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Artificial Intelligence (AI) Implications for Marketing

The Role of Identity-Based Motivation

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NOVA Information Management School
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The Role of Identity Based Motivation

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March 2024

Universidade Nova de Lisboa

STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism or any form of undue use of information or falsification of results along the process leading to its elaboration. I further declare that I have fully acknowledge the Rules of Conduct and Code of Honor from the NOVA Information Management School.

Lisbon, March 2024

Ana Rita Gonçalves

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DEDICATION

I hereby declare that I composed this dissertation entirely myself and that it describes my own research, except where explicitly stated otherwise in the text. Part of the material has already been presented in the European Marketing Academy Conference, in the AMS World Marketing Congress, in the AIRSI2023 The Metaverse Conference, in the Frontiers in Service, published or accepted for publication at International Journal of Contemporary Hospitality Management (ABS3), International Journal of Information Management (Q_1), Emerging Science Journal (Q_1) and International Journal of Bank Marketing (Q_2), and submitted for review at Journal of Business Research (ABS_3), including collaborations with top researchers from Europe and the USA.

Lisbon, March 2024

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ABSTRACT

In a series of thirteen studies, including a qualitative and neurophysiologic study, this thesis explores the different implications of artificial intelligence (AI) outcomes on consumers' self and identity. In particular, chapter 2 introduces the dilemmas, tensions, or contradictions that can arise from the interaction between AI technology and consumers' reduced autonomy and opens the research for the first consequences of those tensions, namely, on satisfaction and performance expectancy. Chapter 3 advances how the inner self, through differentiation motives, can shape consumers' willingness to receive luxury hospitality recommendations and provide insights into how immersive technologies using AI can shape luxury value and consumer differentiation. Chapter 4 reveals the unique underlying mechanism of smart service failures: consumers' self-identification. It explores the impact of AI classification failures on consumers' self-identification and how self-expression shapes this impact. Chapter 5 explores the role congruity and the consumers' rejection sensitivity to process AI rejections and how it shapes their satisfaction. Taken together, the findings have critical implications for researchers and managers on how to mitigate the downstream consequences of AI on consumers' self and how to deal with different saliences of identity.

KEYWORDS

artificial intelligence; autonomy; consumer; identity; tensions

Sustainable Development Goals (SGD):

3 GOOD HEALTH AND WELL-BEING

8 DECENT WORK AND ECONOMIC GROWTH

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- Me, Myself, and My AI: How Artificial Intelligence Classification Failures Threaten Consumers' Self-Expression. ABS3. With Diego Costa Pinto, Hector Gonzalez, and Anna Mattila. **Under Review**

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LIST OF ABBREVIATIONS AND ACRONYMS

AI	Artificial Intelligence
AMS	Academy of Marketing Science
EMAC	European Marketing Academy
EU	European Union
UK	United Kingdom
USA	United States of America
XR	xReality

Chapter 1- Introduction

1.1 Introduction

Artificial intelligence (AI) has led to changes in several domains, such as streaming, luxury, hospitality, and financial services (Ameen et al., 2021; Davenport et al., 2020; Garvey et al., 2023; Huang & Rust, 2022; McLean & Osei-Frimpong, 2019). Marketers have adopted AI to better understand and anticipate consumers' wants, allowing enterprises to make optimal decisions and improve the lifetime value of customers (Nam et al., 2021; Peddireddy, A., & Peddireddy, K., 2023). However, despite the notable advantages of AI for the services industries, it does not always satisfy consumers' expectations (Ahn et al., 2022; Davenport et al., 2020). Nonetheless, little is still known about its implications on consumers' identity and self.

There are different definitions of artificial intelligence, and De Bruyn et al. (2020, p. 93) have specified AI as "machines that mimic human intelligence in tasks such as learning, planning, and problem-solving through higher-level, autonomous knowledge creation". The potentialities of AI lead many marketers to be excited, namely, to increase in-store or online sales, as well as potential cross-sell/up-sell to improve supply chain efficacy, store operations, and payments (Guha et al., 2021; Huh et al., 2023). Thus, AI is having a significant effect on demand and supply. On the one hand, with AI, marketers can better understand and anticipate what consumers want and, consequentially, make the optimal decision and improve the lifetime value of customers. On the other hand, supply chains are becoming more efficient through the help of AI, which also allows the optimization of inventory management and logistics (Belhadi et al., 2022). Therefore, using AI represents the potential to reduce costs and increase revenues (Davenport et al., 2020) with the potential impact on consumers' identity.

In recent years, much work has been done about AI and its impact on marketing and consumer behaviour. Especially after 2016, there was a rapid increase in publications showcasing the growth of the research's interest in the field and the increased use of AI (Mustak et al., 2021). Nonetheless, several questions still need the researcher's attention. Although using AI seems like a growing trend (Li et al., 2019; Lv et al., 2022; Tung & Law, 2017), there is still ample discussion on the implications of AI for marketing and of consumers' acceptance of AI (Chi et al., 2023; Elmashhara et al., 2024). Previous studies show that using AI provides personalized services, thus enhancing the customer experience (Nam et al., 2021) or that AI is perceived as more competent than humans (Li et al., 2021; Longoni & Cian, 2020). However, on the other hand, recent research suggests that consumers negatively evaluate AI applications (Nozawa et al., 2022) or that human (vs. AI) recommendations are more effective (Kamoonpuri & Sengar, 2023; Wien & Peluso, 2021).

Although AI can be considered a neutral tool whose efficiency and accuracy should be evaluated, this approach ignores the social and individual difficulties that may occur when AI is used. Recent developments in AI enable the automation of consumer chores and provide personalized content through the emergence of big-data-driven and micro-targeting marketing offerings (Agrawal, 2017), contributing to consumers' efficient decision-making. However, if AI can substantially predict their preferences, consumers can also understand it as a loss of autonomy with ethical implications for their choices and evaluations (André et al., 2018). While AI has reshaped the customer experience (Hoyer et al., 2020), employees and consumers resist adopting it (Longoni et al., 2019; McLeay et al., 2021). These concerns with AI appear to be well-founded as the progress in AI's capacity has become more evident over the years (Guha et al., 2021; Lopez & Garcia, 2023). AI can undertake increasingly difficult cognitive tasks, demonstrating a solid ability for data analysis, learning from, and autonomous decision-making (Pelau et al., 2021). Companies progressively rely on AI's predictive capabilities to build ultra-customized services that enhance engagement, relevance, and satisfaction (Kumar et al., 2019; Mulcahy et al., 2024). Nevertheless, the great capacity of AI has quickened exaggerated views on the subject and its potential to impact consumers' daily lives (Cave & Dihal, 2019). Past research on the acceptance of AI has revealed that consumers tend to prefer human labour to AI (Granulo et al., 2021), fearing uniqueness neglect (Longoni et al., 2019) and that AI is unethical (Ameen et al., 2021; Leung et al., 2018). In addition, questions remain regarding the implication of AI on the individuals' sense of self (Khamitov et al., 2020). In line with the notion of self-expression in digital environments (Belk, 2013), a failed recommendation by an AI may thus also impact the consumers perceived ability to engage in self-expression.

Across thirteen studies, including a qualitative and neurophysiologic study applied to different contexts of AI application, this research aims to answer the following research questions:

- To what extent does AI influence **consumers' autonomy**?
- What is the effect of AI on consumers' **differentiation motives**?
- What is the implication of an AI classification failure on consumes' **self-identification**?
- How does **role congruity** shape consumers' satisfaction from an AI rejection?

Hence, this research aims to explore the dilemmas, tensions, and contractions that arise from the interaction between AI and reduced human autonomy. This is achieved, by adding a more nuanced understanding of the impact of AI on marketing and consumer behaviour and how concerns around AI might affect society and consumers' outcomes, such as satisfaction and behavioural intentions, regret, and subscription or quitting behaviours. In addition, this research sheds light on the implications of AI on the self or identity by exploring its underlying mechanism through self-identification, differentiation motives, and role congruity.

By doing so, the current research contributes to the marketing and artificial intelligence literature. First, it extends our understanding of AI classification experience (Puntoni et al., 2021) and identity-based motivation (Oyserman, 2009. While past research (Alabed et al., 2022; Huang & Philp, 2021) has advanced that consumers integrate AI agents as part of the self-concept, this study reveals that AI failures can disrupt this integration. When AI is not able to meet consumers' expectations, i.e., failure in AI classification, it reduces the connection consumers have with a smart service as their needs and wants are not correctly identified. Second, the current research deepens our perception of the downstream consequences of an AI rejection or failure (Choi et al., 2020; Grégoire & Mattila, 2021). This work adds to previous research by exploring how self-expression shapes how smart service failures are processed. Naturally, when consumers indulge in high self-expression, they form strong emotional attachments (Bagozzi et al., 2022; Wang et al., 2022). In addition, this research contributes to past research by showing that the strong emotional connection that consumers create intensifies the negative effects of AI classification failure. Third, the present study contributes to recent studies on consumers' interaction with AI (Ameen et al., 2021) by adding a more nuanced perspective on how AI can impact society and consumers' outcomes and perceptions and, consequently, address recent research calls on the unintended consequences of AI (Omoge et al., 2022; Pinochet et al., 2019; Riedel et al., 2022). This study reveals the detrimental impact of having AI on the decision-making process is contingent on the nature of the decision and how those effects can be mitigated.

Furthermore, recent research identifies situations favouring AI-driven recommendations over human ones, particularly when utilitarian attributes outweigh hedonic considerations (Longoni & Cian, 2022). Research further highlights the importance of AI-based recommendation in terms of personalization and convenience (Ameen et al., 2021). By extending recent studies, this research sheds light on how the integration of AI may potentially reduce customers' intentions to rely on AI-driven recommendations, for instance, in the luxury hospitality and Fintech contexts. Finally, this research postulates essential practical implications for managers in the different areas of interest, namely, luxury hospitality, financial, and streaming services. Aligned with previous studies, this thesis confirms that AI is a powerful tool. However, there are still many concerns about the future that marketing holds with AI. This research provides insights into the best circumstances and conditions for how managers and marketers should employ AI and overcome, for example, AI failures or rejections.

1.2 Thesis and Path of Research

This research aims to understand how to mitigate the unintended consequences of AI that can result from the interaction between AI technology and humans/consumers. In addition, it intends to provide a more nuanced understanding of the implications of AI for marketing and resolve some of the mixed findings found in previous research. For that, the present study focuses on the individual’s identity-based motivation and how it shapes the consumer experience and decision-making. This thesis proposes to collect and deploy an innovative combination of data-driven marketing tools (online, lab trials, and neuroscience tools) to improve quality and offer results relevant to society and business. Figure 1 depicts the structure and essential components of the thesis.

Ph.D. thesis research path is a collection of independent but related peer-reviewed research articles published in conferences and international publications. The articles that form the basis of the thesis are at various phases of development: some have already been approved and published, while others are undergoing revisions in response to reviewers' remarks. Table 1 lists current and upcoming publications.

Chapter 1 (Introduction) is based on the *"Artificial Intelligence and its Ethical Implications for Marketing"* manuscript (paper 1). This research has been recently published in the Emerging Science Journal. This paper develops a conceptual model building on the theory of acceptance, risk, trust, and attitudes towards AI to understand the drivers that lead consumers to accept AI, considering consumers' ethical concerns. This research provides important theoretical and managerial implications for the ethical aspects of AI in marketing by highlighting the ethical and moral questions surrounding AI's acceptance.

Chapter 2 is based on the "Autonomy-Technology Tensions in Streaming Platforms: Artificial Intelligence (vs. Autonomous) Decision-Making" manuscript (paper 2). This paper is published in the special issue Future of AI in Marketing of the International Journal of Information Management and has been presented at the European Marketing Academy (EMAC) in May 2023. This research introduces the dilemmas, tensions, or contradictions that can arise from the interaction between AI technology and humans' reduced autonomy. This research draws on the expectation–confirmation theory and autonomy in artificial intelligence (AI) and investigates how AI (vs. autonomous choice) has detrimental effects on consumer outcomes, creating an autonomy-technology tension — i.e., the conflict arising from AI technology diminishing consumers' autonomy in their choices. Four studies using a mixed-method approach reveal that the use of AI recommendations in streaming platforms creates an autonomy-technology tension that reduces consumers' performance expectancy, thus lowering their satisfaction. However, such effects are contingent on the nature of the AI recommendations. While a mismatch between AI recommendations and consumer preferences might backfire, AI's negative effect is mitigated when choices match consumers' preferences. This work makes significant theoretical and practical contributions to empirical research on consumers' sense of autonomy while interacting with AI.

The next three chapters provide insights into the underlying mechanism of the inner self that shapes consumer behaviour, such as intentions to use AI or feelings of regret. Specifically, Chapter 3 is based on the “The Paradox of Immersive Artificial Intelligence (AI) in Luxury Hospitality: How Immersive AI Shapes Consumer Differentiation and Luxury Value” paper. This paper is accepted for publication at the International Journal of Contemporary Hospitality Management in the special issue “Immersive Technologies in Hospitality and Tourism”. In addition, this paper was accepted to be presented in May 2023 at the AIRSI2023 The Metaverse Conference, a preparatory conference for the special issue and in July 2023 at the 24th AMS World Marketing Congress. This paper aims to bridge the extended reality framework and the luxury hospitality literature by providing insights into how immersive technologies using artificial intelligence (AI) can shape luxury value and consumer differentiation. This paper conducted three experimental studies comparing immersive AI versus traditional hospitality across luxury contexts (hotels, restaurants, and spas). Study 1 investigates the effect of immersive AI (vs. traditional hospitality) on customers’ behavioural intentions and the need for differentiation using virtual-assisted reality. Study 2 tests the underlying mechanism of the need for differentiation and luxury value in an augmented reality context. Study 3 provides additional support for the proposed underlying mechanism using virtual-assisted reality in luxury hospitality.

Chapter 4 is based on the “Me, Myself, and My AI: How Artificial Intelligence Classification Failures Can Threaten Consumers' Self-Identification” paper. Presented in a pre-conference workshop from the Journal of Service Research at Frontiers in Service in June 2023 and under review at an ABS 3 Journal and soon to be presented at the 53rd European Marketing Academy (EMAC) in May of 2024. Drawing from AI classification experience and identity-based motivation, this work explores a unique underlying mechanism of smart service failures: consumers' self-identity connection. Across four studies, this research shows that AI classification failure (vs. success) can reduce consumers' self-identity connection, having downstream effects on regret and subscription behaviours. Consistent with papers’ identity-based account, AI's detrimental effects only happen when identity expression is salient (vs. control).

Chapter 5 is based on the “*Artificial Intelligence (AI) in Fintech Decisions: The Role of Congruity and Rejection Sensitivity”* paper. This research was recently published in the International Journal of Bank Marketing. Two experimental studies revealed that consumers' responses to AI (vs. human) credit decisions depend on the type of credit product. For personal loans, an AI provider's rejection triggers higher satisfaction levels compared to a credit analyst. This effect is explained via the perceived role congruity. Findings further indicate that consumers' rejection sensitivity determines how they perceive financial services role congruity.

Finally, Chapter 6 is devoted to the primary findings from each study, a substantial discussion of the research as a whole and its main limitations, and recommendations for future research.

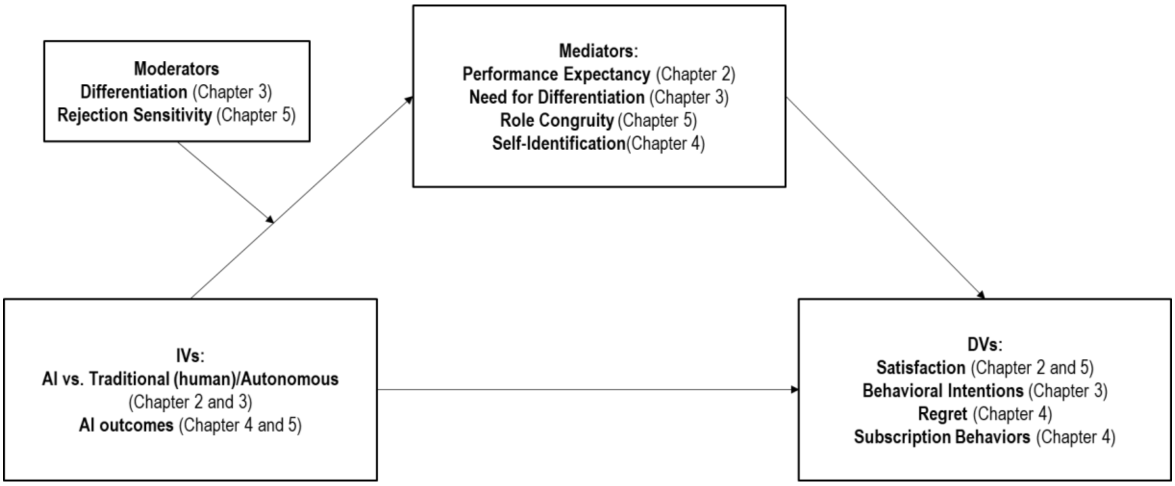

Figure 1. Proposed Research Model

Chapter	**Name**	**Current Stage**
1	Artificial Intelligence and Its Ethical Implications for Marketing	*Accepted* for publication in December 2022, Emerging Science Journal (Q1)
2	Autonomy-Technology Tensions in Streaming Platforms: Artificial Intelligence (vs. Autonomous) Decision-Making	*Accepted for publication* in December 2023, International Journal of Information Management (D1, ABS2) *Accepted* at the 52nd European Marketing Academy (EMAC), May 2023
3	The Paradox of Immersive Artificial Intelligence (AI) in Luxury Hospitality: How Immersive AI Shapes Consumer Differentiation and Luxury Value	*Accepted for publication in March 2024, International Journal* of Contemporary Hospitality Management (D1, ABS3) *Accepted* at the AIRSI2023 The Metaverse Conference, May 2023 *Accepted* at the 24th AMS World Marketing Congress, July 2023
4	Me, Myself, and My AI: How Artificial Intelligence Classification Failures Can Threaten Consumers' Self-Identification	Under review at an ABS3 Journal Accepted at the Frontiers in Service Conference Workshop, June 2023 Accepted at the 53rd European Marketing Academy (EMAC), May 2024
5	Artificial Intelligence (AI) in Fintech Decisions: The Role of Congruity and Rejection Sensitivity	Accepted for publication in April 2023, International Journal of Bank Marketing (Q2, ABS1)

Table 1. Summary of Ph.D. research outcomes

Chapter 2- Autonomy-Technology Tensions in Streaming Platforms: Artificial Intelligence (vs. Autonomous) Decision-Making

2.1 Introduction

Streaming platforms are essential technologies that have disrupted major industries such as movies and music content (Spilker & Colbjørnsen, 2020). Nowadays, 78% of all U.S. households subscribe to at least one or more streaming services, and consumer interest in video game streaming is proliferating among users. The industry contributes $9.3 billion to the economy annually (Forbes, 2023).

Given the abundance of entertainment offered on streaming platforms, companies like Netflix, Spotify, HBO Max, and Disney+ have increasingly relied on AI's predictive capabilities to build ultra-customized services that enhance engagement, relevance, and satisfaction (Kshetri et al., 2023; Kumar et al., 2019). As such, streaming platforms have invested in AI to provide users with the next best content by giving them access to personalized services. For instance, Netflix uses AI to provide tailored movie suggestions based on individuals' prior viewing behavior and contextual information (Puntoni et al., 2021). In particular, Netflix developed a "Play Something" button using AI, allowing its subscribers to play new content without effort while not taking away their control (WSJ, 2021).

Although AI brings countless advantages for firms and consumers (Puntoni et al., 2021), AI might also harm consumers' autonomy, a crucial aspect of consumer choice (Wertenbroch et al., 2020). When human decision-making is replaced with AI systems, it can diminish individuals' autonomy and adversely impact their well-being (André et al., 2018; Dwivedi et al., 2023). Hence, the interaction between AI technology and humans can give rise to dilemmas, tensions, or contradictions that further compound the impact on consumer autonomy (Huang & Rust, 2018; Huang et al., 2019) or on their willingness to adopt AI services (Frank et al., 2023). These conflicts, which we coin as autonomy-technology tensions, emerge due to the inherent differences and complexities in the interaction between AI and human decision-makers.

Despite the evident importance of autonomy in creating sustainable AI (Bjørlo et al., 2021), little is known about the impact of the autonomy-technology tension caused by AI on consumers' decision-making processes. Hence, the present research aims to understand how AI (vs. autonomous choice) has detrimental effects on consumer outcomes, creating the tension between AI technology and reduced autonomy in consumer choice (i.e., autonomy-technology tension).

We bridge this gap by drawing from the literature on expectation confirmation theory (Hossain & Quaddus, 2012) and autonomy in AI (André et al., 2018; Fast & Schroeder, 2020; Wertenbroch et al., 2020) to propose that when AI is part of the decision-making, it creates autonomy-technology tension that reduces consumers' performance expectancy and, consequently, their satisfaction. Our set of studies shows that performance expectancy underlies the impact of AI on consumer satisfaction. That is, the tension between AI and customers' autonomy reduces one's performance expectations, thus lowering satisfaction.

Furthermore, this research explores the role of the nature of the recommendation. Since AI cannot always reflect customer preferences (Puntoni et al., 2021), this research shows that the downstream effect of AI on consumer satisfaction impact is amplified when there is a mismatch between AI recommendations and user preferences. Conversely, the negative impact of AI can be mitigated when AI choices are aligned with users' preferences.

This research provides important theoretical and managerial implications. First, we make valuable contributions to the existing body of knowledge concerning consumers' interactions with AI as a decision-maker by building upon the work of Lee (2018) and Yalcin et al. (2022). Specifically, we shed light on the intricate relationship between consumers and AI in decision-making by offering a more nuanced understanding of the autonomy-technology tension.

Second, this research explores the mediating role of performance expectancy (Araujo et al., 2020; Jung et al., 2018) on the relationship between AI vs. autonomous choice and consumer satisfaction. We investigate how performance expectancy influences the link between AI versus autonomous choice and consumer satisfaction. By uncovering this mediating mechanism, we provide a deeper understanding of the factors driving consumer satisfaction in AI-based decision-making.

Third, we bridge the expectation–confirmation theory (Dabholkar et al., 2000; Oh et al., 2022) and autonomy in AI (André et al., 2018; Wertenbroch et al., 2020) to investigate the dilemmas, tensions, or contradictions that may arise from using AI. Integrating these two research streams allows us to uncover the multifaceted challenges and opportunities that arise from the interaction between AI and human decision-makers. Finally, our study has practical insights for technology companies in balancing AI and consumers' autonomy, offering important insights for the future of AI in marketing.

The remainder of the paper is organized as follows. Section 2 provides a discussion of relevant literature regarding the influence of AI on consumers' decision-making and autonomy and the contribution of the expectation-confirmation theory literature on understating the autonomy-technology tension. The following section describes our mixed-methods approach. Sections 4, 5, and 6 present the quantitative study results, and section 7 details the qualitative study. Finally, section 8 triangulates and theorizes from the findings, including managerial implications, while section 9 outlines the concluding remarks.

2.2 Theoretical Background

2.2.1 AI Decision-Making in Streaming: An Expectation-Confirmation Approach

The Expectation–Confirmation Theory (ECT) suggests that consumer satisfaction is a function of expectation and expectancy disconfirmation – i.e., it depends on the consumer's initial anticipation of the service as well as differences between expectation and actual performance (confirmation) (Oliver, 1977, 1980) Hence, it has been widely used to explain repurchase intentions (Dabholkar et al., 2000; Oh et al., 2022), to understand the entire customer experience (Lee & Kim, 2020; Park, 2020), and users' continuance intention (Hossain & Quaddus, 2012).

Generally, Artificial intelligence (AI) entails system-based computers that interact with and provide services to clients (Wirtz et al., 2018), learning on their own by continually refining and upgrading the content (Kumar et al., 2021) to increase consumers' satisfaction (Ameen et al., 2021; Davenport et al., 2020; McLean & Osei-Frimpong, 2019). According to Morgeson (2012, p.1), "satisfaction judgments are formed through a cognitive process relating prior expectations to perceived performance and the confirmation or disconfirmation of expectations relative to performance." Thus, AI is a crucial tool for helping companies predict customer preferences (Davenport et al., 2020; Wertenbroch et al., 2020), satisfy customer needs and desires, and make their decision-making easier (Guha et al., 2021).

One of the critical factors of the Expectation–Confirmation Theory (ECT) is performance expectancy. Performance Expectancy can be defined as "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" (Venkatesh et al., 2003, p. 447). Since customer satisfaction with technology depends on their expectations for the technology's performance, greater levels of performance expectancy led to increased usage intentions (Choi et al., 2011). Indeed, previous research demonstrates that performance expectancy is an essential predictor of consumer emotions, influencing their acceptance of AI devices in service encounters (Gursoy et al., 2019), such as AI-based robotic devices (Lin et al., 2020) and digital AI assistants (Brill et al., 2019).

2.2.2 Extending Expectation-Confirmation Theory with Autonomy-Technology Tension

Although the Expectation-Confirmation Theory (Hossain & Quaddus, 2012) has shed light on consumers' performance expectancy and satisfaction, it does not provide clear guidance on how new technologies, like the use of AI in streaming platforms, can shape consumers' outcomes. In particular, the present research aims to extend the Expectation-Confirmation Theory by proposing that when AI makes the decision, there is a conflict between autonomy and technology that decreases consumers' performance expectations and, as a result, decreases satisfaction. In particular, we propose that AI can lead to dilemmas, tensions, or contradictions due to reduced consumer autonomy, which we coined autonomy-technology tension. Through autonomy-technology tension, we reflect on the conflict between human autonomy and the use of technology, in particular, AI. In other words, it refers to the dynamic between the desire for increased automation and the need for human control and decision-making. Hence, the tension arises from the attempt to achieve the proper equilibrium between human and technological autonomies in various applications. For instance, in the streaming context, streaming companies frequently use recommendation algorithms to offer viewers content recommendations based on their viewing interests and history. However, the tension is the degree of autonomy these algorithms have in determining users' content consumption. While automation can improve the user experience by providing individualized recommendations, it can limit exposure to a varied range of content.

AI undoubtedly decreases choice overload in the streaming context (Guha et al., 2021). Nevertheless, one point less observed in the Expectation-Confirmation Theory literature is that new technologies like AI can make consumers feel a lack of autonomy, leading to adverse reactions such as reduced satisfaction (Hermann, 2021). Consumers often derive pleasure from their own decisions (He et al., 2019). Indeed, this is supported by studies on autonomy loss, influencing consumer choices and evaluations (André et al., 2018). We thus draw from the literature on psychological reactance (Brehm, 1996) to posit that when consumers feel restricted in their choices, their motivation is undermined, leading to lower satisfaction levels. In sum, we argue that the initial intended benefits of AI from streaming platforms (e.g., reducing choice overload and increasing satisfaction) can backfire and generate consumer reactance if they weaken the sense of autonomy consumers seek in their decision-making processes.

Thus, we contribute to the literature (e.g., Gursoy et al., 2019) by proposing that consumers' increased expectations of AI performance can lead to higher dissatisfaction in case of a negative outcome. This aspect is especially relevant in the streaming context, as consumers often spend too much time searching for what to watch that they end up not making a decision, ending up with negative emotions and reduced satisfaction (Boyer et al., 2021; Deighton, 2021).

2.3 Research Design

We test our predictions using a mixed-method approach. To do so, we conducted three pre-registered experiments and a qualitative study to combine the strengths of both qualitative and quantitative methods (Venkatesh et al., 2013). Study 1 shows that incorporating AI into streaming decisions decreases consumer satisfaction. Study 2 demonstrates that the nature of the streaming content (match vs. mismatch) influences the level of autonomy-technology tension. Study 3 reveals the underlying mechanism of performance expectancy. When AI is the decision-maker, it creates an autonomy-technology tension that reduces consumers' performance expectancy, thus harming satisfaction.

Regarding the experimental studies, a minimum of 50 participants per cell were targeted, excluding responses with missing values or failed attention checks (van Selm & Jankowski, 2006). Experimental studies follow our pre-registered procedures at AsPredicted.org (study IDs #93417, #101107, #89775). By pre-registering our research, we aim to guarantee open informational access to the methodological proceedings outlining our research objectives, hypotheses, procedures, and data analysis strategies. Pre-registration encourages open science and permits inspection by disclosing these facts, which eventually results in a more transparent research process. The Appendix lists the complete procedures and measures of each study. Three experimental studies were designed and conducted between March and June 2022.

Finally, study 4 adopts qualitative research lenses to bridge the experimental findings with consumers' subjective descriptions of their experiences with streaming platforms' AI tools and their perception of AI's effects on performance expectancy. For that, we inverted the usual mixed-method strategy of adopting qualitative research as an exploratory stage to support the hypothesis development (e.g., Shi et al., 2020) to incorporate qualitative research as an explanatory stage offering the consumers' point of view to explain the relations and moderations identified in the previous studies. In doing that, mixed methods provide a broad and deeper data description to support the proposed theories and hypothetical relationships (Venkatesh et al., 2013). The qualitative study was conducted between July and September 2023.

2.4 Study 1: AI (vs. Autonomous) Choice and Consumer Satisfaction

2.4.1 Hypothesis Development

Incorporating AI in human decision-making results in decreased consumer autonomy, which can adversely impact their well-being (André et al., 2018) as consumers often derive pleasure from their own decisions (He et al., 2019). Hence, when consumers feel that they do not have the desired autonomy, it can lead to psychological reactance or negative outcomes, such as lower satisfaction levels (Brehm JW, 1996). As such, we propose that the decreased autonomy resulting from the integration of AI in decision-making leads to decreased satisfaction.

Hypothesis 1: AI vs. autonomous decision-making decreases satisfaction.

2.4.2 Method

The first study was designed to gain an initial understanding of the impact of AI on decision-making in a streaming platform. This study's approach included four steps: creating experiment materials and questionnaires, presenting the materials to participants, having them fill out a survey questionnaire, and doing statistical analysis.

First, experimental materials for the satisfaction variable were developed. Then, 200 US Netflix users were recruited online in exchange for a small nominal payment, and one participant was excluded since they failed attention checks (Amazon Mturk, 54.3% women, M_{age}=41.44; SD_{age}=13.065). Study 1 employed a one-factor between-subjects design (AI vs. autonomous choice).

Participants were randomly assigned to one of the two experimental conditions. They were asked to imagine they were browsing on Netflix for something new to watch. They were also told that Netflix was working on a new AI tool to power its content recommendations.

The two scenarios were adapted from (Chen & Sengupta, 2014). In the autonomous choice condition, participants were told that they could freely choose if they wanted to use the tool that would provide them with options or decide on their own without the help of the AI tool. Conversely, participants in the AI condition were required to use the AI tool.

Finally, we conducted a statistical analysis of the survey. The extent to which participants were satisfied with the new Netflix AI tool was measured using a 3-item satisfaction scale adapted from Chung et al. (2020): "I am satisfied with Netflix's AI tool," "I am happy with Netflix's AI tool," "I think Netflix's AI tool did a good job" (α= 0.924). The participants rated their satisfaction on a 9-point scale (1=Strongly disagree to 9=Strongly agree).

