Artificial Intelligence vs. Human Recommenders: The Influence of Culture on Luxury Fashion Recommendation Acceptance

Dalia Jozani

Dissertation written under the supervision of Professor Cristina Mendonça

Dissertation submitted in partial fulfilment of requirements for the MSc in International Management, at the Universidade Católica Portuguesa, January 2024.

Abstract

With the rapid development of Artificial Intelligence (AI) and globalization, organizations worldwide are increasingly relying on AI to provide product recommendations, including in the luxury fashion industry. However, to replace humans in this area, customers must trust AI recommenders, ideally as much as, if not more than, human recommenders. Organizations also need to understand whether there are cultural differences impacting consumers' willingness to trust recommendations from AI. Therefore, an experimental study was conducted in the scope of this research.

The study examined whether people trust advice from AI or from a human salesperson more when purchasing a luxury item of clothing. The participants in the survey showed algorithm aversion and trusted human recommendations more than those generated by an AI. Furthermore, it has been shown that there is a difference in trust between individualistic and collectivist cultures. In particular, individuals from collectivist cultures exhibited less trust in AI-generated recommendations compared to those from individualistic cultures.

These findings provide valuable implications for organizations considering the use of AI-generated product recommendations in the luxury fashion industry and, in line with previous literature, suggest that human recommenders are more valued. Organizations need to consider cultural differences when implementing AI-driven recommendation systems and encourage collaborative approaches and transparency to increase consumer trust.

Keywords: Machine-Human Interaction, Trust, Cultural Dimensions, Recommender Systems Acceptance, Luxury Fashion Recommendations

Title: Artificial Intelligence (AI) vs. Human Recommenders: The Influence of Culture on Luxury Fashion Recommendation Acceptance

Author: Dalia Jozani

Sumário

Com o rápido desenvolvimento da Inteligência Artificial (IA) e da globalização, as organizações em todo o mundo estão a confiar cada vez mais na IA para fornecer recomendações de produtos, incluindo na indústria da moda de luxo. No entanto, para substituir os humanos nesta área, os clientes devem confiar mais nos recomendadores de IA, idealmente tanto ou mais do que nos recomendadores humanos. As organizações também precisam de compreender se existem diferenças culturais que afetam a vontade dos consumidores de confiar nas recomendações da IA. Por conseguinte, foi efeituado um estudo experimental no âmbito desta investigação.

O estudo examinou se as pessoas confiam mais nos conselhos da IA ou de um vendedor humano quando compram uma peça de vestuário de luxo. Os participantes no inquérito mostraram uma aversão aos algoritmos e confiaram mais nas recomendações humanas do que nas geradas por uma IA. Além disso, foi demonstrado que existe uma diferença de confiança entre culturas individualistas e coletivistas. Em particular, os indivíduos de culturas coletivistas mostraram menos confiança nas recomendações geradas por IA do que as pessoas de culturas individualistas.

Estas conclusões fornecem implicações valiosas para as empresas que estejam a considerar a utilização de recomendações de produtos geradas por IA na indústria da moda de luxo e, de acordo com a literatura anterior, sugerem que os recomendadores humanos são mais valorizados. As organizações precisam de considerar as diferenças culturais quando implementam sistemas de recomendação baseados em IA e encorajar abordagens colaborativas e transparência para aumentar a confiança dos consumidores.

Palavras-chave: Interação Máquina-Homem, Confiança, Dimensões Culturais, Aceitação de Sistemas de Recomendação, Recomendações de Moda de Luxo

Título: Recomendações por Inteligência Artificial vs. Humanos: A influência da cultura na aceitação de recomendações na moda de luxo

Autor: Dalia Jozani

Table of Contents

1. Introduction

"Luxury must be comfortable, otherwise, it is not luxury." – Coco Chanel

With globalization and the continued rise of digitalization, a growing wave of curiosity concerning innovative technologies, such as artificial intelligence (AI), has emerged among consumers, corporations, and society at large (Nozawa et al., 2022). AI has become an integral factor in facilitating our daily lives, present in nearly every sector, ranging from hospitality to healthcare, services, or retail, and is considered revolutionary (Zimmermann et al., 2023). The vast amount of data available to companies, which can be leveraged to make more informed decisions, not only improves value for customers but also assists consumers in decision-making processes through real-time data analysis (Shankar, 2018).

In the field of retail, there has been a shift in customer expectations characterized by a growing demand for omnichannel shopping, more personalization, and increased interactivity (Klaus & Manthiou, 2020). Consequently, brands must find ways to seamlessly integrate AI into their operations, thereby moving towards what is referred to as digital retail (Parise et al., 2016). Research has demonstrated that such integration not only leads to a higher purchase intention but also increases overall actual sales (Lemon & Verhoef, 2016).

While AI is benefitting from substantial growth, an industry within retail that is also growing is the luxury goods industry. It is estimated to reach €530-570 billion by 2030, which is more than double its size in 2020 (Bain & Company, 2023). The luxury sector is demonstrating stable growth in margins and increasing popularity (Bain & Company, 2020).

However, until now, luxury brands have hesitated to embrace technology due to the perception that it contradicts the traditional concepts of craftsmanship and the human touch associated with luxury (Tarquini et al., 2022). Nevertheless, studies have shown that a high level of technological intelligence in the luxury shopping experience positively influences consumers' willingness to buy a product (Sestino & Amatulli, 2023). Indeed, the integration of innovative technologies improves the shopping journey for consumers and enhances positive brand awareness by highlighting the factors of heritage and elite status of these brands (Banister et al., 2020).

In the luxury industry today, the term luxury can be seen as subjective for everyone; therefore, providing personalization as part of the customer experience is vital for companies. This can be achieved through the use of big data and AI (Ramadan, 2019). Leveraging the potential of AI, it finds application in chatbots, virtual style consultants, virtual try-ons, and personalized product recommendations (Y. Liang et al., 2020). In the luxury shopping context, several different factors can significantly influence consumer responses to AI technology. These factors include the acceptance of AI recommendations, the level of trust, variations in purchase intentions, and overall satisfaction with products or recommendations (Zimmermann et al., 2023). Understanding these dimensions is essential for retailers to enhance the user experience and tailor their services to meet the rising expectations of consumers.

An important factor influencing consumer buying behavior in the luxury industry is culture, as customers globally purchase similar luxury products for different motives (Rehman, 2022). This divergence arises because individuals from various nationalities perceive the value of these products differently due to their diverse cultural characteristics (Shukla, 2010). While in the past, some researchers stated that globalization would lead to similar value perceptions and purchase intentions in consumption culture (Hofstede, 1984), studies have revealed that consumers from highly collectivist countries employ simpler criteria when assessing the value of a luxury brand or product compared to consumers from more individualistic nations (Shukla & Purani, 2012).

Therefore, this thesis focuses on the influence of culture on AI recommendation acceptance in the luxury fashion industry by referring to Hofstede's (1984) cultural dimensions and the unified theory of acceptance and use of technology. The central hypothesis is that there is a difference in preference for either AI-based or human-based product recommendations in the luxury industry depending on the cultural background of a person.

1.1 Managerial and Academic Relevance

Despite the increasing fascination with the integration of fashion and digital innovation, very little research has been conducted to understand the role of AI in this context. In contrast, substantial research has focused on AI in other luxury domains, such as gastronomy, healthcare, or tourism (Xu & Mehta, 2022). Past research presented the potential opportunities and disruptions that AI could bring to the global economy but omitted the societal dimensions associated with these emerging digital technologies, which are crucial for understanding whether the public will accept and welcome them (Vu & Lim, 2022). Additionally, there has been a call for research to analyze the influence of AI on fashion products (Y. Liang et al., 2020). Consequently, a noticeable gap exists concerning consumers' responses to these advanced technologies and the potential effect of their integration on purchasing intentions (Sestino & Amatulli, 2023).

Furthermore, research shows that cultural traits influence the relationship between luxury consumption and purchase intention, as evidenced in numerous studies (Eastman et al., 2018). Prior research examining the combination of culture and luxury consumption is very limited, with only a few studies focusing on the intention to purchase luxury products in cross-cultural settings (Aliyev & Wagner, 2018). Despite the assumption that globalization would homogenize preferences, research suggests that cultural factors play a significant role. Thereby, this research aims to contribute to the growing body of literature on AI recommendation acceptance in the luxury industry and the role of culture in determining consumers' preferences for AI or human product recommendations.

The results of this study hold significance for management recommendations for companies in the luxury fashion industry, as their success depends on effectively adopting innovative AI systems and on users' willingness to accept those systems. By understanding the link between culture and AI acceptance, companies can strategically tailor their AI implementations, enhance user experience, and meet consumers' expectations in an increasingly digitalized market.

1.2 Problem Statement

In light of the rapid progress of globalization and digitalization, and considering the needs of both industry and society, this study aims to answer the following main research question: Do cultural factors influence the acceptance of AI in luxury fashion product recommendations?

To address the identified research gap, the main research question was divided into two sub-questions, as follows:

> RQ1: Are consumers generally more likely to accept recommendations from AI advisors or human advisors?
>
> RQ2: How do cultural factors affect consumers' inclination to follow advice from AI or humans?

To address these questions, I conducted an experimental study wherein participants were exposed to different conditions. First, I assessed participants' purchase intentions and purchase frequency for luxury products. Then, they were faced with a scenario where they received a product recommendation for a luxury fashion product either generated by a human salesperson in a shop or an AI system online. I measured and tested whether consumers prefer following product recommendations generated by humans or from an AI and how often they accept product recommendations. Next, I measured recommendation trust to determine the influence on the preference for the source of recommendation. Finally, I examined whether the preference for the source of recommendation impacts the level of satisfaction with the hypothetical purchase decision. This experimental design allowed a differentiated exploration of the factors influencing consumer behavior in response to different recommendation sources.

1.3 Thesis Structure

The structure of this dissertation follows the classical format of empirical research papers: In the introduction, I have presented the general topic, the relevance of this research, the problem statement, and the research questions. To justify the latter and formulate corresponding hypotheses, Chapter 2 presents a review of the existing literature and summarizes relevant concepts related to AI recommendation acceptance, luxury consumption, and cultural dimensions. Chapter 3 describes the study conducted to address the research questions, and Chapter 4 presents the results. In Chapter 5, I discuss the results in relation to the existing literature, draw theoretical and practical implications, and highlight the limitations of this research. Finally, in the conclusion, I will summarize the findings of this dissertation in a way that is actionable for managers and provide recommendations for future research.

2. Literature Review

2.1 Luxury Industry

There is no comprehensive definition for the concept of luxury; however, several factors that consumers associate with it include exclusivity, beauty, quality, and price, creating a sense of brand identity and awareness (Godey et al., 2012). Attempts to explain luxury consumption have led to different theories, some of which will be presented below.

A crucial aspect of luxury products that sets it apart from the purchase and consumption of other products is its social dimension. The conspicuous consumption theory (Veblen, 1900) marked the beginning of understanding luxury consumer behavior, suggesting that consumers purchase products to display their wealth and social status, setting them apart from other social classes. This theory explains that openly displaying luxury possessions enables others to draw conclusions about a consumer's character, helping them attain a higher social standing (Razmus et al., 2023). Consequently, motivation to purchase from luxury brands is driven by socially oriented factors based on the theory of impression management: customers aim to build a positive social image and impress others through their luxury purchases (Eagly & Chaiken, 1993). The signaling theory further reinforces this perspective, proposing that consumers use luxury products to signal their wealth and influence on the outside world because they believe that engaging in costly behavior will increase prestige (Mostafa & Arnaout, 2020). The social comparison theory further emphasizes this wealth-based narrative by arguing that people tend to compare themselves to successful individuals, leading to a desire to match their status through luxury brands (Eastman et al., 2018). Due to the pressures of social comparison, individuals strive to differentiate themselves from others and, thus, develop the need for uniqueness (Vigneron & Johnson, 1999).

A fundamental distinction in purchase motivation in general, based on S. Kim and collaborators' (2016) work lies in hedonic and utilitarian rewards. According to these authors, while consumers who aim to satisfy their utilitarian orientation purchase products for their functionality and practicality, consumers with hedonic motivations do so to reach status and pleasure. Therefore, luxury purchases are considered to fulfill more hedonic motivations than utilitarian ones (S. Kim et al., 2016). For consumers of luxury fashion, the shopping process is an entire experience in which personal interaction and intangible values play a significant role. Traits like empathy and high responsiveness become crucial for the consumer, and environmental and experiential stimuli are more valued in the luxury retail domain than in non-luxury retail (Dabholkar et al., 1996). Such consumption is associated with multi-sensory, imaginative, and emotional dimensions that lead to attachment, ultimately increasing the desire to consume (Hirschman & Holbrook, 1982).

These socially oriented motivations are complemented by personally oriented incentives that emphasize the sense of personal fulfillment and self-expression that consumers derive from purchasing luxury products due to the emotional value that these products provide to them (Vigneron & Johnson, 1999). For consumers of luxury brands, creating a close and personal relationship with the brand is of greater importance than with non-luxury brands (Gupta et al., 2023). Through their purchases, consumers form their own identities, express themselves through the products, and develop personal identification and connection with brands (Shahid & Paul, 2021). Research shows that individuals define and express themselves through their possessions, shaping their identity, therefore, companies must focus on enhancing personalization and creating exceptional experiences for their customers (Klaus & Manthiou, 2020).

