INSTITUTO
UNIVERSITÁRIO
DE LISBOA

The use of Artificial Intelligence in Luxury Fashion Retail: the use of Robots and Virtual Assistants to increase Purchase Intention in physical stores

Mariana Lázaro Vitória

Master in Marketing

Supervisor:
Prof. Dr. Ricardo Godinho Bilro
Assistant Professor
Department of Marketing, Operations and General Management ISCTE Business School

November, 2022

BUSINESS
SCHOOL

Department of Marketing, Strategy and Operations

The use Artificial Intelligence in Luxury Fashion Retail: the use of Robots and Virtual Assistants to increase Purchase Intention in physical stores

Mariana Lázaro Vitória

Master in Marketing

Supervisor:
Prof. Dr. Ricardo Godinho Bilro
Assistant Professor
Department of Marketing, Operations and General Management ISCTE Business School

November, 2022

Acknowledgments

This thesis represents the end of one of the most beautiful chapters of my life, my academic life. I was lucky to have done all my path in Iscte Business School, which went through a degree in Management and now the Master in Marketing. So, my first thanks go to this great University that has given me some of the best moments of my life, and for that, ISCTE will forever be in my heart. I will leave with a feeling of fulfilled duty and an enormous nostalgia.

Secondly, I want to thank my mother for being incredible. She always supported me in everything unconditionally. She celebrated my victories with me and was always with me in the not-so-good moments. It is a privilege to have her as a mother. I want to thank my parents for always giving me the best education possible and encouraging me to do my best in everything I do.

I want to thank my brothers, my cousin, my goddaughter, and my uncles for always being a support in my life and for always having their arms open for me.

My thanks to my friend Bárbara for being the best friend I could have, for listening to me, and for having the ability always to encourage me. I want to thank my friend Mónica for her patience and support by being with me for hours on my cell phone to alert me to weaknesses she detected in my questionnaire and trying to correct them with me. Thank you to these two girls for allowing me to share my academic life with them.

To my supervisor Professor Ricardo Bilro, my most sincere thanks for his availability and knowledge, patience and encouragement, and for guiding me in this dissertation so we could achieve a good result.

I thank the volunteers who answered my questionnaire and helped me finish this dissertation.

Finally, to my grandparents, who will always be my guardian angels in heaven rooting for me.

Abstract

Several Luxury Fashion brands have already implemented AI systems in their businesses. However, with the emergence of robots and virtual assistants, it became essential to understand if and how customers could adopt these new services inside the stores to buy Luxury Products. The robots/virtual assistants aim to offer customers an innovative and personalized shopping experience. This thesis aims to understand which factors contribute most to the Intention to Use these services and how this influences the Purchase Intention.

The data for the development of this study were collected by a questionnaire, distributed online, and built based on the research on the topic of this dissertation. Through the analysis, it is possible to conclude that Fun, Ease of Use, and Quality of Service positively influence the Trust one has in that Service. Convenience is positively influenced by Ease of Use and Service Quality. Enjoyment and Service Quality negatively influence the Need for Human Interaction, decreasing this Need. Furthermore, Trust and Convenience positively influence Use Intention, while Need for Human Interaction has a negative effect on Use Intention. Thus, it is concluded that Use Intention positively impacts Purchase Intention.

Thus, Luxury Brands need to create communication and implementation strategies that facilitate the adoption process of these services.

Keywords: Artificial Intelligence, Robot, Virtual Assistant, Intention to Use, Purchase Intention, Luxury Fashion

JEL: M31, M39

Resumo

Diversas marcas de Moda de Luxo já implementaram sistemas de IA nos seus negócios. Com o aparecimento de robots e assistentes virtuais, tornou-se importante perceber se e de que forma os clientes poderiam adotar estes novos serviços dentro das lojas para comprar Produtos de Luxo. Os robots/assistentes virtuais têm como grande objetivo oferecer ao cliente uma experiência de compra inovadora e personalizada. Esta tese visa compreender quais os fatores que mais contribuem para a Intenção de Uso destes serviços, e de que forma isso influencia a Intenção de Compra.

Os dados para o desenvolvimento deste estudo foram recolhidos por um questionário, distribuído online e construído com base na pesquisa sobre a tópico desta dissertação. Através da análise feita, é possível concluir que o Divertimento, a Facilidade de Utilização e a Qualidade do Serviço influenciam positivamente a Confiança que se tem nesse Serviço. Já a Conveniência é influenciada positivamente pela Facilidade de Utilização e pela Qualidade do Serviço. A Necessidade de Interação Humana é influenciada negativamente pelo Divertimento e pela Qualidade de Serviço, ou seja, diminuem essa Necessidade. Para além disso, é possível verificar que a Confiança e a Conveniência influenciam positivamente a Intenção de Uso, enquanto a Necessidade de Interação Humana tem um efeito negativo na Intenção de Uso. Conclui-se desta forma, que a Intenção de Uso tem um impacto positivo na Intenção de Compra.

Desta forma, as Marcas de Luxo necessitam de criar estratégias de comunicação e de implementação que facilitem o processo de adoção destes serviços.

Palavras-chave: Inteligência Artificial, Robô, Assistente Virtual, Intenção de Uso, Intenção de Compra, Moda de Luxo

JEL: M31, M39

Index

List of Figures

List of Tables

Glossary

AI: Artificial Intelligence

TAM: Technology Acceptance Model

FRA: Fashion Robots Advisors

1. Introduction

Artificial Intelligence is becoming increasingly a reality, present in several activity sectors, and can be used in several functions (Joshi, 2019). In this way, it can be defined as "a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (Kaplan & Haenlein, 2019, p.17). This way, Artificial Intelligence can be integrated into Retail and help companies change their business paradigm, improve processes, and make more efficient management.

Nowadays, Artificial Intelligence is also inserted in fashion retail on several fronts: it allows better communication, more personalized to each customer; it enables making product recommendations based on information such as previous purchases or body type; it allows the launch of new products based on information gathered from customers (Davenport et al., 2020; Kaplan & Haenlein, 2019).

Luxury brands are understood as brands with high quality, a premium price, and a prestigious image that offer their customers authentic value on an emotional and functional level and that build a unique bond with their customers (Ko et al., 2019), have also started to use AI in their business. Luxury fashion brands, too, are already showing changes in this direction. Several brands have already developed systems such as chatbots, and recommendation systems, both on websites and in physical stores, through applications. To this can be added applications that help salespeople to have real-time information about customers (Deloitte, 2020).

With the emergence of service robots, it becomes crucial to understand how much they can help luxury brands improve their business and enhance the customer experience. Applied to the context of this dissertation, robots are seen as Fashion Robots, which adopt human characteristics, and are machines that aim to create a personalized customer experience. They can recommend clothes, entertain customers by talking to them and recognizing their emotions, help the store staff with the information needed to give the customer the best possible service, and even complete transactions (Song & Kim, 2022). Service robots can also be understood as virtual assistants. They are capable of the same activities. However, they express themselves by voice or text (Hsieh & Lee, 2021).

This study aims to understand if adopting these AI services contributes to higher customer purchase intentions and how brands can work to make the acceptance and adoption process more manageable. This study will provide contributions at the theoretical and managerial levels so that brands can implement strategies to address consumers' needs and concerns regarding AI.

1.1. Research objectives and research questions

It is possible to structure the following objectives for this dissertation:

1) Explore Luxury Brand, Luxury Fashion Brand, and Luxury Brand Consumer concepts;
2) Explore the concept of AI, what influences its adoption, and its problems, as well as explore the ideas of Service Robots that include Fashion Robots and Virtual Assistants;
3) Realize how AI is already impacting Luxury Fashion Retail;
4) Explore the concepts of Enjoyment, Ease of Use, Service Quality, Trust, Need for Human Interaction, Convenience, and Intention to Use and how these variables impact Purchase Intention;
5) Provide theoretical and managerial contributions so Luxury Brands can implement strategies to improve the consumer experience.

Primary research will be carried out to meet the objectives mentioned above. This research will be focused on understanding the concept of a luxury fashion brand and the consumer profile of this brand, giving a type of contextualization necessary to understand what AI is, the forms it can adopt, and the impact it has on Luxury Fashion Brands. In addition, this primary research will also address understanding the concepts of Enjoyment, Ease of Use, Service Quality, Trust, Need for Human Interaction, Convenience, Intent to Use, and Purchase Intention and relate them to the theme of this dissertation.

After that, data will be collected through an online questionnaire, and this data will lead to conclusions about customers' perception of AI services, what their needs and concerns are, how likely consumers are to adopt these AI services, and how this can have a positive impact on Purchase Intention. Thus, this study aims to answer the following questions:

i. How does an AI service that is easy to use, provides an enjoyable customer experience, and is perceived as being of high-quality influence Trust, Convenience, and the Need for human interaction?

ii. What role do Trust, Need for Human interaction, and Convenience play in Intention to Use AI Services?

iii. Does Intention to Use of robots/virtual assistants impact the purchase intention in physical stores?

1.2. Dissertation Structure

The present dissertation is divided into five main parts, as shown in Figure 1.1.. The Introduction aims to introduce the theme of this dissertation and its relevance. The next part consists of the Literature Review. It aims to compile relevant concepts and theories for this study and provide the framework for constructing the research model and formulating hypotheses. The Methodology part explains how the study was done and how the data for the study were collected. The results chapter analyzes the data collected through descriptive, reliability, and multiple linear regression analysis to validate the hypotheses and the subsequent discussion of the results. The conclusion and implications are the last chapter of this thesis, which has as its primary objective to summarize the main findings of this study and its implications for management. Also included are the limitations of this study that give rise to suggestions for future research.

