who interacted with a smart robot were happy and had positive feelings, a significant percentage had negative emotions such as fear, anger, and sadness. This was because smart robots sometimes failed to assist customers successfully, or were too slow and annoying. As a result, while robots can be useful in improving business operations by providing consistent service quality, they cannot replace human intelligence, which includes important characteristics such as empathy, flexibility, and intimacy, all of which are essential in tourism and hospitality services (Prentice et al., 2020; Reis et al., 2020).

At the same time, the perception of quality in service-intensive industries such as travel and tourism is significantly influenced by the attitudes and behaviors of employees who serve customers (Anderson S. W. et al., 2009). Positive attitudes and behaviors of employees can strengthen the bond between customers and employees (Anderson S. W. et al., 2009). By demonstrating positive attitudes and behaviors, employees can create the perception that they are doing everything possible to address customer issues, which can help alleviate the negative emotions (X. Xu et al., 2019) resulting from service failures (Wallin Andreassen, 2001). However, researchers (Xiao & Kumar, 2021) have pointed out that smart service recovery may not be able to provide effective human-robot interactions. Due to the technical limitations of smart robots, they may not be able to provide the same level of courtesy as a human being, which may lead to negative feelings such as dissatisfaction and isolation among customers (Xiao & Kumar, 2021).

Furthermore, since effective recovery service strategies play a crucial role, research has shown that they can help dissipate negative emotions (Harrison-Walker, 2019). Conversely, the absence of recovery service strategies, such as an apology, can exacerbate negative emotions (Bunker & Ball, 2008). A sincere apology following a service failure can enhance the perception of the employees' regret and thus strengthen the seller-buyer relationship (Grégoire et al., 2009). Additionally, an apology can positively impact customers' evaluation of the recovery process and, in turn, enhance their positive emotions (Hart et al., 1990). An apology can also help compensate for the damage to customers' ego-identity and self-esteem and reduce their anger towards a service failure(Nguyen & Mccoll-Kennedy, 2003). However, customers tend to perceive an apology from a smart robot differently than from a human, which can significantly impact their emotional state. The reason behind this is that customers consider an apology from a human to be more genuine and truthful (Y. Hu et al., 2021), leading to disparate emotional reactions that need to be studied.

Based on the aforementioned discussion, this study proposes the following hypotheses:

H3a. Emotional engagement moderates the effect of the type of agent and the brand loyalty and negative word-of-mouth.

H3b. Emotional engagement moderates the effect of the type of agent and the recovery strategy (apology and be courteous).

Figure 1 illustrates the research model derived from the preceding hypotheses.

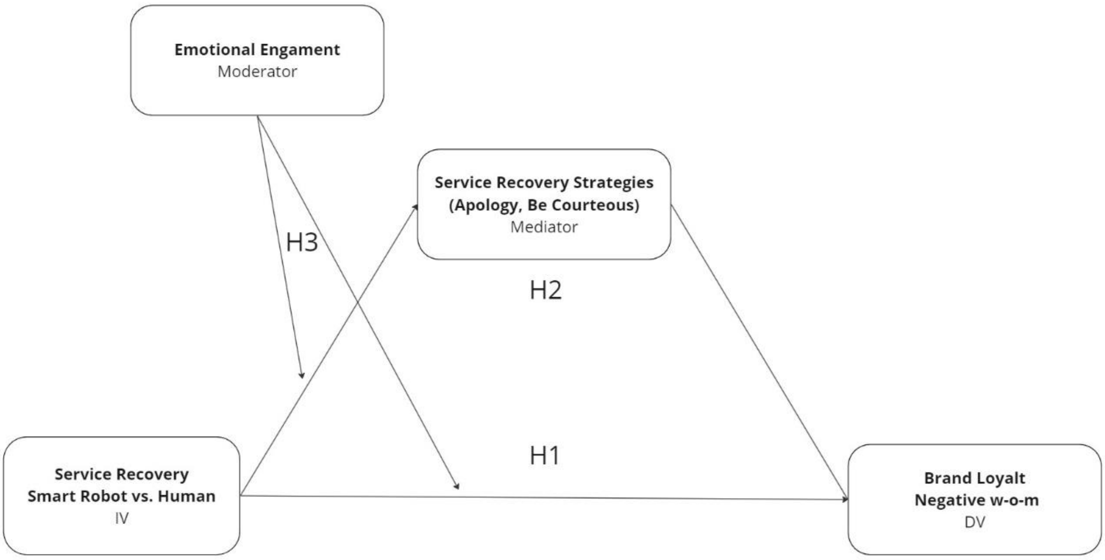

Figure 1 - Research Model

3. METHODOLOGY

3.1. STUDY DESIGN AND MEASUREMENT ITEMS

Two methods were used to achieve the research objectives: a neuromarketing study and an experimental study.

3.1.1. NEUROMARKETING STUDY

The facial expressions of the participants were recorded using FaceReader in the neuromarketing study. FaceReader is a software developed by Noldus that can accurately detect facial emotions at the millisecond level with over 89% accuracy (Lewinski et al., 2014). This commercial software provides an automated analysis of facial expressions for seven emotional states, including happiness, sadness, anger, surprise, fear, disgust, and neutral, which indicates the absence of emotional indicators. By aligning with the Facial Action Coding System (FACS), the software enables quantitative examination of the participant's facial expressions (Yu et al, 2017). The facial feature tracking tools in Noldus's FaceReader identify faces and determine changes from the neutral facial expression, such as shifts in mouth and eye corner movements. Any deviation from this neutral state, indicating emotion, is classified as an Action Unit (AU). Research suggests that there are about 58 distinct Aus (Grafsgaard et al., 2013; Maison & Pawłowska, 2017; Mcdaniel et al., 2007).

The FaceReader™ software was used in the default (general) setting (Lewinski et al., 2014), and two videos[1] were produced to stimulate customers' emotional responses. The first video showcased a human employee assisting a customer who lost their luggage at the airport (45 seconds), and the second depicted the same scenario with a smart robot employee (30 seconds). Each participant watched one of the two videos with a random selection. While the videos were being shown, participants' facial expressions were recorded and analyzed in real-time using advanced technological tools (i.e., FaceReader). To determine any differences in the emotional responses of the participants towards the two types of employees, the highest numerical value for each emotion and participant was extracted.

The FaceReader™ recognizes eight facial expressions, namely neutral, happy, sad, angry, surprised, scared, disgusted, and contempt. The tool measures these expressions on a scale from 0 to 1 (Gunaratne et al., 2019), with happy being deemed as a positive emotion, and sad, angry, scared, contempt, and disgusted being classified as negative emotions. However, surprised expressions can either be positive or negative depending on the context (Bartkiene et al., 2019). Apart from these expressions, there are two additional dimensions: valence and arousal. Valence ranges from -1 to 1 and indicates whether the emotional state of the person is positive or negative. Arousal, on the other hand, is measured on a scale from 0 to 1 and

[1] This is the link to access the videos: AI vs Human lost Luggage 1.zip

reflects the intensity or activity level of the person's response to the stimulus during video recording (Gunaratne et al., 2019).

Alongside the standard facial expressions, the tool provides data on custom expressions, including attention, boredom, confusion, interest, smiling, and leaning forward. FaceReader offers a wide range of customizable expressions and allows users to create new ones if needed (Tess den Uyl, n.d.). However, for the purposes of this study, our attention was directed towards attention, boredom, confusion, interest, smiling, and leaning forward which are measured on a scale from 0 to 1.

Moreover, it was necessary to exclude several factors that could affect the analysis. If not excluded, these factors could lead to a complex analysis with excessive and irrelevant data, which could potentially lead to misleading outcomes. Facial features and actions, such as pitch, yaw, roll, landmarks, 3D landmarks, quality metrics, and specific facial muscle movements labeled as Action Units (AUs), are among these factors. AUs include a variety of facial expressions, such as eyebrow movements, lip actions, chin and mouth gestures, and eye behaviors, as well as indicators like closed eyes. Additionally, physiological metrics like heart rate, heart rate variability (measured by RMSSD and SDNN), heart rate warnings, and confidence levels, as well as behavioral events like intake, chewing, and motion, and positional data such as horizontal and vertical gaze angles, were not taken into account (Ahn & Harley, 2020; Noordewier & van Dijk, 2019; Shen et al., 2022; N. Xu et al., 2018). By excluding these factors, the analysis could be more focused on the relevant aspects of facial expression and emotional response.

In addition, to make data analysis more efficient, we averaged the intensity of each emotion across all participants and consolidated the information into a single file for further examination. However, it is worth noting that many of the custom expressions were labeled as "UNKNOWN" in the output data. To address this challenge, we calculated the average for each custom expression where valid values were present. This approach enables us to use the available data effectively, focusing on instances where the expressions could be reliably identified and measured. Although FaceReader is a dependable tool for analyzing emotional responses via facial cues, its integration into research requires supplementary quantitative inputs and, therefore, an experimental survey is following.