This observation is in line with a noticeable shift in luxury purchase intentions from a wealth-based and external perspective to a competencies-based and personal, experiential perspective where expertise in design and aesthetics taste is relevant to demonstrate sophistication (Wang, 2022). Through globalization, luxury products are now available and attainable for a wider customer base, hence wealth and prestige are not as exclusive as in the past. Luxury is now a more personalized and individual concept than a societal phenomenon, and the value of experience is a focal point (Wang, 2022). Craftsmanship plays a vital role in creating a sense of distinctiveness and an enhanced experience, transmitting values such as authenticity, longevity, rarity, and identity to luxury brand products (Tarquini et al., 2022). The creation of luxury products is seen as a creative, artistic way for designers to create something original and unique (Wang, 2022). Consequently, luxury consumers often prefer shopping in physical stores because they seek not only products but also an enjoyable and memorable shopping experience (Cho & Lee, 2017).

However, the consumer base is evolving as younger individuals, who purchase luxury products more occasionally than regularly, enter the luxury market (Xu & Mehta, 2022). These consumers grew up with technology and form part of a current movement of consumer change that expects companies to adopt innovative technologies to their business models to improve personalized experiences (Aleem et al., 2022).

Overall, the changing landscape in the luxury industry highlights the importance of human contact, experiences, and emotions in luxury consumption. The shift towards younger, tech-savvy luxury consumers and their expectations set the stage for exploring AI's role in the luxury industry in the subsequent section.

2.2 AI in Luxury

In the luxury industry, the integration of AI technologies is an ongoing process (Zimmermann et al., 2023). Various technologies, such as augmented reality shopping, employ machine learning techniques and explainable AI to generate recommendations and product comparisons, ultimately enhancing customer interaction (Zimmermann et al., 2023). These recommendation systems analyze consumers' past behaviors and patterns, utilizing data to determine customer preferences, resulting in higher customer retention, more personalized targeting, and increased satisfaction (Fang et al., 2012). These systems rely on data collected from various sources, which computer algorithms use to create machine-learning models for automated predictive decision-making (Shankar, 2018).

However, as an increasing amount of data is collected, consumers have become more skeptical about the source of these recommendations, leading to decreased trust and rejection (Fu et al., 2020). The accuracy of the provided suggestions plays a crucial role in establishing trust with consumers (Song & Kim, 2022). Many companies use recommendation systems based on data collected from their customers. For example, the outdoor luxury apparel brand The North Face uses location and gender information to suggest the perfect jacket for purchase (Shankar, 2018). This kind of personalization leads to enhanced brand association and awareness, making customers feel more valued (Liang et al., 2011), a particularly critical aspect in the luxury fashion industry (Xu & Mehta, 2022). Innovative technologies in the retailing process have been shown to enhance the quality of the relationship between sellers and buyers, where consumers act as partners, contributing to the creation of better services and motivating retailers to respond to market changes (Kindström et al., 2013). This aligns with findings suggesting that consumers of luxury fashion expect the seamless integration of innovative technologies as a natural progression and enhancement of the brand (Sestino & Amatulli, 2023).

Following the integration of computers into our daily lives, researchers have been interested in investigating the factors that influence the acceptance of new technologies. Davis et al. (1989) introduced the technology acceptance model, which suggests that consumers base their acceptance of information systems on the perceived usefulness and ease of use of innovative technology. Perceived usefulness is the extent to which an individual perceives that using a specific system will improve their performance while perceived ease of use refers to how easy it feels for an individual to use the system (Vu & Lim, 2022). The technology acceptance model has been widely used by researchers (Al-Qaysi et al., 2020), even in the fashion industry (Altarteer & Charissis, 2019), to evaluate customer acceptance rates of technology-related applications. Research has shown that higher perceived usefulness and greater perceived ease of use result in increased acceptance rates (Y. Liang et al., 2020). Building upon this model, Venkatesh et al. (2003) introduced the unified theory of acceptance and use of technology, explaining that technology usage is influenced by factors such as performance expectancy, effort expectancy, and social influence. New variables are still being added to this model, for example, later it was found that technology usage is moderated by age, gender, and voluntariness of use (Srite & Karahanna, 2006). As another example, hedonic motivation was added to this framework to explain the intention to use technology, with studies demonstrating its impact on behavioral intention (Alalwan et al., 2017).

A framework proposed by Huang & Rust (2021) suggests that AI can provide various advantages in three categories of tasks and services: mechanical tasks in transaction services, thinking tasks in utilitarian services, and feeling tasks in hedonic services. Several studies have revealed that consumers prefer human product recommendations when motivated by hedonic goals, while they favor AI recommendations for utilitarian goals (Longoni & Cian, 2022). This preference stems from the assumption that individuals associate AI and utilitarian consumption with values like logic, rationality, or functionality, whereas they link hedonic consumption and human interaction to emotions, sensations, and experiences (Nozawa et al., 2022).

Considering the potential role of trust in the acceptance of AI recommendations, research has shown that consumers, despite the accuracy of AI-based recommendations, tend to engage in a behavior known as algorithm aversion. This phenomenon describes the fact that, despite the performance of AI recommendations, consumers prefer to follow recommendations from other human beings compared to AI systems (Wien & Peluso, 2021). This is because humans mistrust algorithms in roles that involve emotions, subjectivity, and the consideration of individual uniqueness (Xie et al., 2022). This is highlighted by studies showing that trust plays a crucial role in customers' purchase intentions and is a strong predictor of purchase intention (Kim & Peterson, 2017).

Most studies examining AI acceptance in the luxury sector have been conducted within the domains of tourism, restaurants, or the hospitality industry (e.g., Ho et al., 2020). Nonetheless, there have been calls for new studies analyzing the impact of AI in other luxury and retail domains, such as luxury fashion (Gupta et al., 2023; Pantano et al., 2018).

Previous research in luxury fashion primarily concentrated on robot advisers (Song & Kim, 2022) or voice assistants (Y. Liang et al., 2020). However, the results indicate that consumers, on the whole, tend to evaluate services provided by AI more negatively, with this effect being more pronounced in luxury segments than in non-luxury ones, particularly when assessing the service and ambiance quality negatively (Nozawa et al., 2022).

Concerning recommendations, past studies have shown that, for electronic devices such as laptops, headphones, and smartphones, consumers favor human recommenders over AI-based recommendations (Wien & Peluso, 2021). This also holds for medical recommendations (Promberger & Baron, 2006). In the retail sector, researchers found that personalized recommendations via an augmented reality shopping assistant application can elevate the shopping experience through enhanced interactivity, a feature highly valued by consumers of luxury fashion (Zimmermann et al., 2023). Additionally, it was revealed that consumers engage in AI aversion behavior when experiential products, such as wine or perfume, are recommended (Xie et al., 2022).

Based on these findings, my first two hypotheses are as follows:

> H1: Individuals tend to be more willing to rely on human luxury fashion recommendations than on those generated by AI when making purchase decisions.
>
> H2: Individuals have lower trust in AI luxury fashion recommendations, leading to a preference for human recommendations over AI recommendations.

2.3 Culture

Culture is an intangible and abstract concept that broadly refers to a complex and diverse set of ideas, values, and beliefs shared by a group of people, distinguishing its members from others (Hofstede, 1984). It is essentially a pattern of thinking, feeling, and potential behavior developed over an individual's lifetime, characterized by stability and resistance to change (Lu et al., 2018). In the existing cross-cultural research literature, different cultures are often compared using samples from various countries, implying that culture is equal to national culture based on geographical location (Taras et al., 2016). However, this is a somewhat oversimplified representation, as these patterns of thinking and potential behavior can vary significantly even within national borders (Nistor et al., 2014).

Notably, there is evidence suggesting that the variance of culture within countries reduces the impact of theories based on national culture, leading to recommendations for a more unified consumer segmentation strategy that crosses international borders (Taras et al., 2016). The underlying assumption is that there are consumer segments globally that share common characteristics and preferences, irrespective of their geographical location (Hennigs et al., 2012). Additionally, research suggested that culture is now dynamic and not restricted by national boundaries anymore, so a global consumer culture has emerged and increased cultural diversity among consumers, even within the same country or culture (Carpenter et al., 2012).

Schwartz (1994) disagrees with the notion that cultures are based on shared values and the average of those across countries. Instead, he suggests that culture functions as a latent, normative system exerting pressure on individuals, thereby presenting culture as a more individual-level concept based on human values. He proposes four value orientations: 1) openness to change, which includes self-direction, stimulation, and hedonism; 2) self-transcendence, which includes universalism and benevolence; 3) conservation, which includes conformity, security, and tradition; and 4) self-enhancement, which includes power and achievement.

Although various models and concepts exist, Hofstede's cultural dimensions model is the most widely used and credited model, with studies continuing to rely on it to this day, repeatedly extending and confirming his results (Lu et al., 2018).

Hofstede (1984) collected data from over 50 countries worldwide, conducting his research within the multinational corporation IBM, and subsequently published the findings based on cultural dimensions. Derived from this research, he suggested various cultural dimensions, namely: 1) individualism / collectivism: the degree to which individual freedom and independence are valued compared to group harmony and interdependence, 2) power distance: the extent to which unequal distribution of power and authority is accepted and expected within a society, 3) masculinity / femininity: the degree to which traditionally masculine values such as assertiveness and competitiveness are emphasized in a culture compared to traditionally feminine values such as nurturing and cooperation, 4) uncertainty avoidance: the extent to which a society tolerates ambiguity and uncertainty, and 5) long-term / short-term orientation, which was added later. This last dimension reflects society's focus on long-term goals, such as perseverance and thrift, compared to short-term gains (Minkov & Hofstede, 2012).

On Hofstede's dimensions, which use a 100-point scale, a high score (50 or above) in individualism emphasizes the importance of self-actualization and loyalty based on a preference for people as well as a sense of duty and responsibility. In contrast, a low score (below 50), makes a culture a collectivistic one, where individuals prefer belonging to a larger social framework. In terms of power distance, a low score shows a high level of decentralization, direct communication, and participation. In opposition, a high score in this dimension highlights the acceptance of hierarchical distance and the privilege of those in powerful positions. In terms of masculinity, a country with a high score is considered to have a culture with more masculine values, emphasizing the importance of achievement and success as well as a preference for showing status through symbols such as cars, watches, or technological devices. In contrast, a country with a low score is considered to have a more feminine culture emphasizing values such as consensus, well-being, equality, and solidarity over status symbols. Cultures with high levels of uncertainty avoidance put emphasis on rules, precision, punctuality, security, and hard work while cultures with low levels of uncertainty avoidance accept imperfections and take a more relaxed approach to adjusting plans and being more flexible with change**.** Lastly, concerning long-term orientation, a high score illustrates an ability to adapt to change and focus on perseverance to achieve results. In contrast, cultures with low scores have more respect for traditions, place less emphasis on saving for the future, and prioritize quick results.

Research has continued to improve and expand Hofstede's cultural dimensions. For example, the GLOBE culture study (House et al., 2004) takes into consideration the distinction between practices, which refer to how values are put into action within a society, and values, which refer to people's perceptions of how these values should ideally be implemented in a society (Fleischmann et al., 2020).

While criticisms exist regarding employing Hofstede's cultural dimensions beyond country-level studies and using country-level scores to forecast individual behavior (Straub et al., 2002), many researchers have used them at the individual-level. They argue that, at the individual-level of analysis, culture can be seen as an individual difference variable, making it suitable and meaningful for analysis (Srite & Karahanna, 2006). In this thesis' study, Hofstede's cultural dimensions were used at the country-level. This generalist approach was chosen for its efficiency, as participants only need to specify their country of origin rather than responding to multiple questions to assess an individual-level cultural dimensions scale.

In summary, the Hofstede country comparison reveals cultural differences which can significantly influence various aspects of business and social interactions (Kirkman et al., 2006) and I turn to its potential effect on luxury consumption next.

2.4 Culture and Luxury

Different cultures have different consumption patterns based on the purpose of their purchase, even when buying from the same brand or the same product (Shukla & Purani, 2012). This variance is due to differing perceptions of luxury's usability, distinctiveness, and social value shaped by consumers' cultural backgrounds (Stathopoulou & Balabanis, 2019). Notably, in emerging markets, local culture significantly influences consumer behavior compared to developed markets (Rehman, 2022).

Research has shown that individuals from collectivist cultures often view luxury goods as a means of seeking prestige, which, in turn, serves to justify higher prices (Aliyev & Wagner, 2018). They tend to associate the willingness to invest more with the overall value of luxury brands. In contrast, individualists prioritize personal goals and aim to remain uninfluenced by group opinions when evaluating luxury purchases (Shukla & Purani, 2012).

Based on these insights, the following hypothesis is proposed:

> H3: Overall, individuals from collectivist countries are more likely to purchase the luxury product compared to individuals from individualistic countries.

Individualism is also associated with self-gratification, with individuals prioritizing personal achievements, material possessions, and success (Minkov & Hofstede, 2012). This connection highlights the significance of hedonism in influencing luxury purchase intentions among individualists (Aliyev & Wagner, 2018). This leads to the following hypothesis:

> H4: Individuals from individualistic countries more often report being motivated to buy luxury products for hedonic reasons than individuals from collectivist countries.

Other research has found that consumers from countries with low power distance tend to place less importance on status considerations. In contrast, those from high power distance countries prefer engaging in status-oriented consumption, especially when others' social status is higher (Aleem et al., 2022). Individuals from cultures with higher power distance are also more inclined to purchase status-oriented brands in comparison to those from cultures with lower power distance (Y. Kim & Zhang, 2014). This is because high-power distance consumers consider societal power imbalances to be normal, viewing luxury brand consumption as a method to enhance their social status (Eastman et al., 2018). From this, I derive the following hypotheses:

> H5: Overall, individuals from high power distance countries are more likely to purchase the luxury product than individuals from low power distance countries.