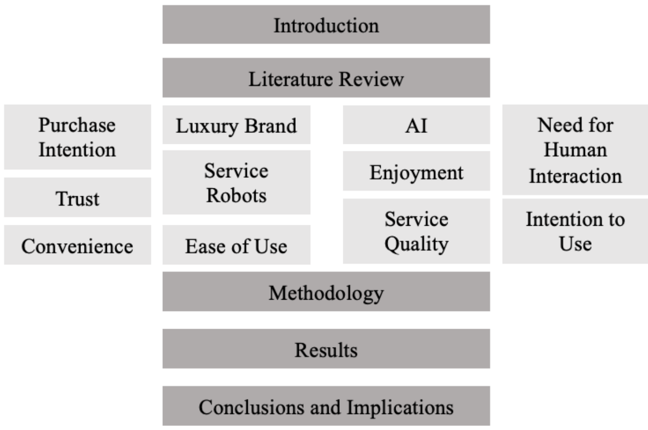


Figure 1.1.: Structure of the dissertation
Source: Own elaboration

2. Literature Review

2.1. Luxury brand and Luxury Fashion Brand

There is no entirely accepted definition of a luxury brand since the concept of luxury is subjective, and the perception of luxury varies over time and space (Cristini et al., 2017; Ko et al., 2019; Mortelmans, 2005). However, several definitions present dimensions such as high quality, rarity, high price, and a distinctive aesthetic. Despite what was mentioned above, a luxury brand ultimately depends on the customers' perception of that particular brand (Ko et al., 2019).

Thus, Ko et al. (2019) propose the following definition:

> A luxury brand is a branded product or service that consumers perceive to be high quality; offers authentic value via desired benefits, whether functional or emotional; has a prestigious image within the market built on qualities such as artisanship, craftsmanship, or service quality; be worthy of commanding a premium price; and be capable of inspiring a deep connection, or resonance, with the consumer. (p. 406)

One characteristic that differentiates luxury brands from non-luxury brands is the psychological and functional benefits since they often correspond to the psychological needs of consumers (Vigneron & Johnson, 2004).

However, luxury is more than a list of attributes. It is a concept and one that is dependent on the social and individual context. Thus, it can be seen through three dimensions: the material, the individual, and the social (Berthon et al., 2009). There is a proposed theory that is based on the "three worlds theory" (Popper, 1979): "World 1) manifest goods and services; (World 2) individual thoughts, emotions, needs, wants, and perceptions; and (World 3) collective narratives, knowledge, symbols, and images." (Berthon et al., 2009, p. 47) In addition, Keller (2002) suggests that consumers attach meaning to a given product's attributes, which can be functional, symbolic, or experiential. For this reason, for Berthon et al. (2009), luxury brands are divided into three dimensions: functional, experiential, and symbolic, relating to the "theory of worlds" mentioned above.

The functional dimension is linked to the material embodiment of the products, i.e., the function the objects perform and the benefits that can be derived from this (Berthon et al., 2009). Luxury brands are strongly associated with high quality, and it becomes unsustainable to maintain a brand image if one does not continue to invest in improving the quality effectively of higher levels (Christodoulides et al., 2009). Therefore, differentiated aesthetics becomes a prominent factor in a luxury brand and the perception of luxury. Brands have their aesthetic design and ideologies enhanced by their creators but also by the creative individuals who contribute to the creation of pieces, often distinguished as works of art that create in the consumer the idea of superiority and exclusivity (Dion & Arnould, 2011; Townsend & Sood, 2012).

Wealth is essential in defining social status and considering cultural aspects (Han et al., 2010). Thus, buying/using high-priced products, or products known to be high-priced, is a factor that contributes to show that one belongs to a higher social status. Consequently, high-priced products are intrinsically linked with luxury for those who do not have enough money to buy them (Eastman & Eastman, 2011). Although a high price does not mean it is a luxury product, it is described as having a premium price compared to products with similar functionality. On the other hand, exclusivity and rarity are unique characteristics of luxury products (Kapferer, 2008).

The experiential dimension is related to the subjective value given to a brand or product and is relative and personal. That is, it is directed to the personal value and hedonic values of the individual. It is related to emotions, feelings, sensations, perceptions, cognitions, and behavioral responses evoked by stimuli provoked by brands (Brakus et al., 2009; Stigler & Becker, 1977).

The symbolic dimension is intrinsically linked with what the brand means to others, that is, what it signals to others, as well as the value that this signalization gives to the consumer, that is, it serves to build or strengthen a particular perception that others have of the consumer (Berthon et al., 2009). Given that luxury products are associated with a higher social status, they signal with those the consumer considers to be in the same social status (Han et al., 2010). The more a product is perceived as unique, the more it is perceived to be valuable (Becker et al., 2018). Consequently, the value of these products is related to their perceived value in a social context and not precisely to their physical characteristics (Vigneron & Johnson, 2004).

The meaning of luxury is a social context-oriented concept as well as self-interest, meaning that luxury has outward-oriented meanings and meaning for the consumer's identity (Llamas & Thomsen, 2016; Wiedmann et al., 2009). It should be noted that these dimensions vary depending on the context. The symbolic and functional dimensions vary according to the context in which the consumer is inserted. As for the experiential dimension, since it is linked to the individual perception of the consumer, it can vary considering the consumer's evolution or change in tastes and preferences (Berthon et al., 2009).

According to Jackson (2004), there are four categories of luxury products: watches and jewelry, wines and spirits, perfumes and cosmetics, and fashion, which encompasses couture, ready-to-wear, and accessories. More recently, other categories have been added: luxury cars, hotels, tourism, private banking, home furnishings, and airlines (Chevalier & Mazzalovo, 2008).

Luxury fashion brands have the characteristics of luxury brands in the fashion industry (Ko et al., 2019). Fionda and Moore (2009) established vital characteristics of a luxury fashion brand. As far as brand identity is concerned, it is linked to the symbolism (intangible values inherent to the brand) that the brand brings beyond all the functional benefits. Functional benefits are another essential product integrity feature encompassing high quality, innovation, and creativity. In addition, brands may not be inserted in the fashion sector, but this represents an ideal weight for their identity (Fionda & Moore, 2009; Jackson, 2004).

Communications in marketing can be "fashion shows, celebrity endorsement, advertising, direct marketing, event sponsorship, and PR" (Fionda & Moore, 2009, p.358). Some of these media aim to raise awareness, as well as make the brand more and more attractive to its target, developing a global reputation, but it is essential to use media that provide a closer relationship with each customer, as well as more personalization (Chevalier & Mazzalovo, 2008; Fionda & Moore, 2009).

All luxury fashion brands need to have a "signature" and be consistent in all their elements, i.e., have a recognizable style in any component of the brand. In addition, many brands have iconic products that further create this idea of "DNA". The iconic products of the brands are those that are the most characteristic and in which are embedded the brand's DNA, as well as characteristics that convey the values of the creators as well as the brand (Fionda & Moore, 2009; Kapferer, 2008; Nueno & Quelch, 1998). The same applies to brand employees, who must follow the "signature", i.e., the brand's values and ideas (Fionda & Moore, 2009).

Price is a factor of great importance when it comes to the characteristics of luxury fashion brands since price induces high quality and distinctive aesthetics, as well as exclusivity because it decreases the number of people with access to the product. Therefore, exclusivity is inherent in luxury brands (Phau & Prendergast, 2000). Exclusivity can be controlled through distribution channels (Fionda & Moore, 2009), and many luxury brands adopt the option of launching limited edition products, which will create in the consumer the idea of these products being more valuable, exclusive, and distinctive (Aggarwal et al., 2011; Jang et al., 2015).

Heritage is also a characteristic of this type of brand and is closely related to the brand's history. It is also based on their country of origin and how they were founded and related to the notions of luxury built in the social context. This induces the idea of authenticity. Companies must not lose this factor and try to keep it present (Alexander, 2009; Fionda & Moore, 2009; Kapferer, 2012).

The store environment is the gateway to many brands. This should be of excellence and give the consumer a different experience since it must differentiate from a typical store. The service is also an integral part of this environment since it must also be of excellence, giving priority to each of the customers and maintaining a close and personalized relationship with the needs of each customer. As for distribution channels, they must follow the brand values and be subject to high control because these channels will also be part of the customer experience (Fionda & Moore, 2009).

The total luxury market decreased by 12.2% in 2020. It can also be seen that most companies in the luxury sector are in "Jewelry and Watches" (33%). However, in the "Clothing and Footwear" category, the sales percentage was higher (34.2%). It is also worth mentioning that the top company of Luxury Goods is LVMH, which owns several top brands such as Louis Vuitton, Christian Dior Couture, Fendi, Loewe, Loro Piana, and many others (Deloitte, 2021).

2.1.1. Luxury Brand Consumer

The oldest theory for the motivation of luxury consumption is that proposed by (Veblen, 1899/2009), who proposes that consumers consume to show off their wealth to others, who subsequently deduce status and power from these consumers.

The theory of social comparison proposes that consumers are embedded in a social group and tend to conform to the norms of that group. This influences the brands adopted, contributing to the acceptance in that social group and the feeling of self-satisfaction (Mandel et al., 2006; Wiedmann et al., 2009). Self-concept theory can be considered another motivator of luxury consumption. Brands can make consumers feel identified and feel good about themselves for having a product of a particular brand (Gil et al., 2012; Shukla & Purani, 2012). In other words, consumers seek luxury brands to improve their self-concept (Ko et al., 2019).