3.1.2. EXPERIMENTAL STUDY

After watching a video, participants were asked to answer a questionnaire on a 9-point scale (ranging from 1 as strongly disagree to 9 as strongly agree). The questionnaire assessed negative word-of-mouth, adapted from (Maxham & Netemeyer, 2002), brand loyalty, adapted from (Dick & Basu, 1994; Buttle & Burton, 2002; Yang & Peterson, 2004), and perceived social service recovery strategies, which included apology and courteous behavior (Mostafa et al., 2015). The scales and their details can be found in Table 1. Additionally, participants were asked to confirm their study number (ranging from 1 to 110, one per participant) and the service provider (human or smart robot) as part of a manipulation check. An attention check was also conducted to ensure participant engagement. Demographic information such as age, gender, salary, and education were collected for analysis.

To ensure that the data collected from the FaceReader and the questionnaire could be accurately synchronized, participants were required to provide specific information that linked the data collected between the two sets of data. During the neuromarketing study, participants were asked to input a unique participant number (ranging from 1 to 110), along with their gender and age, which was also requested in the questionnaire. We established a clear correlation between the datasets by ensuring that participants provided identical details in both the FaceReader and questionnaire sessions. This meticulous matching process allowed us to precisely link the data collected from each participant across both platforms. By verifying that the participant details corresponded in both datasets, we effectively consolidated all the information into a single Excel file for thorough analysis.

Negative word-of-mouth	
I will complain to online sites or on social media about the airline company	Adopted from Maxham & Netemeyer, 2002
I will report my experience to other consumers	
I will spread the word about my misadventure	
Brand loyalty	
I will continue to recommend travel with this airline company to my friends and family	Adopted from Dick & Basu, 1994; Buttle & Burton, 2002; Yang & Peterson, 2004
I will continue to say positive things about this airline company to my friends and family	
I will continue to encourage my friends and family to use this airline company's services	
To travel with this airline company is my first choice	
I will travel again with this airline company in the future	
Social service recovery strategies: Apology	
The service provider apologized to me for what had happened	Adopted from Mostafa et al., 2015

The service provider expressed regret for the mistake that occurred The service provider apologized for the inconvenience the problem had brought to me The service provider apologized for what I had suffered because of the problem	
Social service recovery strategies: Being courteous	
The service provider was friendly to me The service provider was polite to me The service provider showed respect for me The service provider was patient with me	Adopted from Mostafa et al., 2015

Table 1 Summary of Measurement Items

3.2. SAMPLING TECHNIQUE AND DATA COLLECTION

One hundred and ten participants were recruited from the University Nova IMS area, and therefore the overwhelming majority of the participants were students. Initially, the participants had to read and agree on the acquisition of informed consent. Afterward, participants were randomly assigned to watch a video showcasing either a human employee or a smart service. The sample was equally divided, with 55 participants watching an AI video and 55 watching a human video. Right after the video, they had to reply to the questionnaire. However, 3.5% of the original sample had to be discarded due to invalid data resulting from covering their face with their finger, which rendered the FaceReader inoperable. An additional 4.5% of the original sample failed the attention check and were excluded from all analyses.

Since most of the participants were students, it is normal that the majority were under 25 years old (between 18 to 20, 44,6% and 21 to 25, 28,7%), had either graduated from high school (45.5%) or earned a bachelor's degree (35.6%), and had a yearly income of less than €29,000. Table 2 provides a detailed demographic breakdown of the sample.

Demographics	**Results (%)**	
Gender	Male	48,5%
	Female	51,5%
Age	18-20	44,6%

	21-25	28,7%
	26-30	15,7%
	31-35	5,0%
	36-40	2,0%
	>55	4,0%
Income	Prefer not to say	29,7%
	Under 10K€	10,9%
	10K€ – 19K€	16,8%
	20K€ – 29K€	16,8%
	30K€ – 49K€	11,9%
	50K€ - 60K€	7,9%
	More than 70K€	5,9%
Education	High school	45,5%
	Bachelor	35,6%
	Master	17,8%
	PHD	1,0%

Table 2 Respondents' Profile

4. RESULTS

4.1. METHODOLOGICAL APPROACH OF THE DATA ANALYSIS

The collected data was analyzed with the aid of SPSS Statistics version 29 (IBM). First, an independent samples t-test was done to determine the existence of significant differences between the mean scores of the dependent variable across the two groups (Parajuli, 2023). The objective of this test was to evaluate the disparity in service recovery perceptions between interactions with human employees and smart robots. The independent sample t-test was employed to compare the mean scores of the dependent variables, negative word-of-mouth and brand loyalty, and the mediator variables, social service recovery strategies (apology and being courteous) between participants who viewed a scenario featuring a human employee and those who viewed a scenario featuring a smart robot employee. This analysis was to ascertain whether significant differences existed in the perceptions of participants based on the type of service provider depicted in the videos.

Secondly, for a more in-depth analysis, we investigated the relationship between the independent variable (IV = type of employee, human versus smart robot), the dependent variables (DV = brand loyalty and negative word-of-mouth) with mediators the service recovery strategies (apology and be courteous) and the moderator emotional engagement. This entailed using the external tool v4.3 developed by Andrew F. Hayes, specifically applying Models 4 and 8. Model 4 was used in the context of checking the mediation effect of the type of employee on brand loyalty and negative word-of-mouth through apology and courtesy. Model 8 is tailored for conditional process analysis, helping to understand the conditional effects of the moderator on the relationship between the independent and dependent variables (Hayes, 2017). To evaluate the indirect impact and determine the best test of the moderator effect, we utilized the method for measuring indirect impact. Lastly, we determined 95% confidence intervals (CI) to establish the significance of the results.

4.2. DATA ANALYSIS USING INDEPENDENT SAMPLE T-TEST

4.2.1. DEPENDENT VARIABLE (BRAND LOYALTY AND NEGATIVE WORD-OF-MOUTH)

An independent-sample t-test was conducted to compare brand loyalty and negative word-of-mouth scores in human and robot service agent conditions after service failure. The assumption of homogeneity of variances was violated, as assessed by Levene's Test for Equality of Variances (brand loyalty: $F = 2.375$, $p = .126$, negative word-of-mouth: $F = 3.263$, $p = .074$). Therefore, the Welch-Satterthwaite correction was used. There is a significant difference in brand loyalty scores between human ($M = 3.78$, $SD = 1.26$) and robot ($M = 4.68$, $SD = 1.57$) service agents, $t(92) = -3.20$, $p = .002$ (two-tailed). Also, there is a significant difference in negative word-of-mouth scores between human ($M = 6.17$, $SD = 1.26$) and robot ($M = 5.47$, $SD = 1.72$) service agents, $t(87) = 2.34$, $p = .022$ (two-tailed). The mean difference was -0.90 for brand loyalty and 0.70 for negative word-of-mouth with a 95% confidence interval ranging from -1.47 to -0.34 and 0.10 to 1.30. The effect size, as measured by Cohen's d, was d -0.637, 95% CI [-1.03, -0.24] for brand loyalty and d, 0.469, 95% CI [-0.07, -0.86] for negative word-of-mouth, which indicates a medium to large effect size and a medium effect size according to Cohen's conventions, respectively. To summarize, in comparison to the human service agent group, participants in the smart robot service agent group indicated higher levels of brand loyalty and lower instances of negative word-of-mouth.

4.2.2. Mediator Variables (Service Recovery Strategies: Apology and be courteous)

Regarding the mediation effect of the recovery strategies methods and according to the results obtained from the independent-samples t-test analysis of the variable "apology" and "courtesy", a significant difference exists between the mean values of the two groups. More specifically, the assumption of homogeneity of variances is meeting, as assessed by Levene's test for equality of variances (apology: F = 9.603, p = .003, be courteous: F = 7.604, p = .007). The mean apology effectiveness score was significantly higher for the human-robot group (M = 6.64, SD = 1.57) compared to the human-human group (M = 5.09, SD = 2.28), a statistically significant difference, M = -1.56, 95% CI [-2.34, -0.78], t(99) = -3.97, p < .001 (two-tailed). The mean courtesy effectiveness score was also significantly higher for the human-robot group (M = 7.31, SD = 1.38) compared to the human-human group (M = 5.75, SD = 1.96), a statistically significant difference, M = -1.56, 95% CI [-2.23, -0.89], t(99) = -4.61, p < .001 (two-tailed). The effect size for the apology condition was large as indicated by Cohen's d (d = -0.79, 95% CI [-1.19, -0.38]). Similarly, the courtesy condition also showed a large effect size with Cohen's d (d = -0.92, 95% CI [-1.33, -0.51]). Overall, participants in the smart robot group reported higher mean scores for perceptions of apology and courtesy compared to those in the human group, indicating a greater sense of apology and courtesy receipt from smart robot interactions.