> H6: While individuals from countries with low power distance more often report being motivated to buy luxury products for utilitarian reasons, individuals from countries with

high power distance more often report being motivated to buy luxury products for hedonic reasons.

In cultures characterized as masculine, driven by achievement, competition, and success, displaying designer brand labels serves as a visual demonstration of accomplishments and influence (Rehman, 2022). Therefore, I suggest the following hypothesis:

H7: Individuals from masculine countries more often report being motivated to buy luxury products for hedonic reasons than individuals from feminine countries.

Because luxury products tend to ensure rigorous testing and trials, high uncertainty avoidance should lead individuals to purchase more luxury products (Rehman, 2022). This leads to the hypothesis:

H8: Individuals from countries with high uncertainty avoidance purchase luxury products more frequently than individuals from countries with low uncertainty avoidance.

While contemporary society is often characterized by impatience and a desire for immediate satisfaction, resulting in a preference for short-term luxury fashion purchases over fulfilling long-term status needs (Rehman, 2022), it is essential to understand the relationship between cultural perspectives on time and luxury consumption. Thus, I hypothesize:

H9: Individuals from cultures that prioritize long-term perspectives tend to make luxury purchases less frequently than individuals from cultures prioritizing short-term perspectives.

2.5 Impact of Culture on AI Acceptance

Research on technology acceptance in different cultures has seen a significant increase (Vu & Lim, 2022). However, most of the studies were conducted several years ago and focused on the acceptance of technologies such as email, chatbots, or forums (Nistor et al., 2014), instead of today's trends such as AI product recommendations. Nonetheless, these studies have shown significant differences in the acceptance rates of various technologies, specifically in user preferences and behaviors (e.g., Baptista & Oliveira, 2015). Several recent studies aim to investigate the potential impact of Hofstede's cultural values on technology acceptance (F. Huang et al., 2021; Metallo et al., 2022), thereby expanding the unified theory of acceptance and use of technology with various cultural dimensions. There is a consensus that culture influences the acceptance of technological systems and, therefore, it should be considered as a moderator when evaluating technological acceptance in different sectors (Park et al., 2007).

Studies investigating how culture affects the acceptance and usage of technology have identified that individuals from individualistic cultures tend to have more positive expectations regarding technology performance (Fleischmann et al., 2020). This aligns with the finding that individuals from collectivist countries place more emphasis on human relationships and are thus more skeptical of innovative technologies that may disrupt group dynamics (Nistor et al., 2014). They are afraid that technology's capabilities to detect behavior and emotions could affect their relationships with team members and therefore fear losing control of how to present themselves to their teammates. From this, I derive the following hypothesis:

> H10: Individuals from cultures with high collectivism have lower trust in AI recommendations than individuals from cultures with low collectivism.

It has been shown that in cultures that score high in masculinity, individuals have higher performance expectations for technological devices (Nistor et al., 2014). This becomes particularly interesting when considering the context of product recommendations since individuals from cultures with elevated masculinity levels tend to value achievement, competition, and success (Hofstede, 1984). Therefore, those individuals might place more importance on performance, efficiency, and logic when making choices related to technology. Because this leads to a more analytical and data-driven approach, and AI-generated recommendations align more closely with the values of consistency and reliability, I hypothesize:

> H11: Individuals from cultures with high masculinity levels have higher trust and prefer AI recommendations over human recommendations than individuals from cultures with low masculinity.

Additionally, cultures with high scores in uncertainty avoidance typically value structure and order, which they can reinforce through the use of technology (Baptista & Oliveira, 2015). They are prone to dedicate effort to understanding and mastering a particular technology to mitigate uncertainty, especially when dealing with unfamiliar technologies. Studies in this field have shown that investing in the acquisition of technology-related skills can significantly reduce the feelings of uncertainty associated with unfamiliar tools (Fleischmann et al., 2020).

Consequently, it is normal for individuals in these uncertain situations to ask for help or advice and be influenced by others (Venkatesh & Zhang, 2010). Based on these findings, I propose the following hypotheses:

> H12: Individuals from countries with high uncertainty avoidance place greater trust in AI recommendations than individuals from countries with low uncertainty avoidance.

Researchers have shown that the dimension of future orientation has a strong moderating effect on technological acceptance (Baptista & Oliveira, 2015). Cultures that prioritize a long-term, future-oriented perspective tend to emphasize long-term goals and outcomes over immediate, short-term gains, which makes them develop a strong belief in the transformative potential of technological advancement (Fleischmann et al., 2020). Those with a long-term perspective might expect the benefits of technology to positively enhance performance, whereas cultures with a short-term future orientation may be more cautious or skeptical towards technological adoption (Fleischmann et al., 2020). Based on these results, I hypothesize:

> H13: Individuals from long-term-oriented cultures are more likely to trust AI-generated recommendations than individuals from short-term-oriented cultures.

3. Methodology

This thesis' study aimed to investigate how cultural factors influence individuals' preference for receiving product recommendations either from AI or from humans within the luxury fashion industry. To achieve this, I conducted an experimental study because this is a suitable method for examining causality in theoretical scenarios (Malhotra et al., 2017). Researchers often face a balancing act between prioritizing internal validity and control on one hand and external validity and realism, on the other, when creating experiments (Slack & Draugalis, 2001). Therefore, in the current study, I chose a controlled design, emphasizing high internal validity. Simultaneously, I intended to include realistic real-life scenarios to provide a robust level of external validity.

Considering that studies of technology acceptance in the past have mostly been conducted using survey research (Venkatesh et al., 2003), a quantitative online survey was designed and hosted on the widely recognized data collection platform Qualtrics. To ensure the survey's relevance to the cultural research context, participants had to provide their country of origin. The survey was presented in English to create semantic equivalence across both groups, and it was designed to be concise, taking approximately 10 minutes to complete.

3.1 Participants

The minimum required sample size to detect a difference in recommender types was set at 128 participants (power = 80%, α = .05, d = .05, two-tailed; Faul et al., 2007), and I selected participants through personal network connections. Data collection took place online from October 25th to November 13th. A total of 227 surveys were initiated; however, 38 of those were not complete. Furthermore, 48 surveys were excluded because participants failed the attention check, with 4 of those also failing the manipulation check, and 6 more were excluded because participants did not answer the attention check. This resulted in a valid sample of 135 participants (38% male, 62% female, 1% prefer not to say). The age range of the participants in the survey was 18 to 84 years (M = 33.46, SD = 13.08), with most respondents holding either a Bachelor's or Master's degree (N = 91). Employment status varied, with 75 participants being employed and 46 being students at the time of the survey. Most participants held European nationality (N = 120), including 93 participants from Germany and 14 from Portugal. The remaining participants were from Latin American or Middle Eastern countries. On average, participants rated their subjective social standing as 7 out of 10 (SD = 1.32), ranging from 3 to 10. For more details on the sample statistics, see Appendix 1.

3.2 Materials and Procedure

At the beginning of the study, the nationality of participants was asked so that, later, Hofstede's country comparison tool could be used to input the cultural dimension values, a recognized and reliable measure for cultural assessment in research (Rehman, 2022). Based on the country of origin, Hofstede's country comparison tool generates scores for the five cultural dimensions of individualism, power distance, uncertainty avoidance, masculinity, and long-term orientation. I used the obtained scores to categorize participants into two cultural groups per dimension, differentiating between lower scores (0 to 50) and higher scores (51 to 100).

After providing their country of origin, participants were asked, either at the beginning or at the end of the study, about their frequency of purchasing luxury products based on a seven-point Likert scale (1 = *not at all*, 7 = *very often*) proposed by Xu & Mehta (2022) and their general luxury purchase intentions based on a mix of items by Jain & Mishra (2018), Smith & Colgate (2007), and Bian & Forsythe (2012). These items were mixed to accurately represent the purchase intentions associated with values. An example item read: "Purchasing luxury goods indicates a symbol of wealth." (1 = *Strongly disagree*, 7 = *Strongly agree*). As a control variable, participants were asked to express their general preference regarding AI-based product recommendations compared to human product recommendations with a five-point Likert scale adapted from research conducted by Longoni & Cian (2022) (1 = *Definitely AI*, 3 = *Indifferent between the two*, 7 = *Definitely human*). These variables were included since previous research showed that, for hedonic products (which include luxury), individuals prefer human recommendation over AI-based recommendation (Wien & Peluso, 2021).

Then, participants were asked to answer demographic questions, indicating their gender, age, level of education, and current employment status. They were also asked about their perceived social standing measured based on an adapted measure of the MacArthur scale of subjective social status (Adler et al., 2000). In the survey, the image of the ladder was not shown. Instead, participants were asked to imagine a ladder with 10 steps and decide their standing between zero and 10 on a slider.

Following this initial inquiry, participants were presented with a shopping scenario where they got a product recommendation for a luxury cashmere sweater. This scenario was randomly assigned within a two-group experiment, which manipulated the source of recommendation (AI-based vs. human-based). Participants were informed that they were in the market for a new luxury cashmere sweater and that they were entering a physical store or accessing an online website, depending on the experimental condition. After being presented with an image of the sweater, participants were asked to rate their level of liking for the product on a seven-point Likert scale (1 = *Dislike a great deal*, 7 = *Like a great deal*). This assessment aimed to ensure that the product was at least within the interest of most participants.

In response to the scenario, participants were then asked to indicate whether they would consider making a purchase and their willingness to buy the sweater, measured on two items adapted from Dodds et al. (1991). They were asked to indicate their agreement of whether they would consider purchasing the product on a five-point Likert scale (1 = *Strongly disagree*, 5 = *Strongly agree*) and how likely they were to purchase the sweater based on the recommendation on a five-point Likert scale (1 = *Extremely unlikely*, 5 = *Extremely likely*). Afterward, participants answered whether an algorithm or a human provided the recommendation as a manipulation check.

Trust in the recommendation was assessed using a mix of items adapted by Song & Kim (2022) and Hoffman et al. (2018), which included factors related to trustworthiness, reliability, and overall trust in decisions generated by the recommender and trust in the product recommendation measured using a five-point Likert scale. A mix of items was also used to reflect both the trust in the source of the recommendation and trust in the product recommendation itself, that is, in the output. An example item read: "I believe this recommendation is trustworthy" (1 = *Strongly disagree*, 5 = *Strongly agree*). Participants were also asked about the accuracy of product recommendations in general based on a measure proposed by Herlocker et al. (2004), also measured using a five-point Likert scale (1 = *Not accurate at all*, 5 = *Extremely accurate*). Then they were asked to indicate the frequency with which they followed product recommendations either generated by an AI or given by humans measured on a five-point Likert scale (1 = *Never*, 5 = *Always*) and, finally, their level of satisfaction with the last product recommendation they followed (see Appendix 2 for the full survey).

4. Results

4.1 Scale Reliability

The variables for purchase intention, likelihood of purchasing a recommended product, trust, and satisfaction were measured with multi-item scales. Although these scales have already been employed in prior studies, a scale reliability analysis was done to evaluate reliability in the current sample. For this, the commonly used method for assessing internal consistency was used, Cronbach's α (Malhotra et al., 2017). The analysis showed $\alpha = .79$ for purchase intention, $\alpha = .90$ for the likelihood of purchasing a recommended product, $\alpha = .86$ for trust in human salespeople, $\alpha = .88$ for trust in AI-generated product recommendations, $\alpha = .73$ for satisfaction with human product recommendations, and $\alpha = .80$ for satisfaction with AI-generated product recommendations. As reliabilities were all above .70 (Vale et al., 1997), the scales were considered to have acceptable reliability and, therefore, the items were aggregated by calculating the mean.

4.2 Descriptive and Bivariate Analyses

Now follows the statistical analysis of the key control variables and independent variables.

Most participants (56%) purchased luxury fashion goods rarely or less often (for all frequencies, see Appendix 3). Table 1 displays descriptive information on participants' purchase intentions. The answers show that participants agreed particularly strongly with statements related to hedonism and social aspects.

Table 1

Mean and Standard Deviation of Participants' Purchase Intentions

Purchase Intention	*M*	*SD*
Makes me feel acceptable in my circle.	2.52	1.37
Indicates a symbol of wealth.	3.29	1.24
Increases my social status.	2.42	1.37
Increases my happiness.	3.03	1.32

The most frequently chosen purchase motivation was the functionality, usefulness, and high quality of luxury products (55%), followed by liking the brand (48%), and personal fulfillment and self-expression (37%) – for all frequencies, see Appendix 4.

When evaluating the cashmere sweater, the majority of participants stated they somewhat liked the product or liked it a great deal (57%). This is close to the percentage of participants who claimed that they would agree somewhat to consider purchasing the product (51%) and who would purchase it based on the recommendation (44%). Appendix 5 shows more detailed results.

Table 2 displays a comparison of the levels of trust, accuracy, and reliance on human vs. AI-generated recommendations.

Table 2

Mean and Standard Deviation of Participants' Levels of Trust, Accuracy and Reliance

Variable	*M*	*SD*
Trust Human Recommendation	3.49	0.94
Trust AI Recommendation	3.18	1.07
Trust Human Decision	3.31	1
Trust AI Decision	2.93	1.01
Accuracy Human Recommendation	3.13	0.75
Accuracy AI Recommendation	2.88	0.91
Reliance Human Recommendation	3.56	1.04
Reliance AI Recommendation	2.93	1.15

While 71.6% of participants never followed AI-generated product recommendations ($M = 2.15$, $SD = 0.88$) or only sometimes, 58.8% of participants followed human product recommendations about half of the time, most of the time, or always ($M = 2.87$, $SD = 1.02$).