The need for uniqueness in the human being (Singularity theory) makes him need to seek the difference from others, and this can be done through the consumption of luxury products since they are scarce products due to their characteristics and that are not within reach of most people (Bian & Forsythe, 2012), which may improve the image that he has of himself as well as how others perceive him (Tian et al., 2001). The extended self is another theory based on using certain products and brands to form and change their identity to meet what they hope to be. It also reinforces the symbolic value that luxury products have for the consumer as a way of extending their identity (Belk, 1988; Han et al., 2010; Hung et al., 2011).

McFerran et al. (2014) suggest that authentic pride, which is associated with consumer success, is a motivator of luxury consumption which is no longer the case with hubristic pride, which refers to an exaggerated pride linked to narcissism. Wang and Griskevicius (2014) suggest that demographics also impact the type of consumer and their motivations: men use luxury branded goods to highlight their wealth and success. On the other hand, women tend to use luxury goods to indicate to other women that their partner is dedicated to them.

2.2. Artificial Intelligence

Kaplan and Haenlein (2019) describe "AI (Artificial Intelligence) as a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (p.17). AI is understood as a system that mimics human intelligence and function through learning systems. First, there is a large amount of data processing, and then the display is adapted to the function for which they were designed (Kaplan & Haenlein, 2019; Syam & Sharma, 2018).

AI has already affected various sectors because it is already used in various functions. The degree of similarity of AI in replicating the human brain serves as the criteria for establishing the types of AI. One of the classifications is based on the similarity of the AI system to the human mind and other capabilities referring to humans. Thus, there are four types of AI: reactive machines, limited memory, theory of mind, and self-aware (Joshi, 2019).

Relative machines are the oldest form of AI and have limited capabilities, i.e., they have no memory-based functionality, meaning they cannot "learn" from past experiences. They only can respond to stimuli (set of inputs). AI systems with limited memory are almost all known today. This type of machine has the same capacity as the previous one, but it can also learn from previous data, which, after being processed, leads to decision-making; that is, they use past models to be able to give answers in the future. Theory of Mind AI is the next level of AI that researchers are working on developing. This level of AI will have the ability to understand the entities it is interacting with, i.e., it will have to have the ability to understand humans and all that they encompass, such as emotions, expressions, needs, thought patterns, and beyond that, the various factors that can interfere with people. The last one is the self-aware AI, which, as the name implies, will have self-concern and be the most like a human. It will be able to understand everything around it, but will also have its consciousness, i.e., develop its ideas and beliefs, and feel and create its own needs. This level of AI is still hypothetical, but it raises some problems since it will almost have a "life of its own," which calls into question inevitable existing ethical values (Joshi, 2019).

According to Kaplan and Haenlein (2019), there are three types of AI evolution stages: artificial narrow intelligence (ANI) refers to performing specific tasks in a particular area with the inability to proceed in other areas. When it comes to the second phase, Artificial General Intelligence (AGI), it is already an AI that is at the human level. Therefore, it can perform various tasks, even those for which it has not been programmed. It is thus on a level equal to that of a human. On the other hand, Artificial Super Intelligence (ASI), the third phase that people may see coming, will be fully conscious systems that can perform any human capability and are therefore considered to be above the human level.

Another distinction regarding intelligence level is task automation versus context awareness (Davenport & Kirby, 2016). The first level of intelligence induces that AI is based on specific rules with a certain logic, which leads to predictable results (Davenport et al., 2020; Huang & Rust, 2018). On the other hand, An AI system that involves context awareness will have to have an extensible processing beyond that for which it was programmed and obtain results according to the context in which it is inserted (Huang & Rust, 2018).

About learning methods: "Supervised learning methods map a given set of inputs to a given set of (labeled) outputs." (Kaplan & Haenlein, 2019, p.19). This means that both the inputs and the outputs need to be known to the analyst (De Bruyn et al., 2020). For example, in an AI system with this learning paradigm, data will have to be labeled first, which can be adversity (Vo et al., 2018). "Unsupervised learning helps find patterns in data without pre-existing labels" (De Bruyn et al., 2020, p.95). This means that the output provided by the AI system is derived from the algorithm itself (Kaplan & Haenlein, 2019). In Reinforcement learning, systems learn to discover complex relationships among the thousands of available data autonomously. In this way, the system learns to make decisions in its context to maximize rewards, i.e., the output variable tends to be maximized (De Bruyn et al., 2020; Kaplan & Haenlein, 2019).

2.2.1. Adoption of AI and AI´s problems

According to Loureiro et al. (2021), using AI has implications for businesses and the entire universe around them. Managers will need to be able to implement AI along with the capabilities of their employees. This management must be based on creating the idea that AI will be an improvement throughout the company and not a way to replace those already working there (Kaplan & Haenlein, 2019). AI will influence the whole sales process, but special attention is needed for salespeople, as they must integrate AI into their role and adapt their skills which means they will have to adapt to the fact that their functions were also performed by the IA (Kaplan & Haenlein, 2019). Salespeople will have to be trained continuously to be able to adapt and make the best use of these systems and also to be able to deal with the associated problems: privacy and ethics (Barro & Davenport, 2019; Davenport et al., 2020).

For an AI system to work, consumers need to accept it and to do that, they need to have confidence in what is being provided. This trust will come through a better understanding by consumers of what AI is. Thus, this adaptation must go through a transparent process in which the brand can show the consumer how these systems work and what benefits they can bring (Davenport et al., 2020; Siau & Wang, 2018). Consumers have high standards regarding AI, particularly regarding errors that may occur, as trust is still low. However, the more evolved the intelligence of AI systems, consumer trust will tend to be lower because they believe that AI cannot have specific emotional or social capabilities (Castelo, 2019).

The demographic factor stands out because women are less likely to adopt IA systems, as they perceive more risk and adopt less risky attitudes (Byrnes et al., 1999; Castelo & Ward, 2016; Gustafson, 1998). AI will also have to be regulated by governments and the entire universe that works with it: there is a need to create legislation that does not allow the misuse of AI. There is also the issue of privacy involving consumers. Europe has created the General Data Protection Regulation. The legislation in each country will have a significant impact on the way AI evolves (Kaplan & Haenlein, 2019).

With AI and data, companies know much about their customers. However, this raises a big question, as customers are concerned about how their data will be used (Martin et al., 2017; Martin & Murphy, 2017). Therefore, companies must assure their customers that their data is only stored for set purposes. However, this assurance is not that easy, as the question arises whether this assurance should be regulated by governments or will be realized by self-regulation. In addition, it is also necessary to know how to manage situations where there is a data privacy breach, and many companies may not be able to do this (Davenport et al., 2020; Verhoef et al., 2017).

Another problem that can arise from using AI is data bias, which can lead to wrong decisions being made, and this data may already be wrong when it enters the AI system (Villasenor, 2019). Another problem inherent in AI is ethical issues, which vary significantly from culture to culture. Thus, corporations must know how to define for what kind of purposes AI can be used since there is no worldwide conduct of what is right or wrong when analyzing and judging situations (Davenport et al., 2020; Vakkuri & Abrahamsson, 2018).

There is a big question related to the third phase of AI evolution- the super artificial intelligence (ASI): whether it is something to use or to avoid since it will quickly perform more than a human would be capable of, much faster. Considering that human, humanly thinks like that, it becomes unfeasible not to understand these kinds of systems and, consequently, the ability to control them entirely. Another primary concern is the replacement of humans by machines. Some tasks are unlikely to be replaced through AI. However, if it happens, this degenerates into more significant problems such as financial issues, ethics, or philosophy, which concerns the life purpose of the human being (Kaplan & Haenlein, 2019).

2.3. The impact of AI in marketing and luxury fashion retail

AI can help companies' marketing and change many business models. This can be done through predictive capability regarding customers. This will allow companies to provide "goods and services to customers on an on-going basis based on data and predictions about their needs." (Davenport et al., 2020, p.35). In addition, AI plays a vital role since it can process a large amount of customer data "involving not just numerical but also text, voice, image, and facial expression data." (Davenport et al., 2020, p.26). Through this process, AI allows companies to shape their advertising, considering customers' preferences and predicting products they might buy, considering previous purchases and searches (Davenport et al., 2020). In customer service, chatbots are already generating automatic responses (Kaplan & Haenlein, 2019).

Furthermore, AI helps in better segmentation, targeting, and more personalized communication, so consumers can access messages and personalized treatment according to their preferences, which can be repeated for all consumers (Kaplan & Haenlein, 2019; Kosinski et al., 2013). It can also influence prices as well as promotions. This way, can be created more adjusted prices, considering the databases created previously and the type of appropriate promotions based on customer behavior processed by the AI (Davenport et al., 2020; Shankar, 2018).

However, Davenport et al. (2020) raise an important issue related to RNPs (Really new products). The prediction that AI can provide to companies will undoubtedly help them in incrementally new products (INPs) since consumers already know about the product and its benefits. Whereas when it comes to RNPs, consumers are not aware of the benefits and usefulness of the new products, and consequently, the involvement may be lower (Hoeffler, 2003; Zhao et al., 2012).

Luxury brands are increasingly betting on analyzing data through AI and using more VR (Virtual Reality) applications. Creating an omnichannel presence is imperative in an increasingly technological world and consumer adoption of online channels. This way, they can create deeper connections with customers through engagement and increase loyalty (Deloitte, 2020).