4.2.3. Moderator Variable (Emotional Engagement)

In the context of discussing the moderator effect, it is essential to note that emotional outcomes from FaceReader analysis reveal a significant difference between the two groups in terms of customer attention, leaning forward, and confusion levels. Levene's Test for Equality of Variances indicated equal variances for attention (F(1,99) = 32.772, p < .001), confusion (F(1,99) = 25.343, p < .001), and leaning forward (F(1,99) = 37.120, p < .001). Participants exhibited significantly higher attention levels during human-robot interactions (M = 0.80, SD = 0.36) compared to human-human interactions (M = 0.03, SD = 0.14), t(99) = -14.37, p < .001, 95% CI [-0.87, -0.66]. Moreover, they reported significantly greater confusion during human-human interactions (M = 0.93, SD = 0.14) than human-robot interactions (M = 0.17, SD = 0.36), t(99) = 14.20, p < .001, 95% CI [0.66, 0.87]. Regarding leaning forward behavior, there is a statistically significant difference between the groups. Leaning forward levels were slightly higher during human-robot interactions (M = 0.02, SD = 0.04) compared to human-human interactions (M = 0.001, SD = 0.007), t(99) = -3.64, p < .001, 95% CI [-0.033, -0.01]. Effect sizes were computed to determine the magnitude of differences. Cohen's d values revealed a moderate effect for attention (d = -2.86, 95% CI [-3.41, -2.30]) and confusion (d = 2.82, 95% CI [2.83, 3.38]), whereas a small effect was observed for leaning forward (d = -.73, 95% CI [-1.13, -.32]). In conclusion, these findings suggest that interactions between humans and robots garner more attention and cause less confusion than human-to-human interactions, with a slight increase in engagement indicated by forward-leaning behavior.

4.3. DATA ANALYSIS USING REGRESSION ANALYSIS TECHNIQUE

4.3.1. MEDIATION EFFECTS OF APOLOGY AND COURTESY ON BRAND LOYALTY AND NEGATIVE WORD-OF-MOUTH

Moving forward, we tested the relationship between the type of service agent (human vs. smart robot), brand loyalty, and negative word-of-mouth through the service recovery strategies. Hayes PROCESS v4.0 Model 4 was used to check the mediating effects of apology and courtesy on brand loyalty and negative word-of-mouth. The model summary for brand loyalty indicates a significant effect ($R^2 = 0.38$, $F(3, 97) = 5.21$, $p = .002$). Table 3 shows that the type of service agent (IV) is positively and significantly associated with brand loyalty ($\beta = 0.61$, $p = .047$), supporting hypothesis H1a. The type of service agent also significantly predicts the effectiveness of apology ($\beta = 1.56$, $p < .001$) and courtesy ($\beta = 1.56$, $p < .001$). However, the direct effects of apology ($\beta = 0.14$, $p = .19$) and courtesy ($\beta = 0.05$, $p = .69$) on brand loyalty are not significant, indicating that these mediators do not independently affect brand loyalty.

The bootstrapping results also show that the direct effect of the type of service agent on brand loyalty is significant ($\beta = 0.61$, $p = .047$, CI = 0.07 to 1.21), and the confidence interval does not encompass zero. The total indirect effect of the type of service agent on brand loyalty through apology and courtesy is significant ($\beta = 0.29$, CI = 0.04 to 0.63), indicating a partial mediation effect, thus supporting hypotheses H2a and H2b. The individual indirect effects through apology ($\beta = 0.22$, CI = -0.10 to 0.59) and courtesy ($\beta = 0.08$, CI = -0.26 to 0.51) were not significant.

Variable	Predictor	β	SE	t	p	LLCI	ULCI	SE	LLCI	ULCI
Apology	Constant	3.53	0.67	5.25	<.001	2.20	4.86			
	IV	1.56	0.39	4.01	<.001	0.79	2.33	0.39	0.81	2.32
Courtesy	Constant	4.18	0.58	7.25	<.001	3.04	5.33			
	IV	1.56	0.34	4.66	<.001	0.90	2.23	0.34	0.92	2.24
Brand Loyalty	Constant	2.17	0.52	4.16	<.001	1.14	3.21			
	IV	0.61	0.30	2.01	0.047	0.01	1.21	0.30	0.01	1.19
	Apology	0.14	0.11	1.32	0.19	-0.07	0.35	0.11	-0.06	0.36
	Courtesy	0.05	0.12	0.41	0.69	-0.19	0.29	0.12	-0.18	0.29

Table 3 Regression result for Brand Loyalty - Model 4

The model summary for negative word-of-mouth shows a significant effect ($R^2 = 0.31$, $F(3, 97) = 3.38$, $p = .021$). Table 4 indicates that the type of service agent does not have a significant direct effect on negative word-of-mouth ($\beta = -0.40$, $p = .209$), thus not supporting hypothesis H1b. The type of service agent significantly predicts the effectiveness of apology ($\beta = 1.56$, $p < .001$) and courtesy ($\beta = 1.56$, $p < .001$). However, the direct effects of apology ($\beta = -0.04$, $p = .781$) and courtesy ($\beta = -0.16$, $p = .281$) on negative word-of-mouth are not significant.

The bootstrapping results (table 5) show that the total indirect effect of the type of service agent on negative word-of-mouth through apology and courtesy is significant ($\beta = -0.31$, CI = -0.62 to -0.03), indicating partial mediation. Thus, this supports hypotheses H2a and H2b for negative word-of-mouth as well. The individual indirect effects through apology ($\beta = -0.06$, CI = -0.34 to 0.42) and courtesy ($\beta = -0.25$, CI = -0.75 to 0.10) were not significant.

Variable	Predictor	β	SE	t	p	LLCI	ULCI	SE	LLCI	ULCI
Apology	Constant	3.53	0.67	5.25	<.001	2.20	4.86			
	IV	1.56	0.39	4.01	<.001	0.79	2.33	0.39	0.77	2.30
Courtesy	Constant	4.18	0.58	7.25	<.001	3.04	5.33			
	IV	1.56	0.34	4.66	<.001	0.90	2.23	0.34	0.90	2.23
Negative WORD-OF-MOUTH	Constant	7.68	0.56	13.76	<.001	6.57	8.79			
	IV	-0.40	0.31	-1.27	0.21	-1.02	0.23	0.31	-1.03	0.18
	Apology	-0.04	0.13	-0.28	0.78	-0.29	0.22	0.11	-0.23	0.23
	Courtesy	-0.16	0.15	-1.08	0.28	-0.46	0.13	0.15	-0.46	0.06

Table 4 Regression result for Negative word-of-mouth - Model 4

Indirect Path	β	SE	LLCI	ULCI
Brand Loyalty				
Total Indirect Effect	0.29	0.15	0.04	0.63
Through Apology	0.22	0.17	-0.10	0.59
Through Courtesy	0.08	0.19	-0.26	0.51
Negative WORD-OF-MOUTH				
Total Indirect Effect	-0.31	0.15	-0.62	-0.03
Through Apology	-0.06	0.18	-0.34	0.42
Through Courtesy	-0.25	0.21	-0.75	0.10

Table 5 Indirect Effects (Bootstrap Results) - Model 4

4.3.2. Moderated Mediation Analysis with Emotional Engaging Moderator

In the next phase, we included the moderator's emotional engagement in our analysis and employed Hayes PROCESS v4.0 Model 8 to examine the moderated mediation effects. The analysis explored how the type of service agent (human vs. smart robot) influences brand loyalty and negative word-of-mouth (word-of-mouth) after a service failure, through mediators like apology and courtesy, with emotional engagement serving as a moderator.

However, this moderator encompasses various emotional states identified by FaceReader. In our analysis, the emotions of happiness, anger, interest, and confusion are in detail explained. The additional results from FaceReader, neutrality, sadness, scared, fear, disgust, contempt, surprise, smiling, boredom, attention, valence, and arousal, along with their statistical results, can be found in the appendix.

Overall, while the type of service agent influenced some outcomes, the moderated mediation effects of emotional engagement were largely non-significant. This suggests that the indirect effects of apology and courtesy on brand loyalty and negative word-of-mouth are not moderated by emotional states like anger, happiness, confusion, neutrality, sadness, fear, disgust, boredom, attention, contempt, surprise, scared, smiling, valence, and arousal. Detailed statistical analyses of these effects are discussed in the next chapters, with additional results provided in the appendix.

4.3.2.1. Moderated Mediation Analysis with Interest as Moderator

The regression results from the brand loyalty as dependent variable (DV) indicate that the type of service agent (IV) significantly predicts the level of apology offered, with a coefficient of 1.553 (95% CI = 0.70; 2.40, $p < .001$). However, the interaction between the type of service agent and emotional engagement (IV x Interest) does not significantly predict the level of apology ($\beta = 10.61$, 95% CI = -36.47; 57.68, $p = .66$). This suggests that while the type of service agent influences apologies, this effect is not moderated by emotional engagement. For courtesy, the type of service agent significantly predicts courtesy levels with a coefficient of 1.54 (95% CI = 0.77; 2.31, $p < .001$). The interaction term (IV x Interest) does not significantly predict courtesy levels ($\beta = 7.01$, 95% CI = -42.95; 56.97, $p = .78$), indicating no moderating effect of emotional engagement.

When considering brand loyalty, the model reveals that both the type of service agent and its interaction with emotional engagement significantly predict brand loyalty (IV: $\beta = 0.64$, 95% CI = 0.05; 1.22, $p = .034$; IV x Interest: $\beta = 17.74$, 95% CI = 2.86; 32.62, $p = .02$). The conditional effect of the type of service agent on brand loyalty is significant at higher levels of emotional engagement (Interest = 0.01, effect = 0.78, 95% CI = 0.17; 1.38, $p = .012$), but not at lower levels (Interest = -0.02, effect = 0.37, 95% CI = -0.25; 0.99, $p = .235$). The indices of moderated mediation for both apology and courtesy are not significant (Apology: index = 1.38 95% CI = -1.55; 8.91; Courtesy: index = 0.28, 95% CI = -3.40; 6.01), suggesting that the indirect effects of the type of service agent on brand loyalty through apology and courtesy are not moderated by emotional engagement.