When rating how satisfied participants were with the last product recommendation they followed, 52.9% were somewhat satisfied when following human recommendations ($M = 4.15$, $SD = 0.98$) while this was only the case for 33.3% of those who followed AI-based product recommendations ($M = 4.03$, $SD = 1.39$).

Overall, the majority of participants indicated a preference for humans as a source of product recommendation over AI ($M = 3.62$, $SD = 1.08$) as can be seen in Table 3.

Table 3

Participants' Preference for Source of Product Recommendation

Source of Recommendation	*N*
Definitely AI	4
Most likely AI	20
Indifferent between the two	29
Most likely human	52
Definitely human	30

Concerning the five cultural dimensions, there were 13 participants from more collectivist countries and 122 participants from more individualistic countries. Regarding power distance, 104 participants were from countries with low power distance, while 31 were from countries with cultures considered to have high power distance. In terms of femininity, 32 participants were from cultures with more feminine values, while 103 individuals were from countries that put more importance on masculine values. Concerning long-term orientation, 35 participants came from countries that focus more on short-term goals, while 99 participants were from countries emphasizing long-term goals. Only two individuals were from countries with low uncertainty avoidance, while the remaining 133 were from cultures with high uncertainty avoidance levels.

A correlation matrix including all variables supporting the findings described above can be found in Appendix 6.

4.3 Hypotheses Testing

To test the hypotheses, different statistical tests were used in SPSS.

4.3.1 Hypothesis on Recommendation Reliance

To test H1, a one-way analysis of variance (ANOVA) was performed comparing the two types of recommenders on the dependent variable: recommendation reliance (for the complete analysis, see Appendix 7). The results showed that there was a significant difference between the two types of recommenders, $F(1, 134) = 11.30$, $p = .001$, with reliance on human product recommendation ($M = 3.56$, $SD = 1.04$) leading to higher reliance on the product recommendation compared to reliance on AI product recommendation ($M = 2.93$, $SD = 1.15$). To show that H1 was robust to control variables and cultural dimensions, an analysis of covariance (ANCOVA) was performed. This analysis showed that there was still a significant difference between the two types of recommenders, $F(1, 134) = 6.61$, $p = .001$, with a higher reliance on human product recommendation ($M = 3.52$, $SD = 1.09$) than for AI recommendation ($M = 2.96$, $SD = 1.13$) whilst holding the control variables individualism, subjective social standing, current employment status, frequency of luxury purchases, and satisfaction with last luxury product recommendation constant. As such, H1 was supported. Of the control variables, the ones that were significant were subjective social standing ($b = 0.15$), current employment status ($b = 0.17$), and satisfaction with the last luxury product recommendation ($b = 0.24$).

4.3.2 Hypotheses on Trust

The hypotheses on trust were tested separately because of the strong inter-correlations among the cultural dimensions, as seen by relationships such as power distance and individualism ($r = -.50$), femininity and power distance ($r = -.90$), and femininity and long-term orientation ($r = -.84$). However, there were also dimensions with low correlations such as individualism and femininity ($r = .47$). To provide a more nuanced understanding of how each cultural dimension contributed to trust, I conducted an initial ANOVA to examine the influence of the recommender type, followed by separate analyses.

The ANOVA was performed comparing the two types of recommenders on the dependent variable trust (for the complete analysis, see Appendix 8). The results showed that there was no significant difference between the two types of recommenders, $F(1, 135) = 3.43$, $p = .066$, with reliance on human product recommendation ($M = 3.34$, $SD = 0.81$) leading to higher reliance on the product recommendation compared to reliance on AI product recommendation ($M = 3.12$, $SD = 0.88$).

To test H2, an independent samples t-test was performed (for the complete results, see Appendix 9). The results indicated that there was a significant difference in participants' level of trust in humans versus AI depending on the condition between participants who received the product recommendation from a human ($M = 3.39$, $SD = 0.81$) and from an AI ($M = 3.12$, $SD = 0.88$), $t(135) = 1.85$, $p = .033$. As such, H2 was supported.

The cultural dimension variables individualism, femininity, short-term orientation, and power distance were treated as dichotomous variables based on the scores obtained from the Hofstede Country Comparison Tool. A score of 0 represented level values ranging from 0 to 50, while a score of 1 represented level values ranging from 51 to 100.

To test H10, an independent samples t-test was performed as well (for the complete results, see Appendix 10). The results indicated that participants from collectivist cultures (M = 2.58, SD = 0.91) had significantly lower levels of trust in AI recommendations than participants from individualistic cultures (M = 3.32, SD = 0.82), t(133) = 3.09, p = .001. Thus, H10 was supported.

The same procedure was used to test H11 (for the complete results, see Appendix 11). The results indicated that there was no significant difference between the level of trust of participants from more feminine cultures (M = 3.11, SD = 1.04) and participants from more masculine cultures (M = 3.30, SD = 0.79), t(133) = 1.08, p = .141. As such, H11 was not supported.

This was repeated to test H13 (for the complete results, see Appendix 12). The results indicated that there was no significant difference between the level of trust of participants from short-term-oriented cultures (M = 3.10, SD = 1.09) and long-term-oriented cultures (M = 3.30, SD = 0.76), t(132) = 1.18, p = .121. Therefore, H13 was not supported either.

4.3.3 Hypotheses on Luxury Item Purchase Intention

To test H3, an ANOVA was conducted (for the complete analysis, see Appendix 13). The analysis showed that there was no significant difference between collectivist (M = 2.65, SD = 1.34) and individualistic (M = 3.11, SD = 1.08) cultures concerning their purchasing likelihood of the luxury product, F(1, 133) = 2.00, p = .160. To show that this null finding was not due to differences in other variables, an ANCOVA was performed. This analysis showed that there was still no significant difference between participants from collectivist versus individualistic cultures with a lower purchasing likelihood for participants from collectivist cultures (M = 2.65, SD = 1.34) than from individualistic ones (M = 3.10, SD = 1.08), even when controlling for power distance, femininity, short-term orientation, and gender, F(1, 134) = 1.10, p = .297. As such, H3 was not supported. From the control variables, only the variable gender was significant (b = 0.36).

Another ANOVA was performed to test H5 (for the complete analysis, see Appendix 14). The analysis showed that there was no significant difference between the level of power distance in a culture concerning purchasing likelihood, $F(1, 134) = 0.01$, $p = .937$, with individuals from low power distance cultures having almost the same purchasing likelihood ($M = 3.06$, $SD = 1.08$) as individuals from high power distance countries ($M = 3.08$, $SD = 1.24$). To show that this hypothesis was robust to control variables, an ANCOVA was performed adding the control variables individualism, femininity, and short-term orientation. This analysis showed that there was still no significant difference between cultures with high versus low power distance, $F(1, 134) = 0.85$, $p = .498$), whilst holding the control variables individualism, femininity, and short-term orientation constant where participants from cultures with low power distance showed a minimal difference in their average purchasing likelihood ($M = 3.05$, $SD = 1.08$) than participants from cultures with high power distance ($M = 3.08$, $SD = 1.24$). As such, H5 was not supported.

4.3.4 Hypotheses on Reasons for Luxury Purchase

To test H4, a χ^2 test of independence was performed to assess the relation between individualism and the preference for hedonic reasons for purchasing luxury products (for the complete numbers, see Appendix 15). The analysis revealed a non-significant relationship, χ^2 $(1, N = 135) = 0.01$, $p = .911$, indicating that collectivists did not consider hedonic reasons significantly more important when making a luxury product purchase than individualists. Specifically, 38.46% of collectivists preferred hedonic purchase motivation, while 36.88% of individualists had a similar preference. As such, H4 was not supported.

To test H6a, a χ^2 test of independence was performed to assess the relation between power distance and the preference for utilitarian reasons for purchasing luxury products (for the complete numbers, see Appendix 16). The analysis revealed a non-significant relationship, χ^2 $(1, N = 135) = 0.17$, $p = .679$, indicating that individuals from low power distance countries did not consider utilitarian reasons significantly more important when making a luxury product purchase than those from high power distance countries. Specifically, 53.84% of participants from low power distance countries preferred utilitarian purchase motivation, while 58.06% of participants from high power distance countries had a similar preference. As such, H6a was not supported.

To test H6b, the χ^2 test of independence revealed a non-significant relationship, χ^2 $(1, N = 135) = 0.39$, $p = .530$, indicating that individuals from high power distance countries did not differ significantly from those in low power distance countries in their preference for hedonic reasons when making luxury purchases (for the complete numbers, see Appendix 17). Specifically, 38.46% of participants from low power distance preferred hedonic purchase motivations, while 32.28% of participants from high power distance countries had a similar preference. As such, H6b was not supported.

Another χ^2 test was performed to test H7. The analysis revealed a non-significant relationship, χ^2 (1, N = 135) = 0.60, p = .438, indicating that individuals from more masculine cultures did not differ significantly from those from more feminine cultures in their preference for hedonic reasons when making luxury purchases (for the complete numbers, see Appendix 18). In this case, 31.25% of participants from more feminine cultures preferred hedonic luxury purchase motivations, while this was the case for 38.83% of participants from more masculine cultures. Thus, H7 was not supported.

4.3.5 Hypotheses on Frequency of Luxury Purchase

Finally, an ANOVA was conducted to test H9 (for the complete analysis, see Appendix 19) and to measure the effect of the level of short-term or long-term orientation on the variable purchase frequency. The analysis showed that there was no significant difference between short-term (M = 3.17, SD = 1.67) and long-term (M = 2.68, SD = 1.27) oriented cultures concerning their frequency of purchasing luxury products, F(1, 133) = 3.31, p = .071, although participants from cultures that prioritize short-term orientation had a higher purchase frequency of luxury purchases on average. To show that these results were robust to control variables, an ANCOVA was performed. This analysis showed that there was still no significant difference between participants from short-term (M = 3.24, SD = 1.65) versus long-term (M = 2.68, SD = 1.27) oriented cultures, F(1, 134) = 0.69, p = .407, whilst holding the control variable purchase intention constant. As such, H9 was not supported. The control variable purchase intention was significant (b= 0.64).

Unfortunately, H8 and H12 could not be tested because there were too few participants in the category of cultures with low levels of uncertainty avoidance.

5. Discussion

AI-based solutions have gained prominence in the retail industry due to their versatility and efficiency. Particularly, AI-generated product recommendations have become integral in decision-making for luxury product purchases, motivating this research. To better understand the differences in reliance and trust regarding the choice to follow AI-based or human-based product recommendations, an experimental study was conducted, testing 11 hypotheses, with 9 focused on analyzing the impact of culture on product recommendation acceptance. This section delves into a detailed discussion of the results and derives practical and theoretical implications.

5.1 Research Findings

The analysis of the survey data unveiled a significant difference in recommendation acceptance among participants from different cultural backgrounds. In the survey, participants were presented with a scenario featuring a product recommendation from either an AI or a human. Subsequently, participants shared insights on trust, reliance, and willingness to purchase a luxury cashmere sweater based on these recommendations.

The results supported H1, aligning with existing literature emphasizing consumers' greater inclination to rely on human-generated product recommendations rather than AI. This agreement underscores the influential role of human-generated recommendations in shaping consumer behavior in the luxury fashion industry. It supports literature on luxury consumption motivations, emphasizing the significance of human influence in luxury consumption decisions (Wang, 2022). Additionally, it echoes the theory of algorithm aversion presented in the literature review, contributing to discussions on skepticism surrounding AI adoption in products fulfilling hedonic purposes (Wien & Peluso, 2021). The examination of survey responses also revealed a significant pattern in trust levels among participants when evaluating AI-generated versus human-generated luxury fashion recommendations, thus supporting H2. This highlights the preference for consumers to trust humans more than AI, despite the potential accuracy of AI recommendations (Song & Kim, 2022).

Concerning the impact of culture on recommendation acceptance, participants from collectivist cultures indeed exhibited lower trust in AI recommendations compared to those from individualistic cultures, as evidenced by the data. This finding aligned with H10 and literature suggesting that interpersonal relationships and human interactions are essential for collectivist cultures due to their fear of technologies interfering in relationships. (Nistor et al., 2014).

It has been shown that in cultures that score high in masculinity, individuals have higher performance expectations for technological devices (Nistor et al., 2014) while individuals from cultures that focus on long-term goals believe more strongly in the transformative potential of technological development (Fleischmann et al., 2020). However, there was no significant evidence for individuals from cultures with high levels of masculinity or long-term orientation to trust AI-generated recommendations more than human-generated product recommendations in this study. Therefore, H11 and H13 were not supported. This might be due to an unequal distribution of participants in the cultural dimensions. Another possible explanation could be that other moderating variables influence the level of trust more, for example, the level of individualism in a culture, as shown above.

While not supporting a significant direct link between individualism and purchasing likelihood (therefore not supporting H3), the result contributed to a broader understanding of the complexity of cultural influences on consumer behavior, emphasizing that cultural effects are multifaceted in the luxury sector. The analysis of survey data did not reveal a significant relationship between power distance and the likelihood of luxury product purchase. Participants from high power distance cultures did not demonstrate a stronger inclination to purchase the luxury cashmere sweater, thus not supporting H5. This challenges existing literature emphasizing the association between the acquisition of luxury products and the enhancement of social status (Aleem et al., 2022). However, this result could be interpreted as an argument showing that societal values and the perception of luxury are changing, agreeing with literature that suggests a global consumer culture with cultural diversity among individual consumers, going beyond geographical borders (Carpenter et al., 2012).

