The Effect of AI versus Human in Emotionally Charged Consumption Contexts – Two Experimental Studies on Customer Service Interactions

Study 1: The Effect of AI versus Human Shopping Assistance on Purchase Intention and the Mediating Role of Feeling Judged

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Abstract

Artificial Intelligence is becoming increasingly embedded in customer service, and therefore it is crucial to understand its impact on consumer behavior. This thesis examines whether AI's emotional neutrality can positively impact consumer responses in emotionally charged service interactions. Two experimental studies compare AI versus human service agents in shopping assistance and service failure recovery. Results show that while AI reduces feelings of judgment and affect-based decision-making, these effects do not increase purchase intention or customer forgiveness. These findings reveal the contextual limitations of AI, suggesting that emotional neutrality alone is not sufficient to generate favorable behavioral outcomes in service settings.

Keywords: Artificial Intelligence, AI versus Human, Feeling of Judgement, Purchase Intention, Affect-Based Decision-Making, Customer Forgiveness, Emotionally Charged Consumption Context

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1. Introduction

Artificial intelligence (AI) is fundamentally transforming the way companies interact with their customers. Driven by rising customer expectations for 24/7 availability, personalization, and self-service, AI has become a core component of modern customer service strategies (Kunz and Wirtz 2023; Mogaji and Nguyen 2021). According to Forbes (2023), 73% of companies already use or plan to use AI-driven systems, such as chatbots, to enable real-time customer interaction (Haan 2023). Chatbots, defined as "interactive, virtual agents that engage in verbal interactions with humans" (Kunz and Wirtz 2023; Przegalinska et al. 2019), are gaining prominence in the marketplace and are projected to either supplement or eventually replace human service providers across multiple industries (De Keyser and Kunz 2022). As a result, the global AI market size (including chatbots) is projected to grow significantly, from 184 billion U.S. dollars in 2024 to 826 billion U.S. dollars by 2030, reflecting a compound annual growth rate (CAGR) of 28.4% (Statista 2024). This development underlines the role of AI as a strategic asset for firms (Mozafari, Weiger, and Hammerschmidt 2021), particularly in customer interactions. AI has already led to a significant reduction in direct human contact in customer service (Brendel et al. 2023), with AI expected to handle 95% of all online service interactions by 2025 (Clark 2020). While AI continues to shape the future of service environments, some research suggests that customers may still prefer human interaction in certain situations (Huang, Markovitch, and Stough 2023; Li, Peluso, and Duan 2022; Press 2019). Reflecting this, a deeper understanding of consumer behavior regarding different types of service agents helps companies to better tailor their service strategies and identify new business opportunities (Sohn et al. 2025).

Existing literature emphasizes the growing role of AI-driven agents in customer service (Blazevic and Sidaoui 2022; Roy and Naidoo 2020). However, prior research suggests that consumers' appreciation of AI service agents is largely limited to low-complexity service tasks, where efficiency and convenience are key (Xu et al. 2020). In contrast, human agents are still preferred in emotionally sensitive or high-complexity situations that require empathy, understanding, and trust (De Keyser and Kunz 2022; Feine et al. 2019; Xu et al. 2020). One key reason for this preference is that AI lacks emotional understanding and cannot respond empathetically to human needs (Blazevic and Sidaoui 2022). In addition, Haslam (2006) describes AI as a non-human entity that does not feel, experience, or express emotions. While this fundamental difference is often viewed as a limitation, it raises an important question: Are there consumption contexts in which AI's lack of emotion could be beneficial?

There is emerging evidence that this might be the case, as some research suggests that the absence of emotions can also provide advantages in specific customer interactions. For example, Pitardi et al. (2021) argue that, because AI cannot form thoughts, opinions, or judgments, its emotional neutrality may reduce customer embarrassment. Similarly, Pavone, Meyer-Waarden, and Munzel (2022) suggest that consumers may perceive AI as less emotionally confrontational in stressful service interactions, which can reduce consumer discomfort. To fill this gap, this thesis adopts an experimental approach to examine whether emotionally neutral AI agents might be preferred over human agents in specific, emotionally charged service interactions along the customer journey. Two studies explore how consumers respond to AI versus human agents in such contexts, focusing on their emotional reactions and subsequent decision-making. This leads to the central research question: *How does the type of service agent (AI versus human) influence consumer responses in emotionally charged consumption contexts?*

This thesis builds on dehumanization theory and research on emotions in consumer decision-making and service interactions to explore how the absence of emotions in AI impacts consumer behavior. While previous literature has primarily focused on AI's shortcomings in emotional understanding (Crolic et al. 2021; Kirk and Givi 2024), this research considers whether emotional neutrality could be beneficial in emotionally charged consumption contexts.

To investigate this, two experimental studies examine emotionally charged situations along the customer journey, with a focus on the stages before and after a purchase. Study 1 focuses on the pre-purchase stage and examines how AI shopping assistants, compared to human service agents, influence purchase intention by reducing consumers' feelings of being judged. Study 2 addresses the post-purchase stage, analyzing whether AI agents compared to human service agents, can increase customer forgiveness in service failure recovery by reducing affect-based decision-making. Together, these studies aim to provide new insights into the role of AI's emotional absence and its impact on consumer responses in service interactions.

2. Literature Review

2.1 AI versus Human

Definitions of AI have varied over the past decades, reflecting its expanding scope and applications (Collins et al. 2021). While many studies do not provide a clear definition, this research follows Rai et al. (2019) and describes AI as "the ability of a machine to perform cognitive functions that we associate with human minds, such as perceiving, reasoning, learning, interacting with the environment, problem-solving, decision-making, and even demonstrating creativity" (Rai et al. 2019). In practice, AI systems utilize natural language processing, machine learning and algorithmic data analysis to process information recognize patterns and make automated decisions (Huang and Rust 2018).

As AI continues to evolve, researchers classify it into distinct categories based on its interface and functions (Russell and Norvig 2019). This research focuses on Artificial Narrow Intelligence (ANI), the only form of AI currently in practical use. ANI systems are designed to perform specific tasks and appear in various forms, including chatbots, voice assistants, and robots, each providing a different mode of interaction. Specifically in this thesis, chatbots, which operate through text-based interfaces and are widely used in customer service settings, serve as the operational representation of AI (Sands et al. 2020).

As AI becomes more integrated into customer interactions, its distinction from human agents becomes increasingly evident. Haslam's (2006) dehumanization theory provides a valuable framework for understanding this difference by identifying two fundamental aspects of humanness: unique human characteristics, such as cognitive abilities, and human nature characteristics, including emotional responsiveness. The absence of human nature characteristics leads to mechanistic dehumanization, wherein an entity is perceived as highly rational. While AI can effectively simulate many human cognitive abilities, it remains subject to mechanistic dehumanization, as it lacks the ability to feel, experience or express emotions (Haslam 2006). AI's lack of emotion can also be theoretically explained through mind perception theory. The theory suggests that consumers perceive both human and non-human entities based on agency (i.e., the ability to act and make decisions) and experience (i.e., the ability to feel emotions and sensations) (Pitardi et al. 2021). Human adults are generally seen as possessing both high level of agency and experience, while AI is moderate in agency but low in experience, making it efficient but emotionally detached (Gray, Gray, and Wegner 2007). Consequently, AI's lack of emotion serves as a defining distinction from humans, shaping consumer perceptions and influencing engagement in AI-driven customer services (Yildiz 2025). Therefore, a deeper understanding of how emotions influence consumer decision-making and shape both human-to-human and AI-to-human service interactions is essential for analyzing consumer responses.

2.2 The Role of Emotions in Customer Service Interactions

2.2.1 Emotions in Consumer Decision-Making

Given that the absence of emotion represents the most prominent distinction between AI and human service agents, it is crucial to examine how emotions influence consumer behavior. A fundamental concept in consumer behavior research is that decision-making is driven by two main processes: cognitive-based decision-making and affect-based decision-making. Cognition involves the deliberate and rational processing of information, encompassing thinking, reasoning, and decision-making based on facts. In contrast, affect refers to emotional responses that often emerge spontaneously and are not necessarily governed by rational control (Bagozzi, Gopinath, and Nyer 1999; Cohen and Areni 1991; Shiv and Fedorikhin 1999; Zaltman 2000). Affect-based decision-making plays a dominant role in consumer interactions, particularly in emotionally driven purchasing situations like hedonic consumption and service failure situations, where emotions often override rational analysis (Harrison-Walker 2018; Holbrook and Hirschman 1982). Affect is broadly understood as an emotional state, typically categorized as positive or negative, whereas emotions represent a specific subset that significantly influences consumer perceptions and behaviors. Emotions reflect a mental state of readiness that, according to Bagozzi et al. (1999) and Ortony et al. (1988), emerges based on appraisals of events, objects, or agents and often drives action. Furthermore, emotions are not just affective responses but multidimensional states that shape how individuals interpret and engage with both social and physical environments (Lambie and Marcel 2002; Smith and Ellsworth 1985).

In the consumer context, emotions play a crucial role in shaping behavior by influencing product evaluations, purchase decisions, post-consumption satisfaction, and brand perceptions (Bettiga and Lamberti 2018; Kemp et al. 2017; Menon and Dubé 2000). Overall, emotional responses affect how consumers engage with brands and can impact satisfaction and purchase intentions (Hennig-Thurau et al. 2006; Menon and Dubé 2000; Van Dolen, De Ruyter, and Lemmink 2002).

2.2.2 Emotions in Human-to-Human Service Interactions

Emotions play a critical role in shaping the quality and outcomes of human-to-human service interactions (Mattila and Enz 2002). According to Ortony et al. (1988), emotions emerge as individuals focus on one of three key factors: (1) events, referring to interpretations of past occurrences; (2) objects, encompassing both animate and inanimate entities; and (3) agents, representing those perceived as responsible for outcomes. In customer service interactions, human service agents influence customers through their emotional expressions, which can directly shape customers' emotions and behaviors (Rafaeli and Sutton 1989). This emotional transmission is typically mediated by the customer's affective state, meaning that service employees' expressions first impact the customer's emotions, which then affect perceptions, satisfaction, and behavioral responses – either positively or negatively (Du, Fan, and Feng 2010; Grandey and Gabriel 2015).

Particularly relevant in customer service interactions are social emotions, which arise in interpersonal contexts and depend on the perceived presence, reactions, or judgments of others (Keltner and Haidt 1999; Lewis 2008). Within this category, self-conscious emotions, such as shame, embarrassment, guilt, and pride, are especially important, as they emerge when individuals perceive themselves as being evaluated by others (Bagozzi 2006; Tangney and Fischer 1995). In customer service contexts, human service agents act as social actors, whose emotional expressions and behaviors serve as implicit signals of judgment, influencing how consumers feel about their own behavior, choices, or status (Barger and Grandey 2006; Grandey 2000; Liu, Chi, and Gremler 2019; Rafaeli and Sutton 1989).

A core mechanism underlying emotional dynamics in service interactions is emotional contagion (Hatfield, Cacioppo, and Rapson 1993). This describes how customers subconsciously adopt the emotional expressions of service employees, thereby influencing their satisfaction and decision-making. As a result, customer behavior in service interactions is strongly shaped by affective processes (Wang et al. 2015). Emotional responses often occur automatically and without conscious deliberation, meaning that customers may react to service experiences based on their immediate emotional state rather than rational evaluation (Liu, Chi, and Gremler 2019). While positive emotional expressions by employees can enhance positive consumer feedback and repurchase intentions (Barger and Grandey 2006; Hennig-Thurau et al. 2006; Wang et al. 2015), negative cues may trigger adverse reactions and unfavorable evaluations (Cheshin, Amit, and Van Kleef 2017; Clark and Taraban 1991). Moreover, emotional contagion is reciprocal, meaning that service employees and customers influence each other's emotional states during interactions. (Hatfield, Cacioppo, and Rapson 1994; Pugh 2001). This reciprocal nature is consistent with the emotion cycle model proposed by Hareli and Rafaeli (2008), which suggests that emotions are transmitted continuously between individuals throughout an interaction.

Given the strong impact of emotions in service interactions, emotional intelligence (EI) is a critical competency for service employees. EI entails the capacity to perceive, comprehend, and regulate both personal and others' emotions, enabling employees to interpret complex emotional cues and respond effectively (Kidwell et al. 2011; Mikolajczak et al. 2007). Moreover, employees with high EI are particularly skilled at regulating their emotions, a process known as emotional labor (Grandey 2000; Mayer and Salovey 1995; Tropman and Hochschild 1984). Emotional labour involves displaying positive emotions and suppressing negative ones deliberately, in order to improve the customer experience, regardless of one's actual emotional state (Ashforth, Tomiuk, and Kulik 2008; Tropman and Hochschild 1984). By regulating emotional expressions, service agents help sustain positive emotional cycles and contribute to higher customer satisfaction (Delpechitre and Beeler 2017). In contrast, a lack of appropriate emotional control, whether intentional or not, can harm the customer experience, especially in emotionally charged service situations where negative emotions are likely to arise (Liu, Chi, and Gremler 2019; Spanjol et al. 2015). Such emotional transmission may initiate a downward spiral of negativity, which can evolve into a self-reinforcing and harmful cycle (Garland et al. 2010). Exposure to negative emotional cues from a service agent can cause customers to disengage, ultimately lowering the chance of purchase completion (Holthöwer and van Doorn 2022; Grace 2007).

2.2.3 Emotions in AI-to-Human Service Interactions

While emotions play a crucial role in human-to-human interactions, the rise of AI-powered agents calls for a deeper examination of how emotional neutrality in AI-based service interactions shapes consumer responses. Most studies emphasize that the absence of emotion in AI is a critical limitation in customer service contexts, often resulting in negative outcomes for consumers (Belk 2020; Chaturvedi and Verma 2023; Kattara and El-Said 2013; Puntoni et al. 2020). One of the key limitations of this inability to understand or express emotion is that it prevents the replication of the warmth and subtlety of human interaction (Chen et al. 2023). Rather than offering emotional support, AI agents frequently provide factual responses that may overwhelm users with information, leading to cognitive overload and decreased satisfaction (Bawden and Robinson 2008; Chaturvedi and Verma 2023).

The emotional limitations of AI are further reflected in unnatural conversational flow, inauthentic responses, and an inability to address complex consumer concerns, factors that collectively reduce the perceived quality of the interaction. This lack of emotional sensitivity has been directly linked to customer dissatisfaction and can trigger intense negative emotions (Pavone, Meyer-Waarden, and Munzel 2022; Zhang et al. 2024). In addition, the growing integration of AI into service contexts has raised concerns regarding a diminishing sense of social connection (Belk 2020). Kattara and El-Said (2013) demonstrate that consumers often prefer human employees over AI, as these technologies lack the authenticity, empathy, and warmth of real human interaction. The shift toward automation can therefore amplify feelings of isolation or irritation, particularly when AI systems fail to meet consumers' expectations for empathy and responsiveness (Ameen et al. 2020; Chaturvedi and Verma 2023, Puntoni et al. 2020) Taken together, these findings suggest that

AI's lack of emotional intelligence frequently undermines service quality and contributes to negative consumer experiences.

At the same time, under specific conditions, AI's emotional neutrality may offer distinct advantages. While most research emphasizes the drawbacks of this emotional deficit, few studies explore its potential benefits. According to the Computer as Social Actors (CASA) theory (Reeves and Nass 1997), customers often perceive AI service agents, such as chatbots, as social entities and interact with them in similar ways to human employees (Beattie, Edwards, and Edwards 2020; Song et al. 2022). Building on this, research has shown that in certain social contexts, consumers may even prefer AI-based over human-provided services, a phenomenon known as "algorithm appreciation" (Logg, Minson, and Moore 2019). In particular, AI-driven interactions without human service personnel can enhance consumers' sense of control and protect their perceived privacy (Kunz and Wirtz 2023).

Furthermore, Holthöwer and van Doorn (2022) demonstrate that consumers prefer AI agents to human service providers when purchasing embarrassing products due to the perceived inability of AI to make personal judgements. Similarly, Pitardi et al. (2021) show that consumers feel less discomfort and embarrassment when interacting with an AI rather than a human service agent in the context of sensitive purchases (e.g., antifungal treatments). Moreover, AI's emotional neutrality eliminates the need for emotional labor, as it does not require emotional regulation and avoids emotional fatigue. This enables more consistent and emotionally neutral interactions (van Doorn et al. 2017; Wirtz and Jerger 2016). According to the theory of emotional contagion, maintaining neutrality reduces emotional interaction and minimizes the risk of negative emotional contagion, particularly in stressful or complaint-related scenarios (Du, Fan, and Feng 2010; Hatfield, Cacioppo, and Rapson 1993).

These findings suggest that AI's lack of emotion may be beneficial in specific contexts. However, the existing literature remains limited. The following chapter examines the impact of

AI across the customer journey to better understand when AI's emotional neutrality leads to favorable consumer outcomes.