Items	Strongly Disagree								Strongly Disagree
I am satisfied with Netflix's AI tool	1	2	3	4	5	6	7	8	9
I am happy with Netflix's AI tool	1	2	3	4	5	6	7	8	9
I think Netflix's AI tool did a good job	1	2	3	4	5	6	7	8	9

Table 2. Survey Items for Satisfaction. Adapted from Chung et al. (2020)

As for a manipulation check, participants were asked to indicate if they had the freedom to decide between the two different options or if the tool assigned them to one of the two (1=Freedom to 9=Assigned).

2.4.3 Results

Manipulation Check. The results from an Independent Samples T-test show that the autonomy manipulation worked as expected. Participants in the AI condition reported lower levels of freedom (M_{AI} = 4.19, SD_{AI}= 3.126) in comparison to participants in the autonomous choice condition ($M_{autonomous}$ = 5.89, $SD_{autonomous}$ = 2.854; $t\ (197)$ =38.70, $p < 0.001$)

Satisfaction. An independent-Samples T-Test reveals that participants in the autonomous choice condition had higher satisfaction than participants in the AI condition ($M_{autonomous}$= 6.48 vs. M_{AI}=5.86; $t\ (197)$ =1.197; p=0.025, d= 0.281, *95%CI* = [-0.0003;1.2547]).

Study 1 provides initial evidence that reduced autonomy resulting from AI reduces satisfaction compared to a situation where consumers can freely choose the content to watch.

2.5 Study 2: AI (match vs. mismatch) vs. Autonomous Choices and Consumers' Satisfaction

2.5.1 Hypothesis Development

Drawing from the Expectation-Confirmation Theory (Hossain & Quaddus, 2012), in the case of a match, consumers will be equally satisfied by AI recommendations and their autonomous choices – i.e., the detrimental effects of the autonomy-technology tension can be mitigated. Thus, a match between the consumers' expectations and perceived performance results in satisfaction (Oliver et al., 1994).

Yet, although algorithms are now more sophisticated than ever, they do not always reflect customer preferences (Puntoni et al., 2021). AI algorithms sometimes fail to match consumers' expectations (Davenport et al., 2020). We propose that a mismatch between consumer preferences and AI recommendations will amplify the negative impact on consumer satisfaction due to autonomy-technology tension. More formally, we propose:

Hypothesis 2: A mismatch between consumer preferences and AI recommendations will amplify the negative impact on consumer satisfaction.

2.5.2 Method

Study 2 shows how aligning the AI recommendations with consumer preferences can enhance satisfaction while the opposite occurs with a mismatch. This study's approach included the same four steps as before.

Participants were recruited using Prolific in exchange for a small nominal payment. In addition to Netflix users, we also recruited users from other streaming platforms (e.g., HBO, Disney+, Hulu, and Amazon Prime). At the beginning of the study, participants were asked to indicate their favorite streaming platform and answer a battery of questions. Two hundred fifteen participants were recruited, and 203 were included in the analysis (65.5% women, M_{age}=36.64; SD_{age}=12.72). The study employed a one-factor between-subjects design with three experimental conditions (autonomous choice vs. AI (match) vs. AI (mismatch)).

Participants were randomly assigned to one of three conditions. In the autonomous choice condition, participants were informed that they could choose a movie from the streaming platform or use the new AI tool to suggest a list of movies for them to watch. In the AI conditions, participants had to use the AI tool that would only provide them with a few options. The different options' content matched or mismatched their preferences for a comedy or a drama.

A three-item satisfaction scale adapted from Chung et al. (2020) was used as before: *"I am satisfied with the AI tool," "I am happy with the AI tool," and "I think the AI tool did a good job"* (α= 0.934). The participants rated their satisfaction on a 9-point scale (1=Strongly disagree to 9=Strongly agree).

As for manipulation checks, there were two questions. First, participants had to indicate whether they could choose to use the AI tool, or they had to use it (1=Choice; 9=Implied). They also indicated if the suggestions from the AI tool were based on their preferences or not (1=Match; 9=Mismatch).

2.5.3 Results

Manipulation Checks. The One-way ANOVA results suggest that the level of autonomy manipulation was successful. Specifically, participants in the mismatch and match condition reported higher levels of forced choice ($M_{\text{AI(mismatch)}}$ = 4.84, $SD_{\text{AI(mismatch)}}$= 3.061), ($M_{\text{AI(match)}}$ = 3.99, $SD_{\text{AI(match)}}$= 3.048) than their counterparts in the autonomous choice condition ($M_{\text{autonomous}}$= 2.64, $\text{SD}_{\text{autonomous}}$= 2.165; F(2, 200) = 10.687, p < .001, ηp^2 = 83.335). Regarding the mismatch question, participants in the AI (mismatch) condition reported higher levels of preference mismatch ($M_{\text{AI(mismatch)}}$ = 6.33, $SD_{\text{AI(mismatch)}}$= 2.837) than participants in the autonomous choice condition ($\text{M}_{\text{autonomous}}$ = 3.78, $SD_{\text{autonomous}}$= 2.575) and the AI (match) condition ($M_{\text{AI(match)}}$ = 2.10, $SD_{\text{AI(match)}}$ = 1.680; F(2, 200) = 53.763, p < .001, ηp^2 = 308.989).

Satisfaction. A main effect was observed on satisfaction (F (2, 200)=9.795, p<0.001, d= 0.89, 95%CI =[0.024; 0.165]. In addition, the multiple Sidak comparisons indicate a significant difference in satisfaction between the AI (match) vs. AI (mismatch) conditions (M_{match}=6.17. SD_{matc} =1.95 vs. $M_{mismatch=}$4.56, $SD_{mismatch}$ =2.38, p<0.001).

Study 2 replicates the results from Study 1. Lower decision autonomy due to AI reduces customer satisfaction when the recommendations do not match consumer preferences. However, this effect can be mitigated when AI recommendations align with consumer preferences.

2.6 Study 3: The Underlying Effect of Performance Expectancy

2.6.1 Hypothesis Development

Consumer satisfaction is formed through a cognitive process that links prior expectations to perceived performance and confirms or disconfirms expectations concerning the actual performance (Morgeson, 2012). In digital services, specifically in the adoption of AI, performance expectancy is an important predictor of customer emotions, as higher levels of performance expectancy lead to increased usage intentions (Choi et al., 2011; Gursoy et al., 2019). Thus, this research proposes that performance expectancy is the underlying mechanism explaining the effect of AI vs. autonomous choices on satisfaction. In particular, when AI makes the decision, there is a conflict between autonomy and technology that decreases consumers' performance expectations and, as a result, decreases satisfaction.

Hypothesis 3: Performance expectancy mediates the effect of AI vs. autonomous choices on satisfaction.

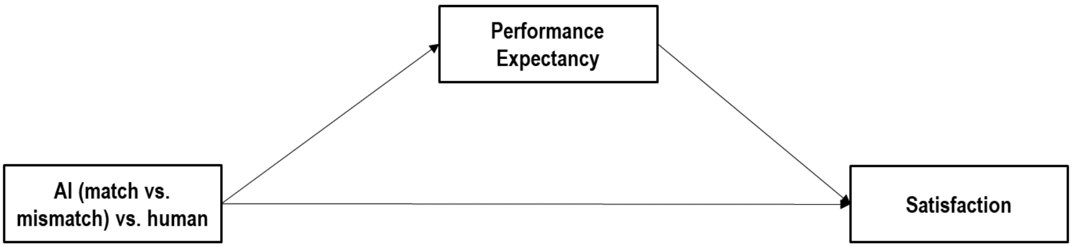

Figure 2. Conceptual Model

2.6.2 Method

The objective of the third study was to gain deeper insights into how AI algorithms influence consumers' perceptions. Hence, Study 3 examines the mediating role of performance expectancy in the relationship between autonomous vs. AI (match vs. mismatch) choices on satisfaction. The same four steps were followed.

Study 3 employed a one-factor between-subjects design with three experimental levels (autonomous choice vs. AI (match) vs. AI (mismatch)). Then, 330 US Netflix users were recruited through Mturk in exchange for a small nominal payment, and 323 were included in the analysis (53% men, M_{age}=38.83; SD_{age}=11.058). Besides using the established satisfaction scale, we also developed experiment materials and a questionnaire on performance expectancy.

Participants were randomly assigned to one of the three conditions. Participants were asked to imagine they were browsing Netflix looking for something new to watch. They were informed that Netflix was developing a new AI tool to power its content recommendations and that it would pop up on their screen with two options. In the autonomous choice condition, participants were told that they could choose one of the two options. Participants in the AI condition were asked to indicate which option they would like to pick. However, they were informed that to balance the number of viewers for each show and guarantee the maximum streaming quality, Netflix's new AI tool was designating them to watch the option different from the last viewer using the tool. They were, in fact, randomly assigned to an option that was aligned with or against their preferences. The three scenarios were adapted from Chen and Sengupta (2014).

Satisfaction with the new Netflix AI tool was measured using a 3-item satisfaction scale adapted from Chung et al. (2020): *"I am satisfied with Netflix's AI tool," "I am happy with Netflix's AI tool," "I think Netflix's AI tool did a good job"* (α= 0.981). The participants rated their level of satisfaction on a 9-point scale (1=Strongly disagree to 9=Strongly agree).

Performance expectancy was captured with three items adapted from Venkatesh et al. (2003): "I find this Netflix AI tool useful in deciding what to watch," "Using this Netflix AI tool enables me to decide what to watch quickly," "Using this Netflix AI tool increases my efficiency in deciding what to watch" (α= 0.969). The same 9-point scale was used as before.

Items	Strongly Disagree								Strongly Disagree
"I find this Netflix AI tool useful in deciding what to watch	1	2	3	4	5	6	7	8	9
Using this Netflix AI tool enables me to decide what to watch quickly	1	2	3	4	5	6	7	8	9
Using this Netflix AI tool increases my efficiency in deciding what to watch	1	2	3	4	5	6	7	8	9

Table 3. Survey Items for Performance Expectancy. Adapted from Venkatesh et al. (2003)

As a manipulation check, participants were asked to indicate if they had the freedom to decide between the two options or if the tool was assigned to them (1=Freedom to 9=Assigned).

2.6.3 Results

Manipulation Check. The results from a one-way ANOVA table show that the autonomy manipulation was successful. Participants in the AI (mismatch) condition reported higher levels of assigned choice ($M_{AI(mismatch)}$ = 6.22, $SD_{AI(mismatch)}$= 0.255) than participants in the AI (match) condition ($M_{AI(match)}$ = 6.03, $SD_{AI(match)}$= 0.265) or in the autonomous choice condition ($M_{autonomous}$ = 5.42, $SD_{autonomous}$ = 0.265; $F(2, 320) = 2.561$, $p = .079$, $\eta p^2 = 18.842$).

Satisfaction. A main effect was observed on satisfaction (F (2, 320)=4.267, p=0.015, d= 0.026, 95%CI =[0.001;0.065]).). Naturally, participants who were allowed to make their autonomous choices ($M_{\text{autonomous}}$=6.91) were more satisfied than those assigned to a movie that did not match their preferences ($M_{\text{AI(mismatch)}}$=6.22; p=0.014). There was no significant difference between the autonomous choice condition and AI (match) ($M_{\text{AI(match)}}$=6.69; p=0.753).

Mediation Effect of Performance Expectancy. A mediation analysis using the Hayes Process (model 4, Hayes, 2017; with 5000 Bootstrapping) was conducted. The mediator was performance expectancy, the independent variable was AI (match vs. mismatch) vs. autonomous choice, and the dependent variable was satisfaction. The effects were tested using a bootstrap estimation approach with 5000 samples. Mediation results indicated the significant direct effect of AI vs. autonomous choice on satisfaction (direct effect [c] = 0.1442; 95% CI: 0.0107 to 0.2776) and significant mediation effect of performance expectancy on the relationship of AI vs. autonomous choice on satisfaction (indirect effect (a × b) = 0.2007; 95% CI: 0.0069 to 0.4067).

Study 3 replicates the findings that consumers are willing to give up some control if AI can provide them with recommendations aligned with their preferences. As expected, this does not happen when the recommendations do not match their preferences. The findings further demonstrate that performance expectancy partially mediates the relationship between AI vs. autonomous choice and satisfaction. The autonomy-technology tension resulting from having AI as the decision-maker damages satisfaction when AI is unable to match consumers' preferences.

2.7 Study 4: Qualitative Study

Our set of experimental studies (Studies 1–3) provided converging evidence regarding the autonomy-technology tension, specifically exploring how the match (vs. mismatch) between autonomous and AI choices influences consumers' reactions. However, to comprehensively grasp the dynamics of this autonomy-technology tension, we acknowledge the need to delve deeper into qualitative insights to further explore the critical moment consumers engage with AI during platform consumption.

Despite AI being perceived as a neutral tool integrated into streaming platforms, it undeniably shapes how consumers perceive and interact with these platforms (Puntoni et al., 2021). Moreover, the inherent opacity of AI technology often prevents consumers from anticipating any tension before experiencing the platform (Zednik, 2021). Belk (2019) highlights that experiential factors during AI interactions reveal the tension between humans and technology, making AI platform interactions a valuable framework for understanding AI's influence and consequences.

In this context, the interaction with AI during platform consumption offers a unique evaluative framework for discerning the influences of AI and can help consumers deal with the tension in technology usage but can also raise concerns about being replaced by technology (Zednik, 2021; Puntoni et al., 2021). Therefore, by meticulously exploring consumers' subjective experiences and perceptions of AI tension while they engage with streaming platforms, we aim to provide a consumer-centric elucidation of the tension observed in our previous studies. This qualitative investigation will offer a more holistic understanding of the complex interplay between autonomy and technology, shedding light on the nuances that quantitative studies alone may not fully capture.

2.7.1 Method

This study was designed to explore consumers' experiences with streaming platforms' AI tools and their subjective perceptions of AI's effects on performance expectancy. Participants were recruited in Portugal and Brazil. The participant selection was guided by convenience sampling. Participants' inclusion-exclusion criteria were: (a) being a subscriber and (b) being a regular consumer of music and/or video streaming platforms services. Participants' selection contemplates gender and age variations, as well as different experience levels: (a) single platform users, (b) multiple platforms users, and (c) users with technology and AI expertise. We also incorporated three verification steps to enhance the trustworthiness and validity of the qualitative study (Morse et al., 2002). Firstly, we conducted data collection and analysis simultaneously to create an iterative process to ensure all themes were covered. Second, during the last interviews, we discussed the main interpretations with the participants to ensure the outcomes were coherent. Finally, we apply the data code and meaning saturation (Hennink et al., 2016) to define the sample size.

In total, we conducted 21 interviews. The data collection reached saturation when the interview data showed no new information (Jacobson & Harrison, 2022). Table 4 describes the participants' demographics. We elaborated an interview guide with 13 questions inspired by the theoretical model tested in previous studies. The average time for each interview was 20 minutes. Interviews were conducted face-to-face and mediated by videoconferencing technology (Zoom) in Portuguese by the last author, who transcribed, anonymized, and translated the scripts into English.

The dataset was initially coded by the authors' team based on the theoretical model constructs – considering (a) factors related to the nature of the recommendation tool, (b) factors related to the autonomy-technology tension with human-autonomous decision-making processes, (c) factors related to consumers' performance expectancy, and (d) factors related to the satisfaction. In addition, the second and third authors combined efforts to identify themes - inspired by Saldaña's (2013) coding manual – that could help explain the quantitative findings. Finally, to ensure the results' reliability, we triangulated quantitative results, theoretical explanations, and interview quotes, as detailed next.

Pseudonym	Gender	Age
1. Manoel	Male	22
2. Maria	Female	28
3. Marcus	Male	22
4. Paulo	Male	43
5. Anne	Female	41
6. John	Male	24
7. Mary	Female	41
8. Marcio	Male	23
9. George	Male	30
10. André	Male	40
11. Bruna	Female	25
12. Eduarda	Female	22
13. Eduardo	Male	30
14. Gabriela	Female	22
15. Rafael	Male	35
16. Tamara	Female	22
17. Diogo	Male	44
18. Isabela	Female	22
19. João Pedro	Male	23
20. Mario	Male	41
21. Lucas	Male	22

Table 4. Demographic characteristics of informants

2.7.2 Results

Qualitative data analysis offers nuances to understand the conceptual model. Firstly, it supports us in understanding the role of AI in streaming platform consumption. In line with previous studies, AI is a neutral element in choosing the streaming service (Belk, 2019). The informants do not choose streaming platforms based on AI existence but based on their content. However, listening to the consumers talk about their experience with streaming platform consumption, we observe they perceive AI as essential in dealing with the content consumers seek: *"Netflix has 90,000 titles; there is no way I can have control. It's not an airplane entertainment system with 50 titles and allows me to navigate from A to Z. I wouldn't have the cognitive power to choose between so many options"* (Rafael).

Rafael has been using Netflix for about 12 years and observes an evolution of AI on the platform due to the increased assertiveness of the recommendation algorithm: "I remember that at the beginning of Netflix, people spent two hours looking for things and then went to sleep without watching anything. Now, it is different. Assertiveness is impressive."

Thus, AI becomes noticeable as a positive tool in facilitating content choices. But, otherwise, it is not a backfire-free effect, as Eduarda complements: *"It saves me time in the content search, but I am afraid that this could make me too comfortable and only watch what the algorithm wants and no longer what I want" (*Eduarda). Following the interviews, a key theme to understanding the consumers' relationship with AI in streaming services is related to the recommendation algorithm. The interaction with AI during content choice and its consequences can facilitate the navigation in the catalog but also create tension between accepting the usability and the related risk.

AI vs. autonomy tension. The interviewees highlighted a pragmatic view about AI during streaming evaluation: *"I don't overcomplicate my relationship with the AI in streaming services. It has to help me gain time in choosing content. If it does that, ok"* (Bruna). However, this pragmatism is attenuated when AI impacts the consumer's autonomy of choice. The emerging tension is present even among those pragmatic consumers like Bruna. She explains: *"AI starts to bother me when I lose the autonomy to search. AI's ability to indicate content I like to watch is good. But I realize it's very repetitive and imposes restrictions in my choice capacity."*

Autonomy is a central theme in all the interviews. The explanation for that resides in the essence of streaming services, as Diogo illustrates: *"The central aspect of the streaming service is precisely the autonomy to choose the content to be watched, when and where in contrast to traditional TV channels that do not grant this autonomy."*

In addition, AI recommendation system facilities collide with the desire for autonomy of choice, generating tension. As André explains, the problem does not reside in the AI tools in the ordinary consumption experience but in the consequences of it in the consumer's perception of the effects*: "Sometimes I want to watch something at 11 pm, I like when AI indicates something that makes my choice faster. But there's the effect at the cognitive level because I don't need to choose in a way that reduces my curiosity for the search for new things over time"* (Andre). André´s concern about the risk of AI is related to the feeling of AI potentizing ideological eco-chambers (Lim, 2020). Other informants manifest similar concerns about creativity and curiosity curtailment since AI conditions users around a similar content topic. Thus, tension emerges in the paradox of experiencing the facilities of AI support while perceiving the risk of losing content selection autonomy when following AI content indications.

Performance expectancy. AI performance becomes a central theme in tension management by consumers. Interviewed consumers are generally open to using AI since it attends to performance expectations, as illustrated by Maria: *"I expect that the platforms are accessible, and that the algorithm can offer me suggestions based on the programs I like"* (Maria). However, when AI fails to offer useful recommendations, the tension becomes noticeable and triggers reflexivity about the real AI's capacity to substitute human decisions.

Interviewers easily describe examples when AI fails to recommend useful content and allow them to notice the incapacity of algorithms in learning with his preferences: *"I used to access HBO+, and it indicates Friends every time. I don't like friends, but I imagine the algorithm exposes this content because it is the most watched. As many people watched it, I suppose the algorithm recommended Friends even if it doesn't have a match. The failure perpetuation ends up compromising my experience with the platform"* (Rafael).

In line with Belk (2019), consumer expectations are frustrated not only when misunderstood by AI but also when AI cannot alter such misunderstanding. In sum, the interviews allow us to identify two main factors related to AI performance expectations: (a) the capacity to facilitate consumers' navigation through the content catalog and (b) the capacity to recommend useful content. When consumers perceive AI's incapacity to perform these two tasks, they feel misunderstood and put the option of delegating choices to AI in check. This feeling is especially relevant in the streaming context, as consumers do not spend so much time searching for what to watch, and the AI's primary role is to support content selection.

Impacts on satisfaction. As Puntoni et al. (2021) observe, AI consumption satisfaction directly relates to its capacity to understand customer preferences. Our interviewees also report satisfaction as an output of the AI's performance supporting content selection, as André explains: *"My satisfaction with the algorithm is determined by assertiveness. I even tolerate losing 20 minutes searching content if I access the platform once a week, but if I access it every day and don't have access to content I like, it causes dissatisfaction"* (André). Rafael also associates streaming platform satisfaction with its performance in offering content that matches his preferences: *"The fact of having more assertive artificial intelligence ends up impacting satisfaction"* (Rafael).

The second complementary factor impacting consumer satisfaction is the AI's capacity to support a balance between assertiveness in content suggestion and users' autonomy in changing content. Some informants expressed situations where they sought specific content unrelated to their preferences, and after that, the platform started offering only unrelated content without providing possibilities for change. Upset with this tension, they stated that they either canceled their subscription or stopped using that streaming service as often. These consumers' experiences exemplify how the tension in content choice autonomy also impacts the consumers' satisfaction with the platform.

Satisfaction thus resides not in the consumers' capacity to delegate content selection to the AI but in the AI's ability to respond to the consumers' preferences and, in case of failure, offer autonomy of choice. If consumers perceive their mastery over technology (Zednik, 2021; Puntoni et al., 2021), it attenuates the tension and increases satisfaction.

Following the qualitative research, we obtain support to explore the content recommendation system as a visible dimension of AI for streaming platform performance evaluation, provoking tension in case of failure in recommending content aligned with the consumers' preferences and impacting consumers' satisfaction with the platform. By accessing consumers' experiences and perceptions about AI on streaming platforms, the three main categories corroborate previous studies and offer details about when tension emerges and how it reverberates in consumers' (dis)satisfaction.

2.8 Discussion

The widespread adoption of AI resources has significantly reshaped companies' interactions with consumers (Rese & Tränkner, 2023; Dwivedi et al., 2021) and their ability to predict customer preferences for improved content recommendations (Davenport et al., 2020; Wertenbroch et al., 2020). Dwivedi et al. (2023) have recently emphasized AI's transformative impact on marketing activities, particularly in terms of tailoring content and offerings to individuals.

While existing literature has focused on describing the effects of AI at a managerial level (Dwivedi et al., 2023; Dwivedi et al., 2021; Duan et al., 2019), exploring how AI affects consumers' decision-making processes is equally essential. Our approach, centered on the utilization of AI by streaming platforms to predict highly customized content, allows us to delve into the tensions arising from AI technology integrated into streaming service offerings.

In this research, we advance and validate a theoretical model that bridges two distinct domains: the expectation confirmation theory (Hossain & Quaddus, 2012) and the autonomy in AI literature (André et al., 2018; Fast & Schroeder, 2020; Wertenbroch et al., 2020). Unlike prior investigations primarily treating AI as a consumable technology (Belk, 2019), our approach focuses on AI as an integral part of the decision-making process, offering a fresh perspective on AI's potentially detrimental impact on consumer autonomy.

Our set of studies reveals that performance expectancy is a key factor underlying the impact of AI on consumer satisfaction. Specifically, we unveil how the interplay between AI and consumers' autonomy diminishes performance expectations, consequently resulting in decreased satisfaction. Study 1 investigates the impact of AI on consumer satisfaction and finds that decision autonomy restriction leads to decreased satisfaction compared to a scenario where consumers have the freedom to choose content independently. While AI holds promise in enhancing customer experiences (Puntoni et al., 2021), it becomes evident that curbing consumer autonomy in content selection exerts a negative influence on satisfaction, particularly within the context of streaming platforms.

Building on these findings, Study 2 delves deeper into the tensions by revealing that the mismatch between consumer preferences and AI recommendations significantly amplifies the negative impact on satisfaction. However, when AI recommendations align with consumer preferences, the detrimental effects on satisfaction are mitigated. Offering explanatory nuances to the autonomy dilemma in AI (André et al., 2018; Wertenbroch et al., 2020), these results emphasize the pivotal nature of AI-driven decision-making systems on consumer satisfaction, particularly the impact of AI capacity to make decisions that align with consumer preferences.

Our third experiment uncovers the underlying mechanism by which performance expectancy harms satisfaction. Performance expectancy informs the degree to which consumers believe AI can support them in making certain decisions (Venkatesh et al., 2003). Thus, consumer expectations of an AI tool's capacity to make quick and efficient decisions play a significant role in mediating their emotional willingness to relinquish some control to AI. Additionally, our qualitative approach reveals nuances in these emotional perceptions of AI's effects on performance expectancy and satisfaction. The recommendation system is a visible dimension of AI's operation within the streaming platform; consequently, its performance in suggesting content that matches consumer preferences provides objective parameters for evaluating the AI.

In summary, using a mixed-methods approach (experimental and qualitative), our set of studies demonstrates that when AI is involved in consumers' decision-making, it creates an autonomy-technology tension that reduces consumers' performance expectancy and, consequently, their satisfaction. Furthermore, our findings suggest that the downstream effects of AI on consumer decisions are contingent on the AI recommendation's ability to match consumer preferences. Davenport et al. (2020) pointed out that AI algorithms sometimes fail to match consumers' expectations. As such, our results revealed that AI recommendations can backfire when there is a mismatch between consumers' preferences and AI. In contrast, when there is a match with consumers' preferences, the autonomy-technology tension was mitigated, and there was no negative impact on satisfaction despite decreased autonomy. Next, we discuss both the theoretical and practical implications of these findings.

2.8.1 Theoretical Contributions and Implications

This research provides a customer-centric explanation of the tensions generated by AI when personalizing content and offerings (Dwivedi et al., 2023) and its impact on consumer satisfaction. We offer an innovative approach by examining the tensions and outcomes produced when AI operates within the consumer decision-making process, consequently reducing consumer autonomy. This approach complements perspectives on AI marketing management (Dwivedi et al., 2023; Dwivedi et al., 2021) and those considering consumers as autonomous subjects in accepting or rejecting AI (Gursoy et al., 2019a; Peng et al., 2023). In light of this, our understanding of AI algorithms in the context of streaming platforms contributes to the existing literature in three significant ways.

First, we expand on research examining consumer interactions with AI as a decision-maker (Lee, 2018; Yalcin et al., 2022) by demonstrating a more nuanced understanding of how AI decision-making can impact consumer outcomes. While previous studies explore the algorithmic versus human decision-making process (André et al., 2018) and consumer reactions to it (Yalcin et al., 2022), our findings reveal the detrimental impact of incorporating AI into the decision-making process. Specifically, we illustrate that consumer reactions and outcomes (i.e., satisfaction) depend on the nature of the decision. Our theoretical contributions underscore that the nature of consumer reactions, whether positive or negative, is not solely contingent on the involvement of AI in the decision-making process. Instead, it hinges on aligning these algorithmic recommendations with consumer preferences: when AI recommendations diverge from consumer preferences, it has negative consequences for consumers' autonomy; conversely, when AI choices align with consumer preferences, the negative impact of AI is mitigated.

Second, our research extends the expectation confirmation theory (Dabholkar et al., 2000; Oh et al., 2022) by examining the mediating role of performance expectancy between the relationship between AI versus autonomous choices and consumer satisfaction. Consumers naturally evaluate the benefits and costs of using AI devices using performance expectancy, and these factors are significant predictors of their emotions regarding their readiness to use AI (Lin et al., 2020). By highlighting the role of performance expectancy in AI usage, we also add a complementary view to AI technology acceptance (Gursoy et al., 2019a). When consumers nurture expectations regarding AI's capacity to make assertive decisions, it leads to an emotional evaluation of AI technology. In contexts such as streaming platforms, consumers often lack the option to opt in or out of AI-driven decision-making. Our findings highlight that in scenarios where AI assumes the role of the decision-maker, it gives rise to an autonomy-technology tension, leading to a decrease in consumers' performance expectancy. Consequently, this emotional evaluation bears significant implications, affecting not only AI acceptance but also the overall service evaluation.

In bridging autonomy in AI decision-making (André et al., 2018; Wertenbroch et al., 2020) with the role of performance expectancy, we illuminate novel dimensions of the autonomy-technology tension. This tension encapsulates the dilemmas and contradictions that may surface when AI decision-making tools damage consumer autonomy. Our research contributes to the theoretical understanding of an "AI backfire" phenomenon, which manifests when AI inadequately supports consumer choices, leading to dissatisfaction stemming from the perceived loss of autonomy. Paradoxically, we also highlight that positive AI experiences foster satisfaction while not eliminating tension, offering a nuanced perspective on the interplay between AI and consumer autonomy.

2.8.2 Implications for Practice

Our findings have significant practical implications for companies across diverse sectors that employ AI systems to replace consumer decision-making. This type of AI algorithm has been driving transformations in various industries, such as retailing, tourism, and hospitality. However, consumers interact differently with each AI system based on the tasks they delegate. For instance, our qualitative data demonstrates that consumers perceive AI systems associated with the content selection experience in the context of streaming platforms. This phenomenon occurs because consumers evaluate the AI algorithm in conjunction with the service experience it provides. Thus, managers need to assess the impact of incorporating AI decision-making in line with (a) the task AI is replacing - i.e., a more routine, operational task or a more emotionally intense decision task - and (b) the importance of the task in the overall success of the service encounter - i.e., situations where AI replaces decisions on key aspects of the service encounter, such as content choice on a streaming platform, versus situations where AI replaces complementary services, such as chatbots for account management.

Additionally, we highlight those decisions involving higher levels of subjective preferences - such as choosing a film - require well-refined algorithms to successfully replace consumer autonomy in decision-making. To address this, managers must tailor AI recommendation systems based on user profiles and feedback, ensuring a better match between AI suggestions and consumer expectations. In addition, managers should incorporate adaptability into AI systems by developing algorithms that learn and evolve based on user feedback to continually improve the alignment of recommendations with consumer expectations.

We also offer pertinent practical insights for incorporating AI in online platforms. For example, streaming companies can explore AI resources for content recommendation as a powerful tool to facilitate consumer navigation through the content list. However, a significant challenge for companies resides in balancing AI decisions with consumers' autonomy. Therefore, AI development must focus on its capacity to (a) effectively recommend content that matches consumers' preferences while (b) preserving a degree of consumer autonomy. In doing so, instead of investing excessively in tools that increase consumers' opportunities to delegate tasks to AI, platforms can invest in AI to improve the assertiveness of actions and offer consumers the possibility to rectify inconsistencies that may lead to undesirable consequences.

Finally, our study provides insights for decision-makers to reflect on the future of AI adoption in marketing management. AI technology needs to be incorporated with consideration for consumer autonomy and expectancy. When technology triggers a feeling of lost autonomy, it can lead to a psychological rejection of technology and produce negative outcomes, such as negative expectancy and reduced satisfaction levels. This aspect is even more relevant in cases where consumers cannot choose whether to use AI to make decisions, such as the streaming platforms analyzed in this study, in which AI is incorporated into the platform operation. Consumers' feelings of losing autonomy can be mitigated by offering consumers the possibility to manage the degree of AI interference in their decisions as well as making the moments when AI is deciding for consumers patently transparent. Overall, we reinforce the importance of managing autonomy-technology tensions to navigate the opportunities and risks of AI-driven decision-making in marketing environments.