The same applies to the results of H4, which showed no significant difference in the role of hedonism in luxury purchase motivations among individualists and collectivists. Also, the results did not reveal a significant difference in luxury purchase motivations based on power distance. Participants from high power distance cultures did not demonstrate an increased likelihood to engage in luxury consumption for hedonic reasons compared to participants from low power distance cultures, thus H6 was not supported. This challenges literature stating that high power distance consumers place more importance on status-oriented brands than those from cultures with lower power distance (Y. Kim & Zhang, 2014). There might be many different reasons explaining the relationship between purchase motivation and cultural factors and this study did not focus on a specific brand. While providing a potential explanation for the non-significance, as the impact of other factors is unknown, the interpretation of this result becomes hard. The data also did not reveal a significant association between high cultural masculinity and an increased purchasing motivation to buy luxury goods for hedonic reasons, thus not supporting H7 and being inconsistent with literature emphasizing the importance of rivalry and displaying symbols of success in masculine cultures (Rehman, 2022). This might again be proof of the homogenization in luxury consumption preferences, showing that consumers of different cultures now share more common characteristics and preferences (Hennigs et al., 2012).

The data did not provide significant evidence to support H9, as there was no significant difference in the frequency of luxury purchases between individuals from cultures prioritizing long-term perspectives and those prioritizing short-term perspectives. However, in this case, the tendency aligns with H9, underlining the inclination of individuals from long-term focused cultures to purchase luxury products less frequently (Rehman, 2022).

H8 and H12 could not be tested because of too few participants in the category of low uncertainty avoidance.

Further reasons explaining these results are limitations, which are presented in Chapter 5.3.

5.2 Academic and Managerial Implications

The evolving landscape of AI-based solutions in the retail industry, specifically focusing on product recommendations for luxury items, illustrates the increasing importance of the topic. However, there has been a lack of research focusing on the influence of culture on AI versus human recommendation acceptance. Building on research gaps and previous literature, the connection between culture and AI versus human recommendation acceptance was analyzed in more detail, offering theoretical and managerial implications that shed light on consumer behavior in the luxury fashion industry and providing insights for real-world applications.

The study offers theoretical contributions to the field of algorithm aversion within the luxury fashion industry. While existing research shows that people prefer human recommendations to AI recommendations in other luxury markets because they link these sorts of purchases to emotions and individual uniqueness (Xie et al., 2022), there is a research gap specifically exploring algorithm aversion within the luxury fashion industry. This thesis' study fills this gap by demonstrating individuals' preference for human product recommendation over AI in the luxury fashion industry.

The thesis also explores the influence of cultural dimensions on trust in recommendations and adds to the consensus that culture plays a role in shaping the acceptance of technological systems (Park et al., 2007). Notably, the findings reveal that participants from collectivist cultures exhibit lower trust in AI recommendations compared to their individualistic counterparts. This observation aligns with prior research stating that individuals from collectivist cultures are influenced by their peers' opinions and therefore trust AI-generated recommendations less (Shukla & Purani, 2012). Moreover, the study has shown that contrary to expectations, individuals from low power distance cultures did not purchase luxury products predominantly for utilitarian reasons. This challenges existing literature and prompts further investigation to explore alternative influences on luxury purchase intentions to gain a more comprehensive understanding of consumer behavior in these contexts.

Beyond theoretical implications, the study provides valuable insights for real-life managerial applications in the retail and luxury industries. Organizations seeking to integrate AI-based systems for product recommendations can leverage the findings to guide successful implementations. Understanding that individuals overall are more likely to trust humans than AI, managers can encourage the adoption of AI-based decision-making in specific cultures such as highly individualistic ones. Managers should also consider implementing a nuanced approach to implementing AI-driven solutions to address the different purchase motivations (hedonic and utilitarian) of different consumer groups. The research identifies key factors influencing participants' decisions in accepting AI advice, offering concrete suggestions for organizations. Ensuring users' trust in AI-based systems is crucial, emphasizing the importance of maintaining low error rates and transparent processes. This will ultimately lead to reduced concerns about bias and greater acceptance among users (Bonaccio & Dalal, 2006). Although participants expressed a preference for human-generated recommendations, adopting more collaborative approaches that recognize the strengths of both human and AI sources can address concerns about the perceived lack of emotions and feelings in AI, particularly in domains driven by subjective considerations (Xie et al., 2022).

Overall, this research contributes valuable insights offering practical implications for academics and managers to navigate the integration of AI in the luxury retail industry. By combining theoretical advancements with actionable recommendations, this study can help both scholars and industry practitioners leverage the potential of AI-based solutions.

5.3 Limitations and Future Research

While this study provides valuable insights into cultural dimensions influencing individuals' preferences and acceptancy for AI or human-generated product recommendations in the luxury fashion industry, it is important to acknowledge and address certain limitations that may impact the generalizability and robustness of the findings.

Concerning the sample, there are several limitations raising concerns about the generalizability of findings to broader populations. The sample size, although meeting the required minimum for analyzing differences in recommender types, is relatively small and participants were predominantly from European countries, with a focus on Germany and Portugal. Therefore, the participants were not evenly distributed across all cultural dimensions because European cultures tend to have more similarities than comparisons of other cultures. Specifically, this created a challenge in getting enough variation in some cultural dimensions. The limitation in cultural diversity is attributed to the non-probability sampling technique in this case. Additionally, it is essential to note the difficulties encountered in recruiting non-German participants within a limited timeframe. Therefore, future studies should aim for a larger and more balanced cultural representation to enhance the generalizability of the findings.

While Hofstede's country comparison tool is a recognized and reliable measure, it does not capture culture at the individual level. Future researchers could explore the influence of additional cultural dimensions such as indulgence or restraint or use a different technique to assess cultural belonging such as specific cultural clusters or individual-level measurements to achieve a more nuanced understanding of cultural influences on AI acceptance.

The decision-making setup which relied on participants to imagine their reactions in a hypothetical scenario and a different purchase location, introduces potential biases. Participants may find it more challenging to imagine being in a physical store leading to inconsistencies between imagined and actual purchase behavior. Therefore, future studies should opt for real-world settings in authentic retail environments such as physical stores and online platforms, perhaps partnering with retail brands, to observe participants' reactions in authentic decision-making situations with real purchasing incentives. This could also mitigate the limitation of not all participants genuinely liking the luxury cashmere sweater presented in the scenario.

This study encompasses participants who purchase luxury fashion items with a relatively low frequency. To fully understand the influence of AI-generated product recommendations on consumers' decision whether to follow the recommendation, it would be advisable to carry out this experiment with consumers who regularly purchase luxury fashion products. It can also be interesting to assess participants' broader attitudes towards AI in the luxury fashion industry and understand which general perceptions of AI influence specific decisions related to product recommendations.

6. Conclusion

AI-generated product recommendations continue to advance, offering guidance and reshaping decision-making dynamics across various industries. Culture shapes individuals and can, therefore, influence their consumer behavior. Consequently, scholars are interested in studying the effects of culture on product recommendation acceptance. This dissertation reveals that consumers in the luxury fashion industry exhibit a higher inclination to trust and follow human-generated product recommendations compared to those generated by AI. This preference is partly tied to cultural influences on consumer behavior and trust levels. Considering the transformative potential of AI and the continuous development of culture, organizations are prompted to address the challenge of harmonizing the emotional intelligence of humans with the machine intelligence of AI to optimize product recommendations and enhance purchasing decisions within diverse cultural contexts.

References

Adler, N. E., Epel, E. S., Castellazzo, G., & Ickovics, J. R. (2000). Relationship of subjective and objective social status with psychological and physiological functioning: Preliminary data in healthy white women. *Health Psychology*, *19*(6), 586–592. https://doi.org/10.1037/0278-6133.19.6.586

Alalwan, A. A., Dwivedi, Y. K., & Rana, N. P. (2017). Factors influencing adoption of mobile banking by Jordanian bank customers: Extending UTAUT2 with trust. *International Journal of Information Management*, *37*(3), 99–110. https://doi.org/10.1016/j.ijinfomgt.2017.01.002

Aleem, A., Loureiro, S. M. C., & Bilro, R. G. (2022). Luxury fashion consumption: A review, synthesis and research agenda. *Spanish Journal of Marketing - ESIC*. https://doi.org/10.1108/SJME-06-2021-0105

Aliyev, F., & Wagner, R. (2018). Cultural influence on luxury value perceptions: Collectivist vs. individualist luxury perceptions. *Journal of International Consumer Marketing*, *30*(3), 158–172. https://doi.org/10.1080/08961530.2017.1381872

Al-Qaysi, N., Mohamad-Nordin, N., & Al-Emran, M. (2020). Employing the technology acceptance model in social media: A systematic review. *Education and Information Technologies*, *25*(6), 4961–5002. https://doi.org/10.1007/s10639-020-10197-1

Altarteer, S., & Charissis, V. (2019). Technology acceptance model for 3D virtual reality system in luxury brands online stores. *IEEE Access*, *7*, 64053–64062. https://doi.org/10.1109/ACCESS.2019.2916353

Bain & Company. (2023, June 23). *Global luxury goods market accelerated after record 2022 and is set for further growth, despite slowing momentum on economic warning signs* [Press Release]. https://rb.gy/20ttox

Bain & Company. (2020, June 24). *A New Era and a New Look for Luxury*. [Press Release]. https://www.bcg.com/publications/2020/new-era-and-new-look-for-luxury

Banister, E., Roper, S., & Potavanich, T. (2020). Consumers' practices of everyday luxury. *Journal of Business Research*, *116*, 458–466. https://doi.org/10.1016/j.jbusres.2019.12.003

Baptista, G., & Oliveira, T. (2015). Understanding mobile banking: The unified theory of acceptance and use of technology combined with cultural moderators. *Computers in Human Behavior*, *50*, 418–430. https://doi.org/10.1016/j.chb.2015.04.024

Bian, Q., & Forsythe, S. (2012). Purchase intention for luxury brands: A cross cultural comparison. *Journal of Business Research*, *65*(10), 1443–1451. https://doi.org/10.1016/j.jbusres.2011.10.010

Bonaccio, S., & Dalal, R. S. (2006). Advice taking and decision-making: An integrative literature review, and implications for the organizational sciences. *Organizational Behavior and Human Decision Processes*, *101*(2), 127–151. https://doi.org/10.1016/j.obhdp.2006.07.001

Carpenter, J., Moore, M., Doherty, A. M., & Alexander, N. (2012). Acculturation to the global consumer culture: A generational cohort comparison. *Journal of Strategic Marketing*, *20*(5), 411–423. https://doi.org/10.1080/0965254X.2012.671340

Cho, J. Y., & Lee, E. J. (2017). Impact of interior colors in retail store atmosphere on consumers' perceived store luxury, emotions, and preference. *Clothing and Textiles Research Journal*, *35*(1), 33–48. https://doi.org/10.1177/0887302X16675052

Dabholkar, P. A., Thorpe, D. I., & Rentz, J. O. (1996). A measure of service quality for retail stores: Scale development and validation. *Journal of the Academy of Marketing Science*, *24*(1), 3-16. https://doi.org/10.1007/bf02893933

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science*, *35*(8), 982-1003. https://doi.org/10.1287/mnsc.35.8.982

Dodds, W. B., Monroe, K. B., & Grewal. (1991). Effects of price, brand, and store information on buyers' product evaluations. *Journal of Marketing Research*, *28*(3), 307-319. https://doi.org/10.2307/3172866

Eagly, A. H., & Chaiken, S. (1993). *The psychology of attitudes*. Harcourt Brace Jovanovich.