2.3 The Impact of AI on the Customer Journey

Based on previous findings that emotions can influence consumer interactions in both positive and negative ways, it is important to examine how AI's lack of emotion affects consumer behavior and decision-making across different stages of the customer journey.

The traditional customer journey, as defined by Lemon and Verhoef (2016), outlines the consumer decision-making process throughout a purchase cycle divided into three key stages: the pre-purchase, the purchase, and the post-purchase stage. However, other process models in the literature conceptualize this journey differently, expanding it into five to seven distinct phases rather than the widely used three-stage framework proposed by Lemon and Verhoef (Harwardt and Köhler 2023). Prior research has examined how technological advancements influence various stages of the customer journey, with AI playing a significant role in reshaping customer interactions at multiple touchpoints (Grewal and Roggeveen 2020; He and Zhang 2022). As AI becomes increasingly integrated into these interactions, its lack of emotion, as discussed in the previous section, directly affects how consumers experience these stages, shaping both decision-making and service interactions (Maguire and Geiger 2015; Roster and Richins 2009).

In the pre-purchase stage, consumers engage in need recognition, information search, and evaluation of alternatives. Traditional marketing literature has framed this stage as the entirety of the customer experience before purchase, where consumers explore product options and develop purchase intentions (Hoyer 1984; Lemon and Verhoef 2016). As consumers navigate this phase, their decisions are shaped by various factors, including personal preferences, brand perception, and external influences such as reviews and recommendations (Stankevich 2017).

AI-driven applications enhance this phase by offering tailored recommendations, optimizing search functions, and providing shopping assistance (Grewal et al. 2022).

The purchase stage marks the shift from the consumers evaluation to final decision-making and transaction, including ordering and payment (Lemon and Verhoef 2016). AI technologies aim to streamline the purchasing experience by facilitating transactions through automation and enhancing personalization throughout the buying process (Grewal et al. 2022).

Lastly, the post-purchase stage includes product usage, post-purchase engagement, and service requests (Lemon and Verhoef 2016). In practice, this stage encompasses the consumer's consumption experience as well as customer support and service recovery efforts, which have traditionally been handled by humans. AI facilitates post-purchase interactions by offering automated customer support for any inquiries or complaints, as well as collecting consumer feedback (Grewal and Roggeveen 2020).

While all stages of the customer journey are important, this research focuses on the pre-purchase and post-purchase stage, as these are particularly influenced by emotions and therefore most relevant for examining AI's emotional neutrality. This focus is further discussed in the following section.

2.4 AI in Emotionally Charged Customer Journey Stages

While AI has become increasingly embedded across all stages of the customer journey, existing research has primarily focused on its role in the purchase stage, particularly its ability to enhance transactional efficiency and streamline payment processes (Hoyer et al. 2020; Rana et al. 2021). However, service interactions are most prominent and emotionally charged in the pre-purchase and post-purchase stages (Tueanrat, Papagiannidis, and Alamanos 2020). In both phases, previous research has examined various applications of AI, such as automated customer support, and discussed its advantages and disadvantages (Grewal and Roggeveen 2020; Hawardt and Köhler 2023). Furthermore, the literature offers limited insight into how AI's lack of emotion affects consumers' responses in high-emotion and high-interaction contexts. A deeper understanding is needed, especially in contexts where negative emotions are likely to arise.

To address this gap, the following sections examine two emotionally charged situations within the customer journey, scenarios in which emotional reactions are intensified by the nature of the service interaction and the type of service agent. The first section focuses on the pre-purchase stage, where consumers may experience negative emotions such as judgement during product evaluation. The second section explores the post-purchase stage, where consumers encounter a service failure after making a purchase and engage in a recovery process through complaint handling. Both sections aim to uncover how AI's lack of emotion can serve as an advantage in emotionally complex consumption contexts.

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2.4.1 Pre-Purchase Stage

In the pre-purchase stage, consumers are typically involved in evaluating options and gathering information to support their decision-making process (Hoyer 1984; Lemon and Verhoef 2016). As part of this process, they often engage with human service agents to seek advice or clarification. However, research has shown that in human-to-human interactions, consumers may feel evaluated or pressured when seeking product advice, particularly in categories involving personal or sensitive purchases (Roster and Richins 2009). The fear of being judged or appearing uninformed can lead to discomfort or embarrassment, especially in face-to-face encounters (Pitardi et al. 2021). Consequently, consumers may avoid purchasing products due to embarrassment (Grace 2007). Social norms and self-presentation concerns play a crucial role in shaping these responses (Ytreberg 2024). This is particularly relevant in consumer settings, where interpersonal interactions can trigger social evaluative concerns (Leary 1983; White and Dahl 2007). In situations where consumers feel observed by others, the presence of a human service agent is likely to increase the perception of being judged (Dahl, Manchanda, and Argo 2001; Holthöwer and van Doorn 2022) since human interactions are typically associated with higher levels of social presence, social norms, and impression management concerns (Argo et al. 2005; Dahl, Manchanda, and Argo 2001). Prior research suggests that reducing the feeling of judgement may enhance purchase intention (Chen et al. 2023; Holthöwer and van Doorn 2022; Sun et al. 2022). One possibility to reduce discomfort in the pre-purchase stage are AI interactions, which can provide personalized product recommendations and real-time assistance (Grewal et al. 2022). However, research on AI's emotional neutrality in this customer journey stage is limited. While previous research has shown that AI-based service agents can reduce embarrassment and discomfort in sensitive or inherently awkward service situations, such as the purchase of embarrassing medical products, it remains unclear whether these effects extend to other consumption settings without embarrassing stimuli (Holthöwer and van Doorn 2022; Pitardi et al. 2021). In contrast to embarrassment, which typically arises from norm violations or sensitive consumption topics, feeling judged reflects a more subtle and widespread social evaluation concern that can emerge in any socially visible consumption situation (Leary 1983; White and Dahl 2007). Therefore, this study extends prior research by investigating whether interacting with an AI-based service agent reduces consumers' perception of being socially judged, even in non-embarrassing consumption contexts.

To address these gaps, Study 1 focuses on the pre-purchase stage and investigates whether AI shopping assistants influence purchase intention differently than human assistants. Based on previous research suggesting that AI agents are perceived as more emotionally neutral and less socially evaluative than humans, it is predicted that interacting with an AI shopping assistant reduces consumers' perceived feeling of being judged. This reduction in perceived judgment is expected to lead to higher purchase intention. The study therefore examines the mediating role of feeling judged and tests whether consumers report higher purchase intention with AI agents due to AI's lack of emotion. Accordingly, this study investigates the following hypotheses:

H1: Consumers interacting with an AI shopping assistant will have a higher purchase intention compared to those interacting with a human shopping assistant.

H2: The effect of AI versus human shopping assistants on purchase intention is mediated by feeling less judged.

See Appendix A1 for an illustration of the conceptual framework and hypotheses.

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2.4.2 Post-Purchase Stage

Another important phase in the customer journey, as discussed earlier, is the post-purchase stage. This phase becomes especially relevant when a service failure occurs, making effective service recovery a central concern for companies. In this context, consumer emotions are highly salient and can significantly affect behavior towards the company (Svari and Erling Olsen 2012). A service failure – defined as the discrepancy between the customers' expected and perceived performance of a product or service (Hoffman and Bateson 1997) – can trigger strong negative emotional responses, such as anger, frustration, and disappointment. These negative emotions often lead to affective reactions that result in affect-based decision-making, in which customers' emotions override rational analysis (Harrison-Walker 2018). In particular, such responses play a crucial role in shaping behavioral outcomes, which companies seek to address through service failure recovery.

Previous literature has focused on behavioral outcome variables such as negative word-of-mouth (Bougie, Pieters, and Zeelenberg 2003; Gelbrich 2009; Wetzer, Zeelenberg, and Pieters 2007) and repurchase intentions (Ou and Verhoef 2017; Schoefer and Diamantopoulos 2008; Zeelenberg and Pieters 2002). These outcomes primarily reflect consumers' transactional responses to service failures. However, prior research suggests that in emotionally charged service interactions, responses are not purely transactional, as customers may decide against restoring the relationship with the service provider while continuing to make purchases from them in the future (Harrison-Walker 2018). To capture this, customer forgiveness emerges as a distinct and underexplored behavioral response to service failures. Forgiveness is not just the absence of retaliation, it is a transformative process involving a shift towards empathy, compassion and understanding. It entails cognitive reappraisal and emotional regulation (Yagil and Luria 2015). Therefore, forgiveness is shaped by how the recovery interaction is experienced, especially the nature of the service agent involved (Huang and Lo 2025).

Research on service recovery indicates that companies can employ either human or machine-like service agents, which are now increasingly powered by artificial intelligence, to manage service failures (Liu et al. 2024; Luo et al. 2019). Additionally, recent studies suggest that in situations involving negative emotions, interactions with AI-based service agents may be evaluated more favorably than those with human agents, largely due to lower emotional expectations toward AI (Fürst et al. 2025; Ho, Tojib, and Tsarenko 2020). As AI lacks emotional expression, it may help prevent the escalation of negative affect and limit emotional contagion within the interaction. This emotional neutrality can reduce reliance on affect-based decision-making and potentially create a more favorable context for forgiveness.

As such, Study 2 shifts to the post-purchase phase and examines consumer forgiveness in service failure recovery when AI handles their complaint compared to a human agent. This study analyzes the mediating role of affect-based decision-making and explores how AI's lack of emotion may mitigate strong negative emotions, thereby shaping consumers' willingness to forgive in complaint handling situations. The following hypotheses are proposed:

H3: In service failure recovery situations, consumers are more likely to forgive a brand when their complaint is handled by AI compared to a human agent.

H4: The effect hypothesized in H1 is mediated through affect-based decision-making, with AI reducing emotional influence and increasing customer forgiveness.

See Appendix B1 for an illustration of the conceptual framework and hypotheses.

3. Overview of the Studies

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3.1 Study 1: The Effect of AI versus Human Shopping Assistance on Purchase Intention and the Mediating Role of Feeling Judged

3.1.1 Methodology

To empirically test hypotheses H1 and H2, an experiment was conducted to investigate the mediating effect of feeling less judged by an AI (versus human) shopping assistant in a luxury consumption context. Specifically, the study focuses on the context of luxury shopping because consumers in such situations often experience negative emotions, such as social pressure or discomfort (Kim et al. 2016). These emotions are driven by perceived social evaluation, especially when appearance or behavior may signal low status or purchasing power (Dahl, Manchanda, and Argo 2001; White and Dahl 2007). Since luxury goods function as social status symbols (Atwal and Williams 2009), consumers tend to be particularly sensitive to being observed and evaluated in luxury retail environments (Lunardo and Mouangue 2019). Given this sensitivity, luxury settings provide a meaningful context to investigate whether the type of service agents (AI versus human) can influence consumers' reactions.

Data Collection. The data collection was carried out via the online platform Qualtrics, as it enables random allocation of participants to experimental conditions while ensuring a userfriendly and standardized presentation across different devices (Putranto 2019). In order to ensure a diverse sample, participants were recruited through various channels, including personal networks, social media platforms, and email invitations. A preliminary test was conducted prior to the main data collection to ensure the questionnaire's clarity and applicability (Grimm 2010). Data was collected over a ten-day period, from April 22 to May 2, 2025.

Design and Procedure. This study applied an experimental methodology to test the causal connections between the independent variable (IV) (AI versus human) and the dependent variable (DV) (purchase intention) with the mediator (feeling of judgement) (Bell 2009). The study followed a single factor two levels (AI versus human) between-subjects design. Participants were randomly assigned to one of the two experimental conditions (see Appendix A 2.2). Participants were first introduced to the study with a brief general explanation, stating that the research explores how consumers perceive and evaluate service experiences with different types of service providers. To limit demand effects and control for bias, thereby reducing the risk of a Hawthorne effect, no specific hypotheses or details about the experimental design were disclosed (see Appendix A 2.1). A scenario-based experimental design was applied to simulate a realistic consumption situation while ensuring standardization and control over potential confounding variables (Dabholkar and Spaid 2011). The scenarios were written to be identical in content and tone except for the manipulation of the agent type (AI versus human). To ensure a comprehensive presentation of the situation, both scenarios included textual descriptions as well as visual stimuli. The scenario described a situation in which the participant is shopping in a luxury store and consults information about the product. To enhance the realism of the scenario, participants were told that they asked the shopping assistant for the price of the luxury item. Requesting price information was considered a situational trigger that could make participants more sensitive to feeling judged by the shopping assistant. Previous research has shown that asking for the price of a luxury product can lead to uncertainty and self-consciousness, as it may signal a lack of status or purchasing power (Kim et al. 2016; Lunardo and Mouangue 2019). To increase the realism of the scenario and enhance participants' involvement, product images of luxury weekender bags from the brands Louis Vuitton and Celine were integrated into the experiment. (see Appendix A 2.2). These products were chosen for their high level of recognition, their status as visible symbols and their suitability for a broad target group, as the bags are gender-neutral (Atwal and Williams 2009; Brun and Castelli 2013).

Purchase Intention. After the scenario, purchase intention was measured using scales developed by Dodds, Monroe, and Grewal (1991). The items were assessed using a 7-point Likert scale (1 = "*Strongly Disagree*" to 7 = "*Strongly Agree*"). Four items were included, such as "I would consider buying the product in this situation" (see Appendix A 2.3).

Feeling of Judgement. Following the measure of purchase intention, the extent to which participants perceived themselves to be judged by the sales assistant was assessed using five items developed based on scales by Leary (1983), Watson and Friend (1969) and White and Dahl (2007). These scales are commonly used in research on social evaluation and the fear of negative judgement in consumption contexts. The scale included items such as "I felt judged by the shopping assistant", rated on a 7-point Likert scale (1 = "*Strongly Disagree*", 7 = "*Strongly Agree*") (see Appendix A 2.4).

Manipulation Check. To verify the effectiveness of the manipulation (AI versus human), participants were asked to indicate whether they had interacted with an AI or human shopping assistant (see Appendix A 2.5).

Control Variables. Control variables and demographic measures were included to isolate the effect of the independent variable and ensure that alternative explanations for the observed outcomes could be ruled out. Participants were asked to indicate their familiarity with luxury products and their experience with shopping in luxury retail stores to account for prior exposure to the consumption context. Perceived shopping discomfort in luxury settings was measured using a three-item scale adapted from Lunardo and Mouangue (2019) and Dahl et al. (2001). Participants indicated their agreement with statements like “I sometimes feel uncomfortable when shopping in luxury stores” on a 7-point Likert scale (1 = “*Strongly Disagree*”, 7 = “*Strongly Agree*”). The items captured the general feeling of discomfort, anxiety or not belonging in luxury retail environments, which could affect how sensitive they are to feeling judged. Furthermore, to control for prior experience and general attitudes towards AI, which could influence their responses to AI-based service scenarios, participants’ familiarity with AI and their frequency of AI usage were assessed (see Appendix A 2.6). At the end of the survey, participants were asked to provide demographic information, including age, gender, income, occupation, and nationality (see Appendix A 2.7).

Sample. The final sample consisted of N = 112 participants. The largest age group among participants was 25 to 34 years (39.3%), followed by those aged 18 to 24 (31.3%) (see Appendix A 3.2). In terms of gender, 58% of participants identified as female, 40.2% as male, and 1.8% as non-binary (see Appendix A 3.3). Regarding their current occupation, 50.9% of the respondents reported being students, while 29.5% indicated being employed (see Appendix A 3.4). The respondents came from five countries: Germany, Austria, Portugal, Italy and France. The largest proportion of participants were German (89.3% of the total sample) (see Appendix A 3.5). Regarding monthly income, the majority reported earnings between €1000 and €2499 (34.8%) (see Appendix A 3.6).

3.1.2 Data Analysis

The data were analyzed using SPSS. To investigate whether consumers exhibit higher purchase intentions when interacting with an AI shopping assistant compared to a human assistant, an independent t-test was performed using the type of service agent (AI versus human) as the IV and purchase intention as the DV. To test the hypothesized mediation mechanism, Hayes’ Process Model 4 was employed (Hayes 2013). This model enabled the examination of whether the effect of the service agent type on purchase intention is mediated by the feeling of being judged during the shopping experience. In SPSS, control variables were entered as covariates and will be referred to as control variables throughout the following sections.

Data Preparation. Prior to analysis, the dataset was screened to ensure data quality and validity. Participants who did not complete the focal measures of the experiment were excluded during data cleaning (N = 41). Additionally, 15 participants failed the manipulation check and were excluded, as their responses indicated they had not properly processed the scenario. They did not recognize whether the service agent was AI or human, which is a key element of the manipulation. These steps ensured that only valid and reliable responses were retained for further analysis. After these exclusions, the final sample consisted of 112 valid cases used for all subsequent analyses (N = 112). The allocation of participants to experimental conditions was as follows: AI shopping assistant (N = 57), human shopping assistant (N = 55). The IV representing the experimental condition was dummy-coded for analysis, with participants assigned to the AI condition coded as 1 and those in the human condition coded as 0. For the constructs "Feeling Judged, Purchase Intention, and Perceived Shopping Discomfort", composite variables were created by calculating the mean of their respective items, resulting in single averaged scores used for all further analyses.