2.8.3 Limitations and Future Research Direction

While our research has made significant contributions, it also has some limitations that can be addressed in future studies. The first limitation of our scenario-based experiment is that participants in the AI conditions were informed that the company was using AI to provide them with streaming content recommendations. Although our qualitative study explored consumers' experiences with AI during streaming platform consumption, not all consumers are aware of how AI operates to make recommendations or build their front library of movies and shows (PWC, 2021). Thus, further studies can explore the technology-autonomous tension in relation to consumers' level of technological expertise, use frequency, and concerns about its risks. Additionally, we have only compared autonomous versus AI-aided decisions.

Nevertheless, future research should investigate decisions made by human-AI collaboration, considering the varying degrees of consumer awareness and understanding regarding AI's role in platform operations.

Another limitation involves the external validity of our qualitative study. We employed a coding method with a high degree of subjectivity in data interpretation. Future research may consider objective qualitative analysis methods, such as semantic analysis software, to validate the emerging themes further. Furthermore, our studies focused primarily on streaming platforms. Future research should explore the autonomy-technology tension in other digital contexts, such as e-commerce platforms, social media networks, or online service providers. A comprehensive understanding of the phenomena can be obtained by investigating how these conflicts arise and affect consumer decision-making processes across multiple digital realms.

Finally, an important avenue for future research is to further explore, using quantitative methods, how poor recommendations influence consumers' perceptions of the streaming platform's content. For instance, users who receive suggestions that mismatch their preferences may be more averse to using AI tools in the future or may develop negative perceptions. Understanding how mismatches between suggestions and user preferences affect consumer emotions and actions could help improve AI systems and increase consumer satisfaction.

2.9 Conclusions

Our study delves into how technology-autonomy tensions lead to detrimental effects on consumer outcomes. AI technologies offer a plethora of benefits for customers (Puntoni et al., 2021) and marketing management (Dwivedi et al., 2023; Dwivedi et al., 2021). However, the impact of these technologies on consumer decision-making processes is noticeable; it generates tensions that diminish customers' performance expectancy and, consequently, reduce satisfaction. These tensions are amplified when AI makes decisions that diverge from user preferences. Thus, adopting AI decision-making systems poses both benefits and challenges with a substantial impact on consumption outcomes, such as satisfaction. By shedding light on consumer perceptions, we observe that these challenges encompass not only technology acceptance (Gursoy et al., 2019; Peng et al., 2023) but mainly consumer expectations and the subjective feeling of autonomy loss. Finally, we emphasize the importance of a comprehensive understanding of the relationship between AI and consumer decision-making to refine AI systems that continuously respect and enhance user autonomy.

Chapter 3- The Paradox of Immersive Artificial Intelligence (AI) in Luxury Hospitality: How Immersive AI Shapes Consumer Differentiation and Luxury Value

3.1 Introduction

Immersive technologies are revolutionizing many industries by customizing services and experiences (Campbell et al., 2021; Hoyer et al., 2020), offering unique services to customers (Acquisti et al., 2020; Shankar, 2018; van Doorn et al., 2017; Orús et al., 2021), and providing more seamless experiences (Harvard Business Review, 2023; Vorobeva et al., 2022). Artificial intelligence (AI) immersive applications in luxury hospitality are promising (Shin & Jeong, 2022) as they enrich the guest experience (SGEI International, 2020). For instance, Hilton and InterContinental use voice technology to make their guest rooms smarter (Revfine, 2023).

Although using immersive technologies is a growing trend (Li et al., 2019; Lv et al., 2022; Tung & Law, 2017), little is known about immersive AI reality in the luxury hospitality context. While AI might improve efficiency and personalization, luxury customers expect high-quality service and distinctive and memorable experiences (Kapferer et al., 2012). In addition, customers appreciate the human touch and craftsmanship, which can erode with the growing involvement of AI. Hence, understanding how immersive AI reality affects customers' perceptions of luxury value is critical, especially in the luxury hospitality industry.

This research aims to evaluate the impact of immersive AI (vs. traditional) luxury hospitality on behavioral intentions and investigate how AI influences customers' perceptions of luxury value. Building on a sizeable literature on extended reality (XR) (Rauschnabel et al., 2022) and luxury hospitality (Yang & Mattila, 2015), this research proposes that immersive AI can lead to adverse outcomes and damage customers' perceptions of differentiation and luxury value. Across three experimental studies in different luxury hospitality contexts, our findings demonstrate that immersive AI reduces customers' intentions to use such services in the future and their perceptions of luxury value. We also show that the need for differentiation is the underlying mechanism. Finally, consistent with our theoretical account, our findings indicate that immersive AI's detrimental effects only hold when the service highlights differentiation motives.

The current research makes three significant contributions to the literature. First, we examine how embedding AI into immersive hospitality settings influences customers' differentiation motives and luxury value, reducing the intention to use AI recommendations (Chan et al., 2012; Yang & Mattila, 2015). When fully integrated into immersive environments, AI may influence consumer behavior by potentially diminishing their willingness to accept luxury hospitality recommendations. The particular qualities of AI, such as virtual simulation, can provide compelling transient illusions of luxury (Rauschnabel et al., 2022). Drawing on the characteristics of XR, we explore its impact on perceived luxury value, providing a fresh viewpoint on how AR might enhance or damage the luxury experience (Xu & Mehta, 2022). Finally, the study findings offer guidance for luxury hospitality by revealing that priming differentiation motives decrease customers' intentions to use immersive AI.

3.2 Literature Review

3.2.1 Immersive Technologies in Luxury Hospitality

Luxury hospitality products/services are expensive, exclusive, and non-essential, providing customers with symbolic value (Shin & Jeong, 2022, p. 1492). Through emotional involvement and guest-staff interactions or personal touch, luxury hospitality creates extraordinary experiences (Heo & Hyun, 2015).

Luxury hospitality can be defined as "a contemporaneous human exchange that offers extraordinary (i.e., high quality) hedonic accommodation and exclusive dining experiences" (Jain et al., 2023, p.2). Hence, luxury consumption symbolizes high quality and prestige based on customization, increasing customers' sense of differentiation and uniqueness (Kapferer et al., 2012).

Recent immersive technologies using AI have drastically impacted hotel operations and guest experiences (Tussyadiah, 2020; Orús et al., 2021). Defining AI is not an easy task (Kaplan & Haenlein, 2020). Nevertheless, past research has come up with different definitions. Kumar et al. (2016, p. 26) proposed that AI refers to "computational systems that inhabit a complex dynamic environment and continuously perform marketing functions such as (a) dynamic scanning of the environment and market factors including competitors, customers and firm actions impacting the marketing mix; (b) collaborating and interacting to interpret perceptions, analyzing, learning and drawing inferences to solve problems; and (c) implementing customer-focused strategies that create value for the customers and the firm within the boundaries of trustworthiness and policy. Generally, AI entails system-based computers that interact with and provide services to clients (Wirtz et al., 2018), and these systems may learn independently by continually refining and upgrading the content (Kumar et al., 2021), offering new ways for customers to experience reality (Hoyer et al., 2020). Recent developments in AI enable the automation of consumer chores and provide personalized content through the emergence of big-data-driven and micro-targeting marketing offerings (Davenport et al., 2020)

Given AI capabilities and evolution through recent years, AI-enabled technologies demonstrate intelligent features and skills that can be considered humanlike (Li and Suh, 2022). For instance, the application of AI immersive technologies, "augmented reality," is growing across various hospitality contexts (Luxe Digital, 2021). Luxury brands use AI, big data, and other technologies to enhance the customer experience and impact how consumers derive meanings from those experiences (Jung et al., 2021). For example, Marriott developed high-tech showers with touch-sensitive glass, and Amazon recently announced Alexa for Hospitality, which allows hotels to set up customized versions of Echo gadgets serving as in-room digital concierge (Matter of Form, 2019). Additionally, Hotel Icon in Hong Kong uses robots to facilitate the seamless delivery of check-in and check-out for guests (TTG Asia, 2023). As such, luxury hospitality has undergone many transformations throughout history. Nowadays, the uniqueness of virtual luxury relates to its virtual embodiment, components, contexts, scarcity, and appearance (Bao et al., 2024).

Despite the proliferation of immersive technologies, academic definitions of new reality formats remain fragmented and inconsistent. Rauschnabel et al. (2022) propose a new framework that defines XR as an umbrella term encompassing all present and emerging realities. In this paper, we consider AI-powered tools as part of augmented reality where the role of the physical environment is extended – i.e., the physical environment is part of the experience. Due to AR's unique characteristics (i.e., the combination of simulated elements with physical surroundings), such virtual simulations can deliver powerful momentary illusions of luxury (Rauschnabel et al., 2022). Based on the xReality (XR) framework (Rauschnabel et al. 2022), we focus on augmented-assisted reality, where the purpose of the virtual objects is to assist the user in obtaining a better understanding of the physical environment instead of merging virtual objects and the real world.

Consistent with the XR framework (Rauschnabel et al., 2022), we expect that introducing immersive AI technologies in the luxury hospitality sector might influence customers in a way that contrasts with the more traditional approach. Technologies like AI, AR, and VR are transforming the way luxury hospitality is provided (Loureiro, 2022) and the complexity of the sensory experience that can be delivered (Flavián et al., 2021). AI enables companies to enhance efficiency and tailor experiences to customers' individual preferences. However, luxury customers anticipate premium products and unforgettable experiences (Kapferer et al., 2012). These customers expect more than functionality; they seek unique experiences. Customers also value artistry and the human touch, which AI may diminish. Behavioral intention is a sign of a consumer's willingness to carry out a certain activity (Ajzen, 2002) and is a reliable predictor of actual behavior (Venkatesh et al., 2003). Luxury hospitality strongly emphasizes personal touch (Harkison, 2022), exclusivity, and attention to detail (Wirtz et al., 2020). Prior research suggests that luxury customers tend to focus on premium products and unforgettable experiences (Kapferer et al., 2012). Following this rationale, we thus expect that in a luxury context, customers will place greater emphasis on the human touch and may downplay the effect of immersive technology.

Hypothesis 1: Traditional service delivery in luxury hospitality (vs. immersive AI) will have a positive impact on customers' behavioral intentions.

3.2.2 Need for Differentiation and Luxury Value

The need for differentiation refers to the factors that individuals seek to stand out and be different and unique from others (e.g., Tian et al., 2001). Previous research suggests that individuals seek unique consumption experiences (Snyder & Lopez, 2001), and make purchases to differentiate themselves from others (Chan et al., 2012; Dubois, 2020; White & Dahl, 2007). Differentiation is also associated with customers' identities (Bellezza et al., 2014; Ordabayeva & Fernandes, 2018; Yang et al., 2018) and self-expression (Kauppinen-Räisänen et al., 2018).

Recent research and managerial discourse suggest that AI-generated reality is less able to understand and accommodate the preferences and desired identities of customers who place a high value on individuality. That is, relying solely on AI for personalization may fall short of delivering the individualized service that discerning guests expect. Davenport et al. (2020), Stein et al., (2019), and Zotowski, et al. (2017) provide insightful information on the complex interaction between humans who seek differentiation and AI-driven systems.

In this paper, we propose that customers' need for differentiation influences their reactions to immersive AI (vs. traditional) luxury hospitality. Given the unique value of immersive luxury hospitality contexts, we posit that customers who prioritize signaling differentiation might be less inclined to use AI-generated recommendations. In particular, we expect that individuals who value uniqueness might perceive AI-generated reality as less capable of understanding their specific preferences and desired identity (Davenport et al., 2020). They may believe that AI cannot fully capture the nuances of their individuality (Stein et al., 2019; Złotowski et al., 2017). The lack of human qualities increases users' resistance to AI (Mou et al., 2023). In addition, an overreliance on XR technology may divert attention away from conventional differentiators such as customized service, one-of-a-kind facilities, and attention to detail. Hence, if luxury providers favor XR experiences over these essential features, the perceived value may suffer due to the diminished sense of customization that luxury guests expect. We thus propose that customers with a heightened need for differentiation might be less willing to accept immersive AI than traditional hospitality.

Although AI can quickly analyze vast amounts of data, it might neglect humans' needs for differentiation and uniqueness (Kallel et al., 2023). Hence, relying on humans in a luxury hospitality setting might increase customers' perceptions of luxury value, especially financial value. That is because using AI might make customers infer that the company is attempting to increase efficiency, giving the impression that the company is aiming to reduce costs by automating processes (Dogru & Keskin, 2020). Conversely, a human touch implies that the company heavily invests in customer relationships, making the service higher in perceived luxury value. Luxury value in hospitality is associated with personalized service; thus, many hospitality establishments train their staff to anticipate guests' needs and provide customized experiences (Padma & Ahn, 2020). Such value is not limited to traditional hospitality providers but is also important in the sharing accommodation context. For example, personalized interactions are viewed as a form of luxury in Airbnb accommodations (e.g., Farmaki et al., 2021). Finally, recent research indicates that the lack of human interaction when using AI requires efforts from the consumer, thus reducing their overall experience (Ameen et al., 2021). Formally, we propose:

Hypothesis 2: The need for differentiation mediates the relationship between immersive AI (vs. traditional hospitality) and behavioral intentions.

Hypothesis 3: When the need for differentiation is salient, immersive AI (vs. traditional hospitality) will have a detrimental impact on perceived luxury value.

3.3 Overview of Studies

In three experimental studies, we examined whether immersive AI (vs. traditional) luxury hospitality reduces customers' behavior intentions across three different contexts (i.e., hotels, restaurants, and spas). Consistent with the XR framework, each study employed different immersive contexts: virtual-assisted reality (Studies 1 and 3), and augmented reality (Study 2). In study 1 and 3, participants received visual information about the spa or hotel to explore the extended reality framework and they were presented with an online concierge service. In study 2, participants watched a video of the experience expecting them at the restaurant Le Petit Chef at Hilton Plaza, Vienna, which relies on augmented reality. They were told they could enjoy a luxurious dining experience with Le Petite Chef, an interactive show that combines augmented reality and 3D modeling.

Study 1 shows immersive AI (vs. traditional hospitality) reduces customers' intentions to use such technologies in the luxury context. Consistent with our theoretical account, customers' need for differentiation mediates these effects. Study 2 replicates the findings and further shows how AI immersive technologies can shape customers' perceptions of luxury value. Finally, study 3 shows that highlighting the need for differentiation (high vs. low) reduces customers' willingness to accept immersive AI (vs. traditional hospitality) luxury hospitality.

Furthermore, we relied on experimental design to be consistent with prior research on customers' responses to AI (Garvey et al., 2023). Experimental research is well-grounded in literature, as it offers a robust means to prove cause-and-effect relationships through controlled testing (Kuhfeld & Tobias, 1994). Moreover, recent developments in hospitality and tourism research highlight experimental studies' growing importance and benefits (Viglia & Dolnicar, 2020; Choi et al., 2023; Hu et al., 2023; Liu et al., 2023; Shi et al., 2023; Shuqair et al., 2023; Viglia & Dolnicar, 2020).

Across our studies, we used the GPower tool to target a minimum of 80 participants per cell to obtain a power level higher than .90, excluding participants who failed the manipulation checks and responses with missing values. We collected additional responses until the target sample size was achieved (van Selm & Jankowski, 2006). In addition, we included filter questions across the three studies to achieve the eligibility pretended of the participants. For that, we used screening questions from Prolific to filter by travelers who own more than two luxury fashion items, and we asked them if they had bought any of the following luxury brands in the past (Louis Vuitton, Stella McCartney, Bottega Veneta, Gucci). We used the consumption of luxury goods as a proxy for the consumption of luxury services (Wirtz et al., 2020).

3.3.1 Study 1: The underlying effect of differentiation

Study 1 aims to provide initial evidence of the immersive AI effect in the luxury hospitality context. More importantly, it investigates the underlying mechanism of the need for differentiation. We examine how customers' need for differentiation influences their reactions to immersive AI (vs. traditional hospitality) luxury hospitality.

Participants and Design

US participants were recruited using Prolific. They needed to have traveled in the last few years and owned at least two luxury items to qualify. We used screening questions from Prolific to filter travelers who own more than two fashion items that cost over $200.

The sample comprised one hundred and ninety-one participants (65.4% women; M_{age}=40.19, *SD*=12.644). The study employed a single-factor (immersive AI versus traditional hospitality) design. Ninety-seven participants were randomly assigned to the immersive AI condition (69.1% *women;* M_{age}=40.44*; SD*=12.758), and ninety-four participants were assigned to the traditional hospitality condition (61.7% *women;* M_{age}=39.93*; SD*=12.589).

Procedure and Stimuli

Participants were informed that "The Six Senses Hotel Resorts & Spas was rated as the World's Best Luxury Hotel Brand in 2021. It operates 16 hotels and resorts and 25 spas in 19 countries worldwide. At Six Senses, it is never just about a place to stay. It is a luxury place that helps customers reconnect and explore what it means to be mentally, physically, spiritually, and emotionally happy".

Next, they were asked to imagine they had booked a session at one of the Six Senses' luxury spas. Participants received visual information about the spa to explore the extended reality framework (Rauschnabel et al., 2022) (please see appendix for more details). In the immersive AI (vs. traditional) luxury hospitality condition, participants were presented with the following: "Dear Customer, we are very pleased to welcome you soon at our Six Senses Spa. We would like to take this opportunity to let you know that we are developing a new online concierge service that relies on the help of an AI assistant (vs. employee) to provide you with recommendations regarding our services. With this online concierge service and the help of the AI assistant (vs. employee), you can get recommendations about the best treatments at our luxurious spa. We are at your disposal to make your stay as pleasant as possible. We look forward to seeing you soon."

Measures

To measure the need for differentiation, the scale from Yan et al. (2021) was employed: “This concierge service makes me feel different from others”, “This concierge service makes me feel like someone that stands out”, “This concierge service makes me feel differentiated from the group” (α=0.92).

Following recent studies on AI-human interactions (e.g., Ahn et al., 2022; Longoni & Cian, 2020; Wien & Peluso, 2021), we captured behavioral intentions using a scale adapted from Wang et al., 2006: “*I intend to use the Six Senses concierge service*”, "I intend to increase my use of concierge services like this one in the future", "*I plan to use the Six Senses concierge service*" (α=0.93).

Finally, as a manipulation check, we asked respondents whether the hotel concierge service involved an AI assistant or an employee (1=AI assistant; 9=Employee).

Results

The manipulation check worked as expected. Participants in the immersive AI condition perceived that the concierge service involved an AI assistant ($M_{AI}=1.88$, $SD=1.94$), while participants in the traditional hospitality condition were aware that the concierge service was operated by an employee ($M_{traditional}=6.80$, $SD=2.78$, $t_{(189)}=-14.227$, $p < .001$).

Consistent with our theorizing, the results reveal a main effect on the need for differentiation ($M_{\text{AI}}=4.80$ vs. $M_{\text{traditional}}=5.82$, $t_{(189)}=-3.364$, $p<0.001$). In addition, there was a significant main effect of the immersive AI (vs. traditional hospitality) on behavioral intentions ($M_{\text{AI}}=5.95$ vs. $M_{\text{traditional}}=7.09$, $t_{(189)}=-4.046$, $p<0.001$), indicating a reduced behavioral intention to use immersive AI concierge services.

Mediation analysis

We tested the mediation analysis using the macro-PROCESS (model 4; Hayes, 2017) and a bootstrap estimation approach with 5,000 samples. The mediator was the need for differentiation, the independent variable was the immersive AI (vs. traditional hospitality), and the dependent variable was behavioral intentions. The mediation results indicate a significant indirect effect of immersive AI (vs. traditional hospitality) on the need for differentiation (b = 0.427, *BootSE* = 0.167, *BootLLCI* = 0.155, and *BootULCI*=0.793) and a significant total effect of immersive AI (vs. traditional hospitality) on behavioral intentions (b = 0.717, SE = 0.358, p=0.007). These results suggest that the need for differentiation mediates the relationship between immersive AI (vs. traditional hospitality) and behavioral intentions.

Discussion

Study 1 provides initial support for our predictions. First, the findings indicate that immersive AI (vs. traditional hospitality) has a negative impact on the need for differentiation. It also provides evidence for our proposed underlying mechanism of the need for differentiation. Customers' willingness to accept luxury recommendations by immersive AI (vs. traditional) luxury hospitality is lower when the need for differentiation is salient. Moreover, we show that immersive AI (vs. traditional hospitality) has a negative impact on behavioral intentions, reducing the consumer's willingness to use such concierge service in the future. These findings add to previous research (Longoni et al., 2019) suggesting that AI immersive applications might be less effective in conveying differentiation.

3.3.2 Study 2: Do immersive applications increase willingness to accept luxury recommendations?

Study 2 extends Study 1 in three ways. First, it offers a conceptual replication of Study 1. Second, it uses a different context. Third, it tests the mediating effect of luxury value to rule out an alternative explanation for our observed effect.

Participants and Design

UK participants were recruited using Prolific. The sample consisted of one hundred and seventy-nine participants (62% women; M_{age}=39.77, *SD*=10.221) who had traveled in the last few years and owned at least two luxury items, as in Study 1. We asked them if they had bought any of the following fashion brands in the past (Louis Vuitton, Stella McCartney, Bottega Veneta, Gucci). The study employed a single-factor (immersive AI versus traditional hospitality) design. Ninety-two participants were randomly assigned to the immersive AI condition (59.8% women; M_{age}=40.24; *SD*=19.537), and eighty-seven participants were assigned to the traditional hospitality condition (64.4% women; M_{age}=39.28; *SD*=10.932).

Procedure and Stimuli

First, participants were asked to imagine booking a dinner at the fine-dining restaurant Le Petit Chef at Hilton Plaza, Vienna, which relies on augmented reality. They were told they could enjoy a luxurious dining experience with Le Petite Chef, an interactive show that combines augmented reality and 3D modeling.

Next, they were randomly allocated to immersive AI (vs. traditional hospitality) conditions and were told that in order to plan their dining experience, they would use the concierge service of the restaurant and be greeted by the Artificial Intelligence assistant, Le Petit ChefAI (vs. be greeted with the assistant, Le Petit Chef August

Irwin): "*Dear Customer, we are very pleased to welcome you! We would like to take this opportunity to let you know that we are developing a new online concierge service that relies on the help of our Artificial Intelligence assistant (vs. Chef August Irwin) to provide you with recommendations regarding your luxury dining. With this concierge service and the help of our Chef AI assistant (vs. Chef August Irwin), you can get recommendations about menu suggestions. We are at your disposal to make your dining experience as pleasant as possible. We look forward to seeing you soon*". Finally, they were asked to watch a video of the experience of the Le Petit Chef at Hilton Vienna Plaza. (see the Appendix).

Measures

Behavioral intentions were captured using a scale adapted from Wang et al., 2006:" *I intend to use Le Petit Chef (Hilton Plaza) concierge service*.", "*I intend to increase my use of concierge services like this one in the future*", "*I plan to use the Le Petit Chef (Hilton Plaza) concierge service*" (α=0.97). The need for differentiation was measured using the same scale as in Study 1 (α=0.90).

Furthermore, perceived luxury value was captured with multiple dimensions: functional value, hedonic value, symbolic/expressive value, and financial value. This scale was adapted from Yang & Mattila (2015), and the items can be found in the table below (α=0.95).

As a manipulation check, we asked respondents to indicate whether the concierge service had Chef AI's or Chef August's help (1=AI; 9=Traditional). In addition, participants were asked to rank the level of anthropomorphism by indicating if the concierge service didn't look like a human (non-anthropomorphic) (1) or Looked like a human (anthropomorphic) (9).

Functional Value	• "Le Petit Chef (Hilton Plaza) is aesthetically appealing." • "Le Petit Chef (Hilton Plaza) dishes are sophisticated." • "The service provided in the Le Petit Chef (Hilton Plaza) is attentive."
Hedonic Value	• "I dine at Le Petit Chef (Hilton Plaza) for the pure enjoyment of it." • "Dining at the Le Petit Chef (Hilton Plaza) gives me a lot of pleasure." • "I dine at the Le Petit Chef (Hilton Plaza) for self-indulgence."
Symbolic/expressive value	• "Dining at Le Petit Chef (Hilton Plaza) is considered a symbol of social status." • "Dining at Le Petit Chef (Hilton Plaza) helps me to express myself." • "Dining at the Le Petit Chef (Hilton Plaza) helps me communicate my self-identity."
Financial value	• "It is worth the economic investment to dine at the Le Petit Chef (Hilton Plaza)." • "Dining at the Le Petit Chef (Hilton Plaza) is worth its high price." • "Le Petit Chef (Hilton Plaza) usually offers value for money."

Table 5. Items of luxury value adapted from Yang & Mattila (2015)

Results

The manipulation check worked as expected. Participants in the immersive AI condition perceived that the concierge service involved an AI assistant (M_{AI}=2.05, *SD*=2.045), while participants in the traditional hospitality condition were aware that the concierge service was operated by an employee ($M_{traditional}$=6.09, SD=3.109, $t(177)$=-10.318, p < .001) In addition, participants in the traditional condition perceived the concierge service to be more anthropomorphic than their counterparts in the immersive

AI condition (M_{AI}=4.64, SD=2.557; $M_{traditional}$=5.55, *SD*=2,420, *t(177)*=-10.318, *p* =.008)

An independent samples t-test reveals that participants in the traditional hospitality condition had higher behavioral intentions than participants in the AI condition ($M_{traditional}$=5.83 vs. M_{AI}=5.03; *t(177)* =-2.209; *p*=0.014). A significant main effect of the immersive AI (vs. traditional hospitality) was also observed on the need for differentiation (M_{AI}=5.24 vs. $M_{traditional}$=6.08, *t(177)*=-2.522, *p*=0.006). In addition, the independent t-Samples t-test revealed the main effect on financial value (M_{AI}=5.11 vs. $M_{traditional}$=5.77, *t(177)*=-2.019, *p*=0.022) and functional value (M_{AI}=5.11 vs. $M_{traditional}$=5.77, *t*(177)=-2.019, *p*=0.022). However, the mean differences were insignificant for the other value dimensions, i.e., on hedonic value (M_{AI}=6.13 vs. $M_{traditional}$=6.44, *t(177)*=-0.970, *p*=0.167) and symbolic/expressive value (M_{AI}=5.11 vs. $M_{traditional}$=5.49, *t(177)*=-1.270, *p*=0.103).

Mediation analysis

We tested the mediation analysis using the macro-PROCESS (model 4; Hayes, 2017) and a bootstrap estimation approach with 5,000 samples. The mediator was the need for differentiation, the independent variable was immersive AI (vs. traditional hospitality), and the dependent variable was behavioral intentions. The mediation results indicate a significant indirect effect of immersive AI (vs. traditional hospitality) on differentiation motives *(b* = 0.550, *BootSE* = 0.232, *BootLLCI* = 0.119, and *BootULCI*=1.036) and a non-significant direct effect of immersive AI (vs. traditional hospitality) on behavioral intentions (*b* =0.256, *SE* = 0.232, *p*=0.392). These results suggest that differentiation motives mediate the relationship between immersive AI (vs. traditional hospitality) and behavioral intentions.

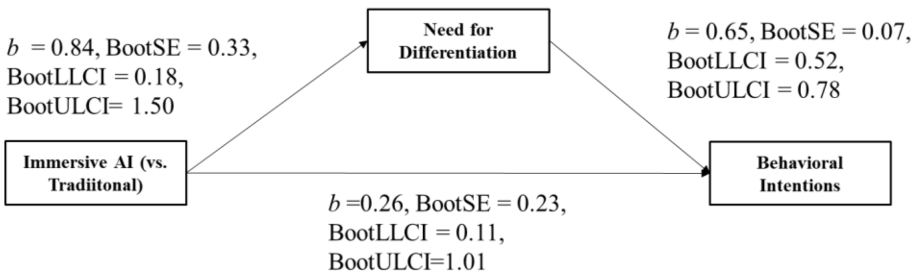

Figure 3. Mediation analysis of differentiation motives

A mediation analysis was conducted using the Hayes Process (model 6, Hayes, 2017; n=5,000). The mediators were the need for differentiation and luxury value, the independent variable was immersive AI vs. traditional, and the dependent variable was a behavioral question. The results revealed that immersive AI (vs. traditional hospitality) significantly predicted differentiation (b= 0.8411, SE=.33; t=2.522, p=0.0125), and differentiation motives have a significant effect on financial value (b= 0.5932, SE=.05; p=0.001). Differentiation has a significant effect on behavioral intentions (b=0.267, t=3.751, p=0.000), and financial value has a significant impact on behavioral intentions (b=0.652, t=8.707, p=0.000). Finally, the direct effect was eliminated as immersive AI (vs. traditional hospitality) does not significantly affect behavioral intentions (b=0.165, t=0.660, p=0.510).

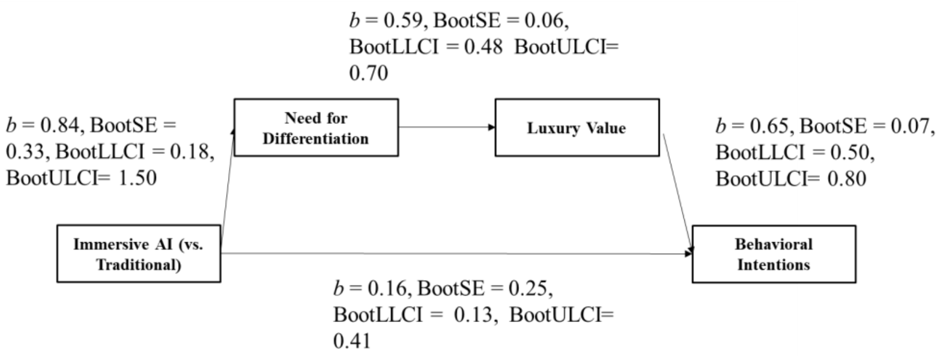

Figure 4. Sequential Mediation analysis of differentiation motives

Discussion

Study 2 further supports our predictions for the underlying mechanism by revealing that the behavioral intention to use immersive AI is lower when the need for differentiation is salient. In addition, we show the detrimental effect that immersive AI can have on luxury value, particularly in the financial and functional dimensions. Finally, our findings indicate a serial mediation of the need for differentiation and perceived financial value on behavioral intention.

3.3.3 Study 3: Do immersive applications increase customers' willingness to accept luxury recommendations?

Study 3 provides further evidence that the need for differentiation influences customers' willingness to accept immersive AI applications. This study primes the need for differentiation (high vs. low) using a between-subjects experimental procedure.

Participants and Design

We recruited Prolific participants in the United States who had booked a hotel in the previous two years. Our sample comprised 385 participants (49.9% women;

M_{age}=38.39, *SD*=11.77). This study employed a 2 (immersive AI versus traditional hospitality) x 2 (differentiation: high vs. low) between-subjects design. Ninety-seven participants were randomly assigned to the immersive AI and low differentiation condition (50.5% *men; Mage*=58.45*; SD*=197.30), ninety-one participants to the immersive AI and high differentiation condition (51.6% *men; Mage*=38.43*; SD*=11.387), one hundred participants to the traditional and low differentiation condition (52% *women; Mage*=38.07*; SD*=12.18), and ninety-five to the traditional hospitality and high differentiation condition (50.5% *women; Mage*=38.58*; SD*=11.58).