The results of the negative word-of-mouth as a dependent variable indicate that the type of service agent significantly predicts apologies ($\beta = 1.55$, 95% CI = 0.70; 2.40, $p < .001$). However, the interaction term (IV x Interest) does not significantly influence apologies ($\beta = 10.61$, 95% CI = -36.47; 57.68, $p = .66$). Similarly, the type of service agent significantly predicts courtesy

(β = 1.54, 95% CI = 0.78; 2.31, $p < .001$), but the interaction term does not (β = 7.01, 95% CI = -42.95; 56.97, p = .78).

For negative word-of-mouth, the model does not find a significant direct effect of the type of service agent (IV: β = -0.42, 95% CI = -1.07; 0.24, p = .21) or its interaction with emotional engagement (IV x Interest: β = -21.02, 95% CI = -50.94; 8.90, p = .17). Additionally, the conditional direct effects of the type of service agent on negative word-of-mouth are not significant at different levels of emotional engagement (Interest = 0.01, effect = -0.59, 95% CI = -1.37; 0.20, p = .14; Interest = -0.02, effect = -0.11, 95% CI = -0.74; 0.54, p = .73). The indices of moderated mediation for both apology and courtesy are also not significant (Apology: index = -0.15, 95% CI = -5.20; 4.71; Courtesy: index = -1.21, 95% CI = -12.14; 3.13), indicating no significant moderated mediation effect on negative word-of-mouth.

To sum up, the analysis supports H1a partially, showing that the type of service agent significantly affects brand loyalty, and this effect is moderated by emotional engagement interest. However, H1b is not supported as the type of service agent does not significantly affect negative word-of-mouth. H2a and H2b are not supported as the indirect effects through apology and courtesy are not significant, and emotional engagement interest does not moderate these mediations. Finally, H3a is partially supported for brand loyalty but not for negative word-of-mouth. The indices of moderated mediation for both dependent variables are not significant, indicating no significant moderating effect of emotional engagement interest on the indirect effects through apology and courtesy (H3b).

4.3.2.2. Moderated Mediation Analysis with Confusion as Moderator

For brand loyalty, the first model tested the mediation effect of apology and courtesy with confusion as a moderator. The overall model was statistically significant with an R-squared of 0.15 ($F(5, 95)$ = 2.88, p = 0.02). However, the direct effect of the type of service agent on brand loyalty was not significant (b = 0.99, 95% CI = -6.74; 8.72, p = 0.80). Neither apology (b = 0.14, 95% CI = -0.07; 0.35, p = 0.19) nor courtesy (b = 0.05, 95% CI = -0.19; 0.29, p = 0.69) showed significant direct effects on brand loyalty. Furthermore, the interaction term (IV x Confusion) was also not significant (b = -0.48, 95% CI = -20.03; 19.08, p = 0.96).

For negative word-of-mouth, the overall model was marginally non-significant with an R-squared of 0.11 ($F(5, 95)$ = 1.913, p = 0.10). The direct effect of the type of service agent on negative word-of-mouth was not significant (b = -0.74, 95% CI = -2.00; 0.53, p = 0.25). Similarly, apology (b = -0.03, 95% CI = -2.00; 0.22, p = 0.82) and courtesy (b = -0.17, 95% CI = -0.46; 0.12, p = 0.25) did not show significant direct effects. The interaction term (IV x Confusion) was also not significant (b = -0.63, 95% CI = -3.58; 2.32, p = 0.67).

The conditional indirect effects of apology and courtesy were also examined. None of the indirect effects were significant across different levels of confusion, as indicated by their confidence intervals crossing zero. For example, the conditional indirect effect of IV on DV brand loyalty through Apology at Confusion = 0.32 had a confidence interval that included zero (LLCI = -0.12, ULCI = 0.70) and on DV negative word-of-mouth through Apology at Confusion = 0.32 had a confidence interval that included zero (LLCI = -0.39, ULCI = 0.44). The index of moderated mediation for both mediators also included zero, indicating no significant moderated mediation effect (Brand loyalty: Apology: index = 0.04, 95% CI = -1.28 to 1.90; Courtesy: index = -0.04, 95% CI = -1.01 to 0.61), (Negative word-of-mouth: Apology: index = -0.01, 95% CI = -1.03 to 0.84; Courtesy: index = 0.15, 95% CI = -0.84 to 2.18).

Overall, the analyses did not support the hypotheses that the type of service agent significantly affects brand loyalty or negative word-of-mouth either directly or indirectly through apology or courtesy. In addition, confusion did not have a significant moderating effect. Therefore, the data did not support hypotheses H1a, H1b, H2a, H2b, H3a, and H3b. The confidence intervals for the indices of moderated mediation consistently included zero, indicating no significant moderating effect of confusion on the indirect relationships between the type of service agent and the outcome variables.

4.3.2.3. Moderated Mediation Analysis with Happy as Moderator

For the moderated mediation model where brand loyalty is the dependent variable, the overall model was significant ($R^2 = .195$, $F(5, 95) = 4.87$, $p = .001$), indicating that the predictors explain approximately 19.5% of the variance in brand loyalty. The direct effect of IV on brand loyalty was not significant ($\beta = .57$, $p = .08$), with the 95% CI ranging from -.067 to 1.204, suggesting no direct influence when considering the entire sample. However, the conditional direct effects of IV on brand loyalty at different levels of happiness revealed a significant effect when happy was low (effect = .93, $p = .015$, 95% CI [.186, 1.668]), but not when happy was high (effect = .14, $p = .79$, 95% CI [-0.96, 1.24]).

The indirect effect of IV on brand loyalty through Apology and courtesy was not significant at any level of happiness (LLCI and ULCI include zero, Table 6), indicating that recovery strategies did not mediate the relationship.

Mediator	Happy Level	β	SE	LLCI	ULCI	Significance
Apology	-0.01	0.19	0.16	-0.09	0.56	Not Significant
	-0.01	0.20	0.16	-0.09	0.56	Not Significant
	0.01	0.25	0.19	-0.10	0.64	Not Significant
Courtesy	-0.01	0.09	0.17	-0.18	0.49	Not Significant
	-0.01	0.10	0.17	-0.19	0.50	Not Significant
	0.01	0.14	0.22	-0.25	0.63	Not Significant

Table 6 Moderated Mediation Model for Brand Loyalty

The index of moderated mediation for happiness was not significant (index = 2.94, SE = 5.36, 95% CI [-10.24, 12.61]), suggesting that emotional engagement did not moderate the mediation effect of either Apology or Courtesy on the relationship between IV and brand loyalty.

On the other side, for the model with negative word-of-mouth as the dependent variable, the overall model was not significant ($R^2 = 0.10$, $F(5, 95) = 1.85$, $p = .11$), indicating that the predictors do not significantly explain the variance in negative word-of-mouth. The direct effect of IV on negative word-of-mouth was not significant ($\beta = -0.40$, $p = .24$, 95% CI [-1.06, .26]), showing no direct influence of service agent type on negative word-of-mouth.

The conditional direct effects of IV on negative word-of-mouth at different levels of happiness were also not significant. The indirect effects of IV on negative word-of-mouth through both Apology and Courtesy were not significant across different levels of happiness, as the LLCI and ULCI contained zero in all instances (Table 7).

Effect Type	Happy Level	β	SE	LLCI	ULCI	Significance
	-0.01	-0.39	0.43	-1.23	0.46	Not Significant
Direct	-0.01	-0.40	0.36	-1.11	0.33	Not Significant
	0.01	-0.41	0.67	-1.74	0.91	Not Significant
	-0.01	0.05	0.17	-0.34	0.35	Not Significant
Indirect (Apology)	-0.01	0.05	0.17	-0.34	0.35	Not Significant
	0.01	0.07	0.19	-0.41	0.38	Not Significant
	-0.01	-0.21	0.19	-0.65	0.08	Not Significant
Indirect (Courtesy)	-0.01	-0.22	0.19	-0.67	0.08	Not Significant
	0.01	0.30	0.24	-0.83	0.11	Not Significant

Table 7 Moderated Mediation Model for Negative word-of-mouth

The index of moderated mediation for happy was not significant (index = -.760, SE = 3.77, 95% CI [-8.97, 7.26] for Apology, and index = -4.52, SE = 5.39, 95% CI [-15.98, 5.53] for Courtesy), indicating that emotional engagement did not moderate the mediation effects of Apology or Courtesy on the relationship between IV and negative word-of-mouth.

The analyses did not support the hypotheses that the type of service agent (human versus smart robot) significantly affects brand loyalty (H1a) and negative word-of-mouth (H1b) after a service failure. Additionally, there was no evidence that apology or courtesy (H2a and H2b) mediated these relationships. Moreover, emotional engagement (happy) did not moderate the effects of the type of service agent on brand loyalty or negative word-of-mouth (H3a), nor did it influence the mediation effects (H3b). The lack of significant moderated mediation effects was further confirmed by the non-significant indices of moderated mediation and the inclusion of zero within the 95% confidence intervals.