Preliminary Analysis. To determine whether the sample size was adequate for analysis, a priori power analysis was conducted using G*Power (Faul et al. 2007). The analyses were conducted assuming a medium effect size (f^2 = 0.15), an alpha level of .05 applied to all statistical tests, and a desired statistical power of .80. The results indicated that a minimum sample size of 68 participants would be required to reliably detect an effect of this magnitude in a model with two predictors (see Appendix A 4.1). A post hoc power analysis with the final sample size of 112 participants yielded a statistical power of .96, supporting that the sample was sufficiently powered to test the hypothesized relationships (see Appendix A 4.2).

Descriptive analyses were conducted for the key continuous variables in the study and the control variables. The average purchase intention was moderately high (*M* = 4.74, *SD* = 1.17), indicating a general tendency toward positive purchase intentions across conditions. The mean for feeling of judgement was lower (*M* = 3.03, *SD* = 1.32), suggesting that participants did not strongly perceive judgement during the interaction. Participants reported moderate discomfort in luxury shopping (*M* = 4.83) and high AI familiarity (*M* = 4.96) and usage (*M* = 5.20) but showed limited experience with luxury products (*M* = 3.78) and shopping frequency (*M* = 2.49). These results provide an initial overview of the central tendencies within the dataset and inform the interpretation of subsequent analyses (see Appendix A 3.1).

To identify potential outliers, box plots were created for all dependent, mediator, and control variables. The analysis revealed one mild outlier in the scale measuring purchase intention and three outliers in the scale for perceived shopping discomfort (see Appendices A 5.1 to A 5.3). Overall, all variables appeared reasonably distributed. Outliers were retained to maintain statistical power, as they did not meaningfully affect results or violate assumptions.

To ensure reliability of the three scales Cronbach's alpha was used for evaluation. All three multi-item scales for purchase intention (α = .927), feeling of judgement (α = .876), and perceived shopping discomfort (α = .827) all demonstrated strong internal consistency with alpha coefficients exceeding the commonly accepted threshold of .70 (George and Mallery 2008). Inter-item and item-total correlations confirmed that each item contributed meaningfully to its respective construct, supporting the reliability of the measures and justifying the retention of all items (see Appendices A 6.1 to A 6.3).

Tests of Statistical Assumptions. Prior to the main analyses, the assumptions of normality and equal variances were assessed using the Shapiro-Wilk and Levene's test. To assess the assumption of normality, both the Shapiro-Wilk test and visual inspection of Q-Q plots were performed for the DV in each condition separately. A Shapiro-Wilk test indicated a significant deviation from normality in the AI condition (p = .005), while the human condition approached significance (p = .051). However, Q-Q plots showed that both distributions were approximately normal (see Appendices A 7.1 and A 7.2). Levene's test indicated a significant violation of the assumption of homogeneity of variances, $F(1, 110) = 5.77$, $p = .018$ (see Appendix A 8). Accordingly, the row "equal variances not assumed" was used for interpreting the t-test results. In addition, Hayes' Process Model 4 is based on ordinary least squares (OLS) regression and therefore requires that several statistical assumptions be met, including the assessment of normality of the variables involved in the mediation model (Hayes 2013). As the IV was categorical, no normality testing was required for this variable. The assumption of normality was tested for the mediator feeling of judgement. The Shapiro-Wilk test suggested non-normality in the AI condition (p = .004), but Q-Q plots showed an approximately normal distribution in both groups (see Appendix 9). Additionally, the sample size (N = 112) is large enough to ensure the mediation analysis remains reliable.

To ensure that multicollinearity did not bias the regression results, collinearity diagnostics were conducted by examining tolerance and variance inflation factor (VIF) values. All VIF values ranged from 1.14 to 2.71, staying well below the critical threshold of 5, while all tolerance values exceeded the minimum acceptable value of .10 (ranging from .369 to .877) (Menard 2002). These results indicate no concerning multicollinearity between predictors. As all predictors contributed distinct information to the model, they were retained for hypothesis testing (see Appendix A 10).

To verify whether the assumptions of normality and homoscedasticity of residuals were met, a detailed residual analysis was conducted based on the linear regression model including the IV, mediator, and DV (see Appendix A 11.1). As the IV was a binary condition (AI versus human), assumption testing focused on the residuals of the overall model rather than the distribution of the predictor itself. Standardized residuals (M = 0.00, SD = 0.99) followed a normal distribution and ranged from -2.66 to 1.94, indicating no influential outliers. The histogram of standardized residuals revealed an approximately bell-shaped distribution, and the normal P-P plot showed the data points closely aligning with the diagonal reference line. These visual patterns support the assumption that the residuals were approximately normally distributed (see Appendix A 11.2 and A 11.3). Furthermore, predicted values ranged from 3.99 to 5.45, and residuals were symmetrically distributed around the mean predicted value (M = 4.74), further supporting the assumptions of linearity and symmetric error distribution (see Appendix A 11.1).

3.1.3 Results and Discussion

H1: Type of Service Agent and Purchase Intention

Purchase Intention. An independent samples t-test was carried out to examine whether the type of service agent (AI versus human) influenced consumers' purchase intention. Participants who interacted with an AI shopping assistant reported significantly lower purchase intention (M = 4.46, SD = 1.28) than those who interacted with a human assistant (M = 5.04, SD = 0.96), $t(110)$ = -2.68, p = .008). The mean difference was -0.58, 95% *CI* [-1.00, -0.15]. The effect size was medium, Cohen's d = -0.51, 95% *CI* [-0.88, -0.13], indicating a meaningful difference in purchase intention depending on the type of service agent (see Appendix A 12.1). These results contradict the initial hypothesis, as participants who interacted with a human assistant reported significantly higher purchase intent than those who interacted with an AI assistant.

ANCOVA. A one-way analysis of covariance was performed to explore the effect of service agent type (AI versus human) on purchase intention while controlling for participants' familiarity with luxury products, frequency of luxury shopping visits, familiarity with AI, frequency of AI usage, and perceived shopping discomfort. The overall model was significant, $F(6, 105) = 3.912$, $p = .001$, indicating that the predictors explained a significant portion of the variance in purchase intention ($R^2 = .183$). After controlling for all control variables, the type of service agent remained a significant predictor of purchase intention, $F(1, 105) = 8.563$, p =

.004. Among the control variables, only perceived shopping discomfort significantly predicted purchase intention, $F(1, 105) = 4.724$, $p = .032$. None of the familiarity or frequency variables reached statistical significance (all p-values > .28) (see Appendix 12.2). These findings suggest that even when accounting for individual differences in shopping habits and AI familiarity, participants who interacted with an AI-based assistant reported significantly lower purchase intentions than those assisted by a human. Additionally, participants who felt more discomfort in luxury shopping contexts were generally less willing to make a purchase.

H2: The Mediating Role of Feeling Judged

Mediation Analysis. A mediation analysis was conducted using Hayes' Process Model 4 (5,000 bootstrap samples) to examine whether the effect of the service agent type (AI versus human) on purchase intention is mediated by feelings of being judged, assessing both direct and indirect effects (Abu-Bader and Jones 2021). The model was statistically significant, $R^2 = .091$, $F(2, 109) = 5.46$, $p = .006$. The direct effect of the IV (AI versus human) on purchase intention remained significant, $b = -0.74$, $SE = 0.23$, $t = -3.22$, $p = .002$, 95% CI [-1.93, -0.28], indicating that participants in the AI condition reported lower purchase intention compared to those in the human condition. Furthermore, the IV had a significant effect on the mediator, $b = -0.99$, $SE = 0.23$, $t = -4.28$, $p < .001$, 95% CI [-1.45, -0.53], showing that participants interacting with AI felt significantly less judged. However, the mediator feeling judged did not significantly predict purchase intention when controlling for the IV, $b = -0.16$, $SE = 0.09$, $t = -1.88$, $p = .062$, 95% CI [-0.34, 0.01]. Furthermore, the indirect effect was not significant, $b = 0.16$, $BootSE = 0.10$, 95% CI [-0.02, 0.37], as the confidence interval included zero (see Appendix 13.1). The results are presented in Figure 1. Accordingly, the results do not provide statistical support for H2. While the AI-based shopping assistant significantly reduced feelings of judgment compared to the human agent, this reduction did not mediate the relationship between assistant type and purchase intention.

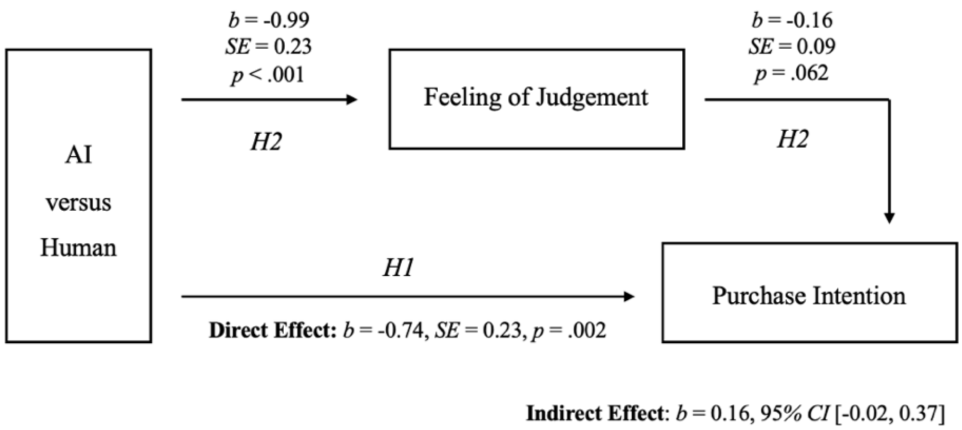

Figure 1: Mediation Analysis Study 1 (Hayes' Process Model 4)

Mediation Analysis with Control Variables. To account for potential confounding influences, a mediation analysis was conducted using Hayes' Process Model 4, this time including the control variables. The analysis tested whether feeling judged mediated the relationship between the type of shopping assistant (AI versus human) and purchase intention, while controlling for these additional factors. The results showed that AI-based agents significantly reduced feelings of judgment (b = -0.9993, $p < .001$, 95% *CI* [-1.4534, -0.5283]), and that perceived discomfort in luxury settings also significantly predicted feeling judged (b = 0.2976, p = .022). However, feeling judged did not significantly predict purchase intention when all control variables were included (b = -0.2012, *BootCI* [-0.4442, 0.0323]), as the confidence interval for the indirect effect still included zero. The direct effect of AI versus human on purchase intention remained significant (b = -0.8255, $p < .001$, 95% *CI* [-1.2762, -0.3768]) (see Appendix 13.2). These findings confirm that even after controlling for relevant control variables, feeling judged still does not mediate the effect of agent type on consumers' purchase intention.

Exploratory Analysis

In addition to the main hypothesis testing, several exploratory analyses were conducted to investigate potential influences of control variables. Specifically, the effects of demographic factors were examined in relation to feelings of judgement and purchase intention. A one-way ANOVA revealed that the effect of monthly net income on purchase intention was not statistically significant, $F(5, 106) = 1.86$, $p = .108$ (see Appendix A 14.1). In contrast, the effect of occupation was significant, $F(6, 105) = 2.60$, $p = .022$, suggesting potential group differences based on employment status (see Appendix A 14.2). To explore whether age moderates the effect of service agent type (AI versus human) on purchase intention, a two-way ANOVA was conducted with age group and agent type as between-subjects factors. The analysis revealed a significant main effect of age, $F(5, 100) = 3.32$, $p = .008$, indicating that purchase intention significantly varied across age groups. Additionally, there was a significant main effect of agent type, $F(1, 100) = 11.40$, $p = .001$, showing that, overall, participants interacting with an AI reported lower purchase intentions compared to those interacting with a human. However, the interaction between age and agent type was not significant, $F(5, 100) = 0.86$, $p = .512$, suggesting that the effect of the service agent on purchase intention did not significantly differ across age groups (see Appendix A 14.3).

A separate two-way ANOVA revealed a significant interaction effect between service agent type and gender on purchase intention, $F(2, 107) = 4.575$, $p = .035$. While the main effect of gender was not significant, the significant interaction indicates that gender moderates the effect of the agent type on purchase intention. Descriptive statistics suggest that female participants showed a stronger preference for human agents over AI, with higher purchase intentions in the human condition ($M = 5.18$, $SD = 0.98$) compared to the AI condition ($M = 4.23$, $SD = 1.27$), whereas male participants' purchase intentions remained relatively stable across both conditions (see Appendix A 14.4).

To investigate whether individual characteristics related to the luxury shopping context influence the perceived feeling of judgement, exploratory Pearson correlations were calculated between the mediator and three context-relevant control variables: luxury product familiarity, (Fam-LuxPr), luxury store visit frequency (FreShop), and perceived shopping discomfort (Discomf). The results revealed a significant positive correlation between Discomf and feeling of judgement, $r = .235$, $p = .013$, indicating that participants who generally feel uncomfortable in luxury shopping settings also report stronger feelings of being judged. In contrast, FamLuxPr ($r = .028$, $p = .772$) and FreShop ($r = .134$, $p = .161$) were not significantly related to feeling of judgement (see Appendix A14.5). These findings suggest that psychological discomfort in luxury environments may be more relevant to social evaluative concerns than actual exposure or experience. Familiarity with AI showed a positive correlation with purchase intention ($r = .414$, $p = .001$), suggesting that participants who were more familiar with AI exhibited a greater willingness to purchase. Additionally, AI familiarity was negatively correlated with feelings of being judged ($r = -.304$, $p = .022$), indicating that more familiar users felt less judged during the shopping interaction. Similarly, the frequency of AI usage was positively associated with purchase intention ($r = .321$, $p = .015$), and negatively associated with feelings of judgement ($r = -.427$, $p < .001$) (see Appendix A 14.6). These findings suggest that both frequent and familiar users of AI may perceive such interactions as less socially pressuring and more favorable to purchase behavior.

Summary of Findings and Discussion

This study examined how the service agent type (AI versus human) influences consumer behavior in the pre-purchase stage. Based on Haslam's (2006) dehumanization theory and mind perception theory by Gray, Gray and Wegner (2007), it was hypothesized that AI' lack of emotion would reduce social evaluative pressure, operationalized as "feeling judged" and as a result increase purchase intention (Grewal and Roggeveen 2020; Holthöwer and Van Doorn 2022).

Contrary to H1, participants interacting with a human assistant reported significantly higher purchase intention than those interacting with an AI assistant. It remained significant even when controlling for prior luxury experience, AI familiarity, and shopping discomfort. These results suggest that although AI may offer emotional neutrality, this characteristic alone does not necessarily enhance consumers' willingness to purchase in a luxury context.

Although participants in the AI condition reported lower feelings of being judged, H2 was not supported. This aligns with previous research on AI's lower social presence (Holthöwer and van Doorn 2022; Pitardi et al. 2021; Roster and Richins 2009). However, this variable did not significantly predict purchase intention. The mediation analysis revealed a significant direct effect of agent type, but no significant indirect effect through feeling judged.

The results highlight that while AI reduces social pressure, this benefit does not necessarily translate into positive behavioral outcomes. In contexts such as luxury shopping, where social signaling, personal attention, and emotional engagement play a central role, consumers may still prefer human interaction despite the potential for social pressure (Atwal and Williams 2009). This is an important finding that suggests several opportunities for future research and will be discussed in more detail in Chapter 4. Furthermore, the results indicate the importance of consumers' general discomfort in luxury shopping environments. Perceived shopping discomfort was positively correlated with the feeling of being judged, suggesting that consumers who feel self-conscious in such settings are more likely to experience social evaluation. These findings underline that beyond the type of service agent, individual psychological predispositions such as discomfort in high-status retail environments shape how consumers respond during the pre-purchase stage. This insight emphasizes the need to account for situational and dispositional factors when evaluating the effectiveness of AI-based service tools. Additionally, exploratory analyses showed that consumers who were more familiar with AI and used it more often reported higher purchase intention and felt less judged. This supports previous findings on algorithm appreciation and growing trust in AI (Belanche et al. 2021; Logg et al. 2019). Additionally, this study aligns with the findings of Chen and Huang (2015), who demonstrated that men tend to have more positive attitudes towards AI technology than women.

This is evident from the fact that female participants displayed a stronger purchase intention in the human condition.