AI already has significant power in the fashion industry because it can predict which garments best fit the customer's style. This can help the garments' sales and creation since the designers know consumers' preferences. This AI system involves the customer's previous preferences, preferences of customers who have similar choices to that same consumer, and their research on other platforms. It is also able to define a customer's overall style. In this way, designers can extract information, bring their creations closer to customers' choices, and thus boost sales (Davenport et al., 2020)

Several brands already use AI systems to be able to go more and more to their customers. Gucci, in partnership with Farfectch, has launched a system that allows retail staff to send recommendations to their customers' smartphones inside the stores based on the customer's profile, the products he has already bought in the store, and his wish list. Furla created an app that allows salespeople, in real-time, to access the brand's database, where information such as preferences and customer histories are available. This way, stores are more adapted to the geographic point where they are located. Several brands, like Tommy Hilfiger, Louis Vuitton, or Dior, have already created chatbots. Hugo Boss has installed an AI system in its factory in order to improve its production process and avoid errors by collecting data from workers and machines (Deloitte, 2020)

2.4. Service robots, Fashion Robots Advisors and Virtual Assistants

The study of consumer experience can be extended when including the study of robots that provide services (Lu et al., 2019). Robots are beginning to be seen as a future practice in people's daily lives (Choi et al., 2020). Service robots are present in various industries, robots can take the physical form in which they act face-to-face with the consumer, or they can take a virtual form (Huang & Rust, 2018; Lu et al., 2019). Based on artificial intelligence, service robots aim to serve the customer as a human. In this way, they aim to interact and communicate and provide services. Imitating human intelligence, they make autonomous decisions through processing received data, as mentioned before (Lu et al., 2019; Wirtz et al., 2018). "They are usually designed to (...) perform cognitive–analytical tasks or emotional-social tasks empowered by a computerized system."(Lu et al., 2019, p.37).

"FRAs are AI machines designed to create personalized shopping experiences by recommending clothing, providing product information, entertaining customers, collaborating with in-store human staff, updating real-time inventory information, and completing purchase transactions." (Song & Kim, 2022, p.5). Robots can have several functions, most notably assisting the customer in all stages of the sales process and helping the store staff in the sales process (Song & Kim, 2021; Song & Kim, 2022).

Robots, especially those related to fashion, have increasingly been programmed to adopt human characteristics, both in appearance and functionality. The humanoid characteristics enhance the interaction between the customer and the robot and make the whole process easier and more pleasant (Song & Kim, 2022). In addition, they are also an extremely relevant factor in the co-creation process of the brand, providing insights for improvements of the system itself in order to improve the consumer's whole experience, as well as providing insights for the brand to create products that meet their needs and desires (Song & Kim, 2021; Wirtz et al., 2018).

Pepper is an example of a human-like robot that can recognize and interpret "customers' facial expressions, body movements, and verbal expressions" (Song & Kim, 2022, p.5) and thus can interact socially with customers, as well as interpret their emotions (Song & Kim, 2022).

"Virtual assistants are computer programs that understand user queries and complete a limited set of tasks for the user" (Hoyer et al., 2020, p.59). Virtual assistants have been shown to have numerous technical capabilities, including voice recognition and subsequent language processing (Shum et al., 2018).

The communication capabilities that this type of AI system has, which can be either by voice or text, is a notable evolution of more traditional recommender systems, as an identity is created with which customers can maintain an interactive relationship (Hsieh & Lee, 2021). Chatbots are virtual assistants that can conduct a conversation as if they were a human, providing the customer with the information he needs (Hoyer et al., 2020). Virtual assistants differ from recommender systems in that the former can converse with customers, offering a more interactive experience and solving customers' problems as they arise (Rafailidis & Manolopoulos, 2019).

2.5. TAM

"TAM, introduced by Davis (1986), is an adaptation of TRA specifically tailored for modeling user acceptance of information systems." (Davis et al., 1989, p.985). Its main objective is to predict and explain why a new technology system is acceptable or unacceptable from the customers' point of view. TAM is currently one of the most used theoretical frameworks to explain customer acceptance of new technology (Hubert et al., 2017).

Thus, TAM proposes variables that can help predict consumer behavior toward a new technological system (Davis et al., 1989). This model is based on a paradigm that belief leads to attitude, which leads to intention, and that intention leads to behavior (Kim et al., 2017). In addition, the TAM model considers Perceived Ease of Use and Perceived Usefulness as crucial determinants that influence the rest of the model and, consequently, the acceptance of new technology (Davis, 1989; Davis et al., 1989). To these two variables was added the Perceived Enjoyment, proposed by Davis et al. (1992).

TAM makes a few assumptions: a) Intention to use is what affects the actual use of technology, b) Intention to use is affected by the usefulness of a technology, which in turn also affects attitude toward using, c) Attitude toward using is affected simultaneously by usefulness and ease of use, d) ease of use affects usefulness (Chang et al., 2013).

Suppose external variables are to be added to the TAM. In that case, they must be carefully selected because they can affect, in addition to usefulness and ease of use, the acceptance and subsequent continued use of a technology (Chang et al., 2013).

Adapting to the context of this dissertation, it is also worth considering that Enjoyment is an essential factor for TAM (Dabholkar, 1994; Dabholkar & Bagozzi, 2002). In addition, Ease of Use and Enjoyment were considered crucial factors for technology-based self-service technologies.

2.6. Enjoyment

One's emotions and feelings influence behaviors and motivations (Chuah & Yu, 2021). Therefore, emotions are essential in building communication between a robot and a person, as it facilitates the relationship. Furthermore, this makes it easier for customers to trust AI services (Chuah & Yu, 2021; Rincon et al., 2019).

Enjoyment, in this context, is related to the customer's state of mind when using an AI service. This state of mind is related to increased concentration, more significant curiosity, and more pleasure triggered by using an AI system (Chang et al., 2013). Therefore, the concept of Enjoyment, applied to the AI context, is related to the pleasure and satisfaction one has in using an AI system (Lu et al., 2019; Song & Kim, 2021).

Chang et al. (2013) state that if the AI service is more pleasurable for the customer, he tends to do his task more effectively and efficiently, bringing more advantages to the customer. If using an IA service is an enjoyable experience, that is, an experience that creates fun and happiness, it may increase the likelihood of regular use of the technology (Ashfaq et al., 2020; Song & Kim, 2021; Song & Kim, 2022).

Thus, Enjoyment is expected to positively affect Trust, Need for Human Interaction, and Convenience:

H1a. Enjoyment has a positive effect on Trust.

H1b. Enjoyment has a positive effect on Need for Human Interaction.

H1c. Enjoyment has a positive effect on Convenience.

2.7. Ease of use

Ease of Use is one of the main determinants of the TAM model and, consequently, a critical factor in the acceptance of a technology (Davis et al., 1989). The ease of use is a factor that brings together the functional component of these services and the utility. Therefore, it is critical factor for accepting these services since it meets what customers want (Lu et al., 2019; Song & Kim, 2021). Ease of use can be defined as the extent to which a person believes using a particular technology is effortless (Davis et al., 1989). These technologies, having the power to interact with consumers, speed up the processes, not requiring demanding learning processes (Lu et al., 2019).

Thus, based on the TAM model, it is believed that the intention to interact with these AI systems will increase if it is easy to learn how to use these services, the process of using them is also easier and, therefore, the customer does not have to make an increased effort, as well as relevant technological skills (Lu et al., 2019; Song & Kim, 2021). Davis et al. (1989) also conclude that improving Ease of Use would reduce the effort devoted to a particular technological system. However, it will allow the customer to perform the same task with less effort and time.

Thus, the following hypotheses were proposed:

H2a. Ease of Use has a positive effect on Trust.

H2b. Ease of Use has a positive effect on Need for Human Interaction.

H2c. Ease of Use has a positive effect on Convenience.

2.8. Service quality

The concept of service quality was created apart from the expectation-disconformity theory, and several researchers have used it to measure service quality (Collier & Bienstock, 2006). In the most conventional sense, the quality of a service is based on the difference between the service customers expect and how they perceive the service they have been provided (Parasuraman et al., 1994). The model proposed by (Grönroos, 1984) emphasizes two factors that affect service quality: functional quality, which refers to the consumer's experience when using a service, and technical quality, which refers to the result obtained after using a service (Grönroos, 1984) Thus, these two factors influence service quality (Choi et al., 2004).

Service Quality is measured in 5 dimensions: Tangibles, Responsiveness, Reliability, Empathy, and Assurance (Berry et al., 1988; Parasuraman, 2000). Tangibles refer, in this context, to the appearance of the entities that represent a service. Reliability relates to delivering the service a brand commits to reliably and accurately to the customer. Responsiveness refers to the ability to help customers assertively and quickly. To build customer trust and confidence, assurance is related to courteous knowledge and expertise. Finally, empathy refers to giving individualized customer service and taking care of him according to his needs (Li & Lai, 2021).

It is essential to keep in mind that there are customers who value different dimensions of service quality. Thus, consumers' evaluation of the quality of AI systems is still not the best since it is not yet following their expectations, considering that the assurance and reliability dimensions are the most valued (Chiang & Trimi, 2020).

The ability to collect customer data is one factor that increases the quality of an AI service a brand provides (Ameen et al., 2021). Thus, to ensure that consumers make informed decisions, it is necessary to ensure that AI services can obtain customer information, e.g., media, preferences, and old pieces they have purchased and be able to match this data with existing inventory (Song & Kim, 2022).

While many researchers are looking at service quality research, there remains a gap in research that addresses consumer response to services delivered by AI technologies, as they differ significantly from services provided in a traditional way, which is based on interpersonal relationships (Prentice et al., 2020).