Procedure and Stimuli

In the immersive AI (vs. traditional hospitality), participants were presented with the following virtual check-in: *"You checked in at the hotel you booked for your travel. To plan your activities for the day, you open the hotel's virtual concierge app. The hotel's R&D department has spent the past two years developing an artificial intelligence assistant to improve customer service* [*vs. You are greeted by John, Senior Customer Manager, who spent the past two years in this hotel to improve customer service].*

To manipulate the need for differentiation, participants were told that The Artificial Intelligence assistant [vs. John] greets you with the following: *Dear Guest, I look forward to welcoming you today. For you to enjoy several luxury experiences, we would like to provide you with the most visited and popular recommendations chosen by the majority of our guests [vs. Tailored and special experiences exclusive for our VIP guests]. Please do not hesitate to ask any questions*."

Measures

The extent to which the participants would like to receive recommendations from an immersive AI (vs. traditional hospitality) was rated on a 9-point scale (1= Strongly disagree to 9= Strongly agree). Participants evaluated the following luxury recommendations: a "*fancy restaurant downtown", "most exclusive wines in the region", "special VIP concerts and shows", "best concerts/shows in town", "luxury shops", " premium local gifts to buy", "the best massage and spa salon", "a private driver"* (α= 0.90), adapted from the experience economy from HBR (1998) and considering the categories of recommendations that are mostly provided by the concierge services (Forbes, 2023).

For a manipulation check, participants indicated whether the experience with hotel concierge service was either AI or human-assisted (1=Human to AI=9). In addition, participants rated whether the recommendations were based on popular guest choices or tailored to VIP guests (1=Low Differentiation to 9= High Differentiation)

Results

Manipulation checks worked as intended. The results from a two-way ANOVA revealed that participants in the immersive AI condition (M_{AI}=7.45, *SD*=0.162) were more likely to agree that AI provided the service than their counterparts in the traditional hospitality condition ($M_{traditional}$=5.07, SD=0.178, $F(1, 381)$=32.121, p<0.01). In addition, participants in the high differentiation M_{High}=6.92, *SD*=0.163) condition perceived the recommendations as more unique than those in the low differentiation condition (M_{Low}=5.63, *SD*=0.158, $F(1,381)$=88.123, p<0.01).

A two-way ANOVA using 2 (immersive AI (vs. traditional hospitality)) X 2 (differentiation (high vs. low)) shows that the main effect of immersive AI (vs.

traditional hospitality) ($F(1, 381)=0.0528$, $p=0.468$) and differentiation (high vs. low) ($F(1, 381)=0.191$, $p=0.662$) were insignificant. Moreover, the predicted interaction effect on customers' willingness to accept luxury recommendations was significant ($F(1, 381) = 4.17$, $p=.042$). Specifically, the propensity to accept immersive AI recommendations (vs. traditional hospitality) was higher ($F(1,381)=4.168$, $p=0.042$, $M_{AI}=6.5$, $SD = 0.211$; $M_{traditional}=5.895$, $SD=0.208$) in the low differentiation condition. When differentiation motives were salient, immersive AI (vs. traditional hospitality) yielded similar results ($F(1,381)=0.943$, $p=0.332$, $M_{traditional}=6.253$, $SD=0.214$; $M_{AI}=5.957$, $SD=0.217$).

Discussion

Study 3 further shows that priming the need for differentiation lowers customers' preference for AI immersive luxury applications. Moreover, when differentiation motives were not salient (low), customers' willingness to receive luxury hospitality recommendations was higher when provided by immersive AI (vs. traditional hospitality). These findings contribute to recent studies on AI acceptance and aversion (Castelo et al., 2019).

3.4 General Discussion

Our findings demonstrate that immersive AI luxury hospitality may lessen customers' intention to use AI recommendations. This reluctance highlights a potential conflict between AI technology and customers' behavioral intentions (Nozawa et al., 2022). Furthermore, customers' willingness to embrace AI recommendations depends on their need for differentiation. In immersive contexts, customers with a strong need for differentiation are less likely to use immersive AI. We extend previous research

(Zotowski et al., 2017) by demonstrating the impact of the need for differentiation in influencing customers' adoption of immersive technologies within the luxury hospitality sector.

Additionally, immersive AI might have a negative impact on perceived luxury value. Customers may believe that AI technologies compromise the traditional luxury elements associated with exclusivity, craftsmanship, and a personalized human touch (Kapferer et al., 2012). We extend recent research in AI immersive technologies, such as augmented reality in the luxury context (Javornik et al., 2021) and the luxury hospitality literature (Dubois et al., 2021; Yang & Mattila, 2016). We also provide important theoretical and managerial implications for the need for uniqueness, optimal distinctiveness, and AI-human interaction literature.

3.4.1 Theoretical Implications

This research deepens our understanding of AI immersive applications in the luxury hospitality context. By drawing from the extended reality (Flavián et al., 2019; Rauschnabel et al., 2022) and luxury hospitality literature (Jain et al., 2023; Yang & Mattila, 2015), we examine the effect of AI on customers' need for differentiation and perceived luxury value, eventually influencing their propensity to use AI recommendations.

Second, our study focuses on the unique characteristics of augmented extended reality, namely its ability to generate an engaging and transitory illusion of luxury (Rauschnabel et al., 2022). Specifically, we investigate the impact of AR on customers' perceptions of luxury value, with a particular emphasis on financial value. Extending the findings of Xu and Mehta (2022), who argue that using technology in the luxury product design process negatively impacts emotional value but enhances the associated functional value, we provide a unique viewpoint of immersive AI in either complementing or detracting from the luxury hospitality experience specifically its financial value.

This research also reveals under which conditions immersive technologies such as virtual assisted reality (Studies 1 and 3) and augmented reality (Study 2) can support the unique characteristics that luxury hospitality brands aim to deliver (Javornik et al., 2021). Specifically, we extend recent studies (e.g., Ahn et al., 2022; Longoni & Cian, 2020; Wien & Peluso, 2021) to demonstrate how immersive AI (vs. traditional hospitality) may lead to negative outcomes (e.g., lower acceptance of recommendations/ reduced behavioral intentions) when the need for differentiation is a salient consumption motive. We show that the presence of virtual and physical objects through augmented reality enhances the differentiation guests seek in a luxury hospitality experience. Furthermore, this research adds to recent research on the challenges of AI (e.g., Dubois et al., 2021; Kim et al., 2021), showing that AI immersive technologies can have downstream consequences on luxury hospitality depending on customers' motives, i.e., differentiation motives.

Finally, our findings demonstrate effective ways to mitigate customers' resistance to immersive AI in luxury hospitality. Findings from Study 3 revealed that when participants were primed with the need for differentiation, their preference for AI immersive luxury applications decreased, suggesting that customers perceive AI-driven experiences as less able to satisfy their demand for exclusivity or individuality. However, when customers' need for differentiation is low, they are more open to embracing AI immersive applications in luxury hospitality. This research contributes to the ongoing literature on the intersection of AI, luxury hospitality, and consumer behavior (Nozawa et al., 2022; Wang & Papastathopoulos, 2023).

3.4.2 Practical Implications

From a managerial perspective, the findings of this study offer valuable guidance for the luxury hospitality industry to integrate immersive technologies effectively. Several recent examples illustrate how various luxury hospitality firms integrate AI into their services, from Ritz-Carlton's AI-powered chatbot to Hilton's AI-driven recommendations (Luxury Lifestyle Awards, 2023). These technologies are no longer merely a source of entertainment for guests; they have become an integral part of luxury brands' strategic initiatives (Javornik et al., 2021). This research provides a fresh perspective for marketers to attract potential luxury customers through immersive AI. Therefore, luxury managers have compelling reasons to incorporate augmented reality into their offerings. However, a cautious approach is needed, one that aligns with the distinctive attributes of luxury service. In this regard, luxury hospitality managers should be careful about using immersive AI in their services arbitrarily.

Immersive AI plays an important role in the luxury hospitality sector as it can either enhance or hinder customers' behavioral intentions, depending on whether it resonates with customers' desire for differentiation. When the need for differentiation is high, luxury hospitality managers should prioritize traditional luxury hospitality. Personalized luxury experiences, which signify exclusivity and distinctiveness, should be entrusted to human agents (Fan et al., 2022). Personalized luxury offers in hospitality signaling differentiation or uniqueness should be delivered through human agents, such as the case of specialized concierge services, where staff members are trained and considerate, meeting each guest's unique desires and preferences.

The lack of human touch when using AI services requires extra customer effort, thus lowering their overall experience (Ameen et al., 2021). While AI excels at processing large volumes of data, it may inadvertently overlook the human desire for uniqueness and individuality (Kallel et al., 2023). As a result, in luxury hospitality, human interactions rather than AI can heighten customers' perception of luxury value, particularly its financial worth. AI may lead customers to believe that the organization primarily focuses on efficiency and cost-cutting through automation (Dogru & Keskin, 2020). Hence, to surpass this disadvantage, luxury hospitality managers could devote their attention to, for instance, personalized concierge services, exclusive event planning, tailored recommendations based on individual preferences, or invest in user-friendly interfaces to mitigate the perceived lack of human touch. On the other hand, the human touch may signal that the service provider is investing in guest relations, raising the perceived value of the service.

In conclusion, luxury hospitality brands should embrace immersive technologies to enhance the luxury experience. However, these technologies should be employed judiciously, aligning with customers' need for differentiation. For instance, hospitality managers could establish channels for gathering customer feedback on immersive AI services and use it to make continuous improvements, addressing any issues related to the perceived sacrifice or lack of personalization, underlining the company's dedication to upholding a high standard of customized service. By strategically combining AI with human agents, luxury managers can preserve the core elements of luxury value while meeting the evolving expectations of luxury customers.

3.4.3 Limitations and Future Research

Despite this research's contribution to luxury hospitality, it is essential to acknowledge some limitations. First, our studies focused only on augmented reality-assisted applications, excluding mixed reality. Future studies could explore the impact of using AI mixed reality or virtual reality applications where the physical environment is not part of the experience. Furthermore, it is important to acknowledge that all our participants were recruited from prolific online panels. Although Prolific.co is recognized for its reliability and transparency in providing a representative participant population (Palan & Schitter, 2018). However, future studies should be conducted in a real setting to increase the ecological validity of our findings. In addition, we didn't control for the sociodemographics of our participants. Nonetheless, this characteristic should be considered in future studies in the luxury hospitality realm. In addition, future studies should test whether differences in perceptions of AI-based services and brands change their behavioral intentions and perceptions of luxury value.

Furthermore, our study only analyzed the participants' perception of anthropomorphism of the scenario presented but ignored features such as AI voice, physically embodied machines (e.g., robots), virtually embodied machines, warmth, or other anthropomorphic characteristics (Kim et al., 2021). Such features may influence customers' perceptions of AI. Finally, further research is needed to examine the behavioral psychology of travelers (Wang et al., 2020), which could potentially influence their willingness to accept immersive technologies for luxury services. Exploring this issue may provide deeper insights into the complicated interplay between the human psyche and evolving technology in luxury hospitality.

Chapter 4- Me, Myself, and My AI: How Artificial Intelligence Classification Failures Threaten Consumers' Self-Expression

4.1 Introduction

Artificial Intelligence (AI) has impacted many industries, as AI-powered recommendations have become a must-have to increase the revenues of digital services (Chinchanachokchai et al., 2021; Huang & Rust, 2018; Wu & Monfort, 2023). As such, AI has reshaped the human experience, influencing how we work, play, buy, and express ourselves (Hoyer et al., 2020; Puntoni et al., 2021; Xie et al., 2022). Not surprisingly, AI-based services are expected to add $15.7 trillion to the global economy in the next decade, providing users with personalized services and identity-relevant content (Forbes, 2022).

Smart services leverage AI to enhance their recommendation quality and provide personalized content for the users, such as in streaming platforms. For instance, Netflix and Amazon Prime Video use recommendation algorithms powered by machine learning to analyse user viewing habits and preferences. Despite the notable advantages of AI for smart services, it does not always satisfy consumers' expectations (Ahn et al., 2022; Davenport et al., 2020), leading to AI-enabled classification failures (Grégoire & Mattila, 2021; Puntoni et al., 2021). Some of these failures tie in with the notion of AI classification experience, defined as the experience of receiving AI's personalized predictions.

Moreover, a growing body of evidence suggests that interactions with technological devices also affect the consumer self (Frank et al., 2021). For instance, using the latest technology generally translates into an innovative self-image and social image (Frank et al., 2015b). The notion of self is integral to consumption choices, helping consumers define, reinforce, and transmit their identities (Escalas, 2013). Thus, avoiding AI classification failures is important for consumers' sense of self because consumers, in such instances, use defensive mechanisms (Gruber & Schlegelmilch, 2014) to protect their identity and self-expression. Indeed, self-expression has become a key factor in AI-based platforms, as consumers are more likely to engage in activities motivated by their need to express themselves (Rifkin & Etkin, 2019) through digital content. Yet, the extant literature on service failure-recovery (Khamitov et al., 2020) does not offer much insight into AI classification failure's effects on consumers' sense of self.

To address this gap, this research investigates the unexplored effect of AI classification failure on the self by proposing a unique underlying mechanism of smart service failures: consumers' self-identification. Self-identification refers to one's identification with the totality of all selves, identities, and schemas that form a person's sense of self (Markus, 1977). Consumers are driven to engage in consuming habits that allow them to further establish themselves favorably (Davvetas & Diamantopoilos, 2017). Arguably, in line with the notion of self-expression in digital environments (Belk, 2013), a failed classification by an AI may thus also impact the consumers' perceived ability to engage in self-expression. While the managerial implications are extensive, the specific implications of AI classification failures on consumers' self-defensive mechanisms are understudied.

Drawing on AI classification experience (Puntoni et al., 2021) and identity-based motivation (Oyserman, 2009), we posit that AI failures can make consumers engage in self-defensive mechanisms, reducing their self-identification and increasing negative outcomes such as regret (studies 1a, 1b and 2), defensive neurophysiological cues (study 3), and adverse downstream behaviors for service providers (studies 1a, 1b). Consistent with our theorizing, we further propose that when self-expression is salient (salient vs. not), it shapes how smart service failures are processed. In particular, we predict that when consumers are motivated to use AI to express themselves, failures driven by AI classification can amplify the downstream effects, such as regret of using AI, and influence subsequential behavioral outcomes (e.g., subscription and quitting behavior).

Across four studies, this research provides important theoretical and practical implications (1) by bridging AI classification experience (Puntoni et al., 2021) and identity-based motivation (Oyserman, 2009); (2) by examining the mechanism of self-identification to uncover how individuals perceive AI classification experience failures; and (3) by exploring how consumers' self-expression shapes the impact of AI classification experiences on consumer outcomes. Finally, we provide guidelines to service providers by suggesting managerial approaches to recover from AI classification failures. This entails fostering better user experiences and, ultimately, improving the overall effectiveness of the AI system and maximizing the AI classification experience.

4.2 Theoretical Background

4.2.1 AI recommendation systems and classification failure

Recommendation systems have become essential for many companies (Fayyaz et al., 2020). They assist users in finding products, services, or content (e.g., movies, music, books, travel destinations) by computing data from current and past users (Park et al., 2012). Recommendation systems are also widely applied to personalize content that matches consumer preferences, thus increasing user engagement and satisfaction (Esmeli et al., 2022; Jannach & Jugovac, 2019).

Noteworthy is that AI-based technologies are leveraged in these recommendation systems. AI can collect and process large amounts of data to produce fast and relevant user recommendations (Kim et al., 2021; Longoni and Cian, 2022). For instance, companies such as Spotify or Netflix use AI to provide users with music or video content. In order to positively influence users' judgments about the company or service, the provided information (e.g., content such as a movie) must be aligned with consumer expectations (Aslam, 2023; Kim et al., 2021).

To accomplish this goal, AI classifies consumers based on their personal characteristics and usage history (Rai, 2020). According to Puntoni et al. (2021, p.137), this leads to a particular type of experience (i.e., AI classification experience), described as an experience "in which consumers perceive AI-enabled personalized predictions to be the result of being classified as a certain consumer type". On the one hand, adequate classification can lead to personalized and satisfactory recommendations. These recommendations result from categorizations based on genres, topics, or themes that allow targeting customers with personalized strategies that enhance the overall shopping experience by suggesting products that align with a user's preferences and browsing history (Gao & Lui, 2020). Summers et al. (2016) even argue that categorizations that lead to personalized offers that suggest membership in an aspirational group can help customers affirm their self-expression. However, there is also the risk that AI recommendation systems fail in the classification process, thus leading to unsatisfactory recommendations. Namely, without understanding the context adequately, the system may make recommendations irrelevant to the user's current situation or continue providing outdated recommendations (Puntoni et al., 2021).

Notably, Puntoni et al. (2021) argue that failed classification experiences can make consumers feel misunderstood because they perceive that the AI has assigned them to the wrong group. Such an interaction could even lead to regret for using an AI to obtain a recommendation, as regret emerges when people realize that their present situation could be better if they had made different decisions in the past (Zeelenberg & Pieters, 2007). Moreover, considering that satisfactory recommendations can positively affirm a user's self (e.g., Summers et al., 2016), failed classification experiences can negatively affect a person's self-identity. This notion warrants further discussion on the self and how AI-based technologies can affect consumers self-identity (Cukier, 2021; Hoffman et al., 2022; Longoni & Cian, 2022) and self-expression (Davvetas & Diamantopoulos, 2017; Kim et al.,2021; Vaid et al., 2023).

4.2.2 AI recommendations and self-expression

The role of the self in consumer behavior and decision-making is well-documented (e.g., Gollwitzer & Sheera, 2009; Gonzalez-Jimenez, 2017). Research on identity-based consumer behavior suggests that humans have a fundamental drive to understand who they are; thus, it is not surprising that they engage with products, brands, and other consumption practices that can be associated with their selves (Reed II et al., 2012).

Consumers seek to express their self-identity by consuming brands and services (Davvetas & Diamantopoilos, 2017). Self-expression is thus the act of externalizing or displaying one's unobservable self-identity, which includes personality traits, preferences, values, beliefs, opinions, or even attitudes (Morgan & Townsend, 2022). In recent years, people also engage in self-expression through their consumption in the digital space, including streaming music and videos (Belk, 2013; Wallace et al., 2021).

Using novel technology, such as streaming content, can even be associated with consumers' creative expression of their self-identity (Frank et al., 2015; Jenkins et al., 2019), influencing the level of the arousal perceived by consumers, i.e., the strength of the associated emotional state (Citron et al., 2014).

As consumers generally aspire to have a positive self-view (Dunning, 2007), they are motivated to engage in consumption practices that allow them to positively substantiate their self-expression (Wallpach et al., 2017). In contrast, consumption practices that may negatively affect a person's self-expression (e.g., online social comparisons might result in feelings of inadequacy and a biased self-perception) are highly undesirable. Such experiences can shake a person's self (Gao et al., 2009). Hence, to offer a satisfactory experience, AI agents mustn't fail (Reed et al., 2007) to avoid consumer regret (Davvetas & Diamantopoulos, 2017).

Relying on a growing body of literature on the interactions between humans and artificial entities (Giroux et al., 2022; Paschen et al., 2020; Vorobeva et al., 2022), we aim to explore how AI classification failures (Puntoni et al., 2021) affect consumers' self-identity with a particular focus on self-expression. Research on the relationship between AI agents and users' identities is scant (Frank et al., 2021). For notable exceptions, Alabed et al. (2022) and Huang and Philp (2021) suggest that users can extend and integrate AI agents as part of themselves. This notion is congruent with a wider body of research theorizing that consumers integrate and use non-human objects (e.g., brands) as part of self-expression (e.g., MacInnis and Folkes, 2017; Belk, 2013).

4.2.3 AI Classification Failures

Service failures reflect situations where a consumer experiences a loss due to a service provider's failure to deliver the expected service (Patterson et al., 2006). A service failure can lead to negative behavioral outcomes, such as negative word of mouth (Gannon et al., 2023; Kim et al., 2009; Lteif et al., 2023) and customer complaints (Heung & Lam, 2003). Due to its relevance to a company's image and bottom line, service failure and recovery have received much attention from scholars (e.g., Bae et al., 2021; Grégoire & Mattila, 2021; Kim & Jang, 2016). Service failure/recovery research seeks to deliver management insights into optimizing the recovery process and customer-firm relations. As a result, it focuses mainly on performance measurements such as satisfaction (Khamitov et al., 2020). However, Grégoire & Mattila (2021) point out that although the service failure-recovery field is mature, there are still several research opportunities. One such avenue is understanding how AI-based failures influence consumer perceptions of smart services and the underlying mechanisms of these effects.

In recent years, there has been an increase in AI-based recommendation systems to cater to individual customers' needs. Indeed, AI-based recommendations are used across hospitality, retailing, and healthcare (Acquisti et al., 2020; Shankar, 2018; van Doorn et al., 2017). AI-based recommendations have gained importance in the service sector because they can suggest fast, self-relevant content to reflect consumers' preferences and wants (Kim et al., 2021; Pitardi & Marriott, 2021). For instance, about 80% of Netflix's streaming hours are influenced by its recommendation systems (Du & Xie, 2021).

In the context of the current research, consumers will rely on an AI to make adequate content recommendations, for instance, of movies or shows that align with their expectations. Puntoni et al. (2021, p. 137) define classification experience as "one in which consumers perceive AI-enabled personalized predictions to be the result of being classified as a certain consumer type." Service providers increasingly aim to exploit AI's capability to create customized offerings that enhance users' engagement and satisfaction with the service provider (Kumar et al., 2019c). Thus, successful classification experiences make the customer feel deeply understood, leading to positive perceptions toward the company (Puntoni et al., 2021).

However, if the AI provides a classification that is not in line with expectations – i.e., fails on their classification – consumers will feel misunderstood and are left with scepticism (Adam et al., 2021). In other words, consumers may think that the AI has inaccurately assigned them to the wrong group, which can lead to identity conflict (Reed II et al., 2012). Such an experience can lead the consumer to develop feelings of regret, which refers to negative emotions that people experience when they realize that their current situation would have been better if they had made a different decision (Zeelenberg, 1999). Indeed, if consumers perceive that they received inadequate service, they are likely to experience regret about their consumption decisions (Voorhees et al., 2009). Prior research has already ventured into the digital sphere, suggesting that, for instance, excessive use of social media can lead to regret (Dhir et al., 2016) and that virtual assistants are expected to help consumers make purchase decisions that they will not regret (Lin et al., 2021). Consequently, service providers must minimize regret threatening the brand image, leading to lower re-purchase intent and switching behaviour (Davvetas & Diamantopolous, 2017). In this study, we posit that consumers may experience regret stemming from a failed classification experience that results in an unsatisfactory recommendation. In other words, we predict that AI classification failures (versus successes) are anticipated to elevate feelings of regret.

4.2.4 An Identity-Based Motivation Account of AI Classification Failures

Consumers' self-identity is critical in driving consumers' consumption choices (Escalas, 2013; Gonzalez-Jimenez, 2017), helping them define, reinforce, and transmit their identities (Berger & Heath, 2007). Identity influences how people process information, react to certain objects, and why they participate in specific activities. Ample research suggests that consumers seek products and services that allow them to foster their self-identity (Schwartz & Cheek, 2017). For instance, Belk (2013) argues that people use digital possessions and services such as music and movies to represent themselves. In other words, these products entail a way to display one's unobservable self-identity (Morgan &Townsend, 2022).

In this research, we argue that consumer's self-identification is the underlying mechanism explaining the effect between AI failure (vs. success) and its downstream consequences. Self-identification is based on the idea that consumers integrate and connect with an AI (Alabed et al., 2022, 2023; Huang and Philp, 2021), similar to how they connect with brands (Casidy et al., 2021; Escalas & Bettman, 2003). Puntoni et al. (2021) further argue that consumer categorizations performed by an AI can contribute to consumers' self-validation process if their identity motives are satisfied. Conversely, when AI has failed to provide consumers with an adequate recommendation (failure scenario), they may feel that the usage of that AI may not align with their self-identity. Consumers may assume that these recommendations are based on their classification as a particular sort of person since they are frequently uninformed about how algorithms function. The human propensity for categorical thinking in person- and self-perception amplifies such assumptions (Puntoni et al., 2021; Turner & Reynolds, 2011). This is important because research suggests that not satisfying self-related expectations can have negative psychological consequences, such as diminished feelings of autonomy and control (Deci & Ryan, 2000). Thus, a failed recommendation by an AI may also impact the consumers' perceived ability to validate their self-identity, disrupting their self-identification.

Consumption experiences can be both self-constructive and self-destructive (Oyserman, 2009). Indeed, prior research suggests that threats to identity consistency through brand purchases can lead to consumers' regret (e.g., Davvetas and Diamantopoulos, 2017; Kirmani, 2009). Regret is also prevalent in consumer decision-making, as products and services are associated with a certain degree of performance uncertainty (Hur & Allenby, 2022). Noteworthy is that beyond products, entertainment options such as movies are also considered self-relevant (Rozenkrants et al., 2017). Aligned with Puntoni et al. (2021), failed classification experiences may cause customers to feel misled if they believe AI incorrectly allocated them to a group or made biased predictions based on group assignment, generating self-identity consequences such as regret. Arguably, a failed AI recommendation may also impact the consumers' perceived ability to validate their self-identity, disrupting their connection with the AI. Thus, we posit that self-identification serves as the fundamental mechanism in smart service failures, leading to feelings of regret. Formally, we hypothesize that self-identification mediates the relationship between AI classification failure (as opposed to success) and the experience of regret.

4.2.5 Self-expression, mindset consumption choices, and AI

A central tenet of this research is that consumers use choices to showcase their uniqueness and individuality (Kim & Drolet, 2003). A person's behaviour is driven by a desire to reaffirm their self-identity (Dunning, 2012; Rogers, 1947). As such, salient self-expression may be a powerful driver of a consumer's perceptions and behaviour because consumption can be identity-based, both self-constructive and self-destructive

(Oyserman, 2009). Mindsets refer to specific sets of activated cognitions that produce particular ways of processing information (Buttner et al., 2013). A particular mindset can influence the products consumers are drawn to and the messages they find most persuasive (Murphy & Dweck, 2016). Recent advances in streaming encourage consumers to self-express by creating assortments (e.g., Flecha-Ortíz et al., 2021; Wallace et al., 2021). Consumers are most likely to join in highly engaging activities when motivated by their need for self-expression (de Vries et al., 2017). Hence, self-expression has become key for consumers to create such self-expressive assortments in AI-based streaming platforms (Rifkin & Etkin, 2019). In our research context, an inadequate content selection (e.g., movies or music) hinders self-expression.

We propose that the salience of self-expression may further accentuate feelings of regret after a smart service failure. Indeed, research argues that self-expression is integral to a person's sense of self (Czerwonka & Karwowski, 2018; Farmer et al., 2003). For instance, people use novel technology to project an innovative self (Frank et al., 2015b), and consumers perceived ability to be creative is part of their self-definition process (Tierney & Farmer, 2002; Von Wallpach et al., 2017). A self-expressive mindset amplifies the negative consequences of a failure to obtain self-relevant content. This effect is based on the notion that people are motivated to act in identity-congruent ways (Oyserman, 2009). An AI misclassification leads to an incongruent identity recommendation. Thus, when self-expression is not salient, the negative effects of AI misclassification are mitigated. Hence, we argue that the adverse consequences of AI classification failures on regret are contingent upon the salience of self-expression (vs. not). More precisely, our hypothesis suggests that the prominence of self-expression (salient versus not) plays a crucial role in influencing the cognitive processing of AI misclassification failures. In instances where self-expression motives drive consumers, AI-driven classification failures can intensify feelings of regret and diminish behavioral outcomes, such as subscription behaviors.

4.3 Overview of Studies

Four experimental pre-registered studies test our predictions. Our first study (S1a) focuses on the underlying mechanism of self-identification. Specifically, it shows that AI classification failures (vs. successes) can hinder consumers' self-identification, increasing regret and reducing subscription behaviors. Study 1b further reveals the effect of AI classification failures on regret by considering a new context, music selection, using GenAI (e.g., ChatGPT). Study 2 further supports our theorizing by showing how self-expression can shape how consumers process AI classifications. The salience of the self-expression mindset may further accentuate consumers' regret after an AI classification failure. Lastly, we conducted a study using neuro-physiological evidence, which allows an objective assessment of emotions and primary reactions using faceReader equipment. It shows that an AI classification failure (vs. success) triggers feelings of sadness and self-defense mechanisms (e.g., eyes closed to avoid watching the AI-recommended content). In addition, it reveals the serial mediation of self-identification and arousal on the relationship between AI classification and liking or disliking the content suggested.

A minimum of 50 participants per cell were targeted, excluding responses with missing values or failed attention checks. Additional responses were collected until the target sample size was reached (van Selm & Jankowski, 2006). Moreover, we followed our pre-registered procedures listed at AsPredicted.org (study IDs #121226, # 136233,

#96639, #132368). The Appendix lists the complete procedures and measures of each study.

4.3.1 Study 1a: The Effect of AI classification experience on behavioural outcomes

Study 1a was designed to understand the impact of an AI classification failure (vs. success) on regret and subsequent behaviors, e.g., subscription behaviors. In addition, it explores the underlying mechanism of self-identification. The context was video streaming (Netflix or HBO).

Participants and Design

Two hundred nine streaming users were recruited online in exchange for a small nominal payment (Prolific, 53.1% women, M_{age}=36.46; SD_{age}=13-.742). Study 1a employed a one-factor between-subject design (failure vs. success) to evaluate the effect on regret and subsequent behaviors.

Procedure and Stimuli

Participants were randomly assigned to one of the two experimental conditions. They were asked to imagine that they were on their favorite streaming platform browsing for something to watch. Next, they were presented with a new streaming platform tool, which relies on AI to power its content recommendations. In addition, they were informed that the AI tool could provide personalized services by using data from previous streaming history and web behavior to estimate consumer interests and preferences. Participants were asked about their preferences (comedy vs. drama, light mood vs. deep emotional entertainment, funny vs. emotional). Later, they were told that the AI tool would suggest three trailers to watch based on their preferences. Participants in the success condition were presented with a trailer aligned with their preferences, whereas the trailers in the failure condition didn't match their preferences.

Measures

The extent to which participants regret using the AI tool was measured using a 3-item scale adapted from (Tsiros & Mittal, 2000): "*I feel sorry for using the AI tool", "I regret using the AI' tool", and "I shouldn't have used the AI' tool* (1= Strongly disagree to 9= Strongly agree).

To capture their behavioral responses, participants were asked if they would subscribe to the AI tool (yes/no).

Self-identification was measured using a nine-item scale adapted from (Huang & Philp 2022): *"The AI tool content reflects part of me and who I am"; "I feel personally connected to the trailers presented by AI tool*".

As for a manipulation check, participants were asked to indicate if the experience with the AI tool was a success or a failure (1=Success to 9=Failure).