In summary, the findings refine the current understanding of consumer responses to AI in service interactions. While AI reduces feelings of being judged, this advantage does not automatically translate into increased purchase intention, particularly not in the emotionally charged context of luxury retail. These results suggest that the absence of emotions in AI may have context-specific consequences: it may be beneficial in some social evaluation scenarios, but potentially detrimental in high-involvement, status-driven settings.

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3.2 Study 2: The Effect of AI versus Human in Service Failure Recovery on Customer Forgiveness and the Mediating Role of Affect-Based Decision-Making

3.2.1 Methodology

To empirically test hypotheses H3 and H4, an experimental study was conducted to investigate whether interacting with an AI-based chatbot, compared to a human service agent, in a service failure recovery context leads to a higher level of customer forgiveness. Furthermore, it was hypothesized that this effect is mediated by affect-based decision-making, as AI's lack of emotion might lead to a more rational, less emotionally driven consumer response.

The retail industry, and particularly the online retail sector, was selected as the scenario context for this study because previous research highlights its importance in understanding service failure and recovery. Agnihotri and Bhattacharya (2023) found that consumers experience the highest number of service failures in online retailing, compared to other industries such as banking and aviation. Furthermore, previous research indicates that online retailing is also the industry in which consumers most frequently interact with chatbots during service recovery processes (Agnihotri and Bhattacharya 2023; Luo 2019). This study therefore focuses on a service failure scenario within the online retailing context, specifically on delivery delays.

Delivery speed was selected as the specific scenario because it represents the most common reason for consumer complaints in online shopping worldwide (Statista 2025), ensuring a highly relevant and realistic situation for participants.

Data Collection. For this study, data was collected using an online survey, which provides several advantages over traditional offline methods, such as improved accessibility across devices and enhanced answer comprehensibility (Putranto 2019; Wertenbroch and Skiera 2002). As in Study 1, Qualtrics was used as the survey platform. This allowed for broad distribution via mailing lists, personal networks, and social media channels. Data were collected over a ten-day period, from April 22 to May 2, 2025. Consistent with Study 1, the experimental design followed the guidelines outlined by Bell (2009). To minimize the Hawthorne effect, participants were only given a general overview of the study's purpose (Adair 1984) and were unaware that they were part of an experiment. To ensure clarity and feasibility of the questionnaire, a pre-test was conducted prior to the main data collection (Grimm 2010). The questionnaire was developed based on a thorough review of relevant literature.

Design and Procedure. The present study used a single-factor, between-subjects design with two levels (AI versus human). Participants were randomly allocated to one of the two conditions (AI versus human) to isolate the effect of the service agent type in a service failure recovery context. The independent variable (IV) of this study was the type of service provider (AI versus human), while the dependent variable (DV) was customer forgiveness. Affect-based decision-making was proposed as the mediator to explain the underlying psychological mechanism between the IV and DV (Pieters 2017). This allowed for testing the assumption that the lack of emotion in AI service agents might reduce consumers' affective responses, thereby facilitating forgiveness in the context of a service failure recovery.

After an introduction (see Appendix B 2.1) participants were presented with a scenario-based experiment, a common approach in service failure and recovery research (Andreassen and

Streukens 2013; Park and Ha 2015; Singh and Crisafulli 2015; Smith, Bolton, and Wagner 1999). Scenario-based experiments are frequently used to create realistic and standardized situations that allow for clear comparisons between experimental conditions (Dabholkar and Spaid 2011; Singh and Crisafulli 2015). In line with this approach, participants were presented with a scenario in which they imagined having ordered a set of drinking glasses from an online shop called ShopZone. The product was deliberately chosen to be neutral and of low personal relevance, ensuring that the type of product would not influence participants' responses. In both conditions the delivery was delayed, and participants were told to imagine feeling frustrated and therefore contacted customer service using the chat function on the website. Depending on their experimental condition, participants were shown a picture of a chat in which the complaint was either handled by an AI-based chatbot or a human service agent. To ensure comparability, the content of the response was kept identical across both conditions (see Appendix B 2.2).

Customer Forgiveness. Following the scenario, customer forgiveness was measured using seven items adapted from existing forgiveness scales (Harrison-Walker 2018; McCullough et al. 1998; McCullough et al. 2003; Rye et al. 2001). The items reflect participants' willingness to forgive the brand and continue their relationship despite the negative incident. Responses were collected on a 7-point Likert scale (1 = *Strongly Disagree*, 7 = *Strongly Agre*e), including sample items such as "I forgive the brand for this service failure" and "I do not hold a grudge against the brand because of this incident". Two items were reverse-coded to reduce the risk of response bias and to ensure measurement reliability (see Appendix B 2.3).

Affect-Based Decision-Making. After measuring customer forgiveness, affect-based decision-making was assessed using four items adapted from prior research on emotion-based decision-making (Kidwell, Hardesty, and Childers 2008; Pham 2007). These items assessed the extent to which participants relied on their emotions rather than rational considerations when evaluating the customer service response. Participants were asked to indicate their agreement with statements such as "My reaction to the customer service response would be mainly driven by my emotions" or "I respond more with my heart than with my head when evaluating the customer service response", using a 7-point Likert scale from "Strongly Disagree (1)" to "Strongly Agree (7)" (see Appendix B 2.4).

Manipulation Check. The effectiveness of the manipulation was assessed by asking participants to indicate who handled their complaint in the scenario they had just read, choosing between "An AI-based chatbot" and "A human service agent." In addition, to verify the perceived emotionality of the customer service response, participants rated their agreement with the statement "The customer service response felt emotional" on a 7-point Likert scale (1 = *Strongly Disagree*; 7 = *Strongly Agree*) (see Appendix B 2.5).

Control Variables and Demographics. To control for potential confounding variables, several control variables and demographic measures were included. Participants were asked to report their frequency of shopping online on a 7-point Likert scale (1 = *Never*; 7 = *Extremely Frequently*) and whether they had ever contacted customer service before ("*Yes*" or "*No*"). They also indicated their familiarity with AI-based tools and chatbots (1 = *Not familiar at all*; 7 = *Extremely familiar*), and how frequently they engage with AI tools in their daily life (1 = *Never*; 7 = *Daily*). In addition, participants provided information about their age (categorical), gender, and occupation. These variables were used to control for prior experience with online shopping and AI, as well as demographic differences that might influence consumers' responses toward AI- or human-based service recovery (see Appendix B 2.6 and B 2.7).

Sample. The final sample consisted of 168 participants (N = 168), who voluntarily completed the online experiment. Participants were assigned to one of two experimental conditions: 83 interacted with an AI-based chatbot, and 85 interacted with a human service agent. Most respondents (66.1%) were between 18 and 34 years old, with 37.5% (N = 63) in the 18-24 age range and 28.6% (N = 48) in the 25-34 range (see Appendix B 3.2). Regarding gender distribution, 53% (N = 89) of the participants were female, while 46.4% (N = 78) were male, suggesting a relatively balanced distribution (see Appendix B 3.3). In terms of occupation, students represented the largest group of respondents (46.4%), followed by full-time employees (44%), while trainees, retired, and other respondents represented a smaller proportion of the sample (see Appendix B 3.4).

3.2.2 Data Analysis

To assess whether the type of service agent (AI versus human) influences customer forgiveness in a service failure recovery context, an independent samples t-test was conducted with agent type as the IV and customer forgiveness as the DV. The hypothesized mediation effect was tested using Hayes' Process Model 4 (Hayes 2013), which examined whether affect-based decision-making mediates the relationship between the type of service agent and customer forgiveness. In addition, further analyses were conducted to investigate whether control variables (also referred to as covariates) and demographic factors influenced the main effects.

Data Preparation. Data preparation involved several steps to ensure the quality and integrity of the dataset, with SPSS used as the primary tool for statistical analysis. First, participants who did not complete the focal measures of the experiment required to test the hypotheses (N = 22) were excluded from the dataset. Additionally, four participants who indicated "Disagree" on the initial consent question (see Appendix B 2.1) were removed, as they did not provide informed consent to participate in the study. A further 32 participants were excluded based on the manipulation check (see Appendix B 2.5), as they incorrectly identified the type of service agent they had interacted with, suggesting that they may not have read the scenario instructions carefully. After implementing these exclusion criteria, the final sample consisted of 168 participants (N = 168). To prepare the dataset for analysis, a dummy variable was created to distinguish between the two experimental conditions (AI = 1, Human = 0). All scale items measuring customer forgiveness and affect-based decision-making were coded such that higher values reflected greater agreement. Reversed items in the customer forgiveness scale were recoded to ensure consistency, aligning all items in the same conceptual direction (Kernis and Goldman 2006). For both key variables (DV and mediator) composite scores were calculated by computing the mean of all respective items: customer forgiveness (M = 3.68, SD = 1.13) and affect-based decision-making (M = 4.20, SD = 1.19) (see Appendix B 3.1). These data cleaning and preparation steps ensured that the dataset was complete, reliable, and ready for hypothesis testing and further analyses.

Preliminary Analysis. To evaluate whether the sample size was sufficient to detect medium-sized effects, an a priori power analysis was conducted using G*Power (Faul et al. 2007). Assuming an effect size of f^2 = .15, an alpha level of α = .05, and a desired power of 0.80, the analysis indicated that a minimum of N = 92 participants would be required. Given the final sample size of N = 168, statistical power was more than adequate ($1 - \beta$ = 0.996), as confirmed by a post hoc power analysis (see Appendices B 4.1 and B 4.2).

An outlier analysis was performed using boxplots for all continuous key variables. For the scales measuring customer forgiveness, online shopping frequency, AI familiarity and AI usage frequency no outliers were identified, indicating that the data for these variables were evenly distributed and free of extreme values. In contrast, some outliers were observed in the affect-based decision-making scale. Since these values did not result from data entry errors and were within a plausible range, they were retained in the dataset to maintain sample representativeness and variability (see Appendices B 5.1 to B 5.3).

Cronbach’s alpha was used to evaluate the reliability of the two scales employed in this study. The customer forgiveness scale, consisting of 7 items, showed high reliability (α = .862). Similarly, the affect-based decision-making scale, comprising 4 items, demonstrated good reliability (α = .801). These results confirm that both scales were internally consistent and suitable for hypothesis testing (see Appendices B 6.1 and B 6.2).

Tests of Statistical Assumptions. Several pre-tests were conducted to confirm that the assumptions underlying the independent t-test and mediation analysis were met. To assess the normality of the DV (customer forgiveness), the Shapiro-Wilk test and Q-Q plots were examined separately for each experimental condition (AI versus human). The results indicated no significant deviation from normality for either group, $W_{AI}(83) = .985$, $p = .435$, and $W_{Human}(85) = .986$, $p = .477$. In addition, the Q-Q plots visually confirmed the assumption of normality, as data points closely followed the reference line (see Appendices B 7.1 and B 7.2). Based on these results, the normality assumption was considered met. Furthermore, Levene's test revealed no significant difference in variances, $F(1, 166) = 2.40$, $p = .123$, suggesting that the assumption of homogeneity of variances was met. Consequently, the t-test was conducted using the values from the "equal variances assumed" row (see Appendix B 8).

As Hayes Process Model 4 employs ordinary least squares (OLS) regression, a linear relationship between the mediator (affect-based decision-making) and the DV (customer forgiveness) was examined. An initial step involved assessing normality using Shapiro-Wilk tests and Q-Q plots. The Shapiro-Wilk test indicated marginal deviations from normality in the AI condition ($p = .051$), while the Q-Q plots largely supported a normal distribution with only minor deviations (see Appendices B 9.1 to B 9.4). Given the sample size ($N = 168$), the mediation analysis can still be considered reliable, as minor deviations from normality are unlikely to significantly impact the robustness of the results.

Multicollinearity between the IV and the mediator was examined using collinearity statistics. The Variance Inflation Factor (VI*F*) was 1.02 for both predictors, and the corresponding tolerance values were .977, which are well within acceptable thresholds (*VIF* < 5; *Tolerance* > .20) (Menard 2002). These results indicate that multicollinearity is not a concern in the model and support the inclusion of both variables in the mediation analysis (see Appendix B 10).

Lastly, to assess homoscedasticity, residual statistics were reviewed. The standardized residuals ranged from -2.50 to 2.22 with a mean of 0 and a standard deviation close to 1 (SD = .994), suggesting that residuals are approximately evenly distributed around the regression line. These values provide no indication of heteroscedasticity, supporting the assumption of constant variance in the model (see Appendix B 11). In summary, the pre-tests showed that the statistical assumptions were met, supporting the appropriateness of the data for hypothesis testing.

Manipulation Check. To evaluate the effectiveness of the experimental manipulation, an independent samples t-test was used to compare participants' perceptions of emotionality in the customer service response across conditions. As expected, participants in the scenario with a human service agent rated the response as significantly more emotional (M = 4.01, SD = 1.49) than those in the AI service agent scenario (M = 3.45, SD = 1.66), t(163.19) = -2.32, p = .022, d = 0.36. The mean difference of 0.56, 95% CI [-1.04, -0.08] confirms that the manipulation was successful. The human service agent was perceived as more emotionally expressive than the AI-based chatbot (see Appendix 12).

3.2.3 Results and Discussion

H3: Type of Service Agent and Customer Forgiveness in Service Failure Recovery

Independent t-test. An independent samples t-test was employed to determine whether the type of service agent (AI versus human) influenced customer forgiveness during service failure recovery. There was no meaningful difference in forgiveness between participants who interacted with an AI-based chatbot (M = 3.69, SD = 1.24) and those who interacted with a human service agent (M = 3.68, SD = 1.05). This difference was not statistically significant, t(166) = 0.10, p = .918. The mean difference of 0.02, 95% CI [-0.33, 0.36], indicates no reliable effect of agent type on forgiveness (see Appendix B 13.1). Thus, H3, which predicted that the type of service agent would influence customer forgiveness, was not supported.

ANCOVA. Additionally, to examine whether the type of service agent (AI versus human) influences customer forgiveness after controlling for individual differences, a one-way ANCOVA was conducted. The model included four control variables: frequency of online shopping, AI familiarity, frequency of AI use, and prior customer service contact. After adjusting for these variables, the effect of service agent type on customer forgiveness remained non-significant, $F(1, 162) = 0.073$, $p = .787$. This indicates that the type of service agent did not influence participants' willingness to forgive the brand. Only prior customer service contact significantly predicted customer forgiveness, $F(1, 162) = 4.192$, $p = .042$, suggesting that participants with prior customer service experience were generally more likely to forgive. The three remaining control variables did not show significant effects (all p-values > .67). The overall model explained a small proportion of variance in forgiveness, $R^2 = .033$ (Adjusted $R^2 = .003$), indicating that the control variables and the service agent condition together accounted for only a minimal portion of the variability in the DV (see Appendix B 13.2).

H4: The Mediating Role of Affect-Based Decision-Making

Mediation Analysis. To test H4, a mediation analysis was conducted, using Hayes' Process Model 4 with 5,000 bootstrap samples. This enabled for the testing of the direct, indirect, and total effects of the IV on the DV through the mediator (Abu-Bader and Jones 2021). The IV was the type of service agent (AI versus human), the mediator was affect-based decision-making, and the DV was customer forgiveness. As a methodological note, although the effect of service agent type on customer forgiveness (H1) was not significant, mediation analysis was still conducted. According to Zhao, Lynch, and Chen (2010), a significant direct effect is not a prerequisite for testing mediation, only one requirement is needed (i.e., that the indirect effect is significant). This perspective supports the decision to proceed with testing H4.

The initial model without control variables (see Appendix B 14.1) revealed a significant effect of agent type on the mediator, affect-based decision-making ($b = -0.36$, $SE = 0.18$, $t(166) =$ -

2.00, p = .047), indicating that participants who interacted with an AI-based chatbot relied less on affect-based processing than those who interacted with a human service agent. However, affect-based decision-making did not significantly predict customer forgiveness (b = -0.04, SE = 0.07, t(165) = -0.59, p = .556), and the indirect effect of agent type on customer forgiveness mediated by affect-based decision-making was not statistically significant (b = 0.016, 95% CI [-0.06, 0.10]). Similarly, the direct effect of the type of service agent on customer forgiveness was also non-significant (b = 0.002, SE = 0.18, t = 0.01, p = .991), indicating no mediation. The conceptual framework and all corresponding results are presented in Figure 2.