Eastman, J. K., Iyer, R., Shepherd, C. D., Heugel, A., & Faulk, D. (2018). Do they shop to stand out or fit in? The luxury fashion purchase intentions of young adults. *Psychology and Marketing*, *35*(3), 220–236. https://doi.org/10.1002/mar.21082

Fang, B., Liao, S., Xu, K., Cheng, H., Zhu, C., & Chen, H. (2012). A novel mobile recommender system for indoor shopping. *Expert Systems with Applications*, *39*(15), 11992–12000. https://doi.org/10.1016/j.eswa.2012.03.038

Faul, F., Erdfelder, E., Lang, A. G., & Buchner, A. (2007). G* Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior research methods*, *39*(2), 175-191. https://doi.org/10.3758/bf03193146

Fleischmann, C., Cardon, P. W., & Aritz, J. (2020). Smart collaboration in global virtual teams: The influence of culture on technology acceptance and communication effectiveness. *Proceedings of the 53rd Annual Hawaii International Conference on System Sciences*. 363-373. https://doi.org/10.24251/hicss.2020.045

Fu, Z., Xian, Y., Gao, R., Zhao, J., Huang, Q., Ge, Y., Xu, S., Geng, S., Shah, C., Zhang, Y., & De Melo, G. (2020). Fairness-aware explainable recommendation over knowledge graphs. *Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval*, 69–78. https://doi.org/10.1145/3397271.3401051

Godey, B., Pederzoli, D., Aiello, G., Donvito, R., Chan, P., Oh, H., Singh, R., Skorobogatykh, I. I., Tsuchiya, J., & Weitz, B. (2012). Brand and country-of-origin effect on consumers' decision to purchase luxury products. *Journal of Business Research*, *65*(10), 1461–1470. https://doi.org/10.1016/j.jbusres.2011.10.012

Gupta, D. G., Shin, H., & Jain, V. (2023). Luxury experience and consumer behavior: A literature review. *Marketing Intelligence and Planning*, *41*(2), 199–213. https://doi.org/10.1108/MIP-12-2021-0438

Hennigs, N., Wiedmann, K. P., Klarmann, C., Strehlau, S., Godey, B., Pederzoli, D., Neulinger, A., Dave, K., Aiello, G., Donvito, R., Taro, K., Táborecká-Petrovičová, J., Santos, C. R., Jung, J., & Oh, H. (2012). What is the value of luxury? A cross-cultural consumer perspective. *Psychology and Marketing*, *29*(12), 1018–1034. https://doi.org/10.1002/mar.20583

Herlocker, J. L., Konstan, J. A., Terveen, L. G., & Riedl, J. T. (2004). Evaluating Collaborative Filtering Recommender Systems. *ACM Transactions on Information Systems*, *22*(1), 5-53. https://doi.org/10.1145/963770.963772

Hirschman, E. C., & Holbrook, M. B. (1982). Hedonic consumption: Emerging concepts, methods and propositions. *Journal of Marketing*, *46*(3), 92-101. https://doi.org/10.1177/002224298204600314

Ho, T. H., Tojib, D., & Tsarenko, Y. (2020). Human staff vs. service robot vs. fellow customer: Does it matter who helps your customer following a service failure incident? *International Journal of Hospitality Management*, *87*, 102501. https://doi.org/10.1016/j.ijhm.2020.102501

Hoffman, R. R., Mueller, S. T., Klein, G., & Litman, J. A. (2018). Metrics for Explainable AI: Challenges and Prospects. https://arxiv.org/pdf/1812.04608.pdf

Hofstede, G. (1984). *Culture's consequences: International differences in work-related values* (Vol. 5). Sage.

House, R. J., Hanges, P. J., Javidan, M., Dorfman, P. W., & Gupta, V. (2004). *Culture, leadership, and organizations: The GLOBE study of 62 societies*. Sage.

Huang, F., Sánchez-Prieto, J. C., Teo, T., García-Peñalvo, F. J., Olmos-Migueláñez, S., & Zhao, C. (2021). A cross-cultural study on the influence of cultural values and teacher beliefs on university teachers' information and communications technology acceptance. *Educational Technology Research and Development*, *69*(2), 1271–1297. https://doi.org/10.1007/s11423-021-09941-2

Huang, M. H., & Rust, R. T. (2021). Engaged to a robot? The role of AI in service. *Journal of Service Research*, *24*(1), 30–41. https://doi.org/10.1177/1094670520902266

Jain, S., & Mishra, S. (2018). Effect of value perceptions on luxury purchase intentions: An Indian market perspective. The *International Review of Retail, Distribution and Consumer Research*, *28*(4), 414–435. https://doi.org/10.1080/09593969.2018.1490332

Kim, S., Park, G., Lee, Y., & Choi, S. (2016). Customer emotions and their triggers in luxury retail: Understanding the effects of customer emotions before and after entering a luxury shop. *Journal of Business Research*, *69*(12), 5809–5818. https://doi.org/10.1016/j.jbusres.2016.04.178

Kim, Y., & Peterson, R. A. (2017). A meta-analysis of online trust relationships in e-commerce. *Journal of Interactive Marketing*, *38*(1), 44–54. https://doi.org/10.1016/j.intmar.2017.01.001

Kim, Y., & Zhang, Y. (2014). The impact of power-distance belief on consumers' preference for status brands. *Journal of Global Marketing*, *27*(1), 13–29. https://doi.org/10.1080/08911762.2013.844290

Kindström, D., Kowalkowski, C., & Sandberg, E. (2013). Enabling service innovation: A dynamic capabilities approach. *Journal of Business Research*, *66*(8), 1063–1073. https://doi.org/10.1016/j.jbusres.2012.03.003

Kirkman, B. L., Lowe, K. B., & Gibson, C. B. (2006). A quarter century of culture's consequences: A review of empirical research incorporating Hofstede's cultural values framework. *Journal of International Business Studies*, *37*(3), 285–320. https://doi.org/10.1057/palgrave.jibs.8400202

Klaus, P. & Manthiou, A. (2020). Applying the EEE customer mindset in luxury: Reevaluating customer experience research and practice during and after corona. *Journal of Service Management*, *31*(6), 1175–1183. https://doi.org/10.1108/JOSM-05-2020-0159

Lemon, K. N., & Verhoef, P. C. (2016). Understanding customer experience throughout the customer journey. *Journal of Marketing*, *80*(6), 69–96. https://doi.org/10.1509/jm.15.0420

Liang, T. P., Ho, Y. T., Li, Y. W., & Turban, E. (2011). What drives social commerce: The role of social support and relationship quality. *International Journal of Electronic Commerce*, *16*(2), 69–90. https://doi.org/10.2753/JEC1086-4415160204

Liang, Y., Lee, S. H., & Workman, J. E. (2020). Implementation of artificial intelligence in fashion: Are consumers ready? *Clothing and Textiles Research Journal*, *38*(1), 3–18. https://doi.org/10.1177/0887302X19873437

Longoni, C., & Cian, L. (2022). Artificial intelligence in utilitarian vs. hedonic contexts: The "word-of-machine" effect. *Journal of Marketing*, *86*(1), 91–108. https://doi.org/10.1177/0022242920957347

Lu, Q., Pattnaik, C., Xiao, J., & Voola, R. (2018). Cross-national variation in consumers' retail channel selection in a multichannel environment: Evidence from Asia-Pacific countries. *Journal of Business Research*, *86*, 321–332. https://doi.org/10.1016/j.jbusres.2017.09.027

Malhotra, N. K., Nunan, D., & Birks, D. F. (2017). *Marketing research: An applied approach*. Pearson.

Metallo, C., Agrifoglio, R., Lepore, L., & Landriani, L. (2022). Explaing users' technology acceptance through national cultural values in the hospital context. *BMC Health Services Research*, *22*(1), 1-10. https://doi.org/10.1186/s12913-022-07488-3

Minkov, M., & Hofstede, G. (2012). Hofstede's fifth dimension: New evidence from the world values survey. *Journal of Cross-Cultural Psychology*, *43*(1), 3–14. https://doi.org/10.1177/0022022110388567

Mostafa, M. M., & Arnaout, J. P. (2020). What drives Kuwaiti consumers to purchase luxury brands? The *International Review of Retail, Distribution and Consumer Research*, 30(1), 86–102. https://doi.org/10.1080/09593969.2019.1626259

Nistor, N., Lerche, T., Weinberger, A., Ceobanu, C., & Heymann, O. (2014). Towards the integration of culture into the Unified Theory of Acceptance and Use of Technology. *British Journal of Educational Technology*, *45*(1), 36–55. https://doi.org/10.1111/j.1467-8535.2012.01383.x

Nozawa, C., Togawa, T., Velasco, C., & Motoki, K. (2022). Consumer responses to the use of artificial intelligence in luxury and non-luxury restaurants. *Food Quality and Preference*, *96*, 104436. https://doi.org/10.1016/j.foodqual.2021.104436

Pantano, E., Passavanti, R., Priporas, C. V., & Verteramo, S. (2018). To what extent luxury retailing can be smart? *Journal of Retailing and Consumer Services*, *43*, 94–100. https://doi.org/10.1016/j.jretconser.2018.03.012

Parise, S., Guinan, P. J., & Kafka, R. (2016). Solving the crisis of immediacy: How digital technology can transform the customer experience. *Business Horizons*, *59*(4), 411–420. https://doi.org/10.1016/j.bushor.2016.03.004

Park, J., Yang, S., & Lehto, X. (2007). Adoption of mobile technologies for Chinese consumers. *Journal of Electronic Commerce Research*, *8*(3), 196. https://rb.gy/sdqbvj

Promberger, M., & Baron, J. (2006). Do patients trust computers? *Journal of Behavioral Decision Making*, *19*(5), 455–468. https://doi.org/10.1002/bdm.542

Ramadan, Z. (2019). The democratization of intangible luxury. *Marketing Intelligence and Planning*, *37*(6), 660–673. https://doi.org/10.1108/MIP-11-2018-0490

Razmus, W., Czarna, A. Z., & Fortuna, P. (2023). Luxury consumption and the dark triad of personality. *Journal of Business Research*, *169*, 114246 https://doi.org/10.1016/j.jbusres.2023.114246

Rehman, A. U. (2022). Consumers' perceived value of luxury goods through the lens of Hofstede cultural dimensions: A cross-cultural study. *Journal of Public Affairs*, *22*(4). https://doi.org/10.1002/pa.2660

Schwartz, S. H. (1994). Are there universal aspects in the structure and contents of human values? *Journal of Social Issues*, *50*(4), 19–45. https://doi.org/10.1111/j.1540-4560.1994.tb01196.x

Sestino, A., & Amatulli, C. (2023). The challenge of integrating "intelligent" technologies in luxury shopping contexts: The role of brand personality appeal and consumers' status consumption orientation. *Journal of Retailing and Consumer Services*, *76*. https://doi.org/10.1016/j.jretconser.2023.103488

Shahid, S., & Paul, J. (2021). Intrinsic motivation of luxury consumers in an emerging market. *Journal of Retailing and Consumer Services*, *61*, 102531 https://doi.org/10.1016/j.jretconser.2021.102531

Shankar, V. (2018). How artificial intelligence (AI) is reshaping retailing. *Journal of Retailing*, *94*(4), 6-9. https://doi.org/10.1016/s0022-4359(18)30076-9

Shukla, P. (2010). Status consumption in cross-national context: Socio-psychological, brand and situational antecedents. *International Marketing Review*, *27*(1), 108–129. https://doi.org/10.1108/02651331011020429

Shukla, P., & Purani, K. (2012). Comparing the importance of luxury value perceptions in cross-national contexts. *Journal of Business Research*, *65*(10), 1417–1424. https://doi.org/10.1016/j.jbusres.2011.10.007

Slack, M. K., & Draugalis, J. L. R. (2001). Establishing the internal and external validity of experimental studies. *American Journal of Health-System Pharmacy*, *58*(22), 2173–2181. https://doi.org/10.1093/ajhp/58.22.2173

Smith, J. B., & Colgate, M. (2007). Customer value creation: A practical framework. *Journal of Marketing Theory and Practice*, *15*(1), 7–23. https://doi.org/10.2753/MTP1069-6679150101

Song, S. Y., & Kim, Y. K. (2022). Factors influencing consumers' intention to adopt fashion robot advisors: Psychological network analysis. *Clothing and Textiles Research Journal*, *40*(1), 3–18. https://doi.org/10.1177/0887302X20941261

Srite, M., & Karahanna, E. (2006). The role of espoused national cultural values in technology acceptance. *Management Information Systems Quarterly*, *30*(3), 679-704. https://doi.org/10.2307/25148745

Stathopoulou, A., & Balabanis, G. (2019). The effect of cultural value orientation on consumers' perceptions of luxury value and proclivity for luxury consumption. *Journal of Business Research*, *102*, 298–312. https://doi.org/10.1016/j.jbusres.2019.02.053

Straub, D. W., Loch, K. D., Evaristo, J. R., Karahanna, E., & Srite, M. (2002). Toward a Theory-Based measurement of culture. *Journal of Global Information Management*, *10*(1), 13–23. https://doi.org/10.4018/jgim.2002010102

Taras, V., Steel, P., & Kirkman, B. L. (2016). Does country equate with culture? Beyond geography in the search for cultural boundaries. *Management International Review*, *56*(4), 455–487. https://doi.org/10.1007/s11575-016-0283-x

Tarquini, A., Mühlbacher, H., & Kreuzer, M. (2022). The experience of luxury craftsmanship–a strategic asset for luxury experience management. *Journal of Marketing Management*, *38*(13–14), 1307–1338. https://doi.org/10.1080/0267257X.2022.2064899

Vale, L., Silcock, J., & Rawles, J. (1997). An economic evaluation of thrombolysis in a remote rural community. *The BMJ*, *314*(7080), 570. https://doi.org/10.1136/bmj.314.7080.570

Veblen, T. (1900). *The Theory of the Leisure Class*. Routledge.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *Management Information Systems Quarterly*, *27*(3), 425-478. https://doi.org/10.2307/30036540

Venkatesh, V., & Zhang, X. (2010). Unified theory of acceptance and use of technology: U.S. vs. China. *Journal of Global Information Technology Management*, *13*(1), 5–27. https://doi.org/10.1080/1097198X.2010.10856507

Vigneron, F., & Johnson, L. W. (1999). A review and a conceptual framework of prestige-seeking consumer behavior. *Academy of Marketing Science Review*, *1*(1), 1-15. https://rb.gy/zof9mj

Vu, H. T., & Lim, J. (2022). Effects of country and individual factors on public acceptance of artificial intelligence and robotics technologies: a multilevel SEM analysis of 28-country survey data. *Behaviour and Information Technology*, *41*(7), 1515–1528. https://doi.org/10.1080/0144929X.2021.1884288

Wang, Y. (2022). A conceptual framework of contemporary luxury consumption. *International Journal of Research in Marketing*, *39*(3), 788–803. https://doi.org/10.1016/j.ijresmar.2021.10.010