4.3.2.4. MODERATOR MEDIATION ANALYSIS WITH ANGRY AS MODERATOR

In this analysis, the model examines how the type of service agent (human versus smart robot, denoted as IV) impacts brand loyalty (DV) and negative word-of-mouth (DV) after a service failure, through two mediators, apology and courtesy, and with emotional engagement angry as a moderator.

For the outcome variable brand loyalty, the model summary shows a significant overall model (R2 = 0.23, F(5, 95) = 6.121, p < .001). However, individual predictors like IV, apology, and courtesy did not have significant direct effects. IV's direct effect on brand loyalty was not significant (β = 0.57, p = 0.32). The interaction term (IV × Angry) also was not significant (β = -43.92, p = 0.62), suggesting that emotional engagement does not significantly moderate the direct relationship between the type of service agent and brand loyalty. The conditional indirect effects of IV on brand loyalty through apology and courtesy at various levels of anger were also non-significant, as indicated by bootstrap confidence intervals that include zero (table XXX). Specifically, for apology as a mediator, the index of moderated mediation was 0.950 (95% CI: -11.80, 13.09), and for courtesy as a mediator, the index of moderated mediation was -0.08 (95% CI: -8.19, 4.61), indicating no significant moderated mediation.

For the outcome variable negative word-of-mouth, the model summary also indicates a significant overall model (R2 = 0.23, F(5, 95) = 5.515, p < .001). The direct effect of IV on negative word-of-mouth was not significant (β = -0.33, p = 0.37). The interaction term (IV × anger) was again not significant (β = 44.34, p = 0.29), indicating no significant moderating effect of emotional engagement on the relationship between the type of service agent and negative word-of-mouth. The conditional indirect effects of IV on negative word-of-mouth through apology and courtesy across different levels of anger were non-significant. The index of moderated mediation for apology was -0.54 (95% CI: -6.08, 7.61) and for courtesy was 0.54 (95% CI: -11.68, 7.13), both indicating no significant moderated mediation effects.

The findings suggest that the type of service agent (human vs. smart robot) does not significantly impact brand loyalty or negative word-of-mouth directly or indirectly through apology and courtesy when considering the moderating role of emotional engagement. This implies that neither the mediation by an apology and courtesy nor the moderation by emotional engagement significantly influences the relationships hypothesized in H1a, H1b, H2a, H2b, H3a, and H3b. The non-significant indices of moderate mediation further support the lack of significant moderate mediation effects in these models.

DV	Mediator	Angry Level	β	SE	LLCI	ULCI	Significance
Brand Loyalty	Apology	-0.01	0.26	0.18	-0.01	0.71	Non-significant
		-0.01	0.27	0.18	-0.01	0.70	Non-significant
		0.01	0.28	0.21	-0.02	0.80	Non-significant
	Courtesy	-0.01	0.03	0.20	-0.36	0.42	Non-significant
		-0.01	0.03	0.20	-0.36	0.42	Non-significant
		0.01	0.03	0.21	-0.45	0.38	Non-significant
Nwom	Apology	-0.01	-0.15	0.17	-0.45	0.22	Non-significant
		-0.01	-0.15	0.17	-0.45	0.22	Non-significant
		0.01	-0.16	0.18	-0.48	0.24	Non-significant
	Courtesy	-0.01	-0.17	0.20	-0.65	0.15	Non-significant
		-0.01	-0.17	0.20	-0.64	0.16	Non-significant
		0.01	-0.16	0.22	-0.70	0.16	Non-significant

Table 8 Moderator Angry - Regression result (Model 8)

5. DISCUSSION

The findings suggest that despite the statistically significant differences in service recovery strategies between participants exposed to customer service videos featuring either human or smart robot agents, participants exhibited moderate levels of perceived apology and courtesy. At the same time, the mediating roles of apology and courtesy were not as impactful as anticipated. While these strategies are crucial for service recovery (Mostafa et al., 2015), their direct influence on brand loyalty and negative word-of-mouth has a partial mediation effect. This means that the service recoveries (apology and courtesy) were not so effective in the context of a service failure in the aviation industry, in particular, losing a customer's luggage. The importance of effective service recovery strategies is well-documented (Danaher & Mattsson, 1994; Davidow, 2003), as inadequate service recovery can result in negative consequences for both the customer and the organization (Magnini et al., 2007; Ngai et al., 2007). In this case, low brand loyalty levels were noticed among participants exposed to customer service videos featuring either human or smart robot agents, with slightly higher levels for smart service. Additionally, both groups have a moderate tendency to spread negative thoughts about the company, with a higher tendency for the group that was served by a human.

The slight increase in brand loyalty, as well as the reduced tendency to express negative feedback among customers served, which is an outcome of the better performance of the service recovery strategy by smart robots, may be attributed to the innovative and engaging ways in which robots deliver service (Hoyer et al., 2020; Rajapaksha & Jayasuriya, 2020). Simultaneously, at higher levels of emotional engagement of interest, the type of service agent (and in this case, smart robot, since it is one with the higher mean) has a significant positive effect on brand loyalty when customers are highly interested. This is because smart robots, with their engaging and stimulating interactions, are better able to leverage high customer interest to foster stronger loyalty compared to human agents. Interacting with smart robots often evokes a sense of enjoyment and pleasure among customers, distinguishing them from traditional human service (H. Lin et al., 2020). With people constantly familiarizing themselves with new trends in technology and seamlessly integrating artificial intelligence into their lives (R. S. T. Lee, 2020), it makes sense to explore and leverage the advantages that AI and robotic customer service can offer.

The participants' interest in smart robot service is also confirmed by the results from FaceReader, where the higher attention and leaning levels in the smart robot group suggest that interactions with them may be more engaging and cognitively stimulating for customers. This increased engagement slightly enhances the overall customer experience, leading to better information retention and a more positive perception of the service (Hoyer et al., 2020). In contrast, the higher confusion levels in the human interaction group indicate that human-led customer service might sometimes be inconsistent and less courteous, leading to increased cognitive load and frustration for customers (Griffith & Roberts, 2023).

5.1. THEORETICAL IMPLICATIONS

From a theoretical perspective, this investigation significantly extends the literature in several key ways. First, the study's findings have substantial theoretical ramifications for future research in the fields of service recovery and customer relationship management within the aviation sector. While some studies have addressed service recovery in tourism (Chang & Chang, 2010; Kuo et al., 2013; Lv et al., 2022; Valentini et al., 2020; X. Xu et al., 2022; X. Xu & Liu, 2022), this is the first research to consider the implementation of smart services specifically in the aviation industry. Previous studies have typically focused on hospitality, comparing human service to robot service in restaurants (Blöcher & Alt, n.d.; Hwang et al., 2022; X. Zhang et al., 2022) or hotels (Bowen & Morosan, 2018; Kang et al., 2023; Li et al., 2021; H. Lin et al., 2020; Lv et al., 2022; Qiu et al., 2020; Reis et al., 2020). Given the high incidence of service failures in the aviation sector, such as the frequent issue of lost luggage, this study provides valuable insights into handling these situations. Although our research did not yield the desired results, it may inspire future studies to refine the research model and explore alternative strategies that could prove more effective.

Additionally, the study's findings serve as a valuable reference point for those interested in the practical application of AI in customer service roles and the theoretical exploration of human-robot interactions in service settings. The existing literature in the aviation sector has numerous papers investigating effective methods of service recovery after failure, but these primarily focus on traditional human customer service (Bamford & Xystouri, 2005; Chang & Chang, 2010; K.-C. Hu et al., 2013; N. Y. Kim & Park, 2016; Leon & Dixon, 2023; Mantin & Wang, 2012; Migacz et al., 2018; Mostert et al., 2009; Nikbin et al., 2015; Steyn et al., 2011; Tran, 2024; Tsaur et al., 2002; van Hooijdonk & Liebrecht, 2021; Weber & Sparks, 2004; Wen & Geng-qing Chi, 2013; X. Xu et al., 2019). Our research, however, offers insights into the differential impacts of human agents versus smart robots in service recovery scenarios. This introduces a new dimension to understanding how the type of customer service influences customer responses after service failures, particularly concerning brand loyalty and negative word-of-mouth.

Finally, the study's specific findings are essential for anyone interested in FaceReader technology. Few studies utilize FaceReader analysis, a relatively new tool with some limitations, yet it is useful for accurately analyzing human emotions (Peng et al., 2022). By examining the interplay between agent type, recovery strategies, and emotional engagement, our study provides a nuanced understanding of how different elements interact to influence customer outcomes. This research thus contributes to the body of knowledge on the psychological mechanisms underlying customer reactions to service recovery.

5.2. PRACTICAL IMPLICATIONS

With the increasing integration of AI into daily life and companies' ongoing commitment to enhancing customer experiences (Hoyer et al., 2020; Rajapaksha & Jayasuriya, 2020), the inclusion of AI technologies is becoming increasingly prevalent. This research may inspire airlines to explore more effective strategies for addressing service failures. Service failures are a source of frustration for both customers and companies, making prompt and effective resolution crucial (Hocutt et al., 2006; Nikbin et al., 2015).