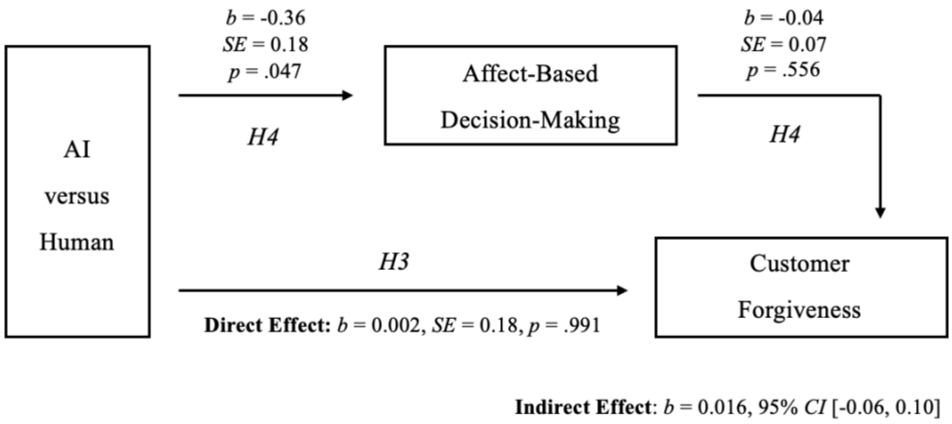

Figure 2: Mediation Analysis Study 2 (Hayes' Process Model 4)

To account for potential individual differences, the mediation model was re-tested with four control variables: frequency of online shopping, prior customer service contact, AI familiarity, and frequency of AI use. In the extended model, the effect of agent type on affect-based decision-making was marginally significant (b = -0.36, p = .051), which indicates that the pattern persists even after adding control variables. Furthermore, the direct effect of service agent type on customer forgiveness (b = 0.03, p = .846) and the indirect effect again remained non-significant (b = -0.04, p = .640). The bootstrapped indirect effect again failed to reach significance, b = 0.013, 95% CI [-0.06, 0.10]. Only one control variable (prior customer service contact) was significantly associated with customer forgiveness, b = -0.53, p = .042, suggesting that greater experience with customer service was linked to lower forgiveness (see Appendix B 14.2).

All in all, although the type of service agent influenced participants' reliance on affect-based decision-making, the mediator did not significantly affect customer forgiveness, and no indirect effect was found.

Overall, these results indicate that affect-based decision-making does not mediate the relationship between service agent type and customer forgiveness, and thus H4 is not supported.

Exploratory Analysis

Following the main hypothesis testing, exploratory analyses were conducted. To explore whether demographic factors influenced customer forgiveness, two separate two-way ANOVAs were conducted. The first analysis tested the interaction between agent type (AI versus human) and participants' gender. The results revealed no significant main effects of agent type ($F(1, 163) = 0.02$, $p = .896$) or gender ($F(2, 163) = 0.11$, $p = .893$), and no significant interaction ($F(1, 163) = 0.85$, $p = .359$). This suggests that gender did not influence the effect of service agent type on customer forgiveness (see Appendix B 15.1). A second two-way ANOVA examined the role of age. Again, there was no significant main effect of agent type ($F(1, 156) = 0.13$, $p = .723$) or age ($F(5, 156) = 0.44$, $p = .824$). However, a significant interaction between agent type and age group was found ($F(5, 156) = 3.26$, $p = .008$). This result suggests that age may moderate the relationship between the type of service agent and customer forgiveness, indicating that the difference in forgiveness between AI and human service agents varied depending on participants' age group (see Appendix B 15.2). Further analyses within each age group would be required to interpret the interaction.

To further explore potential influences on customer forgiveness, the control variables were analyzed. Since customer service contact was measured as a binary variable (0 = "*No*", 1 = "*Yes*"), an independent samples t-test was conducted. Results revealed that participants without prior service experience reported significantly higher forgiveness (M = 4.11, SD = 0.93) than those with experience (M = 3.61, SD = 1.14), t(37.87) = 2.41, p = .021, d = 1.12, suggesting that familiarity with customer service situations might reduce consumer willingness to forgive (see Appendix B 15.3). The remaining control variables were continuous and were therefore examined using Pearson correlations. None of these variables showed a significant relationship with customer forgiveness: frequency of online shopping (r = -.013, p = .868), AI familiarity (r = .078, p = .314), and frequency of AI use (r = .079, p = .310). This indicates AI use and general shopping habits had no substantial effect on forgiveness (see Appendix B 15.4).

Summary of Findings and Discussion

This study explored the impact of the type of service agent – AI-based chatbot versus human agent – on customer forgiveness in the context of service failure recovery in online retail. Furthermore, it examined whether affect-based decision-making mediates this relationship.

The findings of testing H3 revealed that participants who interacted with an AI-based chatbot did not report significantly different levels of customer forgiveness than those who interacted with a human service agent. This difference was not statistically significant, suggesting that the type of service agent did not meaningfully affect consumers' willingness to forgive the brand. These results stand in contrast to previous research that emphasized human interaction as a key driver for restoring relationships after service failures (McColl-Kennedy et al. 2009; Wang et al. 2025). However, the present findings also suggest that AI-based service does not play a decisive role in fostering customer forgiveness either. Instead, the data suggest that the type of service agent may hold limited relevance for customers' forgiveness responses, as consumers might not place significant importance on whether a human or AI agent handles the complaint during the service recovery process. One possible explanation for this result could lie in the study context, which involved a low-involvement product and a routine service failure.

Results from the testing of H4 showed that participants who interacted with an AI agent reported significantly lower levels of affect-based decision-making. This finding supports the theoretical assumption that AI agents, due to their perceived lack of emotional expression, are less likely to evoke affective consumer responses (Kidwell et al. 2008; Pham 2007). Although affect-based decision-making did not significantly predict customer forgiveness, this result is important because it may influence other outcome variables, such as satisfaction, trust, and perceived fairness. Future research should explore these variables. The broader implications of this result will be discussed in Chapter 4. In relation to this finding, the indirect effect of agent type on forgiveness through affect-based decision-making was not significant. This suggests that although AI interactions were perceived as more rational and less emotional, this perception did not translate into a greater or reduced willingness to forgive the brand. These results indicate that AI's lack of emotion may influence how consumers process service interactions but does not necessarily enhance or diminish the effectiveness of service failure recovery. Importantly, this contrasts with expectations that the absence of emotionality in AI might mitigate negative emotional reactions such as anger or frustration (Harrison-Walker 2018). Instead, one possible interpretation is that customer forgiveness is shaped by other psychological processes not fully accounted for by affect-based decision-making alone.

Exploratory analyses revealed additional insights, indicating that prior customer service experience significantly influenced customer forgiveness. Participants who had never contacted customer service reported higher forgiveness levels than those with prior experience. This implies that individuals with past experiences may have stronger expectations or higher standards regarding service recovery. Age also emerged as a potential moderator, as a significant interaction was found between agent type and age group. However, further research with a larger and more diverse sample is needed to explore potential age-related differences in greater depth.

In summary, while prior research emphasizes the importance of emotional intelligence in effective service failure recovery, the findings of this study indicate that the type of service agent did not influence customer forgiveness, suggesting that the presence of emotions is not a necessary condition for effective service failure recovery. These findings raise new questions about the role of emotionality in service interactions and highlight the need for more context-specific models of service recovery in the age of artificial intelligence.

Group Part

4. General Discussion and Managerial Implications

The two experimental studies presented in this thesis provide valuable insights into how the type of service agent (AI versus human) affects consumer behavior in emotionally charged service interactions along the customer journey. These results contribute to the current research on AI in customer service by demonstrating how consumers react to the emotional neutrality of AI-based service agents compared to human service agents.

Study 1 investigated the pre-purchase phase and found that, contrary to initial expectations, consumers interacting with a human shopping assistant reported significantly higher purchase intentions than those assisted by an AI-based agent. While the AI agent significantly reduced the feeling of being judged, this reduction did not increase purchase intention. These findings confirm that AI can lower perceived social evaluation, even in non-sensitive settings such as luxury shopping, thereby extending prior research on more sensitive and embarrassing consumption situations (Holthöwer and van Doorn 2022; Pitardi et al. 2021). Furthermore, the results of this study support the idea that the absence of human social presence in AI interactions can reduce evaluative concerns. This aligns with research suggesting that AI agents are perceived as neutral entities, less likely to provoke embarrassment or judgment (Argo et al. 2005; Dahl et al. 2001; Holthöwer and van Doorn 2022). Overall, Study 1 advances the understanding of how AI's emotional neutrality shapes consumer perception but also demonstrates that reduced social judgment alone does not lead to increased purchase intention for luxury products.

Study 2 examined the post-purchase phase and found that consumers interacting with an AI-based chatbot reported significantly lower levels of affect-based decision-making compared to those assisted by a human service agent. However, this cognitive shift did not result into greater customer forgiveness, as no significant difference was observed between the two agent types. These findings contrast with prior work suggesting that customer forgiveness is shaped by the nature of the service agent involved (Huang and Lo 2025). While the results align with previous arguments that AI agents may be perceived as more objective due to lower emotional expectations from customers (Ho, Tojib, and Tsarenko 2020; Fürst et al. 2025), this study adds new empirical insight by showing that AI reduces affect-based decision-making in service failure recovery contexts. Although this reduction did not foster forgiveness, it remains an important finding, as reduced reliance on affect may influence other outcome variables, such as satisfaction, trust, or perceived fairness. Overall, Study 2 shows that while AI can influence emotional processing through its neutrality, this alone is not sufficient to foster forgiveness, pointing to the need for broader models of service failure recovery.

Together, these studies emphasize that consumer responses to AI-based service agents are shaped not solely by the agents' emotional neutrality, but also by the nature of the interaction context and individual differences, such as AI familiarity, shopping discomfort, and prior expectations. Importantly, both studies identify significant mediating mechanisms: in emotionally sensitive pre-purchase contexts, AI reduces feelings of being judged, while in post-purchase recovery scenarios, it lowers affect-based decision-making. However, these shifts in psychological processing do not automatically result in more favorable behavioral outcomes. This highlights the importance of contextual fit and the role of underlying psychological mechanisms in AI-consumer interactions.

Managerial Implications

As AI-powered service agents become increasingly common in customer-facing roles, companies must carefully consider how consumers perceive and respond to these technologies. This research contributes to the growing literature on AI in service interactions and provides practical guidance for identifying contexts in which AI-based service agents are most appropriate (Davenport et al. 2019; Jain et al. 2023; Wirtz et al. 2018). Findings from both studies suggest that AI is not a universally superior alternative to human service staff. In emotionally charged or socially sensitive interactions, such as luxury shopping or service failure recovery, consumer may still prefer human service agents. Although AI can reduce emotional intensity – such as the feeling of being judged or affect-based decision-making – these effects did not translate into increased purchase intention or customer forgiveness. This implies that emotional neutrality alone is not sufficient to drive favorable behavioral outcomes in high-involvement or emotionally complex situations. In such contexts, qualities like trust and personalized attention, typically associated with human agents, remain critical (Paluch et al. 2020). Luxury shopping, for instance, is often driven by aspirational goals, emotional engagement, and the need for social validation, which are more effectively fulfilled by human staff (Hennig-Thurau et al. 2006; Atwal and Williams 2009). Similarly, in service recovery, customers with prior experience or strong expectations may perceive AI's emotional neutrality as insufficient for rebuilding trust.

Instead, AI could be better positioned in functional, low-risk service encounters where efficiency, consistency, and scalability are prioritized over emotional connection. These include routine interactions such as order tracking, basic product frequently asked questions (FAQ), or standard complaint processes. In these domains, AI can enhance operational performance without undermining customer satisfaction.

However, Study 1 and Study 2 still emphasize that AI can play a supportive emotional role by reducing pressure and emotional intensity in service encounters. Therefore, managers should still view this as an opportunity to remove barriers in early or low-risk stages of the customer journey. For example, AI-powered shopping assistants can support consumers during the initial product exploration phase by offering personalized suggestions without inducing social pressure. Unlike human sales staff, who may be perceived as commission-driven, AI agents provide a neutral and non-evaluative environment, which can help consumers feel more comfortable when browsing or seeking advice. Additionally, in low-risk service failure recovery contexts, such as delivery issues, AI can help reduce affect-based decision-making by maintaining emotional neutrality and preventing escalation, allowing consumers to respond more rationally. Nevertheless, managers must be aware that this emotional relief alone is not sufficient to drive outcomes like purchase behavior or customer forgiveness. Emotional neutrality can act as a facilitator, but it does not replace the relational benefits offered by human interaction. In addition, consumer familiarity and usage frequency with AI is another key factor shaping acceptance. Managers should therefore invest in transparent communication strategies that normalize AI interactions, such as clear AI labeling and highlighting successful use cases. Increased exposure and familiarity can build trust and improve acceptance over time. Given these findings, companies are encouraged to adopt hybrid service models. AI can handle routine or early-stage tasks, while emotionally sensitive or high-involvement issues are escalated to human agents. This approach allows firms to balance efficiency and empathy, optimize resource allocation, and maintain emotional authenticity in customer relationships. Ultimately, AI should not be seen as a replacement for human service, but as a strategic enabler that supports and enhances the human touch. Managers should ensure that AI implementation is aligned with customer expectations, the nature of the interaction, and the emotional tone of the situation. In doing so, companies can enhance the customer journey while maintaining authenticity and trust in their service relationships.

5. Limitations and Directions for Future Research

This thesis offers valuable contributions to both theory and practice. However, several limitations arise due to the studies' context, experimental design, and methodology. These limitations offer meaningful starting points for future research. One key limitation lies in the industry context. The studies focused on the retail sector (luxury fashion and online shopping) where service interactions are highly relevant but context specific. This focus was methodologically necessary to ensure experimental control and internal validity. However, it restricts the generalizability of the findings to other industries. Future research should examine emotionally charged interactions in sectors such as hospitality or healthcare, where AI is already in use, but consumer expectations and emotional stakes differ significantly. In both studies, participants imagined interacting with AI or human agent through hypothetical, text-based scenarios rather than experiencing direct, real-time engagement. Although scenario-based experiments are widely used in service research, they may not fully replicate the emotional dynamics of real customer service interactions (Andreassen and Streukens 2012). This format likely limited emotional engagement and failed to capture nonverbal cues that are critical in service contexts. Future research should consider video-based designs or even real-world experiments in which participants engage directly with AI or human agents to more accurately stimulate naturalistic decision-making (Kuhail et al. 2024). Moreover, the AI agent was presented as a chatbot. Other research could examine alternative forms of AI, such as voice assistants or service robots, to compare consumer responses across different AI types.

Additionally, both studies relied on convenience sampling, which may result in selection bias and limited generalizability (Ferber 1977). Participants were primarily young adults from Europe, offering limited cultural and demographic diversity. Prior research suggests that AI acceptance and emotional expectations can vary significantly across age groups and cultures (Huang and Lo 2025), indicating that future studies should diversify their samples to better capture consumer preferences regarding the type of service agent.

From a methodological perspective, another limitation is the cross-sectional nature of the data collection. Consumer behavior was assessed at a single point in time, which does not account for changing attitudes or behaviors in evolving AI-driven service environments. This limitation could be addressed through field experiments or longitudinal designs that observe behavior in authentic service contexts over time. Furthermore, the studies used measurement scales with seven or fewer items, to keep the survey reasonably short. This may have limited the internal consistency of the constructs. Future research should include scales with a higher number of items to increase the reliability of constructs. Additionally, each study focused on only one mediator, the feeling of judgment in Study 1 and affect-based decision-making in Study 2. While both constructs are theoretically grounded, they do not fully capture the complexity of emotionally charged consumer decisions. Future research should consider multiple mediators such as perceived empathy or trust. Likewise, integrating moderators such as psychological discomfort, product involvement, or prior AI experience would allow for more differentiated insights into when and for whom AI is more or less effective.

In Study 1, the use of a specific high-status product category raises further limitations. Since the participants included individuals who may not have purchased or intended to purchase luxury goods, this may have influenced their level of engagement or the relevance of the scenario. Future research could address this by focusing on individuals who have recently purchased or are interested in the featured products. Moreover, the results showed that general discomfort was positively correlated with feeling judged and negatively with purchase intention, suggesting that future studies might test general discomfort as a potential mediator or explore other judgment-related constructs.

In Study 2, the low-involvement nature of the product also may have limited the emotional impact of the service failure scenario. Furthermore, the service failure (delivery delay) described may not have elicited the level of frustration or anger necessary to activate the hypothesized mechanisms. As a result, the effect of AI's emotional neutrality may have been diminished. Future studies should incorporate more emotionally intense service failures to better assess when AI's emotional neutrality becomes beneficial. Additionally, future research should examine higher-involvement product categories or compare responses across low- and high-involvement settings, where service failures are likely to carry stronger emotional consequences.