Wien, A. H., & Peluso, A. M. (2021). Influence of human versus AI recommenders: The roles of product type and cognitive processes. *Journal of Business Research*, *137*, 13–27. https://doi.org/10.1016/j.jbusres.2021.08.016

Xie, Z., Yu, Y., Zhang, J., & Chen, M. (2022). The searching artificial intelligence: Consumers show less aversion to algorithm-recommended search product. *Psychology and Marketing*, *39*(10), 1902–1919. https://doi.org/10.1002/mar.21706

Xu, L., & Mehta, R. (2022). Technology devalues luxury? Exploring consumer responses to AI-designed luxury products. *Journal of the Academy of Marketing Science*, *50*(6), 1135–1152. https://doi.org/10.1007/s11747-022-00854-x

Zimmermann, R., Mora, D., Cirqueira, D., Helfert, M., Bezbradica, M., Werth, D., Jonas Weitzl, W., Riedl, R., & Auinger, A. (2023). Enhancing brick-and-mortar store shopping experience with an augmented reality shopping assistant application using personalized recommendations and explainable artificial intelligence. J*ournal of Research in Interactive Marketing*, *17*(2), 273–298. https://doi.org/10.5281/zenodo.4723468

Appendix

Appendix 1: Sample Statistics

List of Countries

Country	N
Argentina	1
Austria	1
Brazil	1
Costa Rica	1
France	3
Germany	93
Iran	7
Italy	3
Lebanon	1
Mexico	1
Netherlands	2
Peru	1
Portugal	14
Spain	3
UK	1
USA	1
Venezuela	1
Total	135

Gender

Gender	N
Male	51
Female	83
Prefer not to say	1
Total	135

Highest Level of Education

Level of Education	N
Less than secondary education	4
Secondary education	26
Bachelor’s degree	56
Master’s degree	35
Doctoral degree	8
Other	6
Total	135

Subjective Social Standing

Step	N
3	2
4	2
5	14
6	21
7	50
8	34
9	7
10	5
Total	135

Current Employment Status

Employment status	N
Employed	75
Freelancer	7
Unemployed	3
Student	46
Retired	1
Other	3

Total	135

Appendix 2: Survey

Introduction

Dear survey participant, welcome and thank you for considering participating in this survey on product recommendations. I, Dalia Jozani, am conducting this survey as part of my Master Thesis at Católica Lisbon School of Business and Economics, under the supervision of Cristina Mendonça. This study will present you with a scenario and a series of related questions and will take about 7-10 minutes to complete. The purpose is to gain insight into individuals' motivations to follow product recommendations and to learn more about the luxury retail industry. Your participation will contribute to research on product recommendations. Please answer as honestly as possible. All answers will be kept strictly confidential and are anonymous. This means that it will not be possible to link your responses to your identity. The data collected will be used for research purposes only and may be presented in my thesis or disseminated in academic journals, always in aggregated form, without reference to any individual response. I ask you to complete the study in one go, without interruptions. Please remember that your participation is voluntary, and you have the option to exit the survey at any time by simply closing your browser window. Should you have any questions regarding this study, please feel free to contact me at Dalia Jozani (s-djozani@ucp.pt). By continuing, you agree to participate. Thank you!

Q1: Where are you from?

▼ Afghanistan ... Zimbabwe

Q2: How often do you purchase luxury products (e.g., clothes from luxury brands)?

- ○ Not at all
- ○ Rarely
- ○ Occasionally
- ○ Sometimes
- ○ Frequently
- ○ Often
- ○ Very often

Q3: Why do you buy or use luxury articles? Please select all that apply.

- ○ To feel unique or distinct
- ○ To display wealth, power, and social status
- ○ To build a positive social image
- ○ For their functionality, usefulness, and high quality
- ○ For personal fulfilment and self-expression
- ○ Because I like the brand
- ○ Other ________________________________

Q4: Please indicate your level of agreement with the following statements.

	Strongly disagree	Somewhat disagree	Neither agree not disagree	Somewhat agree	Strongly agree
Luxury goods make me feel acceptable in my circle.	○	○	○	○	○
Purchasing luxury goods indicates a symbol of wealth.	○	○	○	○	○
I buy luxury goods to gain or increase social status.	○	○	○	○	○
Purchasing luxury goods increases my happiness.	○	○	○	○	○

Q5: If you had to choose between two sources of product recommendation: human or artificial intelligence (AI), which one would you pick? Note: Product recommendations generated by AI are personalized product suggestions created by algorithms and machine learning processes based on your individual preferences, past shopping behavior, and data analysis.

- ◯ Definitely AI
- ◯ Most likely AI
- ◯ Indifferent between the two
- ◯ Most likely human
- ◯ Definitely human

Q6: What is your gender?

- ◯ Male
- ◯ Female
- ◯ Other ________________________________
- ◯ Prefer not to say

Q7: How old are you? Please enter your age as a number.

____

Q8: What is your highest level of education?

- ◯ Less than secondary education
- ◯ Secondary education
- ◯ Bachelor’s degree
- ◯ Master’s degree
- ◯ Doctoral degree
- ◯ Other ___________________________________

Q9: Think of a ladder with 10 steps representing where people stand in your country. At step 10 are people who are the best off – those who have the most money, the most education, and the most respected jobs. At step 1 are the people who are worst off – those who have the least money, the least education, and the least respected jobs or no job. Where would you place yourself on this ladder?

	0 1 2 3 4 5 6 7 8 9 10
Standing	

Q10: What is your current employment status?

- ◯ Employed
- ◯ Freelancer
- ◯ Unemployed
- ◯ Student
- ◯ Retired
- ◯ Other ____

You will now be presented with a scenario. Please try to imagine yourself in the described situation and provide your response as authentically as possible. Thank you!

Imagine you are interested in purchasing a new luxury product, specifically a cashmere sweater. You visit the physical store of your trusted luxury brand, where a sales assistant warmly greets you. Based on your specific preferences and requirements, the salesperson recommends a particular cashmere sweater for you.

Imagine you are interested in purchasing a new luxury product, specifically a cashmere sweater. You visit the website of your trusted luxury brand, where you have a member account and a profile. Based on your settings, past online activity, and collected data, the algorithm recommends a particular cashmere sweater tailored to your preferences.

This is the cashmere sweater that the salesperson / artificial intelligence (AI) recommended.

Q11: How much do you like the product shown?

- ◯ Dislike a great deal
- ◯ Dislike somewhat
- ◯ Neither like nor dislike
- ◯ Like somewhat
- ◯ Like a great deal

Q12: Based on this scenario, please indicate your level of agreement with the following statement: I would consider purchasing this product.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Q13: Please indicate how likely you are to purchase this sweater based on the recommendation.

- Extremely unlikely
- Somewhat unlikely
- Neither likely nor unlikely
- Somewhat likely
- Extremely likely

Q14: In the scenario, from whom did you receive the recommendation for the sweater?

- A human
- An AI

Q15: Please indicate your level of agreement with the following statements considering the scenario shown before.

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
I believe this recommendation is trustworthy.	○	○	○	○	○
I consider the sales assistant / AI to be reliable.	○	○	○	○	○
I trust the decision generated by sales assistants / AI.	○	○	○	○	○
I trust product recommendations generated by sales assistants / AI.	○	○	○	○	○

Please indicate your level of agreement with the following statements considering the scenario shown before.
Q16: How accurate do you find human / AI-based product recommendations?

- Not accurate at all
- Slightly accurate
- Moderately accurate
- Very accurate
- Extremely accurate

Q17: Please indicate your level of agreement with the following statement: I am willing to rely on human / AI-generated product recommendations when making purchase-related decisions.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Q18: How often do you follow human / AI-generated product recommendations?

- Never
- Sometimes
- About half of the time
- Most of the time
- Always

Q19: Please rate your satisfaction with the last human / AI-based product recommendation you followed.

- Extremely dissatisfied
- Somewhat dissatisfied
- Neither satisfied nor dissatisfied
- Somewhat satisfied
- Extremely satisfied
- I never followed a product recommendation

Q20: Did the satisfaction you experienced with the product recommendation in your last purchase influence your likelihood of completing that purchase?

- Not at all
- A little
- Moderately
- Significantly
- Greatly
- I never followed a product recommendation

Q21: Please select the option strongly agree for this question.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Do you have any additional comments you would like to share with the researcher? If so, please write your comments below. If you have none, leave this space blank.

Appendix 3: Participants' Luxury Fashion Product Purchase Frequency

Purchase Frequency	*N*
Not at all	18
Rarely	58
Occasionally	19
Sometimes	22
Frequently	12
Often	4
Very often	2
Total	135

Appendix 4: Participants' Luxury Fashion Product Purchase Motivations

Purchase Motivation	*N*
Feel unique or distinct	20
Display wealth, power, and social status	16
Build a positive social image	23
Functionality, usefulness, and high quality	74
Personal fulfillment and self-expression	50
Because I like the brand	65

Appendix 5: Participants' Purchasing Likelihood

Purchasing Likelihood	*M*	*SD*
I would consider purchasing this product.	3.16	1.23
I would consider purchasing it based on the recommendation.	2.98	1.10

Appendix 6: Bivariate Correlation Matrix

Correlations

		Gender	Age	Educ	Employm	Recom pref	Purch freq	Purch Int	Trust	Ind	PD	Fem	UA	ST
Gender	r	1	-,03	-,17	,04	,17*	-,01	-,08	,11	,22**	-,06	,11	,13	,08
	p		,76	,05	,63	,05	,94	,39	,19	,01	,46	,21	,13	,39
	N	135	135	135	135	135	135	134	135	135	135	135	135	134
Age	r	-,03	1	,17*	-,31**	,23**	,07	-,20*	-,08	-,17	,07	-,06	,07	,01
	p	,76		,04	,00	,01	,40	,02	,33	,05	,45	,47	,45	,92
	N	135	135	135	135	135	135	134	135	135	135	135	135	134
Educ	r	-,17	,17*	1	,02	,01	-,16	-,11	,00	,03	,00	-,01	-,03	-,01
	p	,05	,04		,80	,93	,07	,21	,98	,71	,99	,89	,75	,88
	N	135	135	135	135	135	135	134	135	135	135	135	135	134
Employm	r	,04	-,31**	,02	1	-,14	,03	,19*	,19*	,11	,03	-,08	,10	-,07
	p	,63	,00	,80		,11	,77	,03	,03	,22	,69	,37	,24	,41
	N	135	135	135	135	135	135	134	135	135	135	135	135	134
Recom pref	r	,17*	,23**	,01	-,14	1	,03	,01	-,17*	-,07	,19*	-,15	,30**	-,06
	p	,05	,01	,93	,11		,71	,88	,05	,43	,03	,09	,00	,51
	N	135	135	135	135	135	135	134	135	135	135	135	135	134
Purch freq	r	-,01	,07	-,16	,03	,03	1	,49**	,12	-,16	,17*	-,16	-,02	-,16
	p	,94	,40	,07	,77	,71		,00	,18	,07	,05	,07	,83	,07
	N	135	135	135	135	135	135	134	135	135	135	135	135	134
Purch Int	r	-,08	-,20*	-,11	,19*	,01	,49**	1	,09	-,10	,20*	-,22*	,02	-,23**
	p	,39	,02	,21	,03	,88	,00		,32	,26	,02	,01	,81	,01
	N	134	134	134	134	134	134	134	134	134	134	134	134	133
Trust	r	,11	-,08	,00	,19*	-,17*	,12	,09	1	,26**	-,14	,09	-,11	,10
	p	,19	,33	,98	,03	,05	,18	,32		,00	,12	,28	,21	,24
	N	135	135	135	135	135	135	134	135	135	135	135	135	134
Ind	r	,22**	-,17	,03	,11	-,07	-,16	-,10	,26**	1	-,54**	,47**	-,04	,55**
	p	,01	,05	,71	,22	,43	,07	,26	,00		,00	,00	,64	,00
	N	135	135	135	135	135	135	134	135	135	135	135	135	134
PD	r	-,06	,07	,00	,03	,19*	,17*	,20*	-,14	-,54**	1	-,90**	,07	-,84**
	p	,46	,45	,99	,69	,03	,05	,02	,12	,00		,00	,44	,00
	N	135	135	135	135	135	135	134	135	135	135	135	135	134
Fem	r	,11	-,06	-,01	-,08	-,15	-,16	-,22*	,09	,47**	-,90**	1	-,07	,78**
	p	,21	,47	,89	,37	,09	,07	,01	,28	,00	,00		,43	,00
	N	135	135	135	135	135	135	134	135	135	135	135	135	134
UA	r	,13	,07	-,03	,10	,30**	-,02	,02	-,11	-,04	,07	-,07	1	,07
	p	,13	,45	,75	,24	,00	,83	,81	,21	,64	,44	,43		,44
	N	135	135	135	135	135	135	134	135	135	135	135	135	134
ST	r	,08	,01	-,01	-,07	-,06	-,16	-,23**	,10	,55**	-,84**	,78**	,07	1
	p	,39	,92	,88	,41	,51	,07	,01	,24	,00	,00	,00	,44	
	N	134	134	134	134	134	134	133	134	134	134	134	134	134

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

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

The bivariate correlation matrix shows the relationship between the following variables: gender, age, highest level of education, current employment status, source of product recommendation preference, purchasing frequency of luxury products, purchasing intention, trust in recommendations, and the cultural dimensions individualism, power distance, femininity, uncertainty avoidance, and short-term orientation. Significant correlations are denoted by asterisks.