As evidenced by this research, the integration of artificial intelligence can slightly improve the handling of such situations, leading to higher customer satisfaction. Interactions with robots tend to be engaging for customers (Hoyer et al., 2020). Developing sophisticated algorithms for intelligent robots to manage common service failures—such as lost luggage—could alleviate the burden on human workers who must deal with distressed customers.

Additionally, it would be a great idea to conduct pilot tests at major airports where robots are already in use and customers are familiar with interacting with them. This would enable the collection of valuable data on the effectiveness of AI in service recovery and gauge customer acceptance and feedback. Such pilot programs could provide critical insights for airline companies and pave the way for broader implementation of AI solutions in the aviation industry.

5.3. Study Limitations And Future Research

The current research exhibits several limitations. One significant limitation is the scarcity of literature specifically related to customer service in the aviation sector. Most of the existing resources are focused on the hospitality sector (Bowen & Morosan, 2018; Hwang et al., 2022; Kang et al., 2023; Li et al., 2021; H. Lin et al., 2020; Lv et al., 2022; Qiu et al., 2020; Reis et al., 2020; X. Zhang et al., 2022). This limitation highlights the need for more aviation-specific studies to build a robust bibliography in this area.

Another limitation is the study sample, which consisted predominantly of university students under 25 years old. This demographic likely lacks extensive experience with airline companies, potentially introducing bias into the survey results. Additionally, the small sample size further limits the study's generalizability. Future research should address this by conducting similar studies in environments like airports or tourist areas where a more diverse population, including different ages and nationalities, can be surveyed to provide a more comprehensive perspective. Furthermore, this study did not account for participants' prior experiences with airline companies. Failing to consider whether participants had previously faced issues with airlines might have affected their responses. Future research should include questions about participants' past experiences with airlines to control for this variable, as individuals with several bad experiences may have a significantly different perspective compared to those who have not encountered any issues.

There is also a technical limitation related to the FaceReader software used in this study. Although FaceReader is a reliable tool, its accuracy can be compromised by factors such as lighting conditions and participant movements. Additionally, some custom expressions were labeled as "UNKNOWN," which may have influenced the results. Future research should consider these limitations and possibly use complementary emotion detection methods to ensure more accurate data collection.

Moreover, this study focused on only two recovery strategies: apology and courtesy. Future studies should explore a wider range of recovery strategies or different combinations thereof. Specifically, future research should investigate the effectiveness of compensation, problem-solving, speed of response, and explanations, as these factors may also play significant roles in mediating customer satisfaction and loyalty.

Future research should also consider the potential benefits of a hybrid approach to customer service, combining AI-driven solutions with human interventions. The current study suggests that AI can slightly enhance brand loyalty and reduce negative word-of-mouth compared to human-only interactions. However, a hybrid approach might yield even better results. As technology advances and customers become more accustomed to AI-driven solutions, a hybrid approach that combines AI with human interaction could improve customer satisfaction and emotional responses. This investigation of the hybrid approach could offer valuable insights, enhancing brand loyalty, and reducing the negative word-of-mouth.

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APPENDIX

APPENDIX A. NOVA IMS Ethics Committee Approval

NOVA IMS | Ethics Committee - APPROVED

This is to certify that

Project No.: **DDMKT2024-2-216462**

Project Title: **Human or Smart Robots service? The effect of type of employee on brand loyalty and negative w-o-m and the moderator role of emotional engagement**

Principal Researcher: **Efstathia Styliagkatzi**

according to the regulations of the Ethics Committee of NOVA IMS and MagIC Research Center this project was considered to meet the requirements of the NOVA IMS Internal Review Board, being considered **APPROVED** on 2/21/2024.

It is the Principal Researcher's responsibility to ensure that all researchers and stakeholders associated with this project are aware of the conditions of approval and which documents have been approved.

The Principal Researcher is required to notify the Ethics Committee, via amendment or progress report, of

- Any significant change to the project and the reason for that change;
- Any unforeseen events or unexpected developments that merit notification;
- The inability of the Principal Researcher to continue in that role or any other change in research personnel involved in the project.

Lisbon, 2/21/2024

NOVA IMS Ethics Committee
ethicscommittee@novaims.unl.pt

APPENDIX B Summary of t-test results

Variable	Group	Mean (M)	Standard Deviation (SD)	t-value	p-value	95% Confidence Interval	Effect Size (Cohen's d)
Brand Loyalty	Human	3.78	1.26	-3.20	.002	[-1.47, -0.34]	-0.637
	Robot	4.68	1.57				
Negative WORD-OF-MOUTH	Human	6.17	1.26	2.34	.022	[0.10, 1.30]	0.469
	Robot	5.47	1.72				
Apology	Human	5.09	2.28	-3.97	< .001	[-2.34, -0.78]	-0.79
	Robot	6.64	1.57				
Be Courteous	Human	5.75	1.96	-4.61	< .001	[-2.23, -0.89]	-0.92
	Robot	7.31	1.38				
Attention	Human	0.03	0.14	-14.37	< .001	[-0.87, -0.66]	-2.86
	Robot	0.80	0.36				
Confusion	Human	0.93	0.14	14.20	< .001	[0.66, 0.87]	2.82
	Robot	0.17	0.36				
Leaning Forward	Human	0.001	0.007	-3.64	< .001	[-0.033, -0.01]	-0.73
	Robot	0.02	0.04				

APPENDIX C Moderator Neutral - Regression result (Model 8)

DV	Effect Type	**Neutral Level**	β	SE (HC4)	t	p	SE	LLCI	ULCI
Brand Loyalty	**Direct Effect**	-0.17	0.81	0.99	0.81	0.42	-	-	-
		0.06	0.54	0.31	1.75	0.08	-	-	-
		0.13	0.45	0.41	1.10	0.28	-	-	-
	Indirect Effect (via Apology)	-0.17	0.23	-	-	-	0.20	-0.12	0.67
		0.06	0.24	-	-	-	0.19	-0.12	0.64
		0.13	0.25	-	-	-	0.20	-0.11	0.66
	Indirect Effect (via Courtesy)	-0.17	0.07	-	-	-	0.24	-0.31	0.68
		0.06	0.06	-	-	-	0.19	-0.26	0.50
		0.13	0.05	-	-	-	0.18	-0.27	0.47
	Index of Moderated Mediation	-	0.04	-	-	-	0.42	-0.91	0.89
		-	-0.04	-	-	-	0.42	-1.19	0.63
Nwom	**Direct Effect**	-0.17	-0.97	0.67	-1.45	0.15	-	-	-
		0.06	-0.23	0.31	-0.75	0.46	-	-	-
		0.13	0.01	0.40	0.03	0.98	-	-	-
	Indirect Effect (via Apology)	-0.17	-0.08	-	-	-	0.20	-0.42	0.42
		0.06	-0.08	-	-	-	0.20	-0.43	0.40
		0.13	-0.08	-	-	-	0.21	-0.45	0.40
	Indirect Effect (via Courtesy)	-0.17	-0.25	-	-	-	0.28	-0.96	0.17
		0.06	-0.21	-	-	-	0.22	-0.73	0.14
		0.13	-0.20	-	-	-	0.21	-0.72	0.13
	Index of Moderated Mediation	-	-0.02	-	-	-	0.31	-0.71	0.63
		-	0.17	-	-	-	0.60	-0.79	1.67

APPENDIX D Moderator Sad - Regression result (Model 8)

DV	Effect Type	**Sad Level**	β	SE (HC4)	t	p	SE	LLCI	ULCI
Brand Loyalty	**Direct Effect**	-0.04	0.39	0.54	0.72	0.47	-	-	-
		0.02	0.53	0.31	1.72	0.09	-	-	-
		0.04	0.80	0.98	0.82	0.41	-	-	-
	Indirect Effect (via Apology)	-0.04	0.31	-	-	-	0.21	-0.11	0.72
		0.02	0.27	-	-	-	0.18	-0.09	0.65
		0.04	0.20	-	-	-	0.16	-0.06	0.55
		-0.04	0.05	-	-	-	0.18	-0.30	0.45
		0.02	0.05	-	-	-	0.19	-0.28	0.47

	Indirect Effect (via Courtesy)	0.04	0.05	-	-	-	0.20	-0.27	0.55
	Index of Moderated Mediation	-	-1.26	-	-	-	1.46	-4.63	1.26
		-	-0.01	-	-	-	1.00	-1.58	2.64
Nwom	**Direct Effect**	-0.04	0.06	0.41	0.15	0.88	-	-	-
		0.02	-0.25	0.32	-0.76	0.45	-	-	-
		0.04	0.88	0.56	-1.57	0.12	-	-	-
	Indirect Effect (via Apology)	-0.04	-0.10	-	-	-	0.23	-0.47	0.46
		0.02	-0.09	-	-	-	0.20	-0.41	0.41
		0.04	-0.07	-	-	-	0.15	-0.33	0.31
	Indirect Effect (via Courtesy)	-0.04	-0.24	-	-	-	0.23	-0.78	0.13
		0.02	-0.23	-	-	-	0.22	-0.76	0.13
		0.04	-0.23	-	-	-	0.24	-0.79	0.14
	Index of Moderated Mediation	-	0.42	-	-	-	1.21	-2.37	2.76
		-	0.05	-	-	-	1.54	-3.30	3.43