Several potential research topics emerge from the present findings. Building on the findings of Study 1, future research could apply this research design to contexts where judgement is particularly salient. For example, previous studies have shown that consumers with low body appreciation or who are plus size often feel judged in retail settings involving body size and fit and may avoid seeking advice (Bishop et al. 2018; Seekis, Yager, and Paas 2024; Shelton et al. 2023). Further research could examine whether AI reduces the perception of judgement and improves consumer outcomes in such situations. While the current results showed that AI reduced feelings of being judged, this benefit does not translate into higher purchase intention. Investigations could explore whether this reduction in perceived judgment positively influences other outcomes, such as consumer well-being or self-esteem in emotionally charged situations. Based on Study 2, additional studies should investigate more emotionally intense service failures, such as financial errors, to assess whether AI's emotional neutrality fosters greater forgiveness when the stakes are high. Although the present findings indicate that AI reduced affect-based decision-making, this reduction did not influence the customers' willingness to forgive. Upcoming studies could explore whether reduced affect-based decision-making positively influences other behavioral outcomes, such as satisfaction or trust, in emotionally charged situations. As AI technology advances, further studies could also explore how agent design, such as conversational style or voice tone, influences emotional customer responses. By addressing these limitations, future research can clarify how emotional factors influence consumer behavior in emotionally charged contexts and support the development of emotionally intelligent AI solutions along the customer journey.

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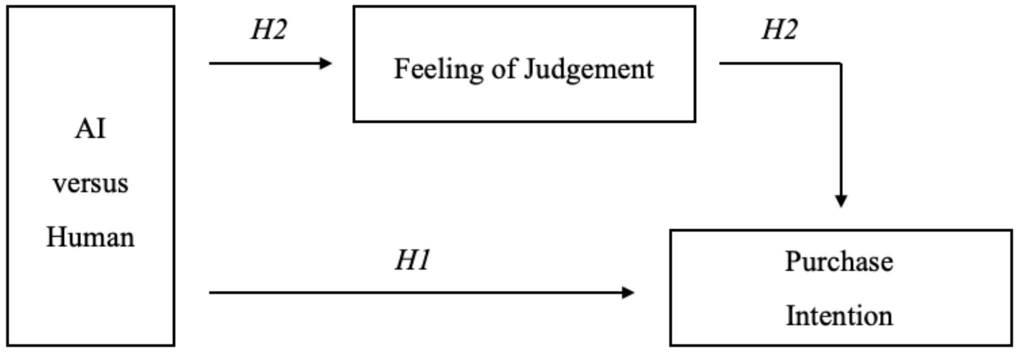
Appendix

Appendix A Study 1

A 1. Conceptual Framework



A 2. Survey

A 2.1 Introduction

NOVA
NOVA SCHOOL OF
BUSINESS & ECONOMICS

Thank you for participating in our research study!
This study investigates how consumers perceive and evaluate service experiences with different types of service providers. Your responses will help us better understand how customer service interactions influence customer reactions and decision-making. The survey will take approximately 5 minutes to complete. Your participation is voluntary, and all responses will be kept anonymous. The results of this study will be used solely for scholarly purposes and may be shared with representatives of Nova SBE.

By clicking "Agree", you confirm that:

- You have read and understood the information above.
- You voluntarily agree to participate.
- You are at least 18 years of age.

If you do not wish to participate, you may decline by selecting "Disagree."

○ Agree

○ Disagree

A 2.2 Experimental Scenario

Scenario 1: Human Service Agent (IV)

Please imagine yourself in the following situation:

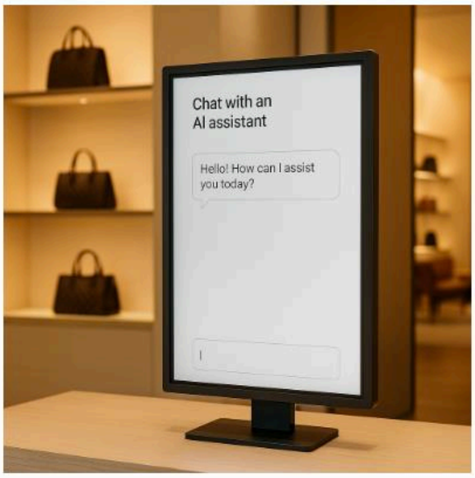
You are visiting a luxury fashion store because you are looking for a high-end travel bag for your upcoming trip – specifically a luxury weekender bag, similar to the one shown below. After entering the store, you take some time to walk around, browse different models, and explore the displays. Several options are available, and you are not entirely sure which product would be the best fit for your needs. To get more clarity, you decide to consult a sales employee who is available in the store to assist customers. You begin the interaction by sharing your preferences. The sales employee listens to your input and presents detailed information about the weekender bag you are currently considering. You specifically ask for the price of the item, and the sales employee immediately provides the price, along with additional product features. The sales employee also offers personalized product recommendations based on your input and shows you other relevant options. You can ask further questions, which the employee answers directly. After the interaction ends, you reflect on the information provided and consider whether to purchase the item recommended by the sales employee.



Scenario 2: AI Service Agent (IV)

Please imagine yourself in the following situation:

You are visiting a luxury fashion store because you are looking for a high-end travel bag for your upcoming trip – specifically a luxury weekender bag, similar to the one shown below. After entering the store, you take some time to walk around, browse different models, and explore the displays. Several options are available, and you are not entirely sure which product would be the best fit for your needs. To get more clarity, you decide to consult a digital AI-based shopping assistant using an interactive screen located in the store. You begin the interaction by entering your preferences. The AI assistant processes your input and presents detailed information about the weekender bag you are currently considering. You specifically ask for the price of the item, and the AI assistant immediately provides the price, along with additional product features. The AI assistant also offers personalized product recommendations based on your input and allows you to explore other relevant options. You can ask further questions by selecting from suggested topics or entering your own queries, which the assistant answers. After the interaction ends, you reflect on the information provided and consider whether to purchase the item recommended by the AI shopping assistant.





A 2.3 Purchase Intention Questions (DV)

How likely are you to purchase a product recommended by the shopping assistant after the interaction? (Please indicate the extent to which you agree with the following statements.)

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
"I would consider buying this product."	○	○	○	○	○	○	○
"The likelihood that I would purchase this product is high."	○	○	○	○	○	○	○
"I would be willing to purchase this product."	○	○	○	○	○	○	○
"I would likely purchase this item."	○	○	○	○	○	○	○

A 2.4 Feeling of Judgement Questions (Mediator)

How did you feel during the interaction with the shopping assistant? (Please indicate the extent to which you agree with the following statements.)

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
"I felt judged by the shopping assistant."	○	○	○	○	○	○	○
"I felt evaluated by the shopping assistant during this situation."	○	○	○	○	○	○	○
"I felt like the shopping assistant formed a negative opinion about me."	○	○	○	○	○	○	○
"I felt critically observed by the shopping assistant."	○	○	○	○	○	○	○
"I was concerned about how the shopping assistant perceived me."	○	○	○	○	○	○	○

A 2.5 Manipulation Check

Please answer the following questions about the customer service situation you just read: Who assisted you during the shopping interaction described in the scenario?

- ◯ AI-based chatbot
- ◯ Human service agent

A 2.6 Control Variables

How familiar are you with luxury products (e.g., bags, clothing, accessories, watches)?

- ◯ Not familiar at all
- ◯ Slightly familiar
- ◯ Moderately familiar
- ◯ Neutral
- ◯ Moderately familiar
- ◯ Very familiar
- ◯ Extremely familiar

How often do you visit or have you visited luxury retail stores (e.g., Louis Vuitton, Celine, Chanel, Loewe, Dior)?

- ◯ Never
- ◯ Very rarely (once a year or less)
- ◯ Rarely (less then every few months)
- ◯ Occasionally (every few months)
- ◯ Frequently (once a month)
- ◯ Very frequently (several times a month)
- ◯ Extremely frequently (at least once a week)

Please indicate to what extent you agree with the following statements when thinking about shopping in a luxury retail store.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
"I sometimes feel uncomfortable when shopping in luxury stores."	○	○	○	○	○	○	○
"I sometimes worry that sales staff in luxury stores might judge me."	○	○	○	○	○	○	○
"I sometimes feel out of place in luxury stores."	○	○	○	○	○	○	○

How familiar are you with AI-based tools and chatbots (e.g. ChatGPT, Alexa, customer service bots)?

- ○ Not familiar at all
- ○ Slightly familiar
- ○ Moderately familiar
- ○ Neutral
- ○ Moderately familiar
- ○ Very familiar
- ○ Extremely familiar

How often do you use AI tools or chatbots in your daily life?

- ○ Never
- ○ Very rarely (a few times per year)
- ○ Rarely (once a month)
- ○ Occasionally (a few times per month)
- ○ Frequently (once a week)
- ○ Very frequently (several times a week)
- ○ Extremely frequently

What is your approximate monthly net income?

- ○ Less than €1,000
- ○ €1,000 - €2,499
- ○ €2,500 - €3,999
- ○ €4,000 - €5,999
- ○ €6,000 or more
- ○ Prefer not to say

A 2.7 Demographics

How old are you?

- ○ 18-24
- ○ 25-34
- ○ 35-44
- ○ 45-54
- ○ 55-64
- ○ 65+

Which gender do you identify with?

- ○ Male
- ○ Female
- ○ Non-binary / third gender
- ○ Prefer not to say

What is your current occupation?

- ○ Student
- ○ Trainee
- ○ Employed
- ○ Self-employed / Freelancer
- ○ Unemployed
- ○ Retired
- ○ Other

What is your nationality?

A 2.8 Debrief and Thank You

NOVA SCHOOL OF BUSINESS & ECONOMICS

We thank you for your time spent taking this survey.
Your response has been recorded.

A 3. Descriptives

A 3.1 Descriptives of Key Variables

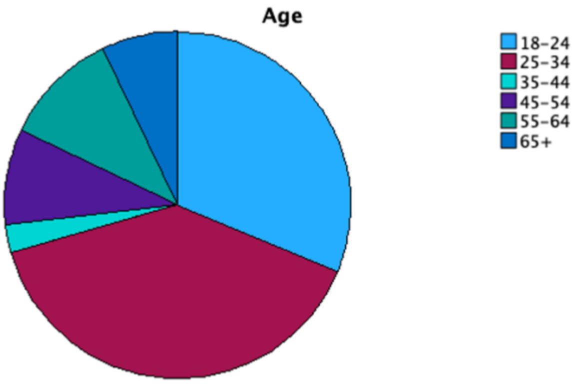
Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Purch	112	1	7	4.74	1.167
Judge	112	1	6	3.03	1.317
Discomf	112	1	7	4.83	1.429
AIFam	112	1	7	4.96	1.708
AIFreq	112	1	7	5.20	1.770
FamLuxPr	112	1	7	3.78	1.844
FreShop	112	1	6	2.49	1.349
Valid N (listwise)	112				

A 3.2 Age Distribution

Age

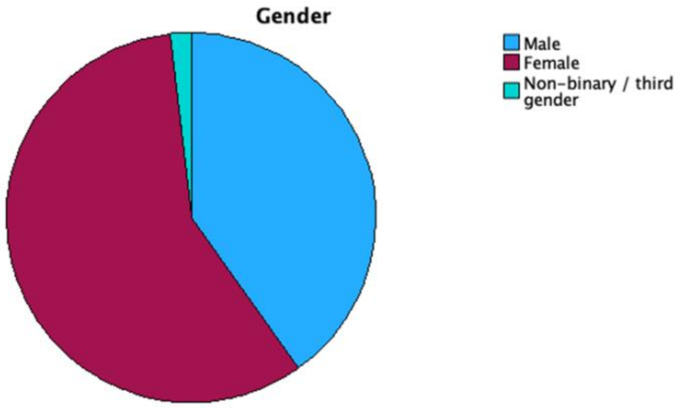
	N	%
18-24	35	31.3%
25-34	44	39.3%
35-44	3	2.7%
45-54	10	8.9%
55-64	12	10.7%
65+	8	7.1%



A 3.3 Gender Distribution

Gender

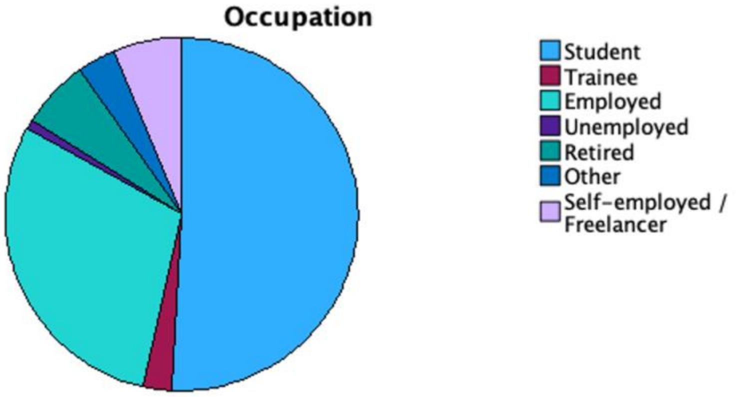
	N	%
Male	45	40.2%
Female	65	58.0%
Non-binary / third gender	2	1.8%



A 3.4 Occupation Distribution

Occupation

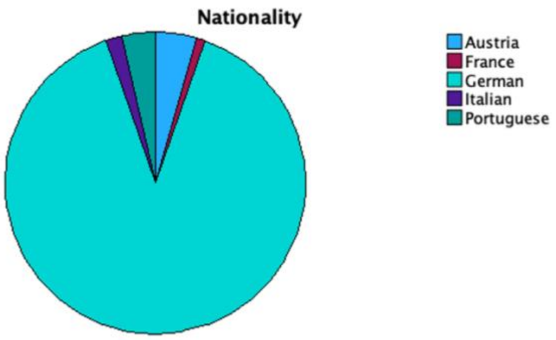
	N	%
Student	57	50.9%
Trainee	3	2.7%
Employed	33	29.5%
Unemployed	1	0.9%
Retired	7	6.3%
Other	4	3.6%
Self-employed / Freelancer	7	6.3%



A 3.5 Nationality Distribution

Nationality

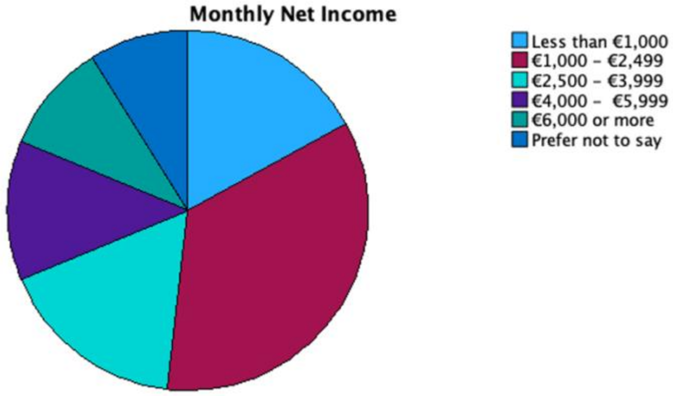
	N	%
Austria	5	4.5%
France	1	0.9%
German	100	89.3%
Italian	2	1.8%
Portuguese	4	3.6%



A 3.6 Monthly Net Income

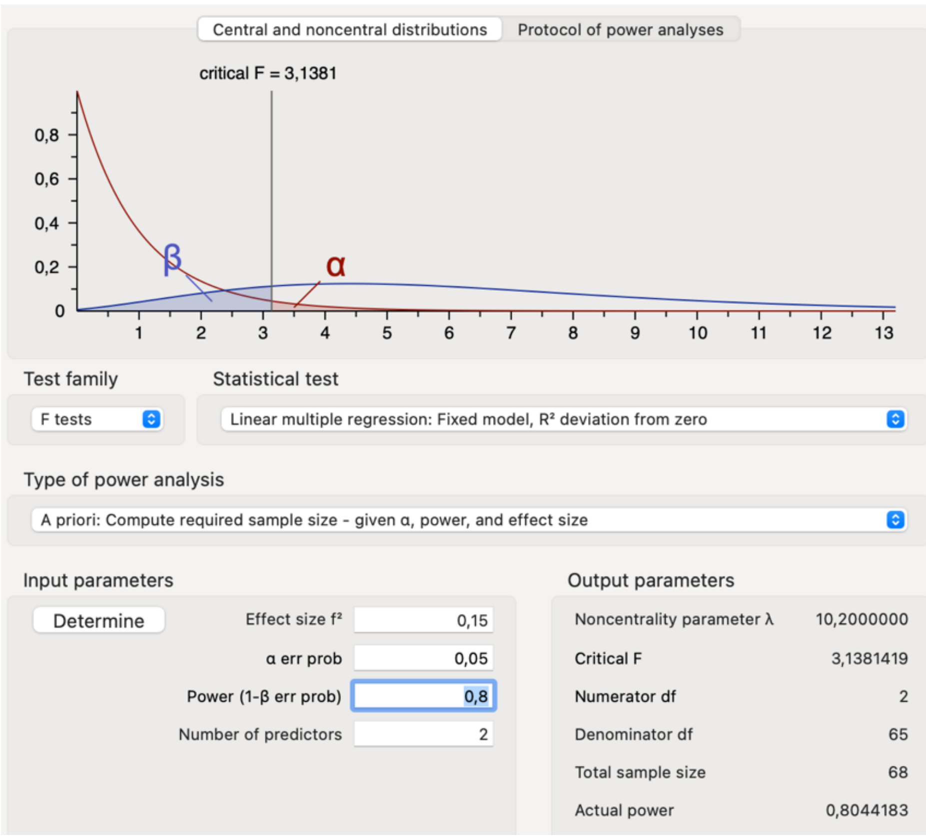
Income

	N	%
Less than €1,000	19	17.0%
€1,000 – €2,499	39	34.8%
€2,500 – €3,999	19	17.0%
€4,000 – €5,999	14	12.5%
€6,000 or more	11	9.8%
Prefer not to say	10	8.9%