Results

Manipulation Checks. The Independent Samples T-test results indicate that the failure manipulation worked as expected. Participants in the failure condition reported higher levels of failure ($M_{failure}$ = 5.89, $SD_{failure}$= 2.933) in comparison to participants in the success condition ($M_{success}$ = 3.57, $SD_{success}$ = 2.316; t (207) =-6.358, p < .001).

Regret. Independent-samples T-Test showed that participants in the failure condition felt higher levels of regret than participants in the success condition ($M_{failure}$ =3.62 vs. $M_{success}$ =2.33; *t (207)* =-4.134; *p* < 0.001).

Subscription Behavior. A logistic regression was used to examine if participants in the success vs. failure condition would be more likely to subscribe to the AI tool. The results show that participants in the failure condition subscribed less than those in the success condition ($\chi^2(1) = 8.776$, p= 0.003).

Mediation Effect of Self-identification on Regret. A mediation analysis was conducted using Hayes Process (model 4, Hayes, 2017; n=5000). The mediator was self-identification, the independent variable was failure vs. success, and the dependent variable was regret. The effects were tested using a bootstrap estimation approach with 5000 samples. The bootstrap analysis reveals the significant mediation effect of failure vs. success on regret (indirect effect (a × b) = 0.3917; 95% CI: -0.1486 to -0.6612) and a significant direct effect on regret (direct effect [c] = 0.8936, p = .0028). These results suggest that self-identification is a partial mediator.

Mediating Effect of Self-identification on Subscription Behaviors. The mediator was self-identification, the independent variable was failure vs. success, and the dependent variable was subscription behavior. The bootstrap analysis reveals the significant mediation effect of failure vs. success on subscription behavior (*indirect effect (a × b)* = 0.5570; *95% CI*: 0.2018 to 0.9710) and no significant direct effect (*direct effect [c]* = 0.4750, *p* = 0.1527) revealing full mediation by self-identification.

Discussion

Study 1a shows that AI classification failure (vs. success) can reduce consumers' self-identification, having downstream effects on regret and subscription behaviors. Specifically, consumers exposed to a failed classification experience exhibited lower levels of self-identification and, consequently, higher regret and decreased subscription behaviors of such AI tools. These findings extend prior work on identity conflict (Reed

II et al., 2012) by showing that when an AI fails to classify a consumer adequately, it can affect the self.

4.3.2 Study 1b: Adverse Consequences of AI Classification Failure

Study 1b aims to further examine the consequences of an AI classification failure, specifically, the effects on quitting behavior and the number of songs listened. In addition, to further the generalizability of the findings, this study considers a new context of music streaming (e.g., Spotify).

Participants and Design

One hundred ninety-six streaming users were recruited online in exchange for a small nominal payment (Prolific, 54.1% women, M_{age}=40.03; SD_{age}=12.220). Study 1b employed a one-factor between-subject design (failure vs. success).

Procedure and Stimuli

Participants were randomly assigned to one of two experimental conditions. They were asked to imagine that they were on Spotify looking for something to listen to. In addition, they were presented with a new service, Spotify powered by ChatGPT. Next, they were told that they had asked for help from ChatGPT, and it replied, "Of course! I'd be happy to help you choose a song on Spotify. Could you please let me know your preferred genre or any specific artists you enjoy? Additionally, do you have a mood or vibe for the song, or would you like me to suggest something based on the current popular trends?" Participants indicated if they wanted to listen to hard rock vs. pop rock, or something energetic vs. calm. In addition, they could provide additional information to ChatGPT. Later, they were informed that they received the following message from ChatGPT "Great! Here are three rock songs that you might enjoy:".

Finally, they had to listen to 3 songs classified as failures vs. successes based on their preferences.

Measures

The extent to which participants regretted using the AI tool was measured using a 3-item scale adapted from (Tsiros & Mittal, 2000): "*I feel sorry for using Spotify by ChatGPT", "I regret using Spotify by ChatGPT l", and "I shouldn't have used Spotify by ChatGPT"* (1= Strongly disagree to 9= Strongly agree).

To further explore other consequences of an AI classification failure, participants were asked if they would quit using Spotify (yes or no). In addition, participants were asked about the number of songs they agreed to listen to.

As for manipulation checks, the respondents were asked to indicate if the experience with the AI tool was a success (correct classification) or a failure (incorrect classification) (1=Success to 9=Failure).

Results

Manipulation Checks. The results from the Independent Samples T-test table indicate that the failure manipulation worked as expected. Participants in the failure condition reported higher levels of failure ($M_{failure}$ = 7.61, $SD_{failure}$= 1.446) than participants in the success condition ($M_{success}$ = 2.81, $SD_{success}$ = 1.463; t (194) =-23.103, $p < .001$).

Regret. Independent-Samples T-Test showed that participants in the failure condition had significantly higher regret than participants in the success condition ($M_{failure}$ =5.25 vs. $M_{success}$ =2.23; *t (194)* =-8.868; $p < 0.001$).

Number of Songs Listened. The results from the Independent Samples T-test table suggest that the participants in the failure condition listened to fewer songs ($M_{failure}$ = 0.277, $SD_{failure}$= 0.709) in comparison to participants in the success condition ($M_{success}$ = 0.558, $SD_{success}$ = 1.629; t (194) =1.580, p=0.058).

Quitting Behavior. The results from a logistic regression show that participants in the failure condition would quit the platform more than participants in the success condition ($\chi^2(1) = 15.496$, $p < 0.001$).

Discussion

Study 1b further replicates the results of the previous study showing the effect of AI classification failure on regret, in this case, by exploring the context of music streaming. In addition, it reveals the impact of AI classification failure on the platform's usage (i.e., the number of songs listened to) and its effect in driving users to quit using the platform.

4.3.3 Study 2: The Moderating Role of Self-Expression

Study 2 further advances the findings of this research by introducing self-expression. It illustrates how self-expression shapes how AI classification failure (vs. success) is processed. When consumers are motivated to use AI to express themself, failures driven by AI classification can amplify the downstream effects, such as regret of using AI, and influence behavioral outcomes.

Participants and Design

Participants were again recruited using Prolific in exchange for a small nominal payment, and users of different streaming platforms were included (e.g., Netflix, HBO, Disney+, Hulu, Amazon Prime). As in the previous study, participants indicated their favorite streaming platform and answered the questions based on that choice. There were 202 participants (71.8% women, M_{age}=33.46; SD_{age}=12.39). The study used a 2x2 between-subjects design (self-expression prime: absent vs. present, AI classification failure vs. success).

Procedure and Stimuli

Participants were randomly assigned to one of the two conditions: self-expression prime (present vs. absent). They were primed to think about how important it is to self-express (vs. not) in their life and why they decide to undertake such tasks (Landau et al., 2011). Then, in a second phase, all participants were assigned to two more conditions (AI classification failure vs. success). First, they were told to imagine using their favorite streaming platform, looking for what to watch next. Second, they were informed that their favorite streaming platform is using a new AI tool that would present three suggestions to them. In the success condition, the suggestions provided by the tool aligned with the preferences of the users. Conversely, in the failure condition, participants were told that the tool would present them with content different from what they would typically consider watching to introduce them to new and different options.

Measures

Regret was evaluated using three items adapted from (Tsiros & Mittal, 2000): "*I feel sorry for using the AI tool", "I regret using the AI' tool", and "I shouldn't have used AI' tool". (*1= Strongly disagree to 9= Strongly agree).

As for manipulation checks, the participants had to answer if, in the priming activity, they had to write about self-expression through creativity (1=Salient; 9=Not) and whether the suggestions from the AI tool were based on their preferences or not (1=Success; 9=Failure).

Results

Manipulation Checks. Results from two-way ANOVA provide support for the main effect of self-expression (F (1, 201) =215679.084, $p < 0.001$, ηp2 = 3170.048, $M_{salient}$ =1.000, $M_{control}$ =8.972). Moreover, results show a main effect of the AI classification manipulation (F (1, 201) = 40.085, $p < .001$, ηp2 = 239.959, $M_{failure}$ =6.081, $M_{success}$ =3.888) and no significant interaction effect between self-expression and failure conditions ($F(1, 201) = 0.854$, $p = 0.356$, ηp2 =0.002).

Regret. A two-way ANOVA using 2 (AI classification: success vs. failure) X 2 (self-expression prime: present vs. absent) on regret shows the predicted interaction effect ($F(1, 201)=4.095$, $p <.044$). Specifically, when participants experienced a failure in the self-expression prime condition, they exhibited higher regret ($M_{failure}$ =3.40, SD =2.086) compared to the success condition ($M_{success}$ =2.19, SD=1.755). However, in the "control" (self-expression prime absent) condition, participants experiencing a failure or success yielded similar results of regret ($M_{failure}$ =2.95, SD=2.109; $M_{success}$ =2.930, SD=2.304). In addition, there was a significant main effect of AI classification failure vs. success (F (1,201)=4.426, p=.037) and no significant main effect of self-expression prime on regret (F(1,201)=0.240, p=.625) (see figure 5 below).

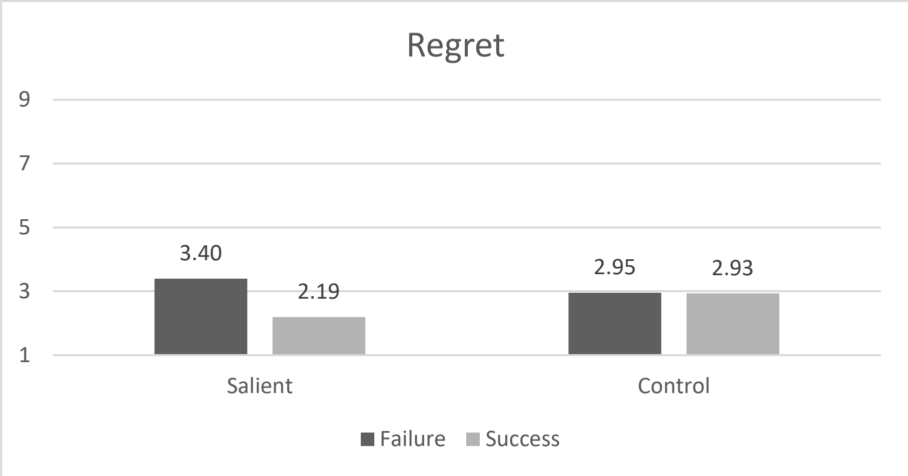

Figure 5. The effect of AI classification: failure vs. success X self-expression

Discussion

Study 2 reveals that self-expression influences how consumers react to AI classification failures. In particular, users primed with self-expression exhibited greater regret when their preferences were ignored. Salience of self-expression increases the negative effects of failure. Higher levels of self-expression lead to increased feelings of regret in the case of irrelevant content, as people are motivated to act in identity-congruent ways (Oyserman, 2009). A consumer can feel misunderstood because a perceived incorrect classification leads to recommendations that are incongruent with their identity.

4.3.4 Study 3: Self-identification: A Facial Expression Recognition Perspective

Study 3 uses a different methodology to examine the effects of AI classification failure on behavioral outcomes. Specifically, facial expression recognition software was used to gain neuro-physiological evidence for the AI classification failure effect.

Participants and Design

Participants were recruited from a large European university in exchange for extra credit. The sample consisted of one hundred participants (69.9% women; Mage=24.69, SD=5.924). The study employed a single-factor AI classification failure vs. success between-subjects design.

Procedure and Stimuli

The experiment took place at a European University using facial expression recognition software, i.e., the FaceReader from Noldus. Participants entered the laboratory and were informed that the study used software to analyze their facial expressions. They came individually to a room where they were invited to sit in front of a computer. Participants were randomly assigned to one of two experimental conditions (AI classification failure vs. success). Participants were asked to imagine that they were on their favorite streaming platform browsing for something to watch. There, they were presented with a new tool provided by the streaming platform, which relies on AI for recommendations. Next, they were told that the AI tool would suggest a trailer based on their preferences. Participants in the success condition were presented with a trailer aligned with their choices, whereas the trailers in the failure condition didn't match their preferences. The following movie genres were included: romance, comedy, action, and animation.

Measures

FaceReader offers automated facial action coding, as well as measures of valance and arousal.

Self-identification was measured using a nine-point scale adapted from (Huang & Philp 2022): *"The AI tool content reflects part of me and who I am"; "I feel personally connected to the trailers presented by AI tool*".

A binominal question to measure behavioral intentions of like and dislike of the content (trailers) suggested was also included.

Finally, as a manipulation check, the respondents were asked to indicate if the experience with the AI tool was a success or a failure (1=Success to 9=Failure).

Results

Manipulation Checks. The results from the Independent Samples T-test table suggest that the failure manipulation worked as expected. Participants in the failure condition reported higher levels of failure ($M_{failure}$ = 4.71, $SD_{failure}$= 2.602) in comparison to participants in the success condition ($M_{success}$ = 2.84, $SD_{success}$ =1.821; t (99) = -4.474, p < .001).

Neutral. A neutral facial expression (i.e., displays minimal or lacks emotional cues) was measured as a control. The Independent-Samples T-Test showed that participants in the failure and success conditions showed similar levels of neutral emotions ($M_{failure}$ =0.78 vs. $M_{success}$ =0.77; *t (99)* =-0.250; *p*=0.401).

Sadness. Sadness was the emotion chosen as a proxy for regret (Zeelenberg and Pieters, 2004). Independent-Samples T-Test showed that participants in the failure condition exhibited higher levels of sadness than participants in the success condition ($M_{failure}$ = 0.12 vs. $M_{success}$ =0.07; *t (99)* =-2.423; *p* = 0.008).

Arousal and Valance. Arousal is the level of autonomic activation that an event creates, and it ranges from low to high intensity (i.e., the strength of the associated emotional state). Conversely, valence is the level of pleasantness that an event generates, and it reflects the extent to which an emotion is positive or negative (Citron et al., 2014). Independent-Samples T-Test showed that participants in the failure condition had lower levels of arousal than participants in the success condition ($M_{failure}$ = 0.28 vs. $M_{success}$ =0.23; t (99) = 3.943; p < 0.001) and higher levels of negative valance ($M_{failure}$ = -0.11 vs. $M_{success}$ = -0.01; t (99) = 3.746; p < 0.008).

Action Units. Action Unit 43, i.e., corresponds to the movement of closing the eyes, suggesting a defensive mechanism (Ekman et al., 2002). The Independent-Samples T-Test revealed that participants in the failure condition reported higher levels of movement action unit 43 ($M_{failure}$ = 0.23 vs. $M_{success}$ =0.14; t (99) = -3.436; p < 0.001) than the participants in the success condition. This means that participants in the failure condition engaged in higher levels of defensive mechanisms representing a proxy of regret (Tykocinski & Steinberg, 2005)

Behavioral Metric. A logistic regression was used to test if the participants in the success vs. failure conditions liked or disliked the suggestion provided by AI. The results show that participants in the success condition liked the suggestion more than those in the failure condition ($\chi^2(1) = 5.066$, p= 0.024).

Serial Mediation Effect of Arousal and Self-identification. A mediation analysis was conducted using the Hayes Process (model 6, Hayes, 2017; n=5000). The mediators were self-identity connection and arousal, the independent variable was failure vs. success, and the dependent variable was a behavioral question of like or dislike. The results revealed that success vs. failure significantly affects self-identity connection (b=-0.8805, t=-2.532. p=0.127) and arousal (b=-0.0379, t=-3.223, p=0.0017). In addition, it showed that self-identity connection has a significant effect on arousal (b=0.0062, t=1.999, p=0.048). Self-identity connection has a significant effect on like/dislike (b=-1.7739, t=-2.794, p=0.0052), and arousal has a significant effect on like/dislike (b=-19.2478, t=-2.225, p=0.0261). Finally, the direct effect was eliminated as success vs. failure does not significantly affect likes/dislikes (b=0.3816, t=0.271, p=0.7865).

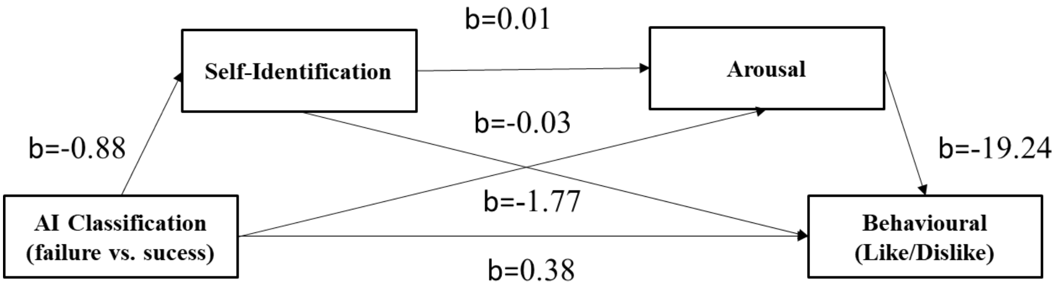

Figure 6. Mediation Model of AI classification success vs. failure on behavioral mechanisms

Discussion

The last study reveals that an AI classification failure leads to higher negative emotions (i.e., higher valance) and defensive mechanisms such as closing the eyes. In addition, it reveals that consumers' likes or dislikes are serially mediated through self-identification and arousal. When streaming users experience an AI classification failure, the level of arousal is reduced, leading to lower self-identifications and, consequently, decreases in the enjoyment of the recommended movie. Previous research shows that when AI provides a content selection that is not aligned with expectations, consumers feel misunderstood and are left with scepticism (Adam et al., 2021). Hence, our research advances the downstream consequences for the self, resulting from AI classification failures.

4.5 General Discussion and Conclusions

We demonstrate the detrimental effect of AI classification failures in four experimental studies using different data sources (online studies, lab study, neurophysiological evidence). Specifically, our findings demonstrate that an AI classification failure reduces consumers' self-identification and consequently negatively impacts regret and subsequent behaviors (e.g., subscription behaviors and self-defensive mechanisms). Moreover, when consumers are motivated to use AI to express themselves, failures driven by AI classification can amplify the downstream effects, such as regret of using AI, and influence behavioral outcomes. This research provides important theoretical and managerial implications for Smart Service Failure Recovery, AI classification experience, and identity-based motivation literature. Hence, we add to the body of literature on consumer acceptance of AI (Zhu et al., 2022), how they engage with AI agents (He & Zhang, 2023), and the role of AI in human interactions (e.g., Blut et al., 2021).

4.5.1 Theoretical Implications

First, our research extends the understanding of AI classification experiences (Puntoni et al., 2021) and identity-based motivation (Oyserman, 2009). Specifically, our research integrates these two research streams, revealing the downstream consequences of an AI classification failure on consumers' sense of self. Consumers are compelled to engage in consumption behaviors that allow them to express themselves. Recent technological improvements in online streaming encourage customers to self-express through assortment creation, and consequently, self-expression has emerged as a critical aspect of AI-based platforms (Rifkin & Etkin, 2019). However, the existing literature provides little insight into AI classification failures' implications on customers' sense of self. This research shows that AI classification failures can make consumers engage in self-defensive mechanisms, increasing adverse outcomes such as regret, defensive neurophysiological cues, and adverse downstream behaviors.

In addition, we examine the underlying mechanism of self-identification to uncover how individuals perceive AI classification failures, a novel inclusion to the two domains of smart service failures. We demonstrate that AI classification failures affect consumers' self-identification – i.e., highlight the relationship between AI service failures and consumers' sense of self. While past research (Alabed et al., 2022, Huang & Philp, 2021) suggests that consumers integrate AI agents as part of their self-concept, this study reveals that AI failures can disrupt this integration. When AI fails to meet consumers' expectations, i.e., failure in AI classification, it reduces consumers' self-identification with a smart service as their needs and wants are not correctly identified. Consequently, AI classification failures can have downstream effects such as regret of using AI or negative subsequent behaviors (e.g., reduced subscription behaviors and even quitting the platform).

Third, we explore how self-expression shapes how smart service failures are processed. Naturally, when consumers indulge in high self-expression, they form strong emotional attachments (Bagozzi et al., 2022; Wang et al., 2022). We contribute to past research by showing that consumers' strong emotional connection, i.e., salient self-expression, with AI intensifies the negative effects of AI classification failure. This study further explores how AI classification failures affect the activation of self-defense mechanisms. Building on Baumeister & Hastings (2013) research, people's self-concept and self-esteem are protected when faced with dangers or challenges to their identities. Our study investigates how unexpected and possibly self-threatening situations like errors in AI classification might cause these self-defense mechanisms to be activated.

4.5.2 Managerial Implications

Our research findings have significant practical implications for streaming platforms. Specifically, we demonstrate the downstream consequences of smart service failures such as switching or quitting behavior, reduced number of songs listened to or liked, or even facial expressions and self-defensive mechanisms (e.g., closing eyes to avoid watching an AI-recommended content).

It is crucial to acknowledge that the occurrence of AI classification failures is inevitable (Puntoni et al., 2021). Nonetheless, streaming platforms should try to minimize the probability of AI classification failure. Streaming platforms must consider identity-relevant factors during the design and architecture of their platforms. This can be achieved by allowing users to customize their experiences. This may include settings that allow users to specify how they want their identity to be recognized or interpreted by the streaming platform. Furthermore, streaming platforms should ensure AI models are trained on a wide range of identities, helping reduce biases and improve the model's accuracy, i.e., reducing situations of classification failures and feelings of regret.

Second, if an AI classification failure occurs, strategies must be explored to minimize the downstream effects of such failures. This research highlights the role of self-expression in shaping consumers' reactions to smart service failures (Rifkin & Etkin, 2019). Platforms that prioritize enhancing users' identity expression, for instance, by fostering self-expression, face unique risks (Wang et al., 2022). These platforms are more likely to encounter increased levels of regret among users in the event of a failure. Therefore, streaming platforms must strike a delicate balance between enabling self-expression and minimizing the negative impact of AI classification failures. When self-expression is salient, service providers should take necessary steps to mitigate AI classification failures and support consumers who experience such failures by providing transparency in the classification factors. Therefore, offering explanations for decisions made by AI can help users understand how their identity is interpreted by a classification experience.

Finally, streaming platforms should improve self-identification, i.e., the connection between streaming users and AI. This can be achieved by a user-centric design that prioritizes the user experience in the platform's design and allows users to provide feedback on their interaction with AI to refine and improve the streaming experience itself. By recognizing and understanding these dynamics, streaming platforms can proactively design their systems and processes to accommodate user identities and mitigate the potential fallout from smart service failures. This requires a thoughtful approach that integrates user-centric considerations and effectively manages the expectations and emotions of users in the face of AI classification failures.

4.5.3 Limitations and Future Research

This research has several limitations that offer avenues for future investigations. First, one notable limitation is the participants' awareness of AI usage by streaming platforms. Acknowledging that not all consumers know that AI algorithms are employed to generate recommendations is important (Consumer Survey of Video Streaming Preferences and Attitudes, 2021). Higher or lower levels of awareness may have influence influenced participants' perceptions and reactions, thus warranting further research. Second, it is crucial to note that the scope of our studies was implementing AI for content selection on streaming platforms. While we provide valuable insights, it is important to delve into the implications of AI-human collaboration (Huang & Rust, 2021), particularly when classification failures occur. For example, AI-human collaboration in this context can focus on "feeding" the algorithm with user preferences. In addition, exploring the aftermath of such failures and understanding the potential adverse consequences of human vs. AI classification errors could shed light on the dynamics of human-AI interaction and guide the development of more robust and effective systems.

Third, although streaming services are vital to understanding how AI classification failures can influence consumers' self-identity implications, future studies should encompass a broader range of digital services, such as social media platforms or gaming services, with a clear public sense of the self. Future research can further expand our knowledge and contribute to developing AI systems that better align with user expectations and requirements by addressing these limitations and delving into these unexplored areas. Overall, including AI recommendation systems in streaming platforms entails many advantages for the company and the user. However, to ensure long-term success, it is integral to consider how consumers' self is connected and reflected by these AI-enabled platforms.

Chapter 5- Artificial Intelligence (AI) in Fintech Decisions: The Role of Congruity and Rejection Sensitivity

5.1 Introduction

By customizing services and experiences, artificial intelligence (AI) is revolutionizing and reshaping the banking industry (Bleier, Goldfarb, & Tucker, 2021; Campbell et al., 2021; Hoyer et al., 2020; Cukier, 2021; Omoge et al., 2022). AI provides commercial banks with countless benefits, such as enhancing customer experience and providing more personalized services (Financial Times, 2018). As such, the use of AI in FinTech is expected to reach USD 26.67 billion by 2026 (Mordor Intelligence, 2022).

Notably, the digital revolution has affected the relationship between financial firms and consumers (Molina-Collado et al., 2021), creating a new generation of FinTech (financial technology) – i.e., "technology used to provide financial markets a financial product or financial service, characterized by sophisticated technology relative to existing technology in that market." (Knewtson & Rosenbaum, 2020, p. 1044).

In practical terms, large financial firms have invested in delivering a better experience by tracking, personalizing, and optimizing consumers' journeys (Johnson, 2017). Through AI, FinTech has provided services to engage consumers, examine accounts and their financial health, and provide financial advice shaping consumers' expectations (Belanche et al., 2019; Bussmann et al., 2020). The use of AI has developed in key financial services areas such as compliance, lending and credit assessment, and trading and investment decisions (Truby et al., 2020).

In our research, we investigate consumers' reactions toward decisions by AI (vs. humans) under (favorable or unfavorable) outcomes. While recent research suggests that consumers react less favorably to AI (vs. human) (Northey et al., 2022; Longoni, Bonezzi, Morewedge, 2019; Yalcin et al., 2022). Our research suggests that in the context of negative (vs. positive) outcomes, consumers react more positively to AI (vs. human).

By drawing on the psychological attribution (Burnkrant, 1975; Okten & Moskowitz, 2018) and role congruence theory (Fan & Mattila, 2021; Solomon et al., 1985), we theorize and find that individuals will react less favorably to rejections by humans (vs. AI), under negative (vs. positive) outcome valence. Recent consumer research indicates that consumers tend to prefer humans over AI, and such an effect is driven by uniqueness (Longoni et al., 2019; Yalcin et al., 2022). Thus, we expect that rejection by AI will not have the same detrimental impact compared to rejection by a human.

This paper sheds light on using AI in the FinTech context by examining consumers' reactions toward AI (vs. human) credit decisions. In two experimental studies, this research reveals that decision-makers' influence on customer satisfaction varies depending on the credit product. In the case of personal loans (Study 1), rejection by an AI induces higher satisfaction than rejection by a credit analyst. In addition, we show that the perceived role congruity is the underlying mechanism of this effect. In Study 2, we observe that a person's rejection sensitivity influences whether they have a more extreme perception of role congruity (high rejection sensitivity) or a less extreme sense of role congruity (low rejection sensitivity) for both outcomes.

By doing so, our findings have important implications for theory and practice, addressing recent research calls on the unintended consequences of AI (Omoge et al., 2022; Pinochet et al., 2019; Riedel et al., 2022), suggesting that the adoption of AI in financial services shapes customers satisfaction outcomes. In addition, we extend the role congruity theory (Biddle, 1986; Broderick, 2006; Broderick, 1998; Ho et al., 2020;

Solomon et al., 1985) by demonstrating that role congruity mediates the relationship between outcome valence of credit requests (approved vs. rejected) and satisfaction. Finally, we introduce rejection sensitivity by bridging AI studies and FinTech (Berenson et al., 2009; Downey & Feldman, 1996).

Managerially, this research offers practitioners insights into adopting AI in banking by examining automated decision-making, particularly in light of the technological advancements in Fintech powered by AI (Belanche et al., 2019; Bussmann et al., 2020). By recommending which scenarios AI technologies should be further included in credit assessment offers and systems, this research can give novel strategies for the Fintech landscape.

5.2 Literature review

5.2.1 Artificial Intelligence and Financial Services

The definition of Artificial Intelligence is not consensus or easy to produce (Kaplan & Haenlein, 2020). Nevertheless, past research has come up with different definitions. Kumar et al. (2016, p. 26) proposed that AI refers to "computational systems that inhabit a complex dynamic environment and continuously perform marketing functions such as (a) dynamic scanning of the environment and market factors including competitors, customers, and firm actions impacting the marketing mix; (b) collaborating and interacting to interpret perceptions, analyzing, learning and drawing inferences to solve problems; and (c) implementing customer-focused strategies that create value for the customers and the firm within the boundaries of trustworthiness and policy". In general, AI involves system-based machines that interact with consumers and provide communication services (Wirtz et al., 2018). In addition, AI systems can self-learn by constantly improving and updating the content (Kumar et al., 2021). Finally, there are different kinds of AI analysis (numeric, text, voice, and image) that are used to analyze customer behavior, allowing for better user experience, demand prediction, personalization, and processes (Shankar, 2018), enhancing the overall experience (Cukier, 2021).

Advancements in data analytics span many industries, including retail (Grewal et al., 2017; Tan et al., 2021), banking (e.g., Kaushik & Rahman, 2015; Omoge et al., 2022), and travel and tourism (Murphy et al., 2019; Pillai & Sivathanu, 2020). Firms today rely on Big Data and AI (Babu et al., 2021; Davenport & Bean, 2018, Payne et al., 2021) and text analysis (Sainaghi et al., 2017) to increase productivity (Makridakis, 2017), to improve the overall experience (Cheng & Jiang, 2020) and tackle problems that humans may find difficult to comprehend (Gupta & Arora, 2017). Such practices allow firms to better tailor consumers' preferences (Puntoni et al., 2021). Indeed, the growth of digital channels has pushed autonomous deployment (Manyika et al., 2017). AI digital assistants simulate human language allowing realistic conversations with consumers, especially compared to the early 2000's assistants (Pantano & Pizzi, 2020, Riikkinen et al., 2018). Moreover, the application of the technology can occur in the back office (for risk assessment, segmentation, recommendation, or process automation), and AI systems usage can have different levels of autonomy: the technology can work as a support tool or completely autonomous – exempting human intervention (de Bellis & Johar, 2020).

The relationship between consumers and AI is complex and nuanced. Among those issues is the increase in privacy concerns (Carmody et al., 2021; Dinev & Hart, 2006; Manikonda et al., 2018; Zarifis et al., 2020), the future of employment, wealth distribution (Lu et al., 2021; Makridakis, 2017), and algorithm bias (Lin & Hsieh, 2007;

Melnychenko, 2020) which in turn led to some ethical and legal concerns (Mehrabi et al., 2021; Nadeem et al., 2020; Ntoutsi et al., 2020).

Various financial services have implemented artificial intelligence to improve business processes (Arli et al., 2020). Previous studies in the field presented the AI system as an agent, such as chatbots/assistants (see Appendix D for details). Some examples comprise fraud detection, trading forecasting, and risk modeling (Almirall, 2022; Gartner, 2022; Danske Bank Fights Fraud with Deep Learning and AI, 2018), posing new challenges to AI-based financial services (Giudici et al., 2019).

5.2.2 Satisfaction and Role Congruity

Companies often seek to satisfy consumers by offering differentiated services (Arbore & Busacca, 2009; Vakulenko et al., 2022). Previous research shows that AI in banking contributes to transactional-oriented value propositions rather than relationship-oriented ones (Payne et al., 2021).