APPENDIX E Moderator Suprised - Regression result (Model 8)

DV	Effect Type	**Surprised Level**	β	SE (HC4)	t	p	SE	LLCI	ULCI
Brand Loyalty	**Direct Effect**	-0.008	0.59	1.51	0.39	0.70	-	-	-
		-0.005	0.60	0.71	0.85	0.40	-	-	-
		0.004	0.62	1.94	0.32	0.75	-	-	-
	Indirect Effect (via Apology)	-0.008	0.20	-	-	-	0.17	-0.10	0.58
		-0.005	0.20	-	-	-	0.17	-0.10	0.58
		0.004	0.23	-	-	-	0.18	-0.11	0.61
	Indirect Effect (via Courtesy)	-0.008	0.07	-	-	-	0.19	-0.28	0.52
		-0.005	0.07	-	-	-	0.19	-0.27	0.50
		0.004	0.08	-	-	-	0.19	-0.27	0.50
	Index of Moderated Mediation	-	2.42	-	-	-	6.77	-13.19	14.73
		-	0.99	-	-	-	6.51	-16.83	12.07
Nwom	**Direct Effect**	-5.57	0.16	0.45	0.35	0.73	-	-	-
		-0.13	0.62	0.32	1.95	0.05	-	-	-
		5.539	1.09	0.48	2.30	**0.02**	-	-	-
	Indirect Effect (via Apology)	-5.57	0.73	-	-	-	0.20	-0.09	0.74
		-0.13	0.23	-	-	-	0.17	-0.08	0.61
		5.539	0.190	-	-	-	0.17	-0.07	0.60
	Indirect Effect (via Courtesy)	-5.57	-0.11	-	-	-	0.24	-0.36	0.62
		-0.13	-0.09	-	-	-	0.20	-0.28	0.50
		5.539	-0.06	-	-	-	0.16	-0.24	0.44
		-	-0.01	-	-	-	0.01	-0.04	0.02

	Index of Moderated Mediation	-	-0.01	-	-	-	0.01	-0.03	0.02

APPENDIX F Moderator Scared - Regression result (Model 8)

DV	Effect Type	**Scared Level**	β	SE (HC4)	t	p	SE	LLCI	ULCI
Brand Loyalty	**Direct Effect**	-23.04	0.20	0.35	0.55	0.58	-	-	-
		-2.89	0.53	0.30	1.76	0.08	-	-	-
		24.84	0.98	0.39	2.50	**0.01**	-	-	-
	Indirect Effect (via Apology)	-23.04	0.20	-	-	-	0.18	-0.12	0.60
		-2.89	0.20	-	-	-	0.17	-0.12	0.57
		24.84	0.20	-	-	-	0.18	-0.12	0.59
	Indirect Effect (via Courtesy)	-23.04	0.12	-	-	-	0.20	-0.24	0.57
		-2.89	0.12	-	-	-	0.20	-0.24	0.56
		24.84	0.12	-	-	-	0.21	-0.23	0.58
	Index of Moderated Mediation	-	0.00	-	-	-	0.01	-0.01	0.01
		-	0.00	-	-	-	0.01	-0.01	0.01
Nwom	**Direct Effect**	-0.003	0.25	0.36	-0.69	0.49	-	-	-
		-0.002	0.28	0.34	-0.84	0.40	-	-	-
		0.002	0.48	0.41	-1.17	0.25	-	-	-
	Indirect Effect (via Apology)	-0.003	-0.06	-	-	-	0.18	-0.36	0.38
		-0.002	-0.06	-	-	-	0.18	-0.36	0.38
		0.002	0.06	-	-	-	0.18	-0.34	0.39
	Indirect Effect (via Courtesy)	-0.003	-0.25	-	-	-	0.20	-0.73	0.09
		-0.002	-0.25	-	-	-	0.20	-0.73	0.10
		0.002	-0.26	-	-	-	0.22	-0.76	0.10
	Index of Moderated Mediation	-	0.48	-	-	-	10.30	-19.10	23.83
		-	-2.10	-	-	-	16.23	-42.14	21.43

APPENDIX G Moderator Disgusted - Regression result (Model 8)

DV	Effect Type	**Disgusted Level**	β	SE (HC4)	t	p	SE	LLCI	ULCI
Brand Loyalty	**Direct Effect**	-0.005	0.39	0.46	0.84	0.40	-	-	-
		-0.003	0.46	0.37	1.23	0.22	-	-	-
		0.005	0.76	0.53	1.43	0.16	-	-	-
	Indirect Effect (via Apology)	-0.005	0.20	-	-	-	0.17	-0.10	0.60
		-0.003	0.20	-	-	-	0.17	-0.10	0.57
		0.005	0.23	-	-	-	0.18	-0.10	0.62
		-0.005	0.11	-	-	-	0.22	-0.31	0.57
		-0.003	0.10	-	-	-	0.21	-0.30	0.53

	Indirect Effect (via Courtesy)	0.005	0.10	-	-	-	0.17	-0.23	0.47
	Index of Moderated Mediation	-	3.24	-	-	-	11.29	-24.49	23.37
		-	-1.77	-	-	-	8.79	-23.19	12.43
Nwom	**Direct Effect**	-0.005	0.50	0.40	-1.23	0.22	-	-	-
		-0.003	0.46	0.36	-1.30	0.20	-	-	-
		0.005	0.29	0.41	-0.70	0.48	-	-	-
	Indirect Effect (via Apology)	-0.005	-0.07	-	-	-	0.19	-0.37	0.38
		-0.003	-0.07	-	-	-	0.19	-0.37	0.37
		0.005	0.08	-	-	-	0.19	-0.39	0.38
	Indirect Effect (via Courtesy)	-0.005	-0.25	-	-	-	0.24	-0.81	0.15
		-0.003	-0.25	-	-	-	0.23	-0.78	0.14
		0.005	-0.22	-	-	-	0.20	-0.67	0.10
	Index of Moderated Mediation	-	-1.14	-	-	-	8.17	-16.96	18.90
		-	4.24	-	-	-	11.96	-10.00	38.27

APPENDIX H Moderator Contempt - Regression result (Model 8)

DV	Effect Type	**Contempt Level**	β	SE (HC4)	t	p	SE	LLCI	ULCI
Brand Loyalty	**Direct Effect**	-0.006	0.63	1.26	0.50	0.61	-	-	-
		-0.005	0.63	1.03	0.61	0.54	-	-	-
		0.003	0.59	2.08	0.28	0.78	-	-	-
	Indirect Effect (via Apology)	-0.006	0.23	-	-	-	0.20	-0.13	0.69
		-0.005	0.23	-	-	-	0.20	-0.13	0.67
		0.003	0.20	-	-	-	0.17	-0.10	0.59
	Indirect Effect (via Courtesy)	-0.006	0.08	-	-	-	0.19	-0.27	0.53
		-0.005	0.08	-	-	-	0.19	-0.27	0.53
		0.003	0.09	-	-	-	0.21	-0.29	0.56
	Index of Moderated Mediation	-	-3.94	-	-	-	11.01	-33.93	10.47
		-	-1.77	-	-	-	6.30	-12.97	13.84
Nwom	**Direct Effect**	-0.006	-0.35	0.46	-0.77	0.45	-	-	-
		-0.005	0.36	0.43	-0.84	0.40	-	-	-
		0.003	0.41	0.52	-0.79	0.43	-	-	-
	Indirect Effect (via Apology)	-0.006	-0.07	-	-	-	0.22	-0.37	0.50
		-0.005	-0.07	-	-	-	0.20	-0.37	0.49
		0.003	0.06	-	-	-	0.17	-0.34	0.38
	Indirect Effect (via Courtesy)	-0.006	-0.23	-	-	-	0.22	-0.76	0.10
		-0.005	-0.23	-	-	-	0.21	-0.76	0.10
		0.003	-0.26	-	-	-	0.23	-0.80	0.11

	Index of Moderated Mediation	-	1.12	-	-	-	8.77	-21.41	17.65
		-	-3.30	-	-	-	10.21	-21.37	21.82

APPENDIX I Moderator Valence - Regression result (Model 8)