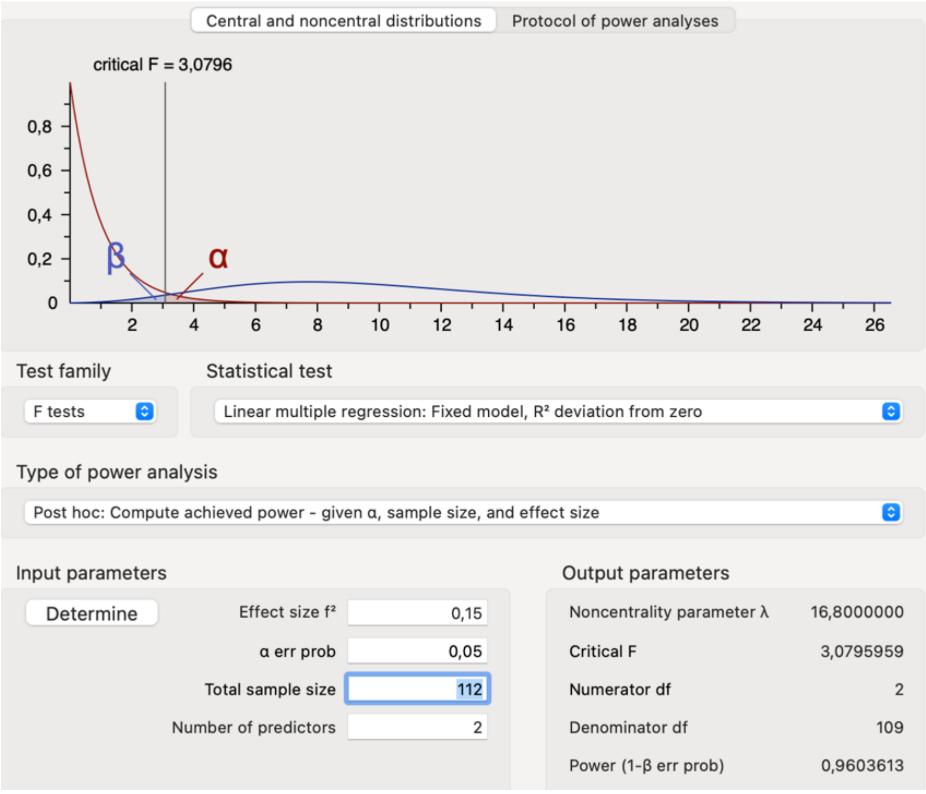


A 4. G* Power

A 4.1 A Priori Power Analysis



A 4.2 Post hoc Power Analysis

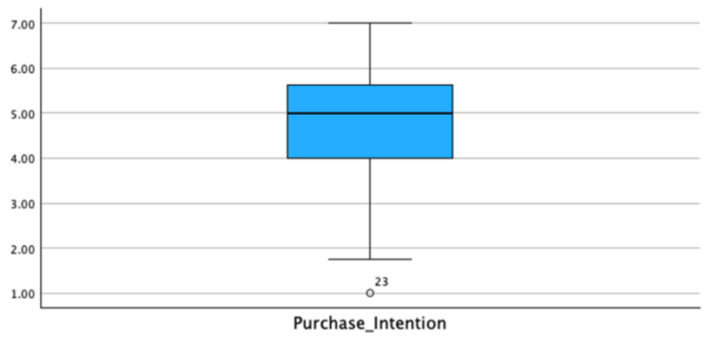


A 5. Outlier Analysis

A 5.1 Purchase Intention Outliers

Case Processing Summary

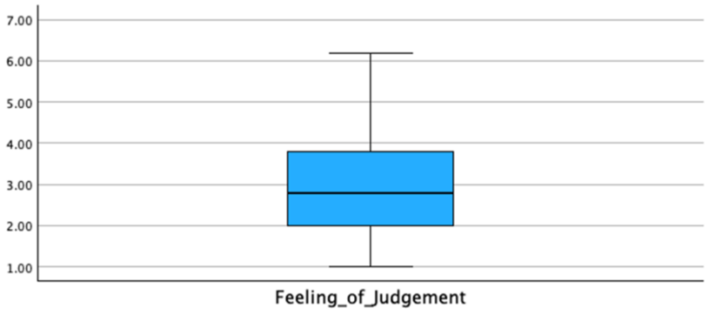
	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
Purchase_Intention	112	100.0%	0	0.0%	112	100.0%



A 5.2 Feeling of Judgement Outliers

Case Processing Summary

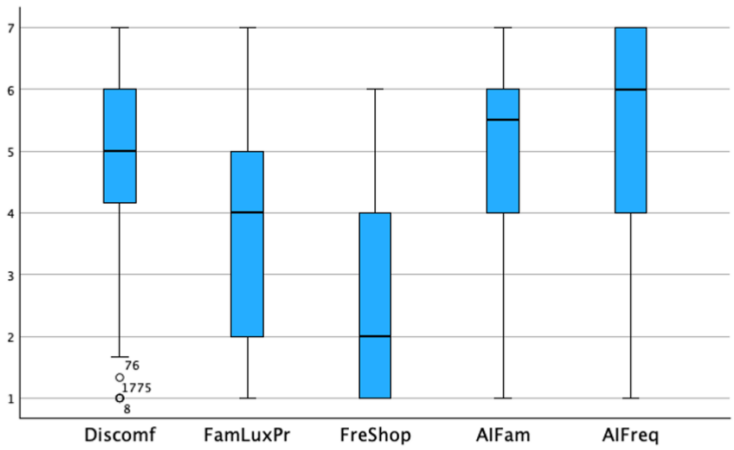
	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
Feeling_of_Judgement	112	100.0%	0	0.0%	112	100.0%



A 5.3 Luxury Product Familiarity, Luxury Store Visit Frequency, AI Familiarity, AI Usage Frequency and Perceived Shopping Discomfort Outliers

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
Discomf	112	100.0%	0	0.0%	112	100.0%
FamLuxPr	112	100.0%	0	0.0%	112	100.0%
FreShop	112	100.0%	0	0.0%	112	100.0%
AIFam	112	100.0%	0	0.0%	112	100.0%
AIFreq	112	100.0%	0	0.0%	112	100.0%



A 6. Reliability Analysis

A 6.1 Purchase Intention Scale

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.927	.927	4

Inter-Item Correlation Matrix

	Purchase_Intention1	Purchase_Intention2	Purchase_Intention3	Purchase_Intention4
Purchase_Intention1	1.000	.672	.701	.737
Purchase_Intention2	.672	1.000	.812	.817
Purchase_Intention3	.701	.812	1.000	.826
Purchase_Intention4	.737	.817	.826	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Purchase_Intention1	14.05	13.240	.751	.573	.930
Purchase_Intention2	14.28	12.580	.839	.729	.902
Purchase_Intention3	14.26	12.662	.858	.748	.896
Purchase_Intention4	14.33	11.701	.876	.772	.889

A 6.2 Feeling of Judgement Scale

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.876	.881	5

Inter-Item Correlation Matrix

	Feeling_Judgement1	Feeling_Judgement2	Feeling_Judgement3	Feeling_Judgement4	Feeling_Judgement5
Feeling_Judgement1	1.000	.658	.563	.572	.452
Feeling_Judgement2	.658	1.000	.519	.556	.426
Feeling_Judgement3	.563	.519	1.000	.789	.658
Feeling_Judgement4	.572	.556	.789	1.000	.770
Feeling_Judgement5	.452	.426	.658	.770	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Feeling_Judgement1	12.12	30.320	.664	.508	.860
Feeling_Judgement2	11.52	28.774	.627	.483	.871
Feeling_Judgement3	12.60	30.152	.769	.648	.841
Feeling_Judgement4	12.07	26.319	.826	.753	.819
Feeling_Judgement5	12.23	27.477	.684	.600	.857

A 6.3 Perceived Shopping Discomfort Scale

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.827	.830	3

Inter-Item Correlation Matrix

	Perceived_Shopping_Discomfort_1	Perceived_Shopping_Discomfort_2	Perceived_Shopping_Discomfort_3
Perceived_Shopping_Discomfort_1	1.000	.651	.665
Perceived_Shopping_Discomfort_2	.651	1.000	.542
Perceived_Shopping_Discomfort_3	.665	.542	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Perceived_Shopping_Discomfort_1	9.55	8.916	.749	.562	.701
Perceived_Shopping_Discomfort_2	9.85	8.454	.653	.445	.799
Perceived_Shopping_Discomfort_3	9.58	9.255	.660	.463	.785

A 7. Normality of DV across Groups

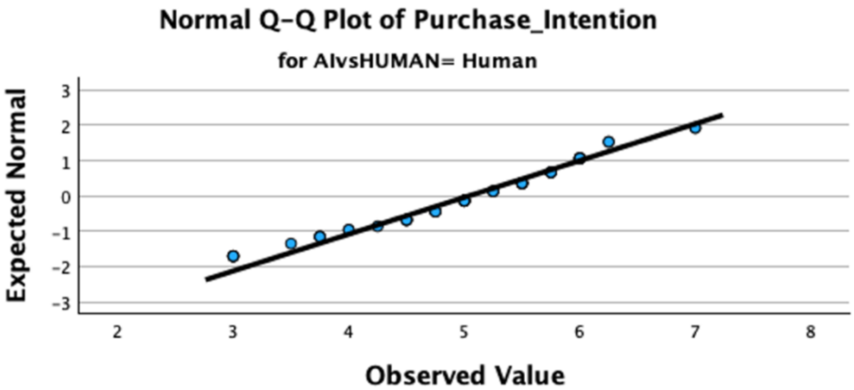
A 7.1 Shapiro-Wilk Test for Purchase Intention

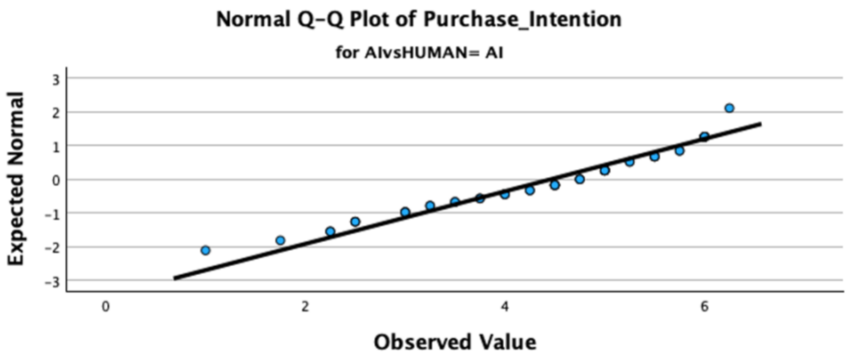
Tests of Normality

		Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	AIvsHuman	Statistic	df	Sig.	Statistic	df	Sig.
Purchase_Intention	Human	.121	55	.043	.958	55	.051
	AI	.137	57	.010	.936	57	.005

a. Lilliefors Significance Correction

A 7.2 Q-Q Plot for Purchase Intention in AI versus Human Conditions





A 8. Homogeneity of Variances of DV

		Levene's Test for Equality of Variances	
		F	Sig.
Purchase_Intention	Equal variances assumed	5.766	.018
	Equal variances not assumed		

A 9. Normality of additional Variables involved in Mediation Model

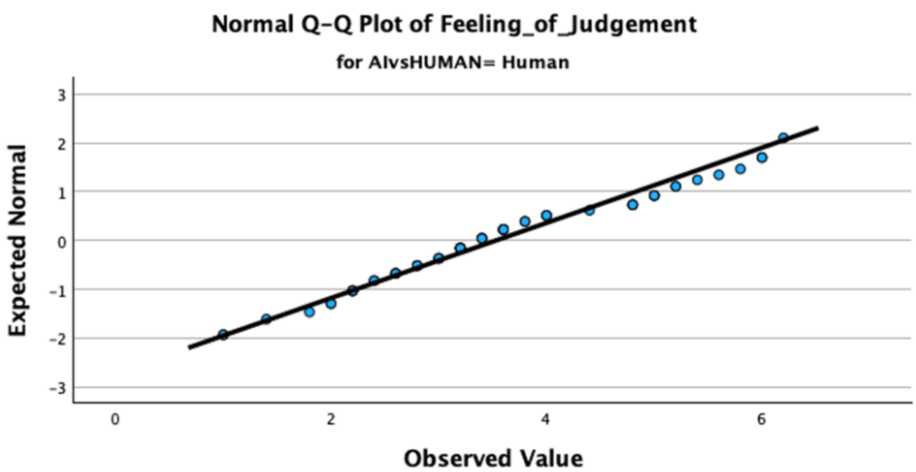
A 9.1 Shapiro-Wilk Test for Feeling of Judgement in AI versus Human Conditions

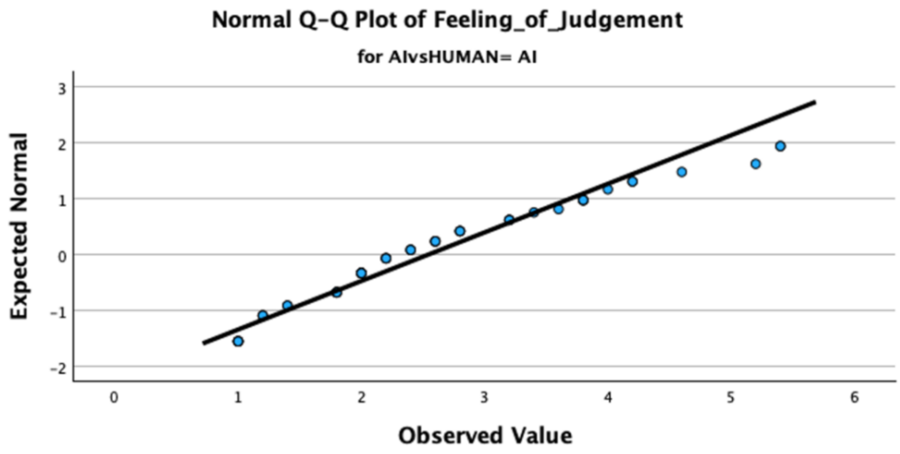
Tests of Normality

		Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	AIvsHuman	Statistic	df	Sig.	Statistic	df	Sig.
Feeling_of_Judgement	Human	.115	55	.066	.969	55	.173
	AI	.125	57	.026	.933	57	.004

a. Lilliefors Significance Correction

A 9.2 Q-Q Plot for Feeling of Judgement in AI versus Human Conditions





A 10. Multicollinearity (VIF and tolerance value for IV and Mediator)