According to Song & Kim (2022), consumers need to be sure that AI services can help them make correct and informed decisions. Thus, brands need to ensure that these services combine certain features that make customers perceive them as above their expectations. Thus, AI systems must be responsive, helpful, and courteous, increasing the customer's confidence both in the service they enjoy and in the brand itself (Wang & Lin, 2017). Thus, the following hypotheses were formulated:

H3a. Service Quality has a positive effect on Trust.

H3b. Service Quality has a positive effect on Need for Human Interaction.

H3c. Service Quality has a positive effect on Convenience.

2.9. Trust

Trust is a multidimensional concept since it can be framed in several aspects (Corritore et al., 2003). In the conventional sense, trust is based on a person acting with another party if the latter will perform according to his expectations (Deutsch, 1958). It is possible to include the risk factor in this definition since trust is only needed if the situation is risky and not secure for the customer (Corritore et al., 2003; Mayer et al., 1995). To add to this, expectation and vulnerability aspects are included (Deutsch, 1958) since the consumer assumes that the other party will not exploit his vulnerabilities either, since they will be exposed (Corritore et al., 2003; Mayer et al., 1995).

It can be stated that trust is crucial in all the connections that the consumer establishes, whether with something or with someone, thus including technology (Li et al., 2008; Siau et al., 2004; Siau & Wang, 2018). However, trust in AI services becomes a more complex process than trust in other technologies since the trust that will be established will be between the customer and the technology itself, but also with the brand that is providing that service, and these two trust processes will influence each other (Hengstler et al., 2016; Siau & Wang, 2018).

Although trust is a gradual process, the first impression someone has of something or someone will tend to influence the established relationship (McKnight et al., 1998). Adapting to the AI context, trust is established, in this type of system, by the first impression that the consumer will have, which is the initial formation, but also as the continuous process that comes from there (Li et al., 2008; Siau et al., 2004).

"Trust is crucial in the development and acceptance of AI." (Siau & Wang, 2018, p.52). The characteristics of each person and the environment in which they are inserted (task characteristics, culture, and institutional factors) will influence the trust they will have in IA systems. Given that AI is evolving and its presence is increasing, it is necessary to remember that these have features that no other technology has (Siau & Wang, 2018). Thus, brands must consider some factors that have made the trust process easier. The ability of a service to be able to create trust in a consumer is a crucial point for the success of that service (Hengstler et al., 2016). The more an AI service looks like a human, the more trust will tend to grow upon its first impression. The more transparent such a service is, i.e., the easier it is to understand how it works, the more trust will grow (Siau & Wang, 2018). Passing the first impression will require these systems to have specific characteristics for customers to move to the adoption stage. These systems must be easy to use and communicate well (Siau & Wang, 2018). In addition, factors such as courtesy, attention, or responsiveness facilitated the trust process (Wang & Lin, 2017). Privacy is also a decisive factor. Privacy becomes significant as consumers want control over what data they provide to brands and what their data will be used for by those brands (Wang et al., 2020).

Trust is a factor that can influence the entire customer experience since trust also increases the likelihood that consumers will share their data with an AI system (Ameen et al., 2021; Song & Kim, 2021). Furthermore, since these systems are based on collecting, analyzing, interpreting, and transmitting this data, the more data these systems have, the better the customer experience (Song & Kim, 2021). Thus, it is expected that Trust positively affects Intention to Use:

H4. Trust has a positive effect on Intention to Use.

2.10. Need for human interaction

The need for human contact is significant to many consumers (Dabholkar & Bagozzi, 2002). The Need for Human Interaction is the importance given to interaction with a service employee, by customers, in the context of providing a service (Dabholkar, 1996). In the technological environment, NFHI is considered a crucial variable to understanding the needs of consumers and, accordingly, how possible AI services are in their daily lives (Ashfaq et al., 2020).

Consequently, to study AI services, it is necessary to remember that customers must interact with the service employee (Dabholkar, 1996). Thus, for AI services to become more attractive to customers with a high Need for Human Interaction and who are the least likely to choose these services, the positive characteristics of these services must be reinforced to compensate for the lack of human interaction (Dabholkar & Bagozzi, 2002). For example, Dabholkar and Bagozzi (2002) argue that if services are more fun, reliable, and easier to use, they become more attractive to consumers. However, this is not the case for consumers with a low Need for Interaction since they will more easily seek these AI services (Dabholkar & Bagozzi, 2002).

Customers tend to believe that human contact will enhance their experience since humans have capabilities that consumers believe AI services do not, such as seeing and understanding the customer's emotions (Ashfaq et al., 2020; Song et al., 2022). Customers believe that because of their lack of emotional perception, AI services cannot deal with difficult situations or solve problems (Song et al., 2022) and can also not provide personalized customer service that takes their emotions into account (Osawa et al., 2017).

AI services would be more advantageous if they worked with human service employees for a better customer experience, acting as a supplement rather than a replacement (Ashfaq et al., 2020). In other words, a consumer experience must be created that balances AI services and human interaction (Ameen et al., 2021).

H5. Need for Human Interaction has a positive effect on Intention to Use.

2.11. Convenience

Convenience is an essential factor that leads consumers to accept and use new technologies or avoid them (Lu et al., 2019), thus becoming a key advantage of AI services (Ameen et al., 2021). This way, it is necessary to consider convenience as an essential factor to understand the consumer better and create a good strategy for adopting these AI services (Ameen et al., 2021).

Convenience in service is related to the ability to perform a task in the least amount of time and effort (Ameen et al., 2021). In addition, it is also the benefit that a customer can get from using a particular IA system in terms of automating processes and speeding them up, improving the way an action is performed (Chang et al., 2013). Consequently, it will be associated with the usefulness of using a given system (Malodia et al., 2022). Thus, adapted to the IA context, Convenience is related to advantages concerning time, space, and use process when using an IA service (Chang et al., 2013).

For these reasons, AI services can be attractive to customers because they can save time since the process is more autonomous, not having to wait for the store staff (Ameen et al., 2021). In addition, it helps the customer's entire buying process because it can give him all the information he needs and help him at every touchpoint so that customer makes the best and most informed purchase possible (Ameen et al., 2021). Furthermore, previous studies reveal that the more a service is perceived as convenient, the better its view is and the higher the intention to use it (Chang et al., 2013).Thus, Convenience is expected to influence Intention to Use positively:

H6. Convenience has a positive effect on Intention to Use.

2.12. Intention to use and Purchase Intention

Intention to Use refers to the customer's willingness to adopt a new technological system (Venkatesh et al., 2012). It can also be defined as “a measure of the strength of one's intention to perform a specified behavior” (Davis et al., 1989, p. 984). Based on TAM, the actual use of a given technology is determined essentially by the intention to use that technology (Davis et al., 1989). Adapting to the context under study, Intention to Use refers to the willingness of a customer to use a particular AI service to purchase their luxury product (Ng et al., 2022). This variable is considered a crucial factor in predicting Purchase Intention (Ng et al., 2022; Venkatesh et al., 2012).

Purchase Intention is the measurement that indicates how much a consumer is willing to buy a product (Pavlou, 2003), i.e., it is related to the willingness and orientation that a consumer must buy a product (Bhagat et al., 2022). Therefore, it is necessary to explore the issue of Purchase Intention since intention will positively impact the purchase of a product (Hung et al., 2011). Thus, Purchase Intention, in the luxury context, can be measured through customers' perceptions of luxury brands and through social influence (Hung et al., 2011). As mentioned earlier in this dissertation, customer perception is studied along three dimensions: symbolic, experiential, and functional, which are relative to the characteristics of luxury brands. Furthermore, social influence impacts the consumer since this consumer profile wants to convey their status (Tsai, 2005). Thus, the following hypothesis is proposed:

H7: Intention to Use positively affects Purchase Intention

2.13. Research Conceptual Model

As Artificial Intelligence is the future, many researchers have studied this concept and applied it to various scenarios and circumstances. "TAM has been widely used to assess consumers' acceptance of technology-related applications in the fashion industry" (Liang et al., 2020). Thus, the proposed model was built based on TAM, adding other variables studied by other researchers. While necessary for predicting the acceptance of other technologies, usefulness does not become relevant for the AI services studied in this dissertation, according to Dabholkar & Bagozzi (2002). Therefore, the scholars in question propose adopting another variable - performance - which has been adapted to Service Quality. These three variables help predict Intention to Use (Dabholkar & Bagozzi, 2002).

The conceptual model was built to study how the customer will perceive the robots/virtual assistants and the possibility of adopting these services in the purchase processes in the Luxury Fashion sector.

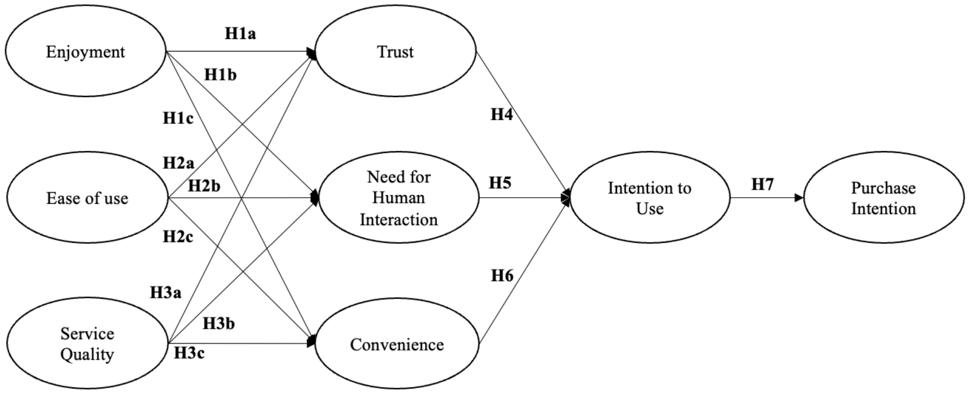


Figure 2.1.: Research Conceptual Model
Source: Own elaboration

3. Methodology

This thesis aims to understand better how consumers will relate to Artificial Intelligence elements, such as robots and virtual assistants, in the buying process and how this will influence and alter their Purchase Intention in luxury brands.