Appendix 7: ANOVA & ANCOVA Hypothesis 1

Descriptives

Average Reliance

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean Lower Bound	95% Confidence Interval for Mean Upper Bound	Minimum	Maximum
,00	68	3,5588	1,04213	,12638	3,3066	3,8111	1,00	5,00
1,00	67	2,9254	1,14566	,13996	2,6459	3,2048	1,00	5,00
Total	135	3,2444	1,13602	,09777	3,0511	3,4378	1,00	5,00

ANOVA

Average Reliance

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	13,542	1	13,542	11,300	,001
Within Groups	159,392	133	1,198		
Total	172,933	134			

Descriptive Statistics

Dependent Variable: Average Reliance

Condition_actual	Mean	Std. Deviation	N
,00	3,5588	1,04213	68
1,00	2,9091	1,14660	66
Total	3,2388	1,13839	134

Tests of Between-Subjects Effects

Dependent Variable: Average Reliance

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	41,048[a]	6	6,841	6,617	<,001
Intercept	1,615	1	1,615	1,562	,214
Individualism_Dummy	,603	1	,603	,584	,446
Subj_Social_Standing	5,032	1	5,032	4,867	,029
Employment_Status	7,942	1	7,942	7,682	,006
Purchase_Frequency	1,666	1	1,666	1,612	,207
Satisfaction_Mean	10,558	1	10,558	10,212	,002
Condition_actual	12,084	1	12,084	11,687	<,001
Error	131,310	127	1,034		
Total	1578,000	134			
Corrected Total	172,358	133			

a. R Squared = ,238 (Adjusted R Squared = ,202)

Parameter Estimates

Dependent Variable: Average Reliance

Parameter	B	Std. Error	t	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Intercept	,519	,654	,793	,429	-,776	1,813
Individualism_Dummy	,236	,310	,764	,446	-,376	,849
Subj_Social_Standing	,152	,069	2,206	,029	,016	,288
Employment_Status	,165	,059	2,772	,006	,047	,283
Purchase_Frequency	-,082	,065	-1,270	,207	-,210	,046
Satisfaction_Mean	,240	,075	3,196	,002	,091	,389
[Condition_actual=,00]	,625	,183	3,419	<,001	,263	,987
[Condition_actual=1,00]	0[a]	.	.	.	.	.

a. This parameter is set to zero because it is redundant.

Appendix 8: ANOVA Hypothesis 2

Descriptives

Average Trust

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean Lower Bound	Upper Bound	Minimum	Maximum
,00	68	3,3860	,80973	,09819	3,1900	3,5820	1,00	5,00
1,00	67	3,1157	,88477	,10809	2,8999	3,3315	1,00	5,00
Total	135	3,2519	,85546	,07363	3,1062	3,3975	1,00	5,00

ANOVA

Average Trust

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	2,467	1	2,467	3,432	,066
Within Groups	95,595	133	,719		
Total	98,062	134			

Appendix 9: Independent Sample t-test Hypothesis 2

Group Statistics

	Condition_actual	N	Mean	Std. Deviation	Std. Error Mean
Average Trust	,00	68	3,3860	,80973	,09819
	1,00	67	3,1157	,88477	,10809

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance				95% Confidence Interval of the Difference	
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
Average Trust	Equal variances assumed	1,4	,238	1,853	133	,033	,066	,27036	,14594	-,01830	,55902
	Equal variances not assumed			1,851	132	,033	,066	,27036	,14603	-,01852	,55924

Appendix 10: Independent Sample t-test Hypothesis 10

Group Statistics

	Individualism_Dummy	N	Mean	Std. Deviation	Std. Error Mean
Average Trust	,00	13	2,5769	,90935	,25221
	1,00	122	3,3238	,82114	,07434

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance				95% Confidence Interval of the Difference	
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
Average Trust	Equal variances assumed	,296	,587	-3,086	133	,001	,002	-,74685	,24200	-1,22552	-,26817
	Equal variances not assumed			-2,840	14,165	,006	,013	-,74685	,26294	-1,31018	-,18352

Appendix 11: Independent Sample t-test Hypothesis 11

Group Statistics

	Femininity_Dummy	N	Mean	Std. Deviation	Std. Error Mean
Average Trust	,00	32	3,1094	1,04136	,18409
	1,00	103	3,2961	,78960	,07780

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance				95% Confidence Interval of the Difference	
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
Average Trust	Equal variances assumed	6,545	,012	-1,079	133	,141	,282	-,18674	,17302	-,52897	,15549
	Equal variances not assumed			-,934	42,650	,178	,355	-,18674	,19985	-,58988	,21640

Appendix 12: Independent Sample t-test Hypothesis 13

Group Statistics

	Shortterm_Dummy	N	Mean	Std. Deviation	Std. Error Mean
Average Trust	,00	35	3,1000	1,09175	,18454
	1,00	99	3,2980	,75566	,07595

Independent Samples Test

		Levene's Test for Equality of ...		t-test for Equality of Means							
						Significance				95% Confidence Interval of the Difference	
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
Average Trust	Equal variances assumed	10,679	,001	-1,178	132	,121	,241	-,19798	,16813	-,5306	,13460
	Equal variances not assumed			-,992	46,034	,163	,326	-,19798	,19956	-,5997	,20370

Appendix 13: ANOVA & ANCOVA Hypothesis 3

Descriptives

Purchasing Likelihood

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
,00	13	2,6538	1,34450	,37290	1,8414	3,4663	1,00	4,50
1,00	122	3,1107	1,08047	,09782	2,9170	3,3043	1,00	5,00
Total	135	3,0667	1,11100	,09562	2,8775	3,2558	1,00	5,00

ANOVA

Purchasing Likelihood

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	2,452	1	2,452	2,001	,160
Within Groups	162,948	133	1,225		
Total	165,400	134			

Descriptive Statistics

Dependent Variable: Purchasing Likelihood

Individualism_Dummy	Mean	Std. Deviation	N
,00	2,6538	1,34450	13
1,00	3,1033	1,08189	121
Total	3,0597	1,11221	134

Tests of Between-Subjects Effects

Dependent Variable: Purchasing Likelihood

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	10,292[a]	5	2,058	1,708	,137
Intercept	11,928	1	11,928	9,900	,002
Powerdistance_Dummy	,698	1	,698	,580	,448
Femininity_Dummy	,017	1	,017	,014	,905
Shortterm_Dummy	,314	1	,314	,260	,611
Gender	6,081	1	6,081	5,047	,026
Individualism_Dummy	1,321	1	1,321	1,097	,297
Error	154,231	128	1,205		
Total	1419,000	134			
Corrected Total	164,522	133			

a. R Squared = ,063 (Adjusted R Squared = ,026)

Parameter Estimates

Dependent Variable: Purchasing Likelihood

Parameter	B	Std. Error	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	2,198	,633	3,471	<,001	,945	3,451
Powerdistance_Dummy	,459	,602	,761	,448	-,733	1,650
Femininity_Dummy	,061	,511	,120	,905	-,950	1,073
Shortterm_Dummy	,211	,413	,510	,611	-,607	1,029
Gender	,360	,160	2,246	,026	,043	,677
[Individualism_Dummy=,00]	-,420	,401	-1,047	,297	-1,214	,374
[Individualism_Dummy=1,00]	0[a]	.	.	.	.	.

a. This parameter is set to zero because it is redundant.

Appendix 14: ANOVA & ANCOVA Hypothesis 5

Descriptives

Purchasing Likelihood

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
,00	104	3,0625	1,07642	,10555	2,8532	3,2718	1,00	5,00
1,00	31	3,0806	1,23893	,22252	2,6262	3,5351	1,00	5,00
Total	135	3,0667	1,11100	,09562	2,8775	3,2558	1,00	5,00

ANOVA

Purchasing Likelihood

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	,008	1	,008	,006	,937
Within Groups	165,392	133	1,244		
Total	165,400	134			

Descriptive Statistics

Dependent Variable: Purchasing Likelihood

Powerdistance_Dummy	Mean	Std. Deviation	N
,00	3,0534	1,07765	103
1,00	3,0806	1,23893	31
Total	3,0597	1,11221	134

Tests of Between-Subjects Effects

Dependent Variable: Purchasing Likelihood

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	4,211[a]	4	1,053	,847	,498
Intercept	35,099	1	35,099	28,243	<,001
Individualism_Dummy	3,133	1	3,133	2,521	,115
Femininity_Dummy	,216	1	,216	,174	,677
Shortterm_Dummy	,255	1	,255	,205	,651
Powerdistance_Dummy	1,322	1	1,322	1,064	,304
Error	160,312	129	1,243		
Total	1419,000	134			
Corrected Total	164,522	133			

a. R Squared = ,026 (Adjusted R Squared = -,005)

Parameter Estimates

Dependent Variable: Purchasing Likelihood

Parameter	B	Std. Error	t	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Intercept	2,669	,314	8,491	<,001	2,047	3,291
Individualism_Dummy	,629	,396	1,588	,115	-,155	1,413
Femininity_Dummy	,215	,514	,417	,677	-,803	1,232
Shortterm_Dummy	,190	,420	,453	,651	-,640	1,021
[Powerdistance_Dummy =,00]	-,626	,607	-1,031	,304	-1,827	,575
[Powerdistance_Dummy =1,00]	0[a]	.	.	.	.	.

a. This parameter is set to zero because it is redundant.

Appendix 15: Chi-square test Hypothesis 4

		Individualism_Dummy ,00 Count	Individualism_Dummy 1,00 Count
Purchase motivation - for personal fulfilment and self-expression	For personal fulfilment and self-expression	5	45

Results						
	Hedonic reasons	Not				***Row Totals***
Collectivistic	5 (4.81) [0.01]	8 (8.19) [0.00]				13
Individualistic	45 (45.19) [0.00]	77 (76.81) [0.00]				122
Column Totals	50	85				**135 (Grand Total)**

The chi-square statistic is 0.0125. The *p*-value is .910917. The result is *not* significant at $p < .05$.

Appendix 16: Chi-square test Hypotheses 6a

		Powerdistance_Dummy	
		,00	1,00
		Count	Count
Purchase motivation - for their functionality, usefulness, and high quality	For their functionality, usefulness, and high quality	56	18

Results						
	Utilitarian reasons	Not				***Row Totals***
Low power distance	56 (57.01) [0.02]	48 (46.99) [0.02]				104
High power distance	18 (16.99) [0.06]	13 (14.01) [0.07]				31
Column Totals	74	61				**135 (Grand Total)**

The chi-square statistic is 0.1716. The *p*-value is .678715. The result is *not* significant at $p < .05$.

Appendix 17: Chi-square test Hypothesis 6b

		Powerdistance_Dummy	
		,00	1,00
		Count	Count
Purchase motivation - for personal fulfilment and self-expression	For personal fulfilment and self-expression	40	10

Results						
	Hedonic reasons	Not				***Row Totals***
Low power distance	40 (38.52) [0.06]	64 (65.48) [0.03]				104
High power distance	10 (11.48) [0.19]	21 (19.52) [0.11]				31
Column Totals	50	85				**135 (Grand Total)**

The chi-square statistic is 0.3941. The *p*-value is .530151. The result is *not* significant at $p < .05$.

Appendix 18: Chi-square test Hypothesis 7

		Femininity_Dummy	
		,00	1,00
		Count	Count
Purchase motivation - for personal fulfilment and self-expression	For personal fulfilment and self-expression	10	40

Results						
	Hedonic reasons	Not				***Row Totals***
Feminine	10 (11.85) [0.29]	22 (20.15) [0.17]				32
Masculine	40 (38.15) [0.09]	63 (64.85) [0.05]				103
Column Totals	50	85				**135 (Grand Total)**

The chi-square statistic is 0.6023. The *p*-value is .437689. The result is *not* significant at $p < .05$.

Appendix 19: ANOVA & ANCOVA Hypothesis 9

Descriptives

Purchase frequency

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean Lower Bound	95% Confidence Interval for Mean Upper Bound	Minimum	Maximum
,00	35	3,17	1,671	,283	2,60	3,75	1	7
1,00	99	2,68	1,268	,127	2,42	2,93	1	7
Total	134	2,81	1,395	,121	2,57	3,04	1	7

ANOVA

Purchase frequency

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	6,327	1	6,327	3,306	,071
Within Groups	252,628	132	1,914		
Total	258,955	133			

Descriptive Statistics

Dependent Variable: Purchase frequency

Shortterm_Dummy	Mean	Std. Deviation	N
,00	3,24	1,653	34
1,00	2,68	1,268	99
Total	2,82	1,392	133

Tests of Between-Subjects Effects

Dependent Variable: Purchase frequency

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	64,247[a]	2	32,124	21,816	<,001
Intercept	15,676	1	15,676	10,646	,001
Purchase_Intention_Mean	56,352	1	56,352	38,270	<,001
Shortterm_Dummy	1,018	1	1,018	,691	,407
Error	191,422	130	1,472		
Total	1313,000	133			
Corrected Total	255,669	132			

a. R Squared = ,251 (Adjusted R Squared = ,240)

Parameter Estimates

Dependent Variable: Purchase frequency

Parameter	B	Std. Error	t	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Intercept	,967	,302	3,200	,002	,369	1,565
Purchase_Intention_Mean	,642	,104	6,186	<,001	,437	,847
[Shortterm_Dummy=,00]	,206	,248	,832	,407	-,284	,696
[Shortterm_Dummy=1,00]	0[a]	.	.	.	.	.

a. This parameter is set to zero because it is redundant.