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	95,0% Confidence Interval for B Lower Bound	95,0% Confidence Interval for B Upper Bound	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	3.309	.767		4.317	<.001	1.789	4.829		
	Judge	-.093	.087	-.105	-1.072	.286	-.265	.079	.877	1.141
	AIFam	.079	.103	.115	.762	.448	-.126	.283	.370	2.700
	AIFreq	.074	.098	.113	.759	.450	-.120	.269	.381	2.626
	FamLuxPr	.066	.096	.104	.690	.491	-.124	.256	.369	2.713
	FreShop	-.132	.131	-.153	-1.011	.314	-.391	.127	.370	2.704
	Discomf	.181	.083	.221	2.183	.031	.017	.345	.820	1.220
	Gender	.181	.227	.081	.799	.426	-.269	.631	.812	1.232
	Income	-.051	.078	-.067	-.645	.520	-.206	.105	.791	1.265

a. Dependent Variable: Purch

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions (Constant)	Judge	AIFam	AIFreq	FamLuxPr	FreShop	Discomf	Gender	Income
1	1	8.017	1.000	.00	.00	.00	.00	.00	.00	.00	.00	.00
	2	.284	5.317	.00	.04	.00	.00	.08	.11	.03	.01	.01
	3	.259	5.560	.00	.02	.01	.01	.00	.00	.01	.00	.51
	4	.200	6.339	.00	.21	.05	.04	.00	.03	.00	.04	.03
	5	.101	8.899	.00	.59	.01	.00	.00	.00	.06	.30	.07
	6	.058	11.737	.00	.06	.01	.06	.04	.00	.63	.36	.02
	7	.043	13.689	.00	.02	.01	.00	.86	.84	.02	.02	.02
	8	.022	19.081	.01	.00	.91	.76	.00	.01	.00	.13	.04
	9	.016	22.306	.98	.06	.00	.12	.01	.01	.26	.14	.31

a. Dependent Variable: Purch

A 11. Residual Analysis

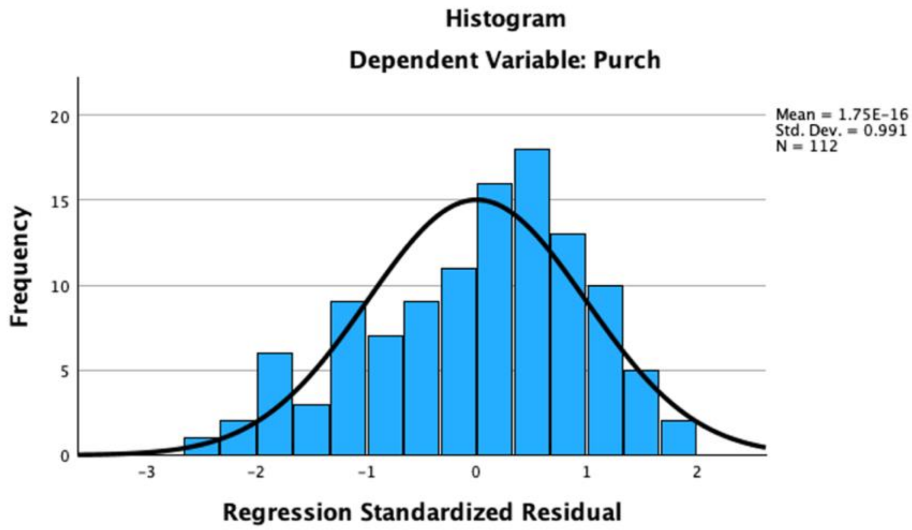
A 11.1 Residual Statistics of Linear Regression Model (IV, Mediator, DV)

Residuals Statistics[a]

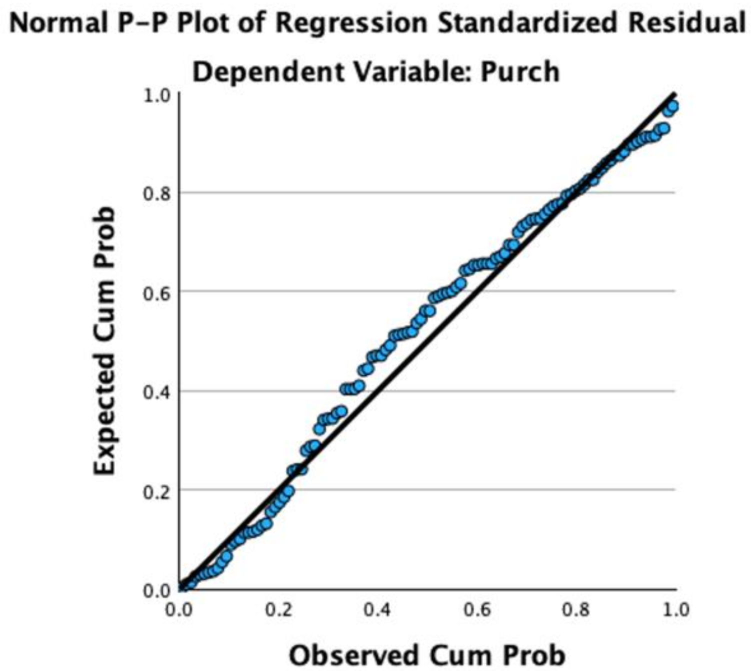
	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	3.9902	5.4526	4.7433	.35191	112
Residual	-2.99021	2.17236	.00000	1.11222	112
Std. Predicted Value	-2.140	2.016	.000	1.000	112
Std. Residual	-2.664	1.935	.000	.991	112

a. Dependent Variable: Purch

A 11.2 Histogram of Standardized Residuals



A 11.3 Scatterplot of Standardized Residuals against Standardized Predicted Values



A 12. Testing of Hypothesis 1

A 12.1 Independent t-test between AI and Human (IV) and Purchase Intention

Group Statistics

	AIvsHuman	N	Mean	Std. Deviation	Std. Error Mean
Purchase_Intention	AI	57	4.4605	1.28156	.16975
	Human	55	5.0364	.96035	.12949

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance				95% Confidence Interval of the Difference	
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
Purchase_Intention	Equal variances assumed	5.766	.018	-2.684	110	.004	.008	-.57584	.21458	-1.00109	-.15058
	Equal variances not assumed			-2.697	103.718	.004	.008	-.57584	.21350	-.99923	-.15245

Independent Samples Effect Sizes

		Standardizer[a]	Point Estimate	95% Confidence Interval Lower	95% Confidence Interval Upper
Purch	Cohen's d	1.135	-.507	-.883	-.130
	Hedges' correction	1.143	-.504	-.877	-.129
	Glass's delta	.960	-.600	-.984	-.210

a. The denominator used in estimating the effect sizes.
Cohen's d uses the pooled standard deviation.
Hedges' correction uses the pooled standard deviation, plus a correction factor.
Glass's delta uses the sample standard deviation of the control (i.e., the second) group.

A 12.2 ANCOVA with Control Variables

Tests of Between-Subjects Effects

Dependent Variable: Purchase_Intention

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	27.598[a]	6	4.600	3.912	.001	.183
Intercept	42.468	1	42.468	36.119	<.001	.256
Familiarity_LuxuryProduct	.520	1	.520	.443	.507	.004
Frequency_LuxuryshopVisit	.895	1	.895	.762	.385	.007
FamiliartyAI	1.382	1	1.382	1.176	.281	.011
Frequency_AI	1.056	1	1.056	.898	.345	.008
Perceived_Shopping_Discomfort	5.555	1	5.555	4.724	.032	.043
AIvsHUMAN	10.068	1	10.068	8.563	.004	.075
Error	123.460	105	1.176			
Total	2670.938	112				
Corrected Total	151.057	111				

a. R Squared = .183 (Adjusted R Squared = .136)

A 13. Testing of Hypothesis 2 with Hayes Process Model 4

A 13.1 Mediation Analysis

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : Purch
    X  : AIvsHum
    M  : Judge

Sample
Size:  112

**************************************************************************
OUTCOME VARIABLE:
 Judge

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .3777      .1427     1.5005    18.3039     1.0000   110.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     3.5309      .1652    21.3772      .0000     3.2036     3.8582
AIvsHum      -.9906      .2315    -4.2783      .0000    -1.4494     -.5317

**************************************************************************
OUTCOME VARIABLE:
 Purch

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .3017      .0910     1.2597     5.4560     2.0000   109.0000      .0055

Model
              coeff         se          t          p       LLCI       ULCI
constant     5.6171      .3436    16.3479      .0000     4.9361     6.2981
AIvsHum      -.7388      .2291    -3.2244      .0017    -1.1929     -.2847
Judge        -.1645      .0874    -1.8826      .0624     -.3376      .0087


****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
     -.7388      .2291    -3.2244      .0017    -1.1929     -.2847

Indirect effect(s) of X on Y:
          Effect     BootSE   BootLLCI   BootULCI
Judge      .1629      .0987     -.0196      .3660

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

Number of bootstrap samples for percentile bootstrap confidence intervals:


  5000

------ END MATRIX -----
```

A 13.2 Mediation Analysis with Control Variables

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : Purch
    X  : AIvsHum
    M  : Judge

Covariates:
 FamiAI   FreAI    Discomf  FamLuxPr FreShop

Sample
Size:  112

**************************************************************************
OUTCOME VARIABLE:
 Judge

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .4830      .2333     1.4058     5.3241     6.0000   105.0000      .0001

Model
              coeff         se          t          p       LLCI       ULCI
constant     2.4242      .5613     4.3187      .0000     1.3112     3.5372
AIvsHum      -.9909      .2333    -4.2475      .0000    -1.4534     -.5283
FamiAI        .0498      .1047      .4753      .6356     -.1578      .2573
FreAI        -.0875      .0983     -.8904      .3753     -.2823      .1073
Discomf       .1896      .0804     2.3577      .0202      .0301      .3490
FamLuxPr     -.0917      .1001     -.9160      .3618     -.2901      .1068
FreShop       .2991      .1330     2.2491      .0266      .0354      .5627

**************************************************************************
OUTCOME VARIABLE:
 Purch

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .4722      .2230     1.1286     4.2639     7.0000   104.0000      .0004

Model
              coeff         se          t          p       LLCI       ULCI
constant     3.8578      .5458     7.0683      .0000     2.7755     4.9401
AIvsHum      -.8255      .2263    -3.6485      .0004    -1.2742     -.3768
Judge        -.2031      .0874    -2.3225      .0222     -.3765     -.0297
FamiAI        .1139      .0939     1.2131      .2278     -.0723      .3001
FreAI         .0674      .0884      .7627      .4473     -.1078      .2426
Discomf       .1983      .0739     2.6828      .0085      .0517      .3449
FamLuxPr      .0423      .0900      .4696      .6396     -.1363      .2208
FreShop      -.0454      .1220     -.3721      .7106     -.2873      .1965


****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y



     Effect         se          t          p       LLCI       ULCI
     -.8255      .2263    -3.6485      .0004    -1.2742     -.3768

Indirect effect(s) of X on Y:
         Effect     BootSE   BootLLCI   BootULCI
Judge      .2012      .1084      .0233      .4442

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000

------ END MATRIX -----
```

A 14. Exploratory Analysis

A 14.1 One-Way ANOVA: Monthly net Income × Purchase Intention

ANOVA

Purchase_Intention

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	12.175	5	2.435	1.859	.108
Within Groups	138.882	106	1.310		
Total	151.057	111			

ANOVA Effect Sizes[a,b]

		Point Estimate	95% Confidence Interval Lower	95% Confidence Interval Upper
Purchase_Intention	Eta-squared	.081	.000	.153
	Epsilon-squared	.037	-.047	.114
	Omega-squared Fixed-effect	.037	-.047	.113
	Omega-squared Random-effect	.008	-.009	.025

a. Eta-squared and Epsilon-squared are estimated based on the fixed-effect model.

b. Negative but less biased estimates are retained, not rounded to zero.

A 14.2 One-Way ANOVA: Occupation × Purchase Intention

ANOVA

Purch

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	19.532	6	3.255	2.599	.022
Within Groups	131.526	105	1.253		
Total	151.057	111			

ANOVA Effect Sizes[a,b]

		Point Estimate	95% Confidence Interval Lower	95% Confidence Interval Upper
Purch	Eta-squared	.129	.001	.209
	Epsilon-squared	.080	-.056	.164
	Omega-squared Fixed-effect	.079	-.055	.162
	Omega-squared Random-effect	.014	-.009	.031

a. Eta-squared and Epsilon-squared are estimated based on the fixed-effect model.

b. Negative but less biased estimates are retained, not rounded to zero.

A 14.3 Two-Way ANOVA: Age × Service Agent Type on Purchase Intention

Between-Subjects Factors

		Value Label	N
AIvsHum	0	Human	55
	1	AI	57
Age	1	18-24	35
	2	25-34	44
	3	35-44	3
	4	45-54	10
	5	55-64	12
	6	65+	8

Descriptive Statistics

Dependent Variable: Purch

AIvsHum	Age	Mean	Std. Deviation	N
Human	18-24	5.47	.799	18
	25-34	4.94	1.073	20
	35-44	6.00	.	1
	45-54	5.00	.866	3
	55-64	4.61	.900	7
	65+	4.42	.719	6
	Total	5.04	.960	55
AI	18-24	5.09	.637	17
	25-34	4.46	1.268	24
	35-44	3.50	3.536	2
	45-54	3.86	1.533	7
	55-64	4.20	1.137	5
	65+	2.88	.530	2
	Total	4.46	1.282	57
Total	18-24	5.29	.740	35
	25-34	4.68	1.194	44
	35-44	4.33	2.887	3
	45-54	4.20	1.428	10
	55-64	4.44	.978	12
	65+	4.03	.958	8
	Total	4.74	1.167	112

Tests of Between-Subjects Effects

Dependent Variable: Purch

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	33.882[a]	11	3.080	2.629	.005	.224
Intercept	927.605	1	927.605	791.638	<.001	.888
AIvsHum	13.054	1	13.054	11.140	.001	.100
Age	19.455	5	3.891	3.321	.008	.142
AIvsHum * Age	5.031	5	1.006	.859	.512	.041
Error	117.175	100	1.172			
Total	2670.938	112				
Corrected Total	151.057	111				

a. R Squared = .224 (Adjusted R Squared = .139)

A 14.4 Two-Way ANOVA: Gender × Service Agent Type on Purchase Intention

Between-Subjects Factors

		Value Label	N
AlvsHuman	0	Human	55
	1	AI	57
Gender	1	Male	45
	2	Female	65
	3	Non-binary / third gender	2

Descriptive Statistics

Dependent Variable: Purchase_Intention

AlvsHuman	Gender	Mean	Std. Deviation	N
Human	Male	4.7500	.92421	19
	Female	5.1765	.98383	34
	Non-binary / third gender	5.3750	.17678	2
	Total	5.0364	.96035	55
AI	Male	4.7404	1.26190	26
	Female	4.2258	1.27042	31
	Total	4.4605	1.28156	57
Total	Male	4.7444	1.11992	45
	Female	4.7231	1.21845	65
	Non-binary / third gender	5.3750	.17678	2
	Total	4.7433	1.16657	112

Tests of Between-Subjects Effects

Dependent Variable: Purchase_Intention

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	15.481[a]	4	3.870	3.054	.020
Intercept	611.987	1	611.987	482.993	<.001
AlvsHUMAN	6.036	1	6.036	4.764	.031
Gender	.388	2	.194	.153	.858
AlvsHUMAN * Gender	5.797	1	5.797	4.575	.035
Error	135.577	107	1.267		
Total	2670.938	112			
Corrected Total	151.057	111			

a. R Squared = .102 (Adjusted R Squared = .069)

A 14.5 Pearson Correlation between Control Variables (Luxury Product Familiarity, Luxury Store Visit Frequency, Perceived Shopping Discomfort) and Feeling of Judgement

Correlations

		Judge	FamLuxPr	FreShop	Discomf
Judge	Pearson Correlation	1	.028	.134	.235*
	Sig. (2-tailed)		.772	.161	.013
	N	112	112	112	112
FamLuxPr	Pearson Correlation	.028	1	.776**	-.126
	Sig. (2-tailed)	.772		<.001	.185
	N	112	112	112	112
FreShop	Pearson Correlation	.134	.776**	1	-.089
	Sig. (2-tailed)	.161	<.001		.352
	N	112	112	112	112
Discomf	Pearson Correlation	.235*	-.126	-.089	1
	Sig. (2-tailed)	.013	.185	.352	
	N	112	112	112	112

*. Correlation is significant at the 0.05 level (2-tailed).

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

A 14.6 Pearson Correlation between Control Variables (AI Familiarity, AI Usage Frequency) and Feeling of Judgement, Purchase Intention

Correlations

AIvsHum			AIFam	AIFreq	Purch	Judge
Human	AIFam	Pearson Correlation	1	.719**	.140	.221
		Sig. (2-tailed)		<.001	.308	.105
		N	55	55	55	55
	AIFreq	Pearson Correlation	.719**	1	.229	.248
		Sig. (2-tailed)	<.001		.093	.068
		N	55	55	55	55
	Purch	Pearson Correlation	.140	.229	1	.089
		Sig. (2-tailed)	.308	.093		.519
		N	55	55	55	55
	Judge	Pearson Correlation	.221	.248	.089	1
		Sig. (2-tailed)	.105	.068	.519	
		N	55	55	55	55
AI	AIFam	Pearson Correlation	1	.814**	.414**	-.304*
		Sig. (2-tailed)		<.001	.001	.022
		N	57	57	57	57
	AIFreq	Pearson Correlation	.814**	1	.321*	-.427**
		Sig. (2-tailed)	<.001		.015	<.001
		N	57	57	57	57
	Purch	Pearson Correlation	.414**	.321*	1	-.402**
		Sig. (2-tailed)	.001	.015		.002
		N	57	57	57	57
	Judge	Pearson Correlation	-.304*	-.427**	-.402**	1
		Sig. (2-tailed)	.022	<.001	.002	
		N	57	57	57	57

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

*. Correlation is significant at the 0.05 level (2-tailed).

Appendix C

List of Abbreviations

AI….. ....Artificial Intelligence

ANCOVA…................................ ....Analysis of Covariance

ANI…... .... Artificial Narrow Intelligence

ANOVA…................................. ....Analysis of Variance

CAGR... ....Compound Annual Growth Rate

CASA.. ....Computer as Social Actors

DV .... Dependent Variable

EI.. ....Emotional Intelligence

IV.. ....Independent Variable

OLS .... Ordinary Least Squares

VIF... ....Variance Inflation Factor