AI autonomous systems are already a reality, but there is a lack of understanding of the effect of AI decision-making on consumer outcomes (Chumpitaz & Paparoidamis, 2004; Islam et al., 2021; Teeroovengadum, 2022; Walsh et al., 2004).

We draw on the role congruity theory (Solomon et al., 1985; Wang et al., 2019). The role congruity theory asserts that individuals engage in a range of recognized "roles" that help them, and others understand their behavior (Wood & Eagly, 2012). Individuals behave in predictable ways based on the role they are performing, and the social norms related to it (Biddle, 1986). These roles represent the current expectations, preconceptions, and conventions that determine whether a person's conduct is congruent or incongruent (Eagly & Karau, 2002). In the marketing context, the role congruence concept suggests that firms also have a part to observe (Broderick, 1998). The fulfillment of this role influences the perception of a firm's performance (Ho et al., 2020; Sharma et al., 2012; Solomon et al., 1985). More specifically, when applied to service encounters, one assumption would be that for achieving service provision success, a good experience, mutual comprehension, and mastery of the roles to be performed by the client and the organization are required (Broderick, 1998).

Role congruity theory has been widely employed in the study of how people are judged in a range of situations, such as the suitability of leadership behaviors (Abraham, 2020), implications of unethical workplace behavior (Mai et al., 2020), or entrepreneur performance in terms of resource acquisition (Wang et al., 2019). For instance, in the banking context, past research has studied the influence of gender role congruity on financing entrepreneurial ventures (Eddleston et al., 2016).

Previous research on consumers' reactions to service failures by AI (vs. human agent) suggests that consumers recognize them as having a similar role, thus increasing role congruity (Ho et al. 2020, Leo et al., 2020). The theory of role congruity emphasizes the importance of congruence between the service provider and their behavior (Miao, Mattila, & Mount, 2011; Solomon et al., 1985), when the behavior is not congruent with the expectation or roles, then it will likely decrease satisfaction (Sharma et al., 2012). Indeed, prior research supports this assumption. Prior research highlights the importance of congruency in service encounters such as store image congruency (O'Cass & Grace, 2008), or between a customer's self-concept and employee image (Jamal & Adelowore, 2008). For instance, research shows that individuals react more favorably to service encounters when the provider might be more congruent with conversational norms (Choi, Liu, & Mattila, 2019). Additionally, research further highlights the importance of service employee–environment fit and congruence (Lim, Lee, & Foo, 2017).

This research extends the role congruity theory to investigate how consumers react to decisions by an algorithm (vs. human). Generally, after requesting a financial service, consumers make interferences about the outcome: approval (vs. rejection), although it is intuitive to argue that negative outcomes would be more dissatisfying despite the nature of the agent. However, in our research, we expect that rejection by a human is less satisfying compared to AI.

Individuals tend to attribute favorable outcomes to themselves (e.g., Yalcin et al., 2022), whereas negative outcomes are usually attributed externally (e.g., the others–Kelley & Michela, 1980). Recent research suggests that consumers tend to favor humans over AI, due to some factors that are associated with uniqueness (Longoni, Bonezzi, Morewedge, 2019). For instance, Yalcin et al. (2022) found that it is easier to attribute positive outcomes when the agent is AI versus human. Put simply, human agents signal unique cues (this offer is for me because I am special) but rejections might sound personal. Thus, we expect that when the outcome is negative, reactions to a human would be less favorable, due to the lay beliefs that human neglected their unique self (Longoni et al., 2019), whereas, this effect will not be observed for AI, for example, recent research suggests that consumers attribute less responsibility to AI (vs. human) in context of service failure (Ho et al., 2020). Following this reasoning, we postulate that when the outcome is negative, consumers react less favorably to humans (vs. AI). By doing so, we extend prior studies by showing that the decision-maker type (AI vs. human) affects how consumers react to favorable versus unfavorable outcomes.

Therefore, we propose that consumers attribute less responsibility toward AI (vs. human) for a rejected (vs. approved) credit, impacting their satisfaction. More formally, we hypothesize that:

Hypothesis 1: *The type of response (approved vs. rejected) will impact consumers' satisfaction depending on the decision-maker (AI vs. human).*

Hypothesis 2: *Perceived role congruity will mediate the relationship between the response (approved vs. rejected) and satisfaction.*

5.2.3 Rejection Sensitivity in Banking

We further suggest that rejection sensitivity is a boundary condition for our expected effect. Rejection sensitivity is a cognitive-affect processing disposition that leads to an anxiety response (Downey & Feldman, 1996). According to Romero-Canyas et al. (2010, p.120), it is defined as "*the disposition to anxiously expect, readily perceive, and intensely react to rejection*". This anxious expectancy is triggered by situations where both acceptance and rejection are possible, and the answer is overreactive.

Consumers' rejection is rarely discussed in the service literature, thus far, prior research mainly focuses on consumers' decisions to reject or accept service offerings. For example, consumers may be served an unpleasant meal which in turn they decide to return (Gelbrich, Gäthke, & Grégoire, 2014), or how rejection can increase the desire to purchase in the luxury retailing context (Ward & Dahl, 2014). To this end, prior marketing literature falls short of explaining rejection sensitivity.

In the banking context, a study about credit-constrained households indicates that consumers are more reluctant to apply for loans due to fear of rejection (Japelli, 1990). We draw from the rejection sensitivity theory (Ayduk, & Gyurak, 2008), to posit that when individuals are priorly exposed to rejection (Downey et al., 1997), it fosters strengthened sensitivity to future rejection risks, motivating self-protection attempts (Berenson et al., 2009). The rejection sensitivity scale is a compound of rejection/acceptance expectancy and rejection concern, where the rejection concern measures the level of concern/anxiety about the response because of the overreactive response to rejection (Berenson et al., 2009). When rejection is possible, people with high rejection sensitivity are unsure whether they will be accepted or rejected. Nonetheless, the outcome is critical; such instances include cognitive assessments of danger under unknown settings. Conversely, individuals with low rejection sensitivity are less likely to experience heightened defensive motivational system activation in these situations because they consider rejections less likely and significant (Downey et al., 2004). Thus, we propose that:

Hypothesis 3: *Consumers' responses to AI (vs. human) credit decisions will be more extreme for those with high (vs. low) rejection sensitivity.*

5.3 Overview of studies

Two studies tested our predictions. In particular, study 1 shows that for personal loans, the rejection by an AI causes less dissatisfaction than rejection by a credit analyst and that the perceived role congruity mediates this effect. The more the bank fulfills its role, the higher the satisfaction. In study 2, the relationship between the outcome, role congruity, and satisfaction is maintained. In this study, we reveal that a person's rejection sensitivity determines if they will have a more extreme perception of role congruity (high sensitivity) or less extreme (lower sensitivity) for both outcomes. As role congruity mediates the relationship between the outcome and the satisfaction, this effect also can be seen in satisfaction.

A minimum of (*N*=60) participants per cell were targeted, excluding responses with missing values or failed attention checks, and additional responses were collected until the target sample size was reached (van Selm & Jankowski, 2006).

Both studies were scenario-based experiments. For more details, please see appendix B. In the first study, the scenario asked the participants to imagine themselves applying for a personal loan, while in the second study, they were applying for a credit card. In each experiment, the participants were randomly exposed to one of four scenarios that manipulated two conditions 2: decision-maker (credit analyst vs. artificial intelligence) and outcome valence: approved vs. rejected (see Table 6).

		Decision-maker	
		Credit analyst	Artificial intelligence system
Lender's response	Approved	Approved personal loan application by a credit analyst	Approved personal loan application by an AI system
	Rejected	Rejected personal loan application by a credit analyst	Rejected personal loan application by an AI system

Table 6. Conditions of the experimental studies (Study 1 and 2)

Besides the authorization to analyze the participants' data, to ensure only EU inhabitants respond to the survey, the country of residence was asked, as well as a captcha question. To improve the quality of the responses, attention checks were performed. Figure 7 summarizes the study flow.

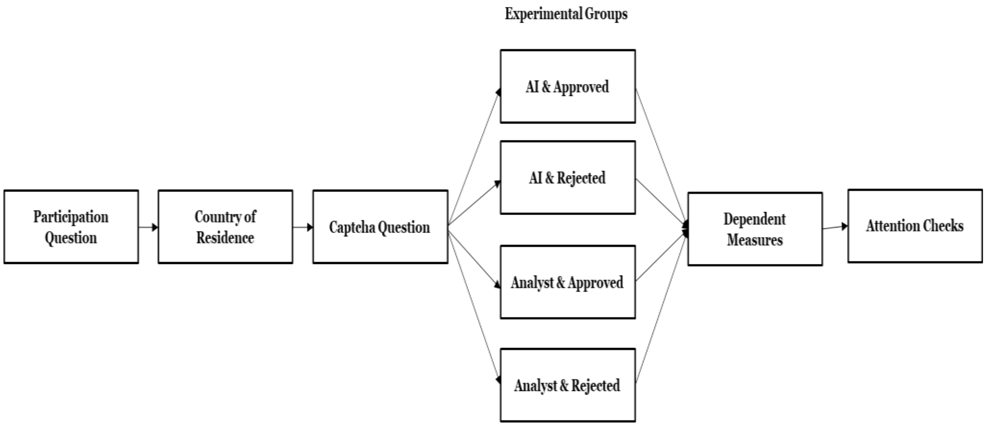

Figure 7. Overview of studies – checkpoints

A test for common method bias for both studies was conducted. To test common method bias, Harman's single factor score was used (Eichhorn, 2014), in which all items were loaded into one common factor. For both study 1 and study 2, the total variance for a single factor is less than 50% (47.01% and 45.46%, respectively). Hence, suggesting that common method bias does not affect our results.

5.3.1 Study 1

This study aims to investigate the joint impact of outcome valence: approval (vs. rejection) and the decision maker: AI (vs. credit analyst). Participants were randomly assigned to one of our four experimental conditions. In the first study, the outcome of a personal loan request and the decision-maker were manipulated to study the impact on satisfaction. Specifically, a scenario-based experiment where participants were asked to imagine themselves in the scenario described. In particular, Study 1 tests the following model (see Figure 8).

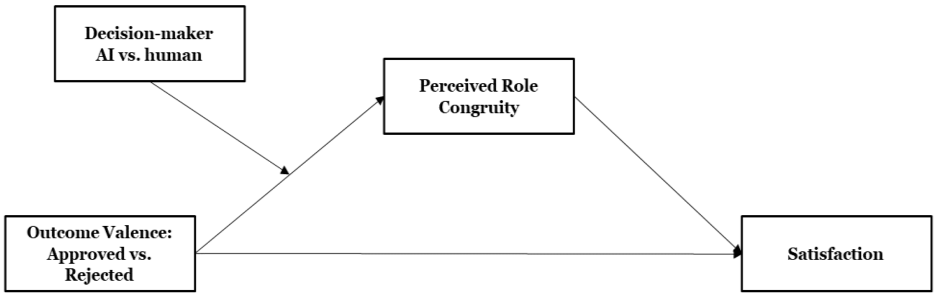

Figure 8. Proposed conceptual model of Study 1

Participants and Design.

Two hundred sixty-one FinTech consumers (M_{age}[1]=32.7) were recruited through the online panel, Amazon Mechanical Turk (MTurk). This platform allows hiring people to perform tasks, such as survey participation. The sample consisted of males (72.4%), from 18 to 44 years old (84.4%), with an education equivalent to or superior to a bachelor's degree (71.2%), with greater participation from residents in Spain, the UK, and Italy. Before starting the research, the participants were screened for their country of residence. The ones who lived outside the EU were not allowed to continue. The study focused on European Union residents over the age of 18. In the EU, it is mandatory to disclose when a customer is subjected to an automated decision-making process (General Data Protection Regulation, Art. 22, 2018). This particularity makes understanding the implications on EU consumers' perceptions even more pressing.

[1] Mage = Mean Age

The procedure, Stimuli, and Measures.

The participants had to agree to participate and pass a captcha verification question – to discard eventual bots-and pass one attention check question. Of the 316 participants that started the survey, 261 were able to finish it. On top of it, the security option "Prevent multiple submissions" at Qualtrics was turned on to prevent participants from answering the survey more than once. All the participants that completed the survey and passed the attention checks were included in the analysis – see Table 7.

Experimental group	*n*
AI system scenario and personal loan approval	67
AI system scenario and personal loan rejection	71
Credit analyst scenario and personal loan approval	62
Credit analyst scenario and personal loan rejection	61
Note: $n = 261$	

Table 7. Summary of experimental groups study 1

Participants were exposed randomly to four conditions: 2 decision-makers (human vs. AI) x 2: outcome (approval vs. rejection). Participants under the AI condition were instructed to read a definition of AI, then we asked them about their prior experience with AI in banking. The exposition and test questions were presented after the scenario and evaluation.

Then participants responded to our measures. Consumer satisfaction was measured by using items from Levesque & McDougall (1996), and the items of perceived role congruity were adapted from Ho et al. (2020). Both constructs used 7-point scale items (1: Strongly disagree; 7: Strongly agree). The items in satisfaction were highly correlated (α = .91) and were averaged into an index of satisfaction. The same procedure was applied for perceived role congruity (α = .82). There were no missing values for either of the scales.

Next, participants answered if they had already interacted with banks and, if so, what type of AI they had interacted with (Chatbot / Assistant, Investment advice, Simulations of loans and mortgages, Risk assessment, or others).The internal consistency of a model is validated by Cronbach's alpha - over 0.6 (Ursachi et al., 2015). To assure acceptable indicator reliability, the outer loadings should be above 0.7. Those results validate the use of the latent variables (Bagozzi & Yi, 1988; Gefen, Straub, & Boudreau, 2000; Nunnally, 1978) to test the conceptual model. In addition, we assessed convergent validity and discriminant validity according to Fornell & Larcker, (1981) where all AVE is above 0.5 (see Tables 8 and 9).

	Role Congruity	Satisfaction
Role Congruity	0.899	
Satisfaction	0.774	0.928

Table 8. Fornell-Larcker criterion study 1

Measurement items	Cronbach's alpha	AVE	Average loading	Item Loading	Correlation	p-value	Sum of squares and cross products	Covariance
Satisfaction (adapted from Levesque & McDougall, 1996)	0.911	0.754	0.868		1	-	816.79	3.18
1. How would you rate your overall satisfaction with the experience?				0.838				
2. How would you rate your overall satisfaction with the decision?				0.872				
3. How would you rate the overall satisfaction with the service of this bank?				0.895				
Perceived role congruity (adapted from Ho et al., 2020)	0.825	0.585	0.765		0.758*	2.3E-49	489.80	1.91
1. The bank has fulfilled its role responsibly.				0.841				
2. The bank fulfilled its role as you would have expected.				0.851				
3. The bank fulfilled its obligations to you.				0.841				

*p<0.001

[a] Items measured on a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree).

Table 9. Properties of measurement items study 1

Results and Discussion.

A two-way ANOVA reveals a significant interaction between decision-maker and outcome (F (3, 257) = 4.595, p = .033, $\eta p2$ = 0.18) on satisfaction.

A main effect of the outcome was observed on satisfaction ($M_{approved}$= 5.70, $M_{rejected}$ = 3.07; t (260) =304.42, p < .001). However, a main effect of the agent was not observed (M_{AI}= 5.70, M_{human} = 0.612; t (260) =, p =0.435). A pairwise comparison shows that for the positive outcome, there was no significant difference between subjects in the AI or Human condition (M_{AI} = 5.64, SD= 1.011 vs. M_{human} = 5.75, SD=.86, p = .599), contributing to recent studies (Ho et al., 2020).

However, in the negative outcome scenario, when rejected by an AI system, the satisfaction was slight - but significantly – higher than the satisfaction of those rejected by a credit analyst (M_{human} = 2.80, SD= 1.36 vs. M_{AI}=3.33 SD = 1.42, p = .013) - see Figure 9.

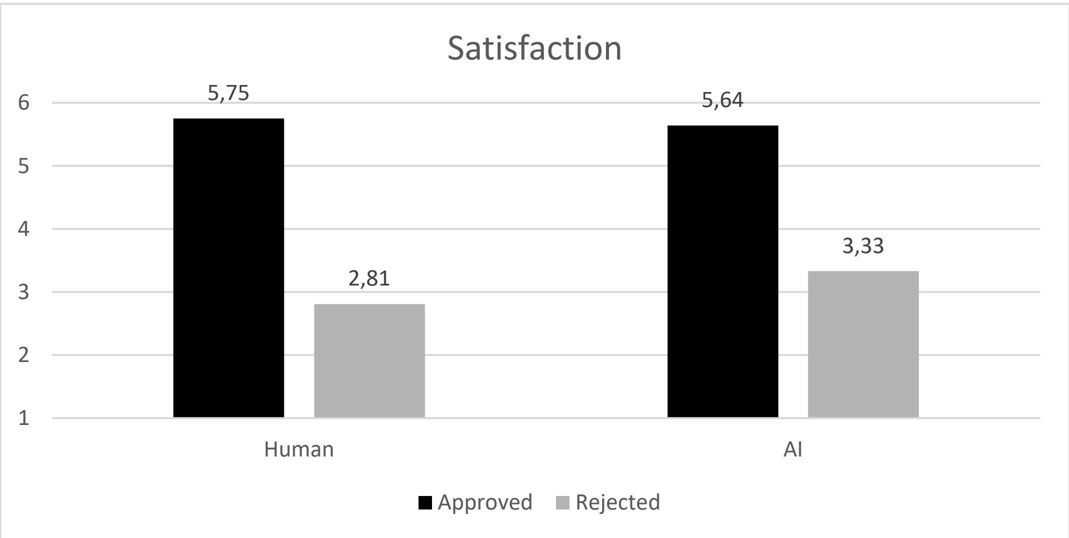

Figure 9. Outcome and satisfaction

This result is counterintuitive because 69.3% of the respondents preferred their credit to be evaluated by a credit analyst (vs. an AI). Nevertheless, this finding helps bring nuance to the theory (Ho et al., 2020), which was not tested in a negative outcome scenario.

The results could be influenced by the belief that AI is more capable of accurately judging a person's capacity to repay the loan (Batara et al., 2021) or given AI systems' technical skills (Xu et al., 2020).

Mediation Analysis.

When the moderated mediation model was analyzed using PROCESS Model 7 (with 5,000 resamples with replacement; Hayes, 2013), the relationship between the outcome and the perceived role congruity was significantly moderated by the decision-maker (b = 0.75, SE = .274, t = 2.741, p = .007).

The higher the perceived Role Congruity, the higher satisfaction. The low perceived role congruity in the rejection cases (M_{Rejected} = 3.091 vs. M_{Approved} = 5.695) indicates that even though the firm representative matters, the role is not exclusive to the front office. The institution also has a role in attending to (Broderick, 1998), defined by its expectations through brand, policies, and previous experiences.

Perceived role congruity partially mediates the relationship between outcome and satisfaction in the presence of the moderator with more impact in the human condition (indirect effect = -1.312, *CL*= [-1.720; -.935]) than in the AI condition (indirect effect = -.844, *CL*= [-1.187; -.533]) (see Table 10).

Relationship	Direct Effect	Indirect Effect	Confidence Interval	
Lender's response -> Role Congruity -> Satisfaction			Lower Bound	Upper Bound
Human	-1.312	.203	-1.720	-0.935
AI	-.844	.168	-1.187	-0.533

Table 10. Moderated mediation analysis study 1

5.3.2 Study 2

This study complements the first one by analyzing the same relationships for credit cards and introducing a new variable. Credit cards are another form of delivery of credit products. In particular, Study 2 tests the following model (see Figure 10):

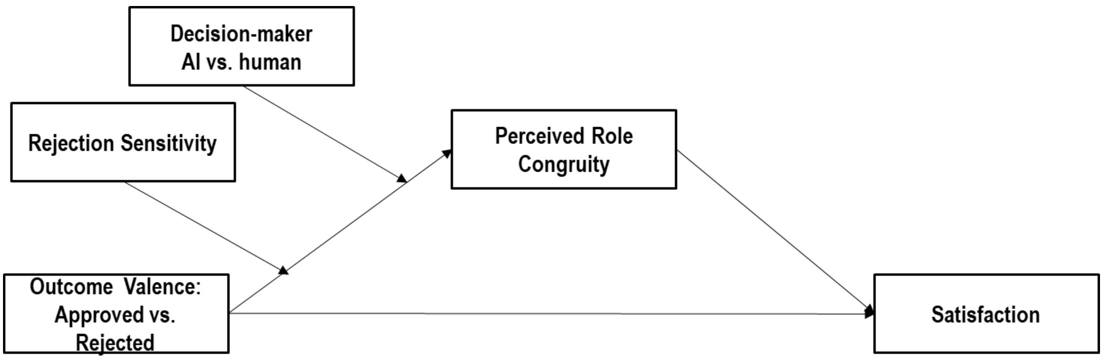

Figure 10. Proposed Conceptual Model of Study 2

Participants and Design.

Two hundred forty-two FinTech consumers (Mage=32.3) who completed the study were recruited through Amazon Mechanical Turk (MTurk). In this study, participants were EU residents over 18.

Of the 372 participants that started the survey, 242 were able to finish it (Mage=32.3). Participants were primarily male (69%), from 18 to 44 years old (84.3%), with an education equivalent to or superior to a bachelor's degree (66.9%), and with greater participation from residents in Italy and Spain.

The procedure, Stimuli, and Measures.

The subjects were exposed randomly to four different scenarios where the decision-maker (human vs. AI) and the outcome valence (approved vs. rejected) were manipulated.

After agreeing to participate and passing the captcha question, the participants were randomly assigned to one of four scenarios. In addition, participants faced an attention check question, the participants who failed had their participation terminated and were not included in the analysis (see Table 11).

Experimental group	*n*
AI system scenario and credit card approval	61
AI system scenario and credit card rejection	60
Credit analyst scenario and credit card approval	61
Credit analyst scenario and credit card rejection	60
Note: $n = 242$	

Table 11. Summary of experimental groups study 2

Two of the constructs used were satisfaction and perceived role congruity. Both scales used 7-point scale items (1: Strongly disagree; 7: Strongly agree). The items in satisfaction were highly correlated (α = 0.90) and were averaged into an index of satisfaction. The same procedure was applied for Perceived role Congruity (Ho et al., 2020) (α = 0.87). The same items were used as in the first study. There were no missing values for either of the scales.

After the participants answered questions about their rejection sensitivity (adapted from Berenson et al., 2009) with a 6-point scale (1: Very unconcerned, 6: Very concerned), the reliability of the scale was a little below the threshold (Cronbach's α = 0.687). Still, in this study, it was considered acceptable (see Tables 12 and 13).

	Role Congruity	Rejection Sensitivity	Satisfaction
Role Congruity	0.910		
Rejection Sensitivity	0.151	0.834	
Satisfaction	0.831	0.201	0.919

Table 12. Fornell-Larcker criterion study 2

Measurement items	Cronbach's α	AVE	Average loading	Item Loading	Correlation	p-value	Sum of squares and cross products	Covariance
Satisfaction (adapted from Levesque & McDougall, 1996)	0.904	0.723	0.851		1	-	695.56	2.89
1. How would you rate your overall satisfaction with the experience?				0.864				
2. How would you rate your overall satisfaction with the decision?				0.786				
3. How would you rate the overall satisfaction with the service of this bank?				0.833				
Perceived role congruity (adapted from Ho et al., 2020)	0.871	0.593	0.770		0.791*	4E-53	509.21	2.11
1. The bank has fulfilled its role responsibly.				0.734				
2. The bank fulfilled its role as you would have expected.				0.810				
3. The bank fulfilled its obligations to you.				0.752				
Rejection sensitivity (adapted from Berenson et al., 2009)	0.687	0.580	0.762		-0.193*	0.00258	-103.97	-0.43
1. When you ask your bank for a loan to help you through a difficult financial time, how concerned or anxious would you be over whether or not your bank approves your request?				0.768				
2. When you ask your bank for a credit card to make an expensive purchase you need, how concerned or anxious would you be over whether or not they deny your request?				0.760				

*p<0.001

[a] Items measured on a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree).

[b] Items measured on a 6-point Likert scale (1 = Not concerned at all, 6 = Very concerned).

Table 13. Properties of measurement items study 2

Results and Discussion.

Unlike study 1, and following the study published by Ho et al. (2020), a two-way ANOVA revealed that for credit card requests, the firm's representative does not influence customer satisfaction ($f\ (238) = 1.334$, $p = .249$). It also does not moderate the relationship between outcome and decision-maker ($b = -0.388$, $t\ (238) = -1.1549$, $p>0.05$).

This supports our predictions for this product request. The difference between the impact of the decision-maker could be due to the nature of the products. While a personal loan is merely a credit product, the credit card is also a payment method, with not only interest rates but also monthly or annual fees.

The Satisfaction score, however, continued to be significantly smaller for those who had their credit card request denied in comparison to those who had the request approved ($M_{\text{Rejected}} = 3.058$, $M_{\text{Approved}} = 5.227$, $F\ (238) = 166.377$, $p<0.01$).

Moderated Mediation Analysis. Using PROCESS Model 8 (with 5,000 resamples with replacement; Hayes, 2013), we confirmed that the mediation effect of perceived role congruity was significant for the analyzed scenarios. This was a moderated mediation analysis, which confirmed the moderation effect of rejection sensitivity in the relationship between outcome and role congruity ($b = -.347$, $SE = 0.135$, $t\ (238) = -2.569$, $p = .011$). The relationship between outcome and satisfaction was not moderated, as expected.

Higher rejection sensitivity will lead to an increase perceived role congruity upon approval, but it will also drive lower scores when rejected (see Figure 11). Low Rejection sensitivity will soften the outcome effect on the perceived role congruity. The indirect effect of the presence of the moderator (at mean level) is -1.368 (*SE* = 0.144, *95% CI* = -1.656; -1.088) (see Table 14).

Relationship	Direct Effect	Indirect Effect	Confidence Interval	
Outcome -> Role Congruity -> Satisfaction			Lower Bound	Upper Bound
Low rejection concern	-1.085	0.197	-1.465	-0.706
Average rejection concern	-1.368	0.144	-1.656	-1.088
High rejection concern	-1.651	0.185	-2.023	-1.295

Table 14. Moderated Mediation analysis study 2

This finding indicates that the channel, the technology, and the process are important, but the characteristics of the customer have a significant role in their perceptions of the service. Consumers with a higher rejection sensitivity will have more extreme reactions to request responses. That means greater satisfaction, which could lead to greater loyalty. These consumers represent an opportunity for a long-term relationship, but their pain points must be addressed – for they will also be more dissatisfied by denials.

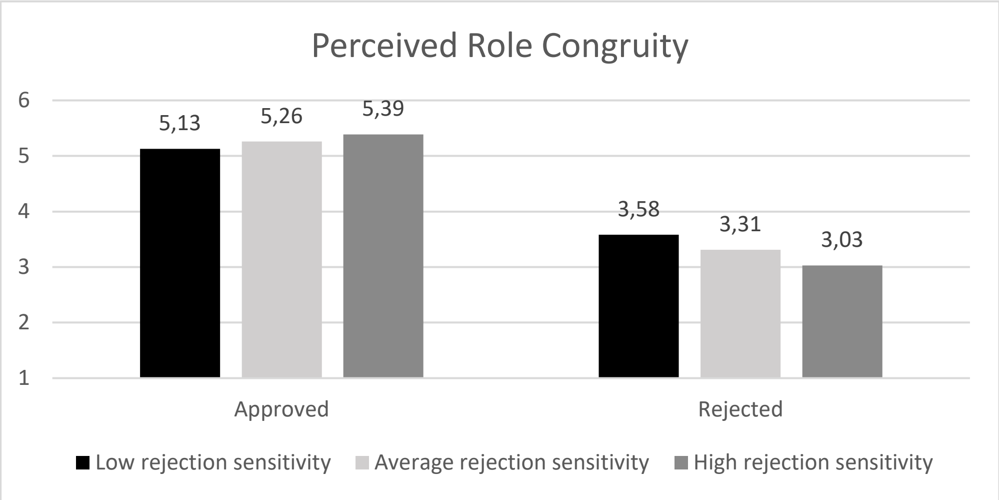

Figure 11. Perceived role congruity vs. Outcome vs. Rejection sensitivity

5.4 General Discussion

This research analyzes the effect of AI decision-making on consumers in the banking context. Our findings contribute to the understanding of how decisions by AI (vs. human) can affect consumers' responses. Although recent studies have highlighted the important role of AI in consumer–provider interaction, this topic has received limited attention in marketing literature. Our findings indicate that rejection by an AI triggers a higher level of satisfaction compared to rejection by a credit analyst for personal loans, due to perceived role congruity. In addition, we observed that consumers' responses to AI vs. human credit decisions are more extreme for those with high (vs. low) rejection sensitivity. Our results imply that relationship-oriented banks should pay attention to and be careful when dealing with customers with high rejection sensitivity, while transaction-oriented banks should focus their efforts on the lower rejection segment of customers. Next, we discuss the theoretical contributions and the practical implications of our work.

5.4.1 Theoretical contributions

Our study findings contribute to literature in at least three significant ways. First, this research extends prior studies on consumers' reactions to decisions by AI (Yalcin et al., 2022), contributing to studies on the use of AI (vs. human) in financial services (Mogaji et al., 2021; Omoge et al., 2022; Riedel et al., 2022). Our research, by examining consumers' reactions to AI (vs. human) credit decisions, has expanded on automated decision-making on satisfaction to show that AI does not negatively influence customer satisfaction. In our study, we investigate how customers would respond to decisions made by AI (vs. humans) under (favorable or unfavorable) outcomes. Our research contributes to previous studies (Ho et al., 2020) by showing that consumers hold AI to be less responsible than humans. Hence, we build on earlier research by demonstrating how customers' responses to approve vs. reject results depend on the decision-maker type (AI vs. human).

Secondly, our research extends the role congruity theory (Biddle, 1986; A. Broderick, 2006; A. J. Broderick, 1998; Ho et al., 2020; Solomon et al., 1985) to the FinTech industry. Drawing on the role congruity theory, we fill a gap in research. Besides the past efforts to explore AI autonomous systems, there was a lack of understanding of the effect of AI decision-making on consumers ' perceptions. Considering that satisfaction impacts loyalty (Chumpitaz & Paparoidamis, 2004; Islam et al., 2021; Teeroovengadum, 2022; Walsh et al., 2004), it could harm long-term economic sustainability. However, our study shows that role congruity mediates the relationship between outcome (approved vs. rejected) and customer satisfaction. Our research contributes to previous studies (Ho et al., 2020) by showing that consumers hold AI to be less responsible than humans. Hence, we build on earlier research by demonstrating how customers' responses to approve vs. reject results depend on the decision-maker type (AI vs. human).

Finally, our study introduces rejection sensitivity (Berenson et al., 2009; Downey & Feldman, 1996) in studies about banking and AI by showing that rejecting sensitivity is key in understanding the preference for AI (vs. human). Prior research has generally concentrated on consumers' choices to accept or reject service offerings, and consumer rejection is rarely mentioned in service literature. In light of this, previous marketing literature does not adequately explain rejection sensitivity. Hence, in our research, we further reveal that the service evaluation is more extreme for those who are already emotionally engaged (high rejection sensitivity) with the outcome than those who are not (low rejection sensitivity).