DV	Effect Type	**Valence Level**	β	SE (HC4)	t	p	SE	LLCI	ULCI
Brand Loyalty	**Direct Effect**	-0.03	0.71	0.82	0.86	0.39	-	-	-
		-0.01	0.57	0.32	1.79	0.08	-	-	-
		0.04	0.46	0.51	0.91	0.91	-	-	-
	Indirect Effect (via Apology)	-0.03	0.20	-	-	-	0.16	-0.09	0.55
		-0.01	0.25	-	-	-	0.18	-0.12	0.63
		0.04	0.29	-	-	-	0.21	-0.14	0.71
	Indirect Effect (via Courtesy)	-0.03	0.06	-	-	-	0.18	-0.22	0.51
		-0.01	0.07	-	-	-	0.20	-0.26	0.52
		0.04	0.08	-	-	-	0.21	-0.30	0.54
	Index of Moderated Mediation	-	1.32	-	-	-	1.42	-1.11	4.41
		-	0.26	-	-	-	1.18	-2.23	2.77
Nwom	**Direct Effect**	-0.03	-0.63	0.44	-1.44	0.15	-	-	-
		-0.01	0.30	0.32	-0.92	0.36	-	-	-
		0.04	0.04	0.40	-0.09	0.93	-	-	-
	Indirect Effect (via Apology)	-0.03	-0.07	-	-	-	0.17	-0.34	0.34
		-0.01	-0.09	-	-	-	0.20	-0.40	0.40
		0.04	0.11	-	-	-	0.23	-0.48	0.45
	Indirect Effect (via Courtesy)	-0.03	-0.22	-	-	-	0.21	-0.72	0.10
		-0.01	-0.25	-	-	-	0.23	-0.77	0.12
		0.04	-0.28	-	-	-	0.25	-0.86	0.12
	Index of Moderated Mediation	-	-0.49	-	-	-	1.27	-3.23	2.12
		-	-0.90	-	-	-	1.84	-5.20	2.42

APPENDIX J Moderator Arousal - Regression result (Model 8)

DV	Effect Type	**Arousal Level**	β	SE (HC4)	t	p	SE	LLCI	ULCI
Brand Loyalty	**Direct Effect**	-0.03	0.43	0.37	1.16	0.25	-	-	-
		-0.01	0.54	0.31	1.78	0.08	-	-	-
		0.04	0.81	0.53	1.51	0.13	-	-	-
	Indirect Effect (via Apology)	-0.03	0.20	-	-	-	0.17	-0.10	0.58
		-0.01	0.21	-	-	-	0.17	-0.11	0.57
		0.04	0.23	-	-	-	0.18	-0.13	0.61
		-0.03	0.08	-	-	-	0.20	-0.28	0.51

	Indirect Effect (via Courtesy)	-0.01	0.07	-	-	-	0.19	-0.24	0.49
		0.04	0.06	-	-	-	0.17	-0.19	0.49
	Index of Moderated Mediation	-	0.52	-	-	-	1.56	-2.17	4.18
		-	-0.31	-	-	-	1.24	-2.91	2.51
Nwom	**Direct Effect**	-0.03	-0.17	0.46	-0.37	0.71	-	-	-
		-0.01	0.33	0.32	-1.02	0.31	-	-	-
		0.04	0.69	0.60	-1.14	0.25	-	-	-
	Indirect Effect (via Apology)	-0.03	-0.03	-	-	-	0.19	-0.34	0.45
		-0.01	-0.03	-	-	-	0.20	-0.34	0.46
		0.04	0.03	-	-	-	0.22	-0.38	0.51
	Indirect Effect (via Courtesy)	-0.03	-0.34	-	-	-	0.25	-0.94	0.05
		-0.01	-0.31	-	-	-	0.23	-0.85	0.05
		0.04	-0.25	-	-	-	0.21	-0.80	0.04
	Index of Moderated Mediation	-	-0.07	-	-	-	1.24	-2.60	2.85
		-	1.30	-	-	-	2.46	-2.97	7.04

APPENDIX K Moderator Smiling - Regression result (Model 8)

DV	Effect Type	**Smiling Level**	β	SE (HC4)	t	p	SE	LLCI	ULCI
Brand Loyalty	**Direct Effect**	-0.001	-0.50	0.32	1.58	0.12	-	-	-
		-0.001	-0.50	0.32	1.58	0.12	-	-	-
		0.000	-0.61	0.35	1.77	0.08	-	-	-
	Indirect Effect (via Apology)	-0.001	-0.24	-	-	-	0.18	-0.09	0.64
		-0.001	-0.24	-	-	-	0.18	-0.09	0.64
		0.000	-0.21	-	-	-	0.18	-0.08	0.61
	Indirect Effect (via Courtesy)	-0.001	-0.10	-	-	-	0.21	-0.30	0.54
		-0.001	-0.10	-	-	-	0.21	-0.30	0.54
		0.000	-0.08	-	-	-	0.19	-0.25	0.52
	Index of Moderated Mediation	-	-43.02	-	-	-	115.70	-183.46	116.92
		-	-20.65	-	-	-	93.91	-152.69	137.67
Nwom	**Direct Effect**	-0.001	-0.27	0.35	-0.79	0.43	-	-	-
		-0.001	-0.27	0.35	-0.79	0.43	-	-	-
		0.000	-0.47	0.35	-1.34	0.18	-	-	-
	Indirect Effect (via Apology)	-0.001	-0.06	-	-	-	0.20	-0.36	0.43
		-0.001	-0.06	-	-	-	0.20	-0.36	0.43
		0.000	-0.05	-	-	-	0.19	-0.34	0.40
	Indirect Effect (via Courtesy)	-0.001	-0.30	-	-	-	0.24	-0.83	0.12
		-0.001	-0.30	-	-	-	0.24	-0.83	0.12
		0.000	-0.25	-	-	-	0.22	-0.75	0.11

DV	Effect Type	Level	β	SE (HC4)	t	p	SE	LLCI	ULCI
	Index of Moderated Mediation	-	10.73	-	-	-	66.62	-115.15	116.30
		-	60.14	-	-	-	115.56	-117.45	291.13

APPENDIX L Moderator Attention - Regression result (Model 8)

DV	Effect Type	**Attention Level**	β	SE (HC4)	t	p	SE	LLCI	ULCI
Brand Loyalty	**Direct Effect**	-0.40	0.74	1.79	0.41	0.68	-	-	-
		0.38	0.74	1.13	0.66	0.51	-	-	-
		0.58	1.26	109.64	0.01	0.99	-	-	-
	Indirect Effect (via Apology)	-0.40	0.23	-	-	-	0.21	-0.11	0.72
		0.38	0.23	-	-	-	0.20	-0.11	0.67
		0.58	0.12	-	-	-	2.67	-8.14	0.51
	Indirect Effect (via Courtesy)	-0.40	0.06	-	-	-	0.19	-0.25	0.53
		0.38	0.07	-	-	-	0.18	-0.23	0.52
		0.58	0.08	-	-	-	1.14	-1.84	1.32
	Index of Moderated Mediation	-	-0.11	-	-	-	2.77	-8.56	0.36
		-	-0.02	-	-	-	1.19	-2.16	1.49
Nwom	**Direct Effect**	-0.40	-1.03	3.11	-0.33	0.74	-	-	-
		-0.38	-1.02	1.73	0.59	0.55	-	-	-
		0.58	-0.86	206.32	0.01	0.99	-	-	-
	Indirect Effect (via Apology)	-0.40	-0.05	-	-	-	0.21	-0.43	0.43
		-0.38	-0.05	-	-	-	0.20	-0.39	0.41
		0.58	-0.03	-	-	-	1.76	-1.74	3.41
	Indirect Effect (via Courtesy)	-0.40	-0.22	-	-	-	0.23	-0.80	0.09
		-0.38	-0.22	-	-	-	0.22	-0.77	0.09
		0.58	-0.29	-	-	-	2.32	-1.09	4.40
	Index of Moderated Mediation	-	0.02	-	-	-	1.87	-2.04	3.71
		-	-0.07	-	-	-	2.41	-0.88	5.05

APPENDIX M Moderator Boredom - Regression result (Model 8)

DV	Effect Type	**Boredom Level**	β	SE (HC4)	t	p	SE	LLCI	ULCI
Brand Loyalty	**Direct Effect**	-0.08	0.98	0.54	1.79	0.08	-	-	-
		0.01	0.55	0.30	1.82	0.07	-	-	-
		0.05	0.36	0.38	0.94	0.35	-	-	-
	Indirect Effect (via Apology)	-0.08	0.27	-	-	-	0.24	-0.19	0.80
		0.01	0.19	-	-	-	0.16	-0.13	0.55
		0.05	0.15	-	-	-	0.15	-0.09	0.49
		-0.08	0.09	-	-	-	0.23	-0.31	0.65

	Indirect Effect (via Courtesy)	0.01	0.07	-	-	-	0.19	-0.26	0.50
		0.05	0.07	-	-	-	1.17	-0.25	0.47
	Index of Moderated Mediation	-	-0.93	-	-	-	1.27	-4.00	1.11
		-	-0.15	-	-	-	0.82	-2.28	1.27
Nwom	**Direct Effect**	-0.08	-0.69	0.62	-1.12	0.27	-	-	-
		0.01	-0.38	0.30	-1.26	0.21	-	-	-
		0.05	0.23	0.37	-0.62	0.54	-	-	-
	Indirect Effect (via Apology)	-0.08	-0.07	-	-	-	0.28	-0.47	0.63
		0.01	-0.05	-	-	-	0.19	-0.34	0.42
		0.05	-0.04	-	-	-	0.16	-0.32	0.34
	Indirect Effect (via Courtesy)	-0.08	-0.30	-	-	-	0.28	-0.98	0.12
		0.01	-0.25	-	-	-	0.22	-0.78	0.10
		0.05	-0.23	-	-	-	0.22	-0.75	0.09
	Index of Moderated Mediation	-	0.29	-	-	-	1.13	-2.74	2.09
		-	0.50	-	-	-	1.34	-1.86	3.76

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