At the first moment, it sought to know more about the various sub-themes that make up this thesis through secondary data. This way, the information was primarily obtained through scientific articles from various authors. Additionally, some information was also collected from books, magazines and websites. Lastly, based on the literature review, a conceptual model was created, and hypotheses were formulated to conduct a study that would respond to the theme of this dissertation.

In order to develop the empirical study, a quantitative approach integrating primary data was adopted. Thus, a questionnaire was conducted in order to obtain the necessary data. The constructs that constitute the conceptual model were measured in this questionnaire through their respective items, adapted from previous research. This study thus consists of an empirical investigation, where conclusions will later be drawn through data analysis using SPSS

3.1. Construct Measurement

This questionnaire was constructed based on the eight constructs: Service Quality, Enjoyment, Ease of Use, Trust, Perceived Convenience, Need for Human Interaction, Intention to use and Purchase Intention.

All the constructs mentioned above and their respective items were measured using scales previously established and validated in previous research, namely on articles related to each construct. In order to adapt the constructs to the research conducted in this thesis, the items had to be adapted to be able to answer the research hypotheses developed.

The independent variables are Service Quality, Enjoyment and Ease of Use. These constructs were measured based on the scale proposed by Song and Kim (2021). Service Quality comprises four items, Enjoyment comprises three items and, lastly, Ease of use is constituted by four items. The previously mentioned constructs influence Trust (Song & Kim, 2021), which is composed of three items, Convenience (Malodia et al., 2022), which comprises five items and Need for Human Interaction (Song et al., 2022), which comprises four items.

Intention to use is measured based on the scale developed by Hsieh and Lee (2021) and is composed of three items and Purchase Intention (Liang et al., 2020) is evaluated by three items.

All items were measured using a 7-point Likert agreement scale, where 1 = Strongly Disagree, 2 = Disagree, 3 = Partly Disagree, 4 = Neither Agree or Disagree, 5 = Partly Agree, 6 = Agree, 7 = Strongly Agree. The scale used to measure the Purchase Intention variable was also a 7-point Likert scale, but in this variable, it was a probability scale from 1 (Very Low) to 7 (Very High).

Table 3.1.: Source of Constructs

Constructs	Source
Enjoyment	(Song & Kim, 2021)
Ease of Use	
Service Quality	
Trust	(Song & Kim, 2021)
Need for Human Interaction	(Song et al., 2022)
Convenience	(Malodia et al., 2021)
Intention to Use	(Hsieh & Lee, 2021)
Purchase Intention	(Liang et al., 2020)

Source: Own elaboration

3.2. Questionnaire design

The survey was developed on the Qualtrics platform. It was developed in Portuguese and was later translated using the automatic translation tool of the Qualtrics platform. Before releasing the final version of the survey, a pre-test was conducted to detect possible errors in the questionnaire and possible bias in the questions. This pre-test also helps to improve the readability of the entire questionnaire. This pre-test was performed by 12 respondents who detected some minor issues and proposed some changes. After the different suggestions were analyzed, some changes were made to release an adapted and improved survey version. After the previously mentioned pre-test was conducted and changes were made, the questionnaire was distributed using different online platforms, namely, social networks such as Facebook, WhatsApp, and Instagram. The sample consisted of 341 respondents and was selected through non-probability convenience sampling with a snowball effect. The questionnaire was publicly available from July 23, 2022, to August 11, 2022.

The questionnaire consists of 6 sections. Starting with the 3rd section, 32 questions follow where the respondents must answer with their degree of agreement with those questions. It should be emphasized that all questions had to be answered. The questionnaire begins with a brief explanation of the purpose of this master's thesis. The following section was intended to briefly explain what service robots are and virtual assistants in the fashion context. The explanations were aided with illustrative images.

The first block containing questions (section 3, respectively) was related to the factors of Service quality, Enjoyment, and Ease of Use which intend to measure the consumer's self-interest in these new technologies. The following section (section 4) focuses on the variables Trust, Convenience, and Need for Human Interaction. The subsequent section (5) focuses on the variables Intention to Use and Purchase Intention and is related to the consumer's approach towards these new technologies and how willing respondents are to purchase a luxury product. All these questions were measured on a Likert scale from 1 to 7 where 1 means "Strongly Disagree" and 7 means "Strongly Agree". The last question of those mentioned above was also answered similarly with the change that it was a probability scale (1= very low and 7= very high).

The last block of questions concerns the respondent's socio-demographic information, namely gender, age and city where he/she lives. Regarding these questions were presented through multiple choice questions.

3.3. Respondent Profile

In order to facilitate data interpretation, respondents were presented with socio-demographic questions - age, gender, and country of residence.

In total, 341 people participated in this study. To measure the gender of the respondents, a multiple-choice question was presented, with three options - Female, Male, and Other. Thus, it can be observed (Figure 3.1.) that most respondents are female, which corresponds to 79.18% (270 respondents), while male respondents correspond to a percentage of 20.53% (70 respondents). Only one respondent chose the option "other", representing a percentage of only 0.29%.

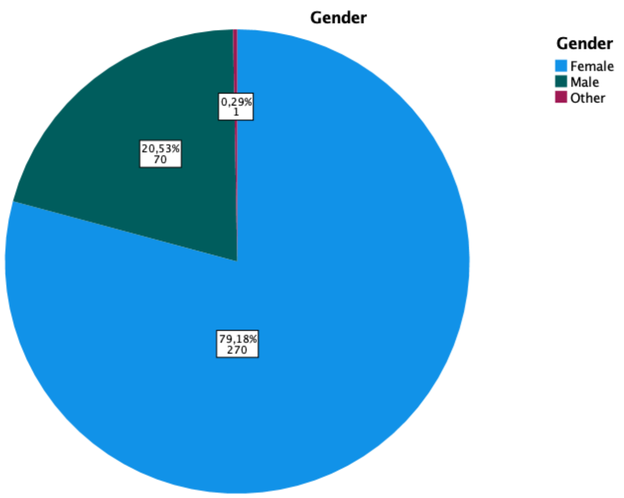


Figure 3.1.: Pie Chart for Gender
Source: Own elaboration using SPSS

Respondents were asked to choose their age group in six multiple-choice questions. Thus (Figure 3.2), most respondents are between 45 and 54 years old (44,25%). This is followed by the percentage of respondents aged 55 to 64, corresponding to 23.17%. The age group with the third highest percentage is respondents between the ages of 35 and 44. This is followed by 9,09% of people aged 18-24, 5,57 between 25-34 and only 3,52% who are more than 65 years old.

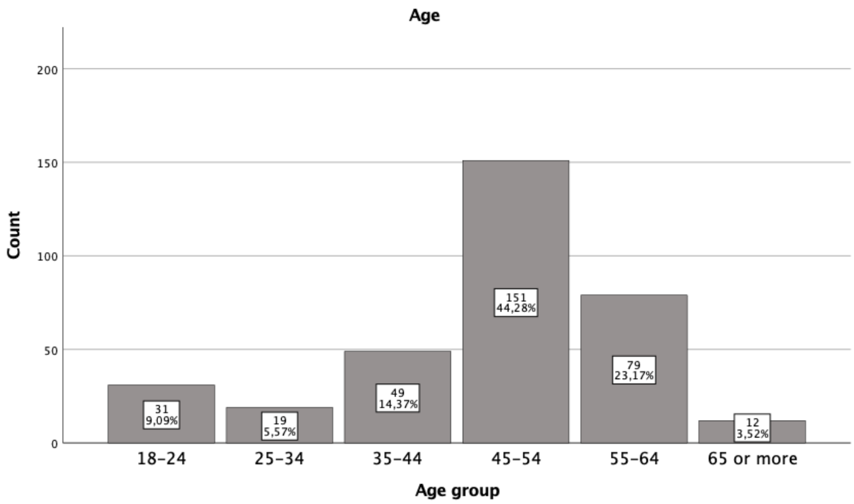


Figure 3.2.: Distribution of Age
Source: Own elaboration using SPSS

Regarding the socio-demographic variables, the last one analyzed was the country of residence (Figure 3.3.). Thus, it can be observed that most respondents live in Portugal (99.41%), except for one person who lives in Canada (0.29%) and another who lives in Switzerland (0.29%).

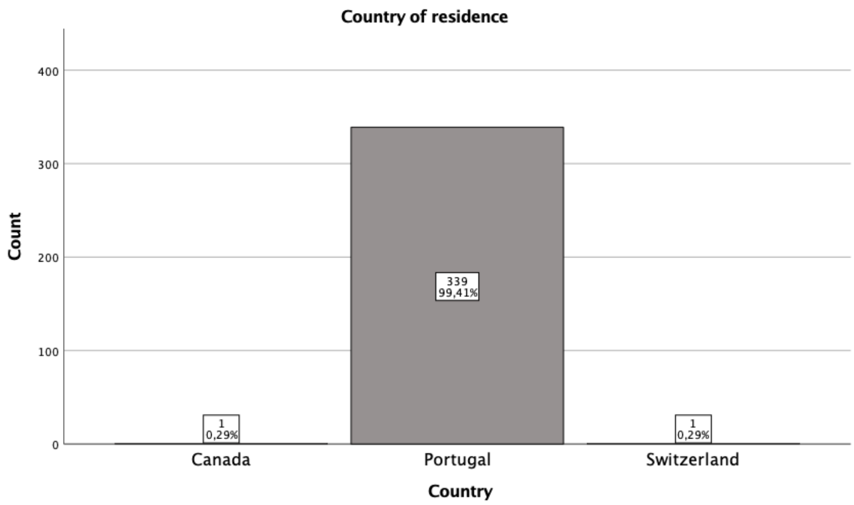


Figure 3.3.: Distribution of Country of Residence
Source: Own elaboration using SPSS

4. Results

4.1. Descriptive statistics

In this chapter, a descriptive analysis of all variables that make up the research model was performed using SPSS Statistics 27. Thus, the mean and standard deviation were calculated for all items comprising the abovementioned variables. It should be noted that the maximum and minimum values for each item have also been indicated. The constructs were calculated by computing a new variable based on the average of the items that integrate it.