5.4.2 Practical contributions

With so many options to deploy AI in financial services, it's critical to choose prospective applications based on the business value they can generate. This research has uncovered important practical implications for managers by exploring automated decision-making, especially given the technical breakthroughs of Fintech driven by AI (Belanche et al., 2019; Bussmann et al., 2020). Our research suggests that the impact of the decision-maker on customer satisfaction varies according to the credit product (Cheng & Jiang, 2020b; Payne, Dahl, et al., 2021). As such, for personal loans, the rejection by an AI causes less dissatisfaction than rejection by a credit analyst, and for credit cards, the decision-maker is not relevant. Hence, the strategies used by the Fintech institutions will depend on the type of product provided. As such, this research can provide interesting strategies for the Fintech landscape by suggesting in which circumstances AI technologies should be further incorporated into credit assessment offerings and systems. Additionally, our conclusions offer insights into the relationship between customers and financial services providers. This research has shown that the customer journey should accommodate the needs of the high rejection sensitivity segment due to its positive response when approved. Hence, to improve the relationship and social connectedness between customers and providers, relationship-oriented Fintech companies should have more care in delivering the rejection response, including information on what the customer needs to do to have access to credit, highlighting the option of contacting a human representative (which already is mandatory by law; General Data Protection Regulation, Art. 22, 2018), and in case a lower value could be granted, check the customer interest in it. Therefore, Fintech institutions should have clear communication with their customers on how AI will be used and why.

Finally, this thesis suggests that transaction-oriented financial service providers should focus their efforts on the lower rejection-sensitivity segment by making the journey as quick and straightforward as possible. Thus, among possible strategies are pre-approved small loans that can be accessed anytime, reducing the response time for values that could not be pre-approved, and in case of rejection, highlighting a digital source of information (e.g., Frequently asked question pages or a chatbot). By putting the client and service delivery first, Fintech companies can provide the groundwork for AI deployment and develop a case for why it should be implemented.

5.4.3 Future research and limitations

Despite the contributions, this study has significant shortcomings that can be addressed in future research. Firstly, research studied the relationship between AI decision-making and satisfaction. Although previous research shows a relationship between satisfaction and loyalty (Chumpitaz & Paparoidamis, 2004; Islam et al., 2021;

Teeroovengadum, 2022; Walsh et al., 2004), as this is a new phenomenon, the impact of AI on end loyalty deserves deeper exploration. Therefore, future research could extend the current research and investigate the impact on end loyalty. In addition, future research could be developed around the bank's relationship, which could be developed into relevant system and strategy development.

Future research might also look at whether the present study's findings hold in diverse circumstances, such as different contexts or markets since this research only considered residents in the European Union for our studies. As such, other markets can present a different response. Even though this thesis claims decision-making (using AI technology) is not significant or produces less customer satisfaction around credit assessment, there is still further research to be considered generalizable. In addition, our study focuses on Fintech. However, more depth around this subject is needed and could be of interest to future research to compare the present results with a retail banking context. In addition, there may also be room for a new type of orientation centered on AI (vs. human) interactions, which may be tested first in banking environments with a strong presence of Fintech applications. Significant emerging issues, namely, cybersecurity, data privacy, misinformation, or trust, still lack theoretical understanding, especially in regard to AI and customer outcomes.

The present study used scenario-based experiments; however, it could be interesting to explore the topic using simulations. The simulations could also explore the AI delivery presentation, comparing customer response to AI systems presented as a form, wizard, or chatbot.

In addition, future studies could address privacy concerns, bias expectancy/perception, or concerns about employment – which could affect customer satisfaction or even incite backlash movements. Furthermore, although this research has advanced the understanding of AI decision-making for consumers, the factor that makes personal loans and credit cards different still demands further investigation. Finally, the application of rejection sensitivity is still incipient and could be explored in future works as well as the extension of the role congruity theory into the use of AI technology with a credit assessment context.

Chapter 6- Thesis General Discussion and Conclusions

Across a series of thirteen studies, this thesis demonstrates that AI can shape consumers' self and identity. Chapter 2 introduces the dilemmas, tensions, or contradictions that can arise from the **interaction between AI technology and consumers' reduced autonomy** and opens the research for the first consequences of those tensions. Chapter 3 sheds light on the dynamics between integrating immersive AI into luxury hospitality and its impact on **consumers' differentiation motives**. Chapter 4 reveals that AI classification failures can diminish **consumers' self-identification**, increasing negative outcomes such as regret, defensive neurophysiological cues, and adverse downstream behaviours for service providers. Finally, chapter 5 analyses the effect of AI reject on consumers in the banking context, exploring the underling mechanism of **role congruity.**

6.1 Theoretical Contributions

This thesis has important theoretical contributions in answering the different research questions across the four main domains. Next, this work presents its theoretical implications for consumers' autonomy (chapter 2), differentiation motives (chapter 3), self-identification (chapter 4), and role congruity (chapter 5).

AI and Consumer Autonomy (Chapter 2): First, in this research, it is advanced and validate a theoretical model that bridges two distinct domains: the expectation confirmation theory (Hossain & Quaddus, 2012) and the autonomy in AI literature (André et al., 2018; Fast & Schroeder, 2020; Wertenbroch et al., 2020). Unlike prior investigations primarily treating AI as a consumable technology (Belk, 2019), the approach followed focuses on AI as an integral part of the decision-making process, offering a fresh perspective on AI's potentially detrimental impact on consumer autonomy. By bridging autonomy in AI decision-making (André et al., 2018; Wertenbroch et al., 2020) with the role of performance expectancy, it illuminates novel dimensions of the autonomy-technology tension. This tension encapsulates the dilemmas and contradictions that may surface when AI decision-making tools damage consumer autonomy. This research contributes to the theoretical understanding of an "AI backfire" phenomenon, which manifests when AI inadequately supports consumer choices, leading to dissatisfaction stemming from the perceived loss of autonomy. Paradoxically, this research also highlights that positive AI experiences foster satisfaction while not eliminating tension, offering a nuanced perspective on the interplay between AI and consumer autonomy. This thesis expands on research examining consumer interactions with AI as a decision-maker (Lee, 2018; Yalcin et al., 2022) by demonstrating a more nuanced understanding of how AI decision-making can impact consumer outcomes. While previous studies explore the algorithmic versus human decision-making process (André et al., 2018) and consumer reactions to it (Yalcin et al., 2022), the research findings reveal the detrimental impact of incorporating AI into the decision-making process. Specifically, it is illustrated that consumer reactions and outcomes depend on the nature of the decision. The theoretical contributions underscore that the nature of consumer reactions, whether positive or negative, is not solely contingent on the involvement of AI in the decision-making process. Instead, it hinges on aligning these algorithmic recommendations with consumer preferences: when AI recommendations diverge from consumer preferences, it has negative consequences for consumers' autonomy; conversely, when AI choices align with consumer preferences, the negative impact of AI is mitigated. By doing so, the present study contributes to recent studies on consumers' interaction with AI (Ameen et al., 2021) by adding a more nuanced perspective on how AI can impact society and consumers' outcomes and perceptions and, consequently, address recent research calls on the unintended consequences of AI (Omoge et al., 2022; Pinochet et al., 2019; Riedel et al., 2022).

AI and Differentiation Motives (Chapter 3): Second, by drawing from the extended reality (Flavián et al., 2019; Rauschnabel et al., 2022) and luxury hospitality literature (Yang & Mattila, 2015), this research examines the effect of AI on customers' need for differentiation and perceived luxury value, eventually influencing their propensity to use AI recommendations. This research suggests that AI integration in immersive environments might diminish consumers' intentions to use AI-driven recommendations. This research reveals under which conditions immersive technologies such as virtual assisted reality and augmented reality can support the unique characteristics that luxury hospitality brands aim to deliver (Javornik et al., 2021). Specifically, this work extends recent studies (e.g., Ahn et al., 2022; Longoni & Cian, 2020; Wien & Peluso, 2021) to demonstrate how immersive AI (vs. traditional hospitality) may lead to negative outcomes (e.g., lower acceptance of recommendations/ reduced behavioural intentions) when the need for differentiation is a salient consumption motive. This thesis shows that the presence of virtual and physical objects through augmented reality enhances the differentiation guests seek in a luxury hospitality experience. Furthermore, this research adds to recent research on the challenges of AI (de Bruyn et al., 2020) (e.g., Dubois et al., 2021; Kim et al., 2021) showing that AI immersive technologies can have downstream consequences on luxury hospitality depending on customers' motives, i.e., differentiation motives.

AI Failure and Self-Identification (Chapter 4): Furthermore, it extends the understanding of AI classification experience (Puntoni et al., 2021) and identity-based motivation (Oyserman, 2009) by revealing that AI failures can disrupt this integration. While past research (Alabed et al., 2022; Huang & Philp, 2021) has advanced that consumers integrate AI agents as part of the self-concept, this research shows that when AI is not able to meet consumers' expectations, i.e., failure in AI classification, it reduces the connection consumers have with a smart service as their needs and wants are not correctly identified. In addition, the current research deepens the understanding of the downstream consequences of an AI rejection or failure (Choi et al., 2020; Grégoire & Mattila, 2021). The thesis added to previous research by exploring how self-expression shapes how smart service failures are processed. Naturally, when consumers indulge in high self-expression, they form strong emotional attachments (Bagozzi et al., 2022; Wang et al., 2022). Furthermore, this work examines the underlying mechanism of self-identification to uncover how individuals perceive AI classification experience failures, a novel inclusion to the two domains in a smart service failure context. In particular, it examines how AI classification failure affects consumers' self-identification – i.e., it highlights the relationship between AI service failures and consumers' sense of self. While past research (Alabed et al., 2022; Huang & Philp, 2021) has advanced that consumers integrate AI agents as part of the self-concept, this study reveals that AI failures can disrupt this integration. When AI is not able to meet consumers' expectations, i.e., failure in AI classification, it reduces the connection consumers have with a smart service as their needs and wants are not correctly identified. A failed classification by an AI may thus also impact the consumers' perceived ability to engage in self-expression. Consequently, failures in AI classification can have downstream effects such as regret of using AI or negative subsequent behaviours (e.g., reduced subscription behaviours and even quitting the platform).

AI Rejection and Role Congruity (Chapter 5): This chapter explores the role congruity and the consumers' rejection sensitivity to process AI rejections and shapes their satisfaction. When the outcome is negative, reactions to a human would be less favourable due to the lay beliefs that humans neglect their unique self (Longoni et al., 2019), whereas this effect will not be observed for AI, for example, recent research suggests that consumers attribute less responsibility to AI (vs. human) in context of service failure. By extending recent studies, this research sheds light on how the integration of AI may potentially reduce customers' intentions to rely on AI-driven recommendations in the Fintech context. In particular, this research extends prior studies on consumers' reactions to decisions by AI (Yalcin et al., 2022), contributing to studies on the use of AI (vs. human) in financial services (Mogaji et al., 2021; Omoge et al., 2022; Riedel et al., 2022). It investigates how customers would respond to decisions made by AI (vs. humans) under (favourable or unfavourable) outcomes. It also extends the role congruity theory (Biddle, 1986; A. Broderick, 2006; A. J. Broderick, 1998; Ho et al., 2020; Solomon et al., 1985) to the FinTech industry, filling a gap in research in understanding the effect of AI decision-making on consumers' perceptions. It also introduces rejection sensitivity into this context, which is key in understanding the preference for AI (vs. human). Previous research has focused on consumers' choices to accept or reject service offerings, and rejection sensitivity is rarely mentioned in the service literature. This research further reveals that the service evaluation is more extreme for those who are already emotionally engaged with the outcome than those who are not.

6.2 Managerial Implications

From a managerial perspective, this thesis postulates essential practical implications for managers in the different areas of interest, namely, streaming, luxury hospitality, and financial services.

AI and Consumer Autonomy (Chapter 2): Consumers interact differently with each AI system based on the tasks they delegate. The qualitative data demonstrates that consumers perceive AI systems associated with the content selection experience in the context of streaming platforms. This phenomenon occurs because consumers evaluate the AI algorithm in conjunction with the service experience it provides. Thus, managers need to assess the impact of incorporating AI decision-making in line with (a) the task AI is replacing - i.e., a more routine, operational task or a more emotionally intense decision task - and (b) the importance of the task in the overall success of the service encounter - i.e., situations where AI replaces decisions on key aspects of the service encounter, such as content choice on a streaming platform, versus situations where AI replaces complementary services, such as chatbots for account management. Additionally, this research highlights those decisions involving higher levels of subjective preferences - such as choosing a film - require well-refined algorithms to successfully replace consumer autonomy in decision-making. To address this, managers must tailor AI recommendation systems based on user profiles and feedback, ensuring a better match between AI suggestions and consumer expectations. In addition, managers should incorporate adaptability into AI systems by developing algorithms that learn and evolve based on user feedback to continually improve the alignment of recommendations with consumer expectations.

AI and Differentiation Motives (Chapter 3): The lack of human touch when using AI services requires extra effort from customers, thus lowering their overall experience (Ameen et al., 2021). While AI excels at processing large volumes of data, it may inadvertently overlook the human desire for uniqueness and individuality (Kallel et al., 2023). As a result, in the context of luxury hospitality, human interactions rather than AI can heighten customers' perception of luxury value, particularly its financial worth. This is because AI may lead customers to believe that the organization is primarily focused on efficiency and cost-cutting through automation (Dogru & Keskin, 2020). Hence, to surpass this disadvantage, luxury hospitality managers could devote their attention to, for instance, personalized concierge services, exclusive event planning, or tailored recommendations based on individual preferences or invest in user-friendly interfaces to mitigate the perceived lack of human touch. The human touch, on the other hand, may signal that the service provider is investing in guest relations, raising the perceived value of the service.

AI Failure and Self-Identification (Chapter 4): This research acknowledges that the occurrence of AI classification failures is an inevitable aspect of these platforms (Puntoni et al., 2021). Nonetheless, streaming platforms should put their efforts into minimizing the probability of AI classification failure. Streaming platforms must take into account identity-relevant factors during the design and architecture of their platforms. This can be achieved by allowing streaming users to customize and personalize their experience with the AI classification experience. This may include settings that allow users to specify how they want their identity to be recognized or interpreted by the streaming platform. Furthermore, streaming platforms should ensure AI models are trained on a wide range of identities, helping to reduce biases and improve the model's accuracy, i.e., reducing situations of classification failures and feelings of regret. Furthermore, if the efforts presented before were not sufficient to prevent an AI classification failure, there is a need to explore strategies for minimizing the downstream effects of such failures. In this regard, this research emphasizes the role of self-expression in shaping the experience of smart service failures (Rifkin & Etkin, 2019). Platforms that prioritize enhancing users' identity expression, for instance, by fostering self-expression, face unique risks, particularly regarding AI classification failures (Wang et al., 2022). These platforms are more likely to encounter increased levels of regret among users in the event of a failure. Therefore, streaming platforms must strike a delicate balance between enabling self-expression and minimizing the negative impact of AI classification failures on user experience. When self-expression is salient, service providers should take steps to minimize AI classification failures and to provide support to consumers who experience them by providing transparency in how the AI classification experience works and the factors it considers during classification. Therefore, offering explanations for decisions made by AI can help users understand how their identity is interpreted by a classification experience.

AI Rejection and Role Congruity (Chapter 5): This research has uncovered important practical implications for managers by exploring automated decision-making, especially given the technical breakthroughs of Fintech driven by AI (Belanche et al., 2019; Bussmann et al., 2020). This research suggests that the impact of the decision-maker on customer satisfaction varies according to the credit product (Cheng & Jiang, 2020b; Payne, Dahl, et al., 2021). As such, for personal loans, the rejection by an AI causes less dissatisfaction than rejection by a credit analyst, and for credit cards, the decision-maker is not relevant. Hence, the strategies used by the Fintech institutions will depend on the type of product provided. As such, this research can provide interesting strategies for the Fintech landscape by suggesting in which circumstances AI technologies should be further incorporated into credit assessment offerings and systems. Additionally, research conclusions offer insights into the relationship between customers and financial services providers. This work has shown that the customer journey should accommodate the needs of the high rejection sensitivity segment due to its positive response when approved.

6.3 Limitations and Future Work

While this research has made significant contributions, it also has some limitations that can be addressed in future studies. The first limitation regarding the scenario-based experiments is that participants in the AI conditions were informed that the company was using AI to provide them with recommendations. Although the qualitative study explored consumers' experiences with AI during streaming platform consumption, not all consumers are aware of how AI operates to make recommendations or build their front library of movies and shows (PWC, 2021). Higher or lower levels of awareness may have influence influenced participants' perceptions and reactions, thus warranting further exploration in future research endeavours. Thus, further studies can explore this implication in relation to consumers' level of technological expertise, use frequency, and concerns about its risks. Additionally, this thesis has only compared autonomous versus AI-aided decisions. Nevertheless, future research should investigate decisions made by human-AI collaboration, considering the varying degrees of consumer awareness and understanding regarding AI's role in platform operations.

Although online panels and student samples are recognized for their reliability and transparency in providing a representative participant population (Palan & Schitter, 2018), future studies should be conducted in a real setting to increase the ecological validity of the findings. In addition, this research didn’t control for the sociodemographic of the participants. Nonetheless, this characteristic should be considered in future studies in the luxury hospitality realm. In addition, future studies should test whether differences in perceptions of AI-based services and brands change their behavioural intentions and their perceptions of luxury value, for instance.

Furthermore, this research only analysed the participants' perception of anthropomorphism of the scenario presented but ignored features such as AI voice, physically embodied machines (e.g., robots), virtually embodied machines, warmth, or other anthropomorphic characteristics (Kim et al., 2021). Such features may influence customers' perceptions of AI (Murphy et al., 2019). In addition, future studies could address privacy concerns, bias expectancy/perception, or concerns about employment – which could affect customer satisfaction or even incite backlash movements. Finally, although this research has advanced the understanding of AI decision-making for consumers, the factor that makes personal loans and credit cards different still demands further investigation.

6.4 Concluding Remarks

In conclusion, this research adds valuable insights to the evolving services industry landscape, enriching the broader discussion on AI and its implications on consumers' identity and self. By showcasing the dilemmas, tensions, or contradictions arising from the interaction between AI technology and consumers' reduced autonomy, it opens the research for the first consequences of those tensions. As AI continues to progress in its rapid advance, the vast possibilities where AI intersects with consumers' identity enhance the need deeper understating regarding the unintended consequences that AI can have on consumers' identity. As such, this work aims shed light on some of the mixed findings found previously and to be a stepping stone on this evolving field.

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Appendix

Appendix A: Studies from Chapter 2

Study 1 *(Aspredicted # 93417)*

Study 1 used a one-factor between-subject design with two experimental levels (AI vs. autonomous choice).

Conditions (Adapted from Chen & Sengupta 2014)

<u>Autonomous Condition (human decision):</u>

Please consider that you are using your Netflix account trying to decide what to watch next!

You've been scrolling for a while on the platform. Netflix has a new tool that relies on artificial intelligence (AI) to power its content recommendations and provides you with the next best choice!

If you decide to select this tool, Netflix will suggest programs based on what you have already seen. Programs that Netflix believes you will like.

This new AI tool has 2 suggestions for you:

Option 1: A new series in the top 10 today worldwide inspired by a true story.

Option 2: A movie favorite of the critics based on a real story.

You have the freedom to continue searching on your own or use the Netflix AI tool and select one of the options.

What do you prefer?

<u>AI Condition:</u>

Please consider that you are using your Netflix account and you're looking for what to watch next.

You've been scrolling for a while on the platform. Finally, it is time to use the new Netflix tool, which relies on artificial intelligence (AI) to power its content recommendations and provides you with the next best choice!

Once you select to use the Netflix AI tool, you will receive suggestions of programs different from what you normally watch. Maybe programs that you have already discarded in the past.

This new AI tool has 2 suggestions for you:

Option 1: A new serie in the top 10 today worldwide inspired by a true story.

Option 2: A movie favorite of the critics based on a real story.

What do you prefer?

Dependent Variable

Satisfaction (Adapted from Chung et al. 2020)

Please indicate from 1 to 9 (1=Strongly Disagree, 9= Strongly Agree) to the extent you agree with the following statements

- I am satisfied with Netflix's AI tool.
- I am happy with Netflix's AI tool.
- I think Netflix's AI tool did a good job.

Note: items were presented in a randomized order.

Manipulation Checks

On a slider from 1 to 9, participants were asked to indicate whether, in the experience with the Netflix AI tool, they had the freedom to choose between the two options of if they were assigned to one. (1=Freedom to 9=Assigned).

Study 2 *(Aspredicted # 101107)*

Study 2 employed a one factor between subject design with three experimental levels (autonomous vs. AI (match) vs. AI (mismatch) choice).

The respondents were asked about their favorite streaming platform.

- Netflix
- HBO Max

- Hulu
- Youtube Video
- Apple TV
- Disney+
- Amazon Prime
- Peacock
- Showtime

Note: items were presented in a randomized order

Conditions

Autonomous Condition (Adapted from Chen & Sengupta 2014)

Imagine that you are at your (@favorite streaming platform selected before) account, and you're deciding what to watch next.

You've been scrolling for a while on the platform. You can use the new (@favorite streaming platform selected before) tool which relies on artificial intelligence (AI) to power its content recommendations and provides you with the next best choice! Or you can continue searching on your own!

Once you select to use the (@favorite streaming platform selected before) AI tool, you will receive some recommendations based on your preferences.

What would you like to do?

- Continue searching on my own.
- Receive the suggestions from the AI tool.

The new AI tool of (@favorite streaming platform selected before) selected 6 entertaining programs that you would like to watch. A small storyline is provided. If you want to skip, you can scroll down and pass to the next page.

1. A mockumentary which follows the everyday lives of the manager and the employees he "manages." The crew follows the employees around 24/7 and

captures their quite humorous and bizarre encounters as they will do what it takes to keep the company thriving.

2. A movie about a weekend trip to Hawaii where a plastic surgeon convinces his loyal assistant to pose as his soon-to-be-divorced wife in order to cover up a careless lie he told to his much-younger girlfriend.
3. A comedy series following the exploits of Det. Jake Peralta and his diverse, lovable colleagues as they police the NYPD's 99th Precinct. Captain Ray Holt takes over Brooklyn's 99th precinct, which includes Detective Jake Peralta, a talented but carefree detective who's used to doing whatever he wants.
4. A movie about Ruth, who after serving time for a violent crime, returns to society, which refuses to forgive her past. Broken down in the place she once called home, her only hope is to find the sister she had been forced to leave behind.
5. A heartwarming and emotional story about a unique set of triplets, their struggles, and their wonderful parents. Rebecca Pearson once had a difficult pregnancy with triplets. The resulting births occurred on the same day as her husband Jack Pearson's thirty-sixth birthday.
6. A series about a financial advisor who drags his family from Chicago to the Missouri Ozarks, where he must launder money to appease a drug boss where he must work to make amends to a Mexican drug cartel, setting up a larger operation in the Ozarks.

AI (match) (Adapted from Chen & Sengupta 2014)

Now imagine that you are at your (@favorite streaming platform selected before) account, and you're looking for what to watch next.

You've been scrolling for a while on the platform. Finally, it is time to use the new (@favorite streaming platform selected before) tool, which relies on artificial intelligence (AI) to power its content recommendations and provides you with the next best choice!

Once you select to use the (@favorite streaming platform selected before) AI tool, you will receive suggestions of programs based on what you have already seen. Entertaining programs that (@favorite streaming platform selected before) AI tool believes you will like and divert you.

Next time I watch an entertaining program at (@favorite streaming platform selected before), I would rather watch:

a) A comedy
b) A drama

Based on your preferences, the new AI tool of (@favorite streaming platform selected before) selected 3 entertaining programs that you would like to watch. A small storyline is provided:

If you want to skip, you can scroll down and pass to the next page.

1. A mockumentary that follows the everyday lives of the manager and the employees he "manages." The crew follows the employees around 24/7 and captures their quite humorous and bizarre encounters as they will do what it takes to keep the company thriving.
2. A movie about a weekend trip to Hawaii where a plastic surgeon convinces his loyal assistant to pose as his soon-to-be-divorced wife in order to cover up a careless lie he told to his much-younger girlfriend.
3. A comedy series following the exploits of Det. Jake Peralta and his diverse, lovable colleagues as they police the NYPD's 99th Precinct. Captain Ray Holt takes over Brooklyn's 99th precinct, which includes Detective Jake Peralta, a talented but carefree detective who's used to doing whatever he wants.

Based on your preferences, the new AI tool of (@favorite streaming platform selected before) selected 3 entertaining programs that you would like to watch. A small storyline is provided:

If you want to skip, you can scroll down and pass to the next page.

1. A movie about Ruth, who after serving time for a violent crime, returns to society, which refuses to forgive her past. Broken down in the place she once called home, her only hope is to find the sister she had been forced to leave behind.

2. A heartwarming and emotional story about a unique set of triplets, their struggles, and their wonderful parents. Rebecca Pearson once had a difficult pregnancy with triplets. The resulting births occurred on the same day as her husband Jack Pearson's thirty-sixth birthday.
3. A series about a financial advisor who drags his family from Chicago to the Missouri Ozarks, where he must launder money to appease a drug boss where he must work to make amends to a Mexican drug cartel, setting up a larger operation in the Ozarks.

AI (mismatch) (Adapted from Chen & Sengupta 2014)

Now imagine that you are at your (@favorite streaming platform selected before) account, and you're looking for what to watch next.

You've been scrolling for a while on the platform. Finally, it is time to use the new (@favorite streaming platform selected before) tool, which relies on artificial intelligence (AI) to power its content recommendations and provides you with the next best choice!

Once you select to use the (@favorite streaming platform selected before) AI tool, you will receive suggestions of entertaining programs different from what you normally watch. Maybe programs that you have already discarded in the past but aim to divert you.

Next time I watch an entertaining program at (@favorite streaming platform selected before), I would rather watch:

a) A comedy
b) A drama

To diversify the content and programs that you watch and allow you to see new and different content, the new AI tool of (@favorite streaming platform selected before) selected 3 entertaining programs different from your preferences for you to watch. A small storyline is provided:

If you want to skip, you can scroll down and pass to the next page.

1. A mockumentary that follows the everyday lives of the manager and the employees he "manages." The crew follows the employees around 24/7 and captures their quite humorous and bizarre encounters as they will do what it takes to keep the company thriving.
2. A movie about a weekend trip to Hawaii where a plastic surgeon convinces his loyal assistant to pose as his soon-to-be-divorced wife in order to cover up a careless lie he told to his much-younger girlfriend.
3. A comedy series following the exploits of Det. Jake Peralta and his diverse, lovable colleagues as they police the NYPD's 99th Precinct. Captain Ray Holt takes over Brooklyn's 99th precinct, which includes Detective Jake Peralta, a talented but carefree detective who's used to doing whatever he wants.

To diversify the content and programs that you watch and allow you to see new and different content, the new AI tool of (@favorite streaming platform selected before) selected 3 entertaining programs different from your preferences for you to watch. A small storyline is provided:

If you want to skip, you can scroll down and pass to the next page.

1. A movie about Ruth, who after serving time for a violent crime, returns to society, which refuses to forgive her past. Broken down in the place she once called home, her only hope is to find the sister she had been forced to leave behind.
2. A heartwarming and emotional story about a unique set of triplets, their struggles, and their wonderful parents. Rebecca Pearson once had a difficult pregnancy with triplets. The resulting births occurred on the same day as her husband Jack Pearson's thirty-sixth birthday.
3. A series about a financial advisor who drags his family from Chicago to the Missouri Ozarks, where he must launder money to appease a drug boss where he must work to make amends to a Mexican drug cartel, setting up a larger operation in the Ozarks.

Dependent variables

Satisfaction (Adapted from Chung et al. 2020)

Please indicate from 1 to 9 (1=Strongly Disagree, 9= Strongly Agree) to the extent you agree with the following statements

- I am satisfied with (@favorite streaming platform selected before) AI tool.
- I am happy with (@favorite streaming platform selected before) AI tool.
- I think (@favorite streaming platform selected before) AI tool did a good job.

Note: items were presented in a randomized order.

Manipulation Checks

On a slider from 1 to 9, participants were asked to indicate whether they chose to use the AI tool, or they had to use it (1= Choice; 9=Implied).

On a slider from 1 to 9, they had to answer if the suggestions from the AI tool were based on their preferences or not (1=Match; 9=Mismatch).

Study 3 (Aspredicted #89775)

Study 3 used a one-factor between-subject design with three experimental levels (autonomous vs. AI (match) vs. AI (mismatch) choice).

Conditions (Adapted from Chen & Sengupta 2014)

<u>Autonomous Condition:</u>

Please consider that you are at your Netflix account deciding what to watch next. You've been scrolling for a while on the platform.

Netflix relies on artificial Intelligence (AI) to power its content recommendations and provide you with the next best choice! Netflix is currently developing a new AI tool to recommend programs to its users.

This new AI tool pop-ups in your screen with 2 suggestions:

Option 1: A new series in the top 10 today worldwide inspired by a true story. Option 2: A movie favorite of the critics based on a real story.

Which one do you prefer to watch?

AI (Match) Condition:

Please consider that you are at your Netflix account looking for what to watch next. You've been scrolling for a while on the platform.

Netflix relies on artificial Intelligence (AI) to power its content recommendations and provide you with the next best choice! Netflix is currently developing a new AI tool to recommend programs to its users.

This new AI tool pop-ups in your screen with 2 suggestions:

Option 1: A new series in the top 10 today worldwide inspired by a true story.

Option 2: A movie favorite of the critics based on a real story.

Which one do you prefer to watch?

Based on your preferences and what you have already seen, Netflix's algorithm has also predicted that you would prefer Option 1/Option 2.

AI (Mismatch) Condition:

Please consider that you are at your Netflix account looking for what to watch next. You've been scrolling for a while on the platform.

Netflix relies on artificial Intelligence (AI) to power its content recommendations and provide you with the next best choice! Netflix is currently developing a new AI tool to recommend programs to its users.

This new AI tool pop-ups in your screen with 2 suggestions:

Option 1: A new series in the top 10 today worldwide inspired by a true story.

Option 2: A movie favorite of the critics based on a real story.

Which one do you prefer to watch?

To balance the number of viewers on the platform of each program and guarantee the maximum quality of streaming, Netflix's new AI tool is designating you to view Option 1 (vs. Option 2) since it is different from the option chosen by the last viewer using this tool.

Dependent Variable

Satisfaction (Adapted from Chung et al. 2020)

Please indicate from 1 to 9 (1=Strongly Disagree, 9= Strongly Agree) to the extent you agree with the following statements

- I am satisfied with Netflix's AI tool.
- I am happy with Netflix's AI tool.
- I think Netflix's AI tool did a good job.

Note: items were presented in a randomized order.

Mediator

Performance expectancy (Adapted from Venkatesh et al., 2003)

Please indicate from 1 to 9 (1=Strongly Disagree, 9= Strongly Agree) to the extent you agree with the following statements

- I find this Netflix AI tool useful in deciding what to watch.
- Using this Netflix AI tool enables me to decide what to watch quickly.
- Using this Netflix AI tool increases my efficiency in deciding what to watch.

Note: items were presented in a randomized order.

Manipulation Checks

On a slider from 1 to 9, participants were asked to indicate whether, in the experience with the Netflix AI tool, they had the freedom to choose between the two options or if they were assigned to one. (1=Freedom to 9=Assigned).

Appendix B: Studies from Chapter 3

Across all studies, the statistical software used was SPSS and the research platforms used was Qualtrics.

Study 1

Study 1 employs a single-factor (immersive AI (vs. traditional hospitality)) between-subjects experimental design.

Scenario:

SIX SENSES

(Visual information provided through all the time required to read the scenario)

The Six Senses Hotels Resorts Spas was considered the World's Best Luxury Hotel Brand for 2021. It counts 16 hotels and resorts and 25 spas in 19 countries worldwide. At the Six Senses, it is never just about a place to stay. It is a luxury place that helps customers reconnect and explore what it means to be mentally, physically, spiritually, and emotionally happy.

Imagine that you have already booked one of Six Senses luxury spas.

But, first, we would like to know when you are visiting us: January to December

Immersive AI reality Condition

Dear Customer,

We are very pleased to welcome you soon at our Six Senses Spa on (@selected month).

We would like to take this opportunity to let you know that we are developing a new virtual concierge service that relies on the help of an AI assistant to provide you with recommendations regarding luxury experiences.

With this virtual concierge service and the help of the AI assistant, you can get recommendations about, for example, the best treatments at our luxurious spa.

We are at your entire disposal to make your stay as pleasant as possible.

We look forward to seeing you soon.

Traditional Condition:

Dear Customer,

We are very pleased to welcome you soon at our Six Senses Spa on (@selected month).

We would like to take this opportunity to let you know that we are developing a new virtual concierge service that relies on the help of an employee to provide you with recommendations regarding luxury experiences.

With this virtual concierge service and the help of the employee, you can get recommendations about, for example, the best treatments at our luxurious spa.

We are at your disposal to make your stay as pleasant as possible.

We look forward to seeing you soon.

Measures

Behavioral Intentions (Adapted from Wang et al., 2006)

" I intend to use Six Senses concierge service."

"I intend to increase my use of concierge services like this one in the future."

"I plan to use the Six Senses concierge service".

Differentiation Motives (Adapted from Yan et al., 2021)

"This concierge service makes me feel different from others."

"This concierge service makes me feel like someone that stands out."

"This concierge service makes me feel differentiated from the group".

Note: options were presented in a randomized order

Manipulation Checks

On a slider from 1 to 9, participants were asked if the concierge service relied on the help of AI assistant or an employee (1- AI, 9-Employee).

Study 2

Study 2 employed single-factor (immersive AI vs. traditional) between-subjects experimental design.

Conditions

Imagine you have booked a dinner at the luxurious restaurant, Le Petit Chef (Hilton Plaza), that relies on augmented reality. At a luxury hotel, guests can enjoy a luxurious dining experience with Le Petite Chef, an interactive show that combines augmented reality and 3D modeling.

Immersive AI condition:

In order to plan your dinner and experiences, you open the concierge service of the restaurant and you're greeted with the Artificial Intelligence assistant, Le Petit ChefAI:

Dear Customer,

We are very pleased to welcome you!

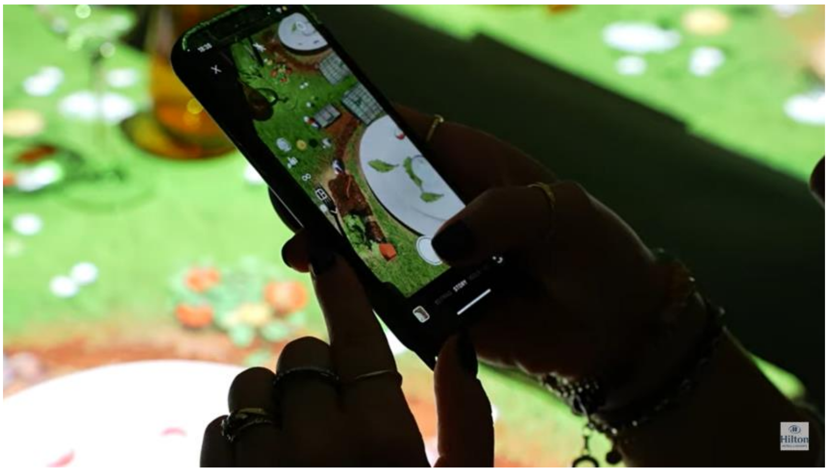
We would like to take this opportunity to let you know that we are developing a new online concierge service that relies on the help of our Artificial Intelligence assistant to provide you with recommendations regarding your luxurious dinner.

With this concierge service and the help of our ChefAI assistant, you can get recommendations about, for example, dinner suggestions.

We are at your disposal to make your stay as pleasant as possible.

We look forward to seeing you soon.

Please watch the next video and see what it is expecting you.



(https://www.youtube.com/watch?v=-KAS77eWtCk)

Traditional Condition:

In order to plan your dinner and experiences, you open the concierge service of the restaurant and you're greeted with the assistant, Le Petit Chef August Irwin:

Dear Customer,

We are very pleased to welcome you!

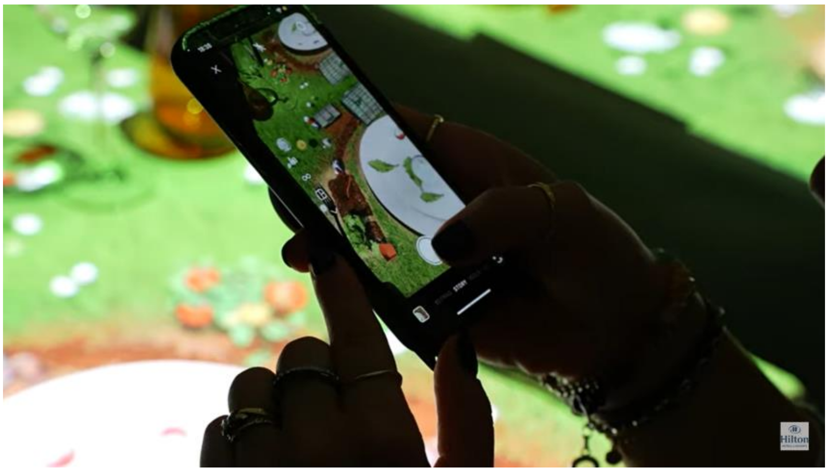
We would like to take this opportunity to let you know that we are developing a new online concierge service that relies on the help of our Chef August Irwin to provide you with recommendations regarding your luxurious dinner.

With this concierge service and the help of Chef August Irwin, you can get recommendations about, for example, dinner suggestions.

We are at your entire disposal to make your stay as pleasant as possible.

We look forward to seeing you soon.

Please watch the next video and see what it is expecting you.



(https://www.youtube.com/watch?v=-KAS77eWtCk)

Measures

Behavioral Intentions (adapted from Wang et al., 2006):

" I intend to use Le Petit Chef (Hilton Plaza) concierge service."

"I intend to increase my use of concierge services like this one in the future."

"I plan to use the Le Petit Chef (Hilton Plaza) concierge service."

Note: options were presented in a randomized order

Differentiation motives (adapted from Yan et al., 2020):

"This concierge service makes you feel different from others."

"This concierge service makes you feel like someone that stands out."

"This concierge service makes you feel differentiated from the group".

Note: options were presented in a randomized order

Luxury value (adapted from Yang & Mattila, 2015)

Functional value:

"Le Petit Chef (Hilton Plaza) is aesthetically appealing."

"Le Petit Chef (Hilton Plaza) dishes are sophisticated."

"The service provided in the Le Petit Chef (Hilton Plaza) is attentive."

Hedonic value:

"I dine at Le Petit Chef (Hilton Plaza) for the pure enjoyment of it."

"Dining at the Le Petit Chef (Hilton Plaza) gives me a lot of pleasure."

"I dine at the Le Petit Chef (Hilton Plaza) for self-indulgence".

Symbolic/expressive value:

"Dining at Le Petit Chef (Hilton Plaza) is considered a symbol of social status."

"Dining at Le Petit Chef (Hilton Plaza) helps me to express myself."

"Dining at the Le Petit Chef (Hilton Plaza) helps me communicate my self-identity."

Financial value

"It is worth the economic investment to dine at the Le Petit Chef (Hilton Plaza)"

"Dining at the Le Petit Chef (Hilton Plaza) is worth its high price."

"Le Petit Chef (Hilton Plaza) usually offers value for money".

Note: options were presented in a randomized order

As manipulation check, participants were asked respondents to indicate whether the concierge service had the help of Chef AI or Chef August (1=AI; 9=Human).

In addition, participants were also asked to rank the level of anthropomorphism by indicated if the concierge service 1= didn't look like human (non-anthropomorphic) to 9= Looked like human (anthropomorphic).

Study 3

Study 3 used a 2 (immersive AI vs. traditional) by 2 (differentiation (high vs. low)) between-subjects experimental design. For the recommendation system, travelers are either presented with a virtual concierge service provided by an AI assistant or a hotel staff member. As for the type of recommendation, participants are presented with unique and exclusive experiences or either popular or well-known ones.

Conditions *(Adapted from* Araujo (2018) *and* Deval et al. (2013)*)*

<u>Immersive AI & Low Differentiation Condition:</u>

Hotel Check-in with Artificial Intelligence

You checked in at the hotel you booked for your travel. To plan your activities for the day, you open the hotel's concierge virtual service. The R&D department of the hotel has spent the past 2 years developing an Artificial Intelligence assistant to improve customer service.

The Artificial Intelligence assistant greets you with the following:

"Dear Guest, I've been very much looking forward to welcoming you today. For you to enjoy a well-known and popular experience, we would like to provide you with the most visited and popular recommendations chosen by most of our guests. Please do not hesitate to ask further questions."

<u>Immersive AI & High Differentiation Condition:</u>

Hotel Check-in with Artificial Intelligence

You checked in at the hotel you booked for your travel. To plan your activities for the day, you open the hotel's concierge virtual service. The R&D department of the hotel has spent the past 2 years developing an Artificial Intelligence assistant to improve customer service.

The Artificial Intelligence assistant greets you with the following:

"Dear Guest, I've been very much looking forward to welcoming you today. For you to enjoy a unique and exclusive experience, we would like to provide you with tailored and special recommendations that are exclusive for our VIP guests. Please do not hesitate to ask further questions."

Traditional &Low Differentiation Condition:

Hotel Check-In with John, Senior Customer Manager

You checked in at the hotel you booked for your travel. To plan your activities for the day, you open the hotel's concierge virtual service. Now, you are being greeted by John, Senior Customer Manager, who spent the past 2 years in this hotel to improve customer service.

John greets you with the following:

"Dear Guest, I've been very much looking forward to welcoming you today. For you to enjoy a well-known and popular experience, we would like to provide you with the most visited and popular recommendations chosen by most of our guests. Please do not hesitate to ask further questions."

Traditional & High Differentiation Condition:

Hotel Check-in with John, Senior Customer Manager

You checked in at the hotel you booked for your travel. To plan your activities for the day, you open the hotel's concierge virtual service. Now, you are being greeted by John, Senior Customer Manager, who spent the past 2 years in this hotel to improve customer service.

John greets you with the following:

"Dear Guest, I've been very much looking forward to welcoming you today. To enjoy a unique and exclusive experience, we would like to provide you with tailored and special exclusive recommendations for our VIP guests. Please do not hesitate to ask further questions."

Measures

Luxury recommendations *(Adapted from* HBR, 1998)

Please indicate from 1 to 9 (1=Strongly Disagree, 9= Strongly Agree to the extent you would like to receive recommendation from the hotel concierge service.

Fancy restaurant downtown.

Most exclusive wine in the region.

Special VIP concerts and shows.

Best concerts/shows in town.

Luxury shops.

Most premium local gifts to buy.

Best massage and spa salon.

Private driver.

Note: options were presented in a randomized order.

For manipulation checks, participants indicated on a slider whether the experience with hotel concierge service was either with an AI assistant or human (1=Human to AI=9). In addition, participants rated whether the recommendations were based on popular guest choices or tailored to VIP guests (1=Low Differentiation to 9= High Differentiation).

Appendix C: Studies of Chapter 4

Study 1a (AsPredicted #121226)

Study 1a employed a one factor between subject design (failure vs. success).

Conditions

Imagine that you are at your favorite streaming platform and you're looking for what to watch next.

You're presented with a new tool of the streaming platform.

This new tool which relies on artificial intelligence (AI) to power its content recommendations and provides you with the next best choice.

AI tool is able to provide a personalized service by using data from previous streaming history and web behavior to estimate interests and preferences.

But first, the AI toll would like to know what would you prefer to watch next:

- Comedy vs. drama
- Light mood entertainment vs. deep emotional entertainment
- Funny vs. emotional

Based on your preferences, the AI tool will suggest you 3 trailers for you to watch before you make a decision. You can click --> to skip the trailers you don't like and go to the next page.

Failure vs. Success:

Randomly, the participants were either presented with 3 trailers aligned (vs. differ) with their preferences (success vs. failure).

Comedy

1. The Office
2. Modern Family
3. Broklyn 99

Note: The trailers appeared in random order

Drama

1. This is Us
2. Ozark
3. 13 Reasons Why

Note: The trailers appeared in random order

Dependent Variable:

Regret (Adapted from Tsiros & Mittal, 2000)

Please indicate from 1 to 9 (1=Strongly Disagree, 9= Strongly Agree) to the extent you agree with the following statements

- *I feel sorry for using* the *AI tool.*
- *I regret using* the *AI' tool.*
- *I shouldn't have used* the *AI' tool.*

Note: items were presented in a randomized order.

Subscription:

Would you subscribe to this AI tool?

- Yes
- No

Mediator:

Self-identification (Adapted from Huang & Philp 2022)

Please indicate from 1 to 9 (1=Strongly Disagree, 9= Strongly Agree) to the extent you agree with the following statements

- The AI tool content reflects part of me and who I am.
- I feel personally connected to the trailers presented by AI tool.

Note: items were presented in a randomized order.

Manipulation Checks

My experience with the AI tool was: 1-Success to 9-Failure.

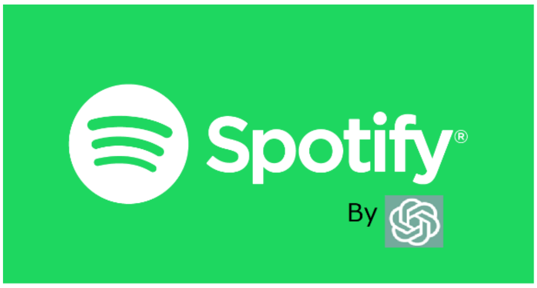
Study 1b (AsPredicted #136233)

Study 1b employed a one factor between subject design (failure vs. success).

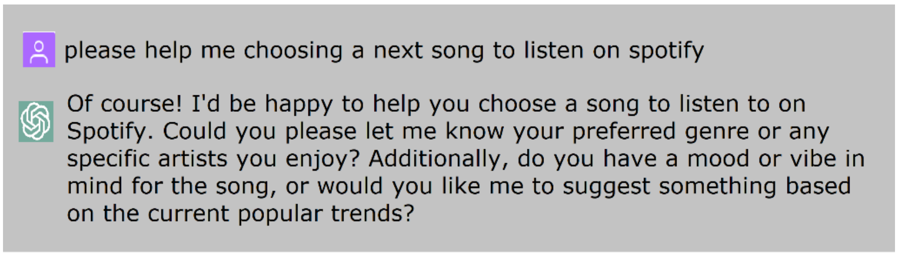
Scenario

In your Spotify account, imagine that you're looking for what to listen next.

You are presented with a new Spotify service that relies on the help of ChatGPT to power its content recommendations and provides you with the next song to listen.



You open Spotify by ChatGPT and ask for help.



Participants had to choose between:

- Hard rock vs. Pop Rock
- Energetic vs. Calm
- Any additional information you would like to provide to Spotify by ChatGPT about your music preferences?

Failure vs. Success:

Randomly, the participants were either presented with 3 songs aligned (vs. differ) with their preferences (success vs. failure).

Certainly! Here are 3 rock songs that you might enjoy:

Energetic:

1. Guns N'Roses: Welcome to the jungle
2. Guns N'Roses: Civil War
3. Guns N'Roses: Paradise City

Calm:

1. Guns N' Roses: Sweet Child O Mine
2. Guns N' Roses: November Rain
3. Guns N' Roses: Paradise City

Dependent Variable:

Regret (Adapted from Tsiros & Mittal, 2000)

Please indicate from 1 to 9 (1=Strongly Disagree, 9= Strongly Agree) to the extent you agree with the following statements

- *I feel sorry for using Spotify by ChatGPT.*
- *I regret using Spotify by ChatGPT.*
- *I shouldn't have used Spotify by ChatGPT.*

Note: items were presented in a randomized order.

Behavioral Intention:

Based on this experience with this new service, would you consider quitting Spotify?

- Yes
- No

Manipulation Checks

My experience with the AI tool was: 1-Success (Right Suggestions) to 9-Failure (Wrong Suggestions)

Study 2 *(Aspredicted #* 96639*)*

Study 2 used a two factor between-subject design (self-expression salient vs. not; failure vs. success).

The respondents were asked about their favorite streaming platform.

- Netflix
- HBO Max
- Hulu
- Youtube Video
- Apple TV
- Disney+
- Amazon Prime
- Peacock
- Showtime

Note: items were presented in a randomized order.

Conditions

Self-Expression Salient Condition

In everything we do in life, it's important to be creative, to "think outside of the box". With this perspective, creativity requires breaking through the walls that constrain ideas.

Creativity allows us to explore new possibilities and learn new things about the world.

Please write down how important it is to be creative in your life and why you decide to undertake creative tasks.

Control Condition

In everything we do in life, it's important to stay focused. With this perspective, it requires keeping our ideas and activities stable.

Focus allows us to restrain possibilities and learn more deeply things about the world.

Please write down how important it is to be focused on your life and why you decide to undertake such tasks.

Aftwards, they were randomly assigned to AI classification failure vs. success conditions:

Success Condition (Adapted from Chen & Sengupta 2014)

Now imagine that you are at your (@favorite streaming platform selected before) account, and you're looking for what to watch next.

You've been scrolling for a while on the platform. Finally, it is time to use the new (@favorite streaming platform selected before) tool, which relies on artificial Intelligence (AI) to power its content recommendations and provides you with the next best choice!

Once you select to use the (@favorite streaming platform selected before) AI tool, you will receive suggestions of programs based on what you have already seen. Entertaining programs that (@favorite streaming platform selected before) AI tool believes you will like and divert you.

Next time I watch an entertaining program at (@favorite streaming platform selected before), I would rather watch:

c) A comedy
d) A drama

Based on your preferences, the new AI tool of (@favorite streaming platform selected before) selected 3 entertaining programs that you would like to watch. A small storyline is provided:

If you want to skip, you can scroll down and pass to the next page.

4. A mockumentary that follows the everyday lives of the manager and the employees he "manages." The crew follows the employees around 24/7 and captures their quite humorous and bizarre encounters as they will do what it takes to keep the company thriving.
5. A movie about a weekend trip to Hawaii where a plastic surgeon convinces his loyal assistant to pose as his soon-to-be-divorced wife in order to cover up a careless lie he told to his much-younger girlfriend.
6. A comedy series following the exploits of Det. Jake Peralta and his diverse, lovable colleagues as they police the NYPD's 99th Precinct. Captain Ray Holt takes over Brooklyn's 99th precinct, which includes Detective Jake Peralta, a talented but carefree detective who's used to doing whatever he wants.

Based on your preferences, the new AI tool of (@favorite streaming platform selected before) selected 3 entertaining programs that you would like to watch. A small storyline is provided:

If you want to skip, you can scroll down and pass to the next page.

4. A movie about Ruth, who after serving time for a violent crime, returns to society, which refuses to forgive her past. Broken down in the place she once called home, her only hope is to find the sister she had been forced to leave behind.
5. A heartwarming and emotional story about a unique set of triplets, their struggles, and their wonderful parents. Rebecca Pearson once had a difficult pregnancy with triplets. The resulting births occurred on the same day as her husband Jack Pearson's thirty-sixth birthday.
6. A series about a financial advisor who drags his family from Chicago to the Missouri Ozarks, where he must launder money to appease a drug boss where he must work to make amends to a Mexican drug cartel, setting up a larger operation in the Ozarks.

Failure Condition (Adapted from Chen & Sengupta 2014)

Now imagine that you are at your (@favorite streaming platform selected before) account, and you're looking for what to watch next.

You've been scrolling for a while on the platform. Finally, it is time to use the new (@favorite streaming platform selected before) tool, which relies on artificial Intelligence (AI) to power its content recommendations and provides you with the next best choice!

Once you select to use the (@favorite streaming platform selected before) AI tool, you will receive suggestions of entertaining programs different from what you normally watch. Maybe programs that you have already discarded in the past but aim to divert you.

Next time I watch an entertaining program at (@favorite streaming platform selected before), I would rather watch:

c) A comedy
d) A drama

To diversify the content and programs that you watch and allow you to see new and different content, the new AI tool of (@favorite streaming platform selected before) selected 3 entertaining programs different from your preferences for you to watch. A small storyline is provided:

If you want to skip, you can scroll down and pass to the next page.

4. A mockumentary that follows the everyday lives of the manager and the employees he "manages." The crew follows the employees around 24/7 and captures their quite humorous and bizarre encounters as they will do what it takes to keep the company thriving.
5. A movie about a weekend trip to Hawaii where a plastic surgeon convinces his loyal assistant to pose as his soon-to-be-divorced wife in order to cover up a careless lie he told to his much-younger girlfriend.
6. A comedy series following the exploits of Det. Jake Peralta and his diverse, lovable colleagues as they police the NYPD's 99th Precinct. Captain Ray Holt

takes over Brooklyn's 99th precinct, which includes Detective Jake Peralta, a talented but carefree detective who's used to doing whatever he wants.

To diversify the content and programs that you watch and allow you to see new and different content, the new AI tool of (@favorite streaming platform selected before) selected 3 entertaining programs different from your preferences for you to watch. A small storyline is provided:

If you want to skip, you can scroll down and pass to the next page.

4. A movie about Ruth, who after serving time for a violent crime, returns to society, which refuses to forgive her past. Broken down in the place she once called home, her only hope is to find the sister she had been forced to leave behind.
5. A heartwarming and emotional story about a unique set of triplets, their struggles, and their wonderful parents. Rebecca Pearson once had a difficult pregnancy with triplets. The resulting births occurred on the same day as her husband Jack Pearson's thirty-sixth birthday.
6. A series about a financial advisor who drags his family from Chicago to the Missouri Ozarks, where he must launder money to appease a drug boss where he must work to make amends to a Mexican drug cartel, setting up a larger operation in the Ozarks.

Dependent variable

Regret (Adapted from Tsiros & Mittal, 2000)

Please indicate from 1 to 9 (1=Strongly Disagree, 9= Strongly Agree) to the extent you agree with the following statements

- *I feel sorry for using* (@favorite streaming platform selected before) *AI tool.*
- *I regret using* (@favorite streaming platform selected before) *AI' tool.*
- *I shouldn't have used* (@favorite streaming platform selected before) *AI' tool.*

Note: items were presented in a randomized order.

Study 3 (*Aspredicted #132368)*

Studu 3 employed a one factor between subject design (failure vs. success). The present study used a facial expression recognition software.

<u>Conditions</u>

Imagine that you are at your favorite streaming platform and you're looking for what to watch next.

You're presented with a new tool of the streaming platform.

This new tool which relies on artificial intelligence (AI) to power its content recommendations and provides you with the next best choice.

But first, the AI toll would like to know what would you prefer to watch next:

- Comedy
- Romance
- Animation
- Action/Adventure

What do you enjoy more about a movie?

- Resonating theme
- Entertainment factors
- True story
- Emotional impact
- Depth of thinking

<u>Failure vs. Success:</u>

Randomly, the participants were either presented a trailer aligned (vs. differ) with their preferences (success vs. failure).

1. Comedy: About my father
2. Romance: Love Again

3. Animation: Elemental
4. Action/Adventure: The Hunger Games: The Ballad of Songbirds & Snakes

Note: All of the chosen movies weren't in the cinemas or streaming platforms by the time of the data collection

<u>Dependent Variable:</u>

Behavioral

Please indicate if you have liked/disliked the movie suggestion:

- Like
- Dislike

<u>Mediator:</u>

Self-identity Connection (Adapted from Huang & Philp 2022)

Please indicate from 1 to 9 (1=Strongly Disagree, 9= Strongly Agree) to the extent you agree with the following statements

- The AI tool content reflects part of me and who I am.
- I feel personally connected to the trailers presented by AI tool.

Note: items were presented in a randomized order.

<u>Manipulation Checks</u>

My experience with the AI tool was: 1-Success to 9-Failure.

Appendix D: Previous studies in the field from Chapter 5

Study	Dependent variable	Rejection Sensitivity	Findings
Manser Payne et al., 2018	Usage	No	There is disparity in how digital natives perceive relative advantage between our two dependent variables. The proportional benefit for AI-enabled mobile banking was not substantial, indicating an additional degree of complexity that goes beyond convenient rapid banking.
Belanche et al., 2019	Intention to use	No	Consumers' attitudes towards robot advisors, mass media, and subjective interpersonal norms are determinants for adoption.
Xu et al., 2020	Usage Intention	No	For low-complexity tasks, consumers prefer using AI while preferring human customer service for high-complexity tasks. The perceived problem-solving ability mediated the usage intentions (AI vs. Human).
Daniel Bagana et al., 2021	Behavioral intention	No	Examines AI banking in Indonesia, and future intentions. Also addressed the lack of community recommendation and distrust towards the information provided.
Atwal & Bryson, 2021	Intention do use	No	Among investors willing to use robot-advisory services, perceived risk, perceived usefulness, ease of use, and social influences impact the intention to use.
Mogaji et al., 2021	-	No	In emerging-markets, infrastructural challenges inhibit the adoption of chatbots. Other factors are UI design, trust, security, and capabilities.
Hari et al., 2021	Customer brand engagement Satisfaction	No	Interactivity, time, convenience, compatibility, complexity, observability, and trialability are antecedents of Brand engagement when using AI. The engagement in use will cause brand satisfaction and brand usage intention.
Nguyen et al., 2021	Use intention	No	A Bank's chatbot users' intention of continued use has as its strongest predictors satisfaction, trust, and perceived usefulness.
Amelia et al., 2022	Customer acceptance	No	The study detected five main themes that influence Customer acceptance of frontline service robots (FSR): Utilitarian aspect, social interaction, customer responses towards FSR, Brand perspective, and individual and task heterogeneity.
Rahman et al., 2022	Intention to adopt	No	Customers' AI adoption is significantly influenced by attitude towards AI, perceived usefulness, perceived risk, perceived trust, and subjective norms. In this study, perceived ease of use and awareness were not.

			For Banks, AI is an essential tool against fraud and risk prevention.
Payne et al., 2021	Assessment of artificial intelligence in mobile banking (AIMB)	No	The customer's role in the value-cocreation process is altered with the introduction of AI in self-service technology channels. AIMB contributes more to transaction-oriented (utilitarian) value propositions than to relationship-oriented (hedonic) value propositions.
Suhartanto et al., 2021	Loyalty	No	Millennial loyalty towards AIMB is significantly determined by Service quality, attitude towards AI, and trust.
Yussaivi et al., 2021	Mobile Banking Usage AI-enabled Mobile Banking Usage	No	Trust is the main determinant of millennial loyalty toward AIMB. Service Quality and attitude were also significant.
Lee & Chen, 2022	AI mobile banking app adoption	No	Through task-technology fit and trust, AI's Intelligence and Anthropomorphism increase users' willingness to adopt AIMB. While both characteristics do not affect perceived risk, Anthropomorphism enhances the users' perceived cost.
Manrai & Gupta, 2022	Behavioral intention to use	No	Trust and subjective norms are key determinants of intention to use AI-based investments. Perceived usefulness, perceived ease of use, and attitude were also significant.
Eren, 2021	Corporate reputation Customer Satisfaction	No	The customer satisfaction of AI Banking users is significantly affected by perceived performance, perceived trust, and corporate reputation. Customer expectation has an indirect positive impact through perceived performance.

Appendix E: Studies from Chapter 5

Study 1

Study 1 used a 2x2 between-subject design (decision-maker: human vs. AI; outcome: approved vs. rejected).

Pre-test

AI can be defined as programmable machines capable of carrying out a complex series of tasks automatically. AI can substitute or assist humans by replicating human actions. Examples of AI applications in banking may include but are not limited to chatbots in public websites, home banking or phone bank and investment advice. Have you ever interacted with AI in Banks?

- Yes
- No

What type of AI in Banks have you interacted with?

- Chatbot / Assistant
- Investment advice
- Simulations of loans and mortgages
- Risk assessment
- Other. (Please specify)

Conditions (Adapted from Riedel et al., 2022)

Imagine that you need a personal loan, upon finishing the application at a bank you are informed that it will be evaluated by an artificial intelligence system / a credit analyst.

Three days later, you received a notification that your application was approved / not approved.

Dependent Variable

Satisfaction

Please indicate from 1 to 7 (1=Strongly Disagree, 7= Strongly Agree) to the extent you agree with the following statements.

- How would you rate the overall satisfaction with the experience?

- How would you rate the overall satisfaction with the decision?
- How would you rate the overall satisfaction with the service of this bank?

Note: items were presented in a randomized order.

Mediator

Perceived role congruity (adapted from Ho et al., 2020)

Please indicate from 1 to 7 (1=Strongly Disagree, 7= Strongly Agree) to the extent you agree with the following statements.

- The bank has fulfilled its role responsibly.
- The bank fulfilled its role as you would have expected.
- The bank fulfilled its obligations to you.

Note: items were presented in a randomized order.

Study 2

Study 2 used a 2x2 between-subject design (decision-maker: human vs. AI; outcome: approved vs. rejected).

Conditions (Adapted from Riedel et al., 2022)

Imagine that you need a credit card, upon finishing the application at a bank you are informed that it will be evaluated by an artificial intelligence system / a credit analyst.

Three days later, you received a notification that your application was approved / not approved.

Dependent Variable

Satisfaction

Please indicate from 1 to 7 (1=Strongly Disagree, 7= Strongly Agree) to the extent you agree with the following statements.

- How would you rate the overall satisfaction with the experience?
- How would you rate the overall satisfaction with the decision?
- How would you rate the overall satisfaction with the service of this bank?

Note: *items were presented in a randomized order*.

Mediator

Perceived role congruity (adapted from Ho et al., 2020)

- The bank has fulfilled its role responsibly.
- The bank fulfilled its role as you would have expected.
- The bank fulfilled its obligations to you.

Note: items were presented in a randomized order.

Rejection sensitivity (adapted from Berenson et al., 2009)

Please indicate from 1 to 6 (1: Very unconcerned, 6: Very concerned), how concerned do you feel in the following situations:

- When you ask your bank for a loan to help you through a difficult financial time, how concerned or anxious would you be over whether or not your bank approves your request?
- When you ask your bank for a credit card to make an expensive purchase you need, how concerned or anxious would you be over whether or not they deny your request?

Note: items were presented in a randomized order.