4.1.1. Enjoyment (E)

The construct Enjoyment consists of 3 items. Table 4.1 presents the descriptive analysis of the corresponding items, as well as of the construct. The highest mean and standard deviation item is E1 – “I would feel relaxed when talking to robots/virtual assistants.”.

The construct Enjoyment (E) was obtained by computing the mean of E1, E2, and E3, as mentioned earlier. Thus, it is observable that the mean of Enjoyment is 3,8710 and the standard deviation is 1,78784. Since the mean is lower than the middle value of the 7-point Likert scale, the respondents consider that they would not enjoy interacting with robots.

Table 4.1.: Descriptive Statistics for Enjoyment

		Minimum	Maximum	Mean	Std. Deviation
E1	I would feel relaxed when talking to robots/virtual assistants	1	7	4,14	1,942
E2	I would appreciate interaction with robots/virtual assistants	1	7	3,84	1,872
E3	I would feel satisfied having a conversation with robots/virtual assistants.	1	7	3,63	1,886
E	**Enjoyment**	**1**	**7**	**3,8710**	**1,78784**

Source: Own elaboration using data obtained through SPSS

4.1.2. Ease of Use (EOU)

Ease of Use comprises four items (EOU1, EOU2, EOU3 and EOU4). The mean, standard deviation, and maximum and minimum values for each item are presented in Table 4. 2. As shown in the table, item EOU1 – “Learning to use a robot/virtual assistant would be easy” – has the highest mean. The mean of all items is positive. The item with the highest standard deviation is EOU3 – “The use of a robot/virtual assistant would be clear and understandable”. This value means that the answers to this item are more distributed around the average than compared to the other items.

The construct Ease of Use was created by computing the means of each item. Analyzing the table, the mean of EOU is 4,5293 and the standard deviation is 1,43238. Since the scale used was a 7-point Likert scale, and the mean is above the middle value of this scale, it is possible to state that respondents tend to believe that it will be easy to use a robot/virtual assistant. However, this evidence is not very significant.

Table 4.2.: Descriptive Statistics of Ease of Use

		Minimum	Maximum	Mean	Std. Deviation
EOU1	Learning to use a robot/virtual assistant would be easy	1	7	4,70	1,587
EOU2	It would be easy to become skilled at using a robot/virtual assistant	1	7	4,64	1,583
EOU3	The use of a robot/virtual assistant would be clear and understandable	1	7	4,31	1,591
EOU4	A robot/virtual assistant would be easy to use	1	7	4,47	1,529
EOU	**Ease of use**	**1**	**7**	**4,5293**	**1,43238**

Source: Own elaboration using data obtained through SPSS

4.1.3. Service Quality (SQ)

Service quality was evaluated through 4 items (SQ1, SQ2, SQ3 and SQ4). Table 4.3. lists the values of the mean, standard deviation, maximum and minimum. The variable Service quality was calculated using the mean of the items composing this construct.

Item SQ4 – “I believe that the services provided by the robot/virtual assistant would meet my expectations about what I consider to be good service” - has the highest standard deviation (σ=1.872) and SQ1 – “My view on the services that a robot/virtual assistant can provide is very good” - has the highest mean ($\bar{x}$=3,95). All questions have a mean value below the middle value of the 7-point Likert scale, so the variable SQ presents a mean of 3.8109 (value below the average value of the scale), which indicates that respondents do not consider that this type of service would not have the desired quality, or that they perceive this service as being below their expectations.

Table 4.3.: Descriptive Statistics of Service Quality

		Minimum	Maximum	Mean	Std. Deviation
SQ1	My view on the services that a robot/virtual assistant can provide is very good	1	7	3,95	1,824

SQ2	Overall, I would be satisfied with the services provided by a robot/virtual assistant	1	7	3,88	1,805
SQ3	Overall, a robot/virtual assistant would help to elevate the quality of service to excellence	1	7	3,76	1,838
SQ4	I believe that the services provided by the robot/virtual assistant would meet my expectations about what I consider to be good service	1	7	3,65	1,872
SQ	**Service Quality**	**1**	**7**	**3,8109**	**1,70341**

Source: Own elaboration using data obtained through SPSS

4.1.4. Trust (T)

Trust is composed of 3 items (T1, T2 and T3). The mean, standard deviation, and maximum and minimum values for each item are presented in Table 4. 4..

Thus, the item with the highest mean is item T2 - " A robot/virtual assistant seems to me to be credible” - while the one with the highest standard deviation is T3 – “Advice from a robot/virtual assistant seems to me to be reliable”. As with the previous variable, the construct Trust (T) was obtained by computing the mean of T1, T2 and T3. The mean of the construct Trust is 4,0489 and the standard deviation is 1,53677. Therefore, it can be concluded that, since the mean is above the middle value of the 7-point Likert scale, respondents tend, very slightly, to trust robots/virtual assistants.

Table 4.4.: Descriptive Statistics of Trust

		Minimum	Maximum	Mean	Std. Deviation
T1	A robot/virtual assistant seems to me to be reliable	1	7	4,08	1,646
T2	A robot/virtual assistant seems to me to be credible	1	7	4,13	1,619
T3	Advice from a robot/virtual assistant seems to me to be reliable	1	7	3,94	1,691
T	**Trust**	**1**	**7**	**4,0489**	**1,53677**

Source: Own elaboration using data obtained through SPSS

4.1.5. Need for Human Interaction (NFHI)

Need for Human Interaction is composed of 4 items (NFHI1, NFHI2, NFHI3 and NFHI4). The mean, standard deviation, and maximum and minimum values for each item are presented in Table 4. 5..

The items have significantly higher means compared to the other variables. The item with the highest mean is NFHI1- “Human contact makes the buying process more pleasant for me” - where the mean is 5,77. The item NFHI4 – “Interacting with a robot/virtual assistant would bother me more than talking to a store assistant” - has a standard deviation of 1,903. This standard deviation is higher than that of the other items, which means that in this question, the respondents' answers are more distributed around the mean than the other items.

The construct NFHI was obtained by computing the mean of NFHI1, NFHI2, NFHI3 and NFHI4. As a result, the mean of NFHI is 5,5169 and the standard deviation is 1.48407. This means that respondents consider human interaction in a buying process necessary.

Table 4.5.: Descriptive Statistics of Need for Human Interaction

		Minimum	Maximum	Mean	Std. Deviation
NFHI1	Human contact makes the buying process more pleasant for me	1	7	5,77	1,605
NFHI2	It is important for me to have personalized service from the store assistant	1	7	5,63	1,623
NFHI3	I like to communicate with a shop assistant	1	7	5,64	1,625
NFHI4	Interacting with a robot/virtual assistant would bother me more than talking to a store assistant	1	7	5,02	1,903
NFHI	**Need For Human Interaction**	**1**	**7**	**5,5169**	**1,48407**

Source: Own elaboration using data obtained through SPSS

4.1.6. Convenience (C)

Convenience was evaluated through 5 items (C1, C2, C3, C4 and C5). Table 4.6. lists the values of the mean, standard deviation, maximum and minimum. The variable Convenience was calculated using the mean of the items that evaluate this construct.

Item C5 – “Interacting with a robot/virtual assistant would be easy and understandable” - has the highest mean ($\bar{x} = 4{,}16$). Item C4 – “I like the ability of a robot/virtual assistant to save me time and effort throughout the purchase process” - has a standard deviation of 1,783, which is the highest.

It is observable that the mean of Convenience is 3,8035 and the standard deviation is 1,39275. Since the mean is lower than the middle value of the 7-point Likert scale, the respondents are neutral or even slightly disagree that it is not convenient for them to use a robot/virtual assistant.

Table 4.6.: Descriptive Statistics of Convenience

		Minimum	Maximum	Mean	Std. Deviation
C1	To help me with the purchase process, it would be more convenient for me to interact with a robot/virtual assistant	1	7	3,21	1,719
C2	Using a robot/virtual assistant would allow me to multitask	1	7	3,75	1,676
C3	I could automate the entire purchase process using a robot/virtual assistant	1	7	4,04	1,584
C4	I like the ability of a robot/virtual assistant to save me time and effort throughout the purchase process	1	7	3,86	1,783
C5	Interacting with a robot/virtual assistant would be easy and understandable	1	7	4,16	1,633
C	**Convenience**	**1**	**7**	**3,8035**	**1,39275**

Source: Own elaboration using data obtained through SPSS

4.1.7. Intention to Use (ITU)

Intention to Use is composed of 3 items (ITU1, ITU2 and ITU3). The mean, standard deviation, and maximum and minimum values for each item are presented in Table 4. 7.. Thus, the item with the highest mean ($\bar{x}$ =4,23) is item ITU1 - " I will interact with a robot/virtual assistant on a regular basis in the future" - while the one with the highest standard deviation($\sigma = 1{,}698$)is ITU3 – "I will recommend to others the use of a robot/virtual assistant".

As with the previous variable, the construct Intention to Use was obtained by computing the mean of ITU1, ITU2 and ITU3. The mean of the construct ITU is 4,0078 and the standard deviation is 1,56658. Therefore, it can be concluded that respondents tend to be neutral regarding the possibility of using a robot/virtual assistant in the future.

Table 4.7.: Descriptive Statistics of Intention to Use

		Minimum	Maximum	Mean	Std. Deviation
ITU1	I will interact with a robot/virtual assistant on a regular basis in the future	1	7	4,23	1,697
ITU2	I will interact with a robot/virtual assistant often in the future	1	7	4,17	1,690
ITU3	I will recommend to others the use of a robot/virtual assistant	1	7	3,62	1,698
ITU	**Intention To Use**	**1**	**7**	**4,0078**	**1,56658**

Source: Own elaboration using data obtained through SPSS

4.1.8. Purchase Intention (PI)

Purchase Intention comprises three items (PI1, PI2, and PI3). The mean, standard deviation, and maximum and minimum values for each item are presented in Table 4.8.. Instead of being rated by an agreement scale like the previous constructs, these items were ordered by a 7-point Likert probability scale.

Thus, the item with the highest mean ($\bar{x}$ = 3,96) and highest standard deviation (σ= 1,819) is item PI1 - "My desire to buy a luxury product.”.

The construct Purchase Intention was obtained by computing the mean of PI1, PI2 and PI3. As a result, the mean of the construct PI is 3,61688 and the standard deviation is 1,59896. Consequently, it can be concluded that respondents tend to be neutral or even slightly unlikely to purchase a luxury product.

Table 4.8.: Descriptive Statistics of Purchase Intention

		Minimum	Maximum	Mean	Std. Deviation
PI1	My desire to buy a luxury product	1	7	3,96	1,819
PI2	The likelihood that I will consider buying a luxury product	1	7	3,59	1,734
PI3	The probability that I will buy a luxury product	1	7	3,30	1,730
PI	**Purchase Intention**	**1**	**7**	**3,6168**	**1,59896**

Source: Own elaboration using data obtained through SPSS

4.2. Explanatory Data Analysis

In this section, the following tests will be performed: reliability analysis, validity analysis, and multiple regression analysis using SPSS 27. Subsequently, the results will be analyzed and detailed.

4.2.1. Reliability and Validity Analysis

To evaluate the quality of the sample, a reliability test was conducted to assess the sample's reliability and validity. Thus, to determine reliability, Cronbach's alphas were calculated for all constructs using SPSS statistics 27. Cronbach's alpha measures the scale's internal consistency and can take a value between 0 and 1. The higher Cronbach's alpha, the higher the reliability. Furthermore, the more the items are correlated, the higher Cronbach's alpha will be. Thus, if the alpha value is below 5 it is not acceptable; if it is between 0.7 and 0.79, it is acceptable; if it is between 0.8 and 0.89, it is good, and equal to or above 0.9, it is excellent.

The results are shown in Table 4.9. All alphas are above 0.8, indicating very good to excellent values with high reliabilities and internal consistencies. Most of the values are above 0.9, which are excellent values. The variable with the highest Cronbach's Alpha is service quality (Cronbach's Alpha = 0.947) and the lowest is Convenience (Cronbach's Alpha = 0.886). The Cronbach's Alpha reliability test was also done for all items and gave a value above 0.9 (Cronbach's Alpha = 0.923), indicating a very high reliability value.

Table 4.9.: Reliability Analysis

Constructs	**Items**	***Cronbach's Alpha***
Enjoyment	E1 E2 E3	0,935
Ease of Use	EOU1 EOU2 EOU3 EOU4	0,931
Service quality	SQ1 SQ2 SQ3 SQ4	0,947
Trust	T1 T2 T3	0,922
Need for Human Interaction	NFHI1 NFHI2 NFHI3 NFHI4	0,899
Convenience	C1 C2 C3 C4 C5	0,886
Intention to Use	ITU1 ITU2 ITU3	0,915
Purchase Intention	PI1 PI2 PI3	0,893
All constructs		**0,923**

Source: Own elaboration using data obtained through SPSS

4.3. Multiple Regression Analysis

The following analysis is the multiple regression analysis, which aims to understand how the constructs that belong to the conceptual model presented in this dissertation relate to each other. Through multiple regression analysis, it is possible to understand the impact that one or more independent variables have on a dependent variable. Through this, it is possible to test the proposed conceptual model.

4.3.1. Assumption of the Multiple Regression

In order to proceed to multiple regression analysis, some requirements must be met according to the Gauß-Markov Theorem:

- Linearity of the Model
- Random sample
- Mean of the Residuals
- Exogeneity of the independent variables
- The constancy of the variances of the residuals across predicted values (homoskedasticity)
- Normally distributed error component
- Linear independence (no multicollinearity)
- Correlation of the Residual Terms

Linearity of the Model

The multiple regression model is the following:

$$\begin{aligned} &Purchase\ Intention \\ &\quad = \beta_0 + \beta_1 x\ Enjoyment + \beta_2 x\ Ease\ of\ Use \\ &\quad + \beta_3 x\ Service\ Quality + \beta_4 x\ Trust \\ &\quad + \beta_5 x\ Need\ for\ Human\ Interaction + \beta_6 x\ Convenience \\ &\quad + \beta_7 x\ Intention\ to\ Use \end{aligned} \tag{1}$$

The theoretical model assumes constructing linearity between independent and dependent variables, so the assumption holds.

Random Sample

One of the goals of this thesis is to be able to generalize the results to the population. To do this, it is necessary to ensure that the sample is random, which applies to this dissertation. Thus, the assumption holds.

Mean of The Residuals

For the mean of the fitted value to be the same as the mean of the observed value, the mean of the residuals must equal 0. Table 4.10 shows that the mean of the residuals is 0, so the assumption holds.

Table 4.10.: Mean of the Residuals

	Minimum	Maximum	Mean	Std. Deviation
Predicted Value	2,4566	4,7470	3,6168	0,45139
Residual	-3,61584	4,24150	0,00000	1,53392
Std. Predicted Value	-2,570	2,504	0,000	1,000
Std. Residual	-2,333	2,737	0,000	0,990

Source: Own elaboration using data obtained through SPSS

Exogeneity of the Independent Variables

One of the assumptions of multiple linear regression is that the independent variables cannot be related to the residuals (which are connected to the part that cannot be explained in the analysis). Thus, a Pearson Correlation analysis was conducted, as shown in Table 4.11.. Table 4.11. shows that all independent variables have a Pearson correlation equal to 0.000 with the residuals, which means that the variables present in Table 4.11. have no relationship with the residuals, so the assumption holds.

Table 4.11.: Correlations between Independent Variables and Residual Terms

	E	EOU	SQ	T	NFHI	C	ITU	Residuals
E	1	0,622	0,815	0,719	-0,604	0,701	0,664	0,000
EOU	0,622	1	0,676	0,633	-0,460	0,638	0,647	0,000
SQ	0,815	0,676	1	0,784	-0,600	0,822	0,786	0,000
T	0,719	0,633	0,784	1	-0,531	0,744	0,696	0,000
NFHI	-0,604	-0,460	-0,600	-0,531	1	-0,568	-0,547	0,000
C	0,701	0,638	0,822	0,744	-0,568	1	0,729	0,000
ITU	0,664	0,647	0,786	0,696	-0,547	0,729	1	0,000
U. Residuals	0,000	0,000	0,000	0,000	0,000	0,000	0,000	1

Source: Own elaboration using data obtained through SPSS

The constancy of the Residual Variance across predicted Values (Homoscedasticity)

Homoscedasticity refers to the condition that the variance of the residuals is constant. Thus, by observing Figure 4.1, the values do not appear to be evenly distributed around zero.

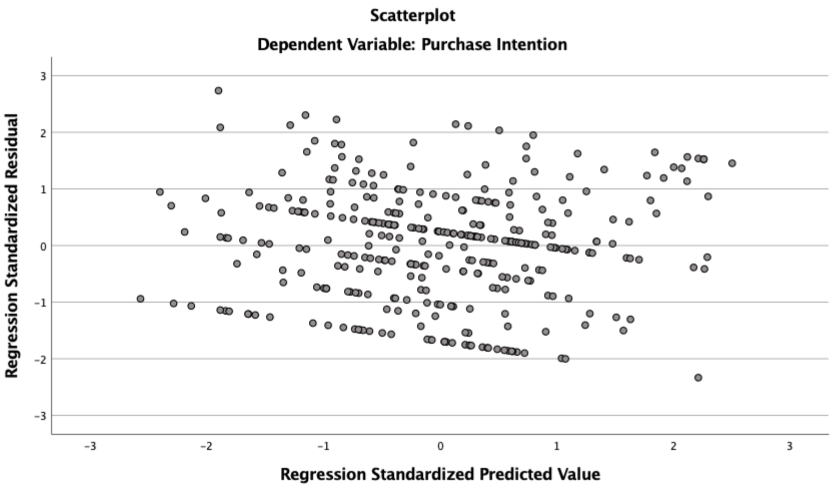


Figure 4.1.: Scatterplot – Distribution of the residuals
Source: Own elaboration using SPSS

Normality of the residuals

The first graph is a histogram of the standardized residuals, showing a normal distribution curve. Thus, this graph aims to verify a distribution's existence more visually. Looking at Figure 4.2., it can be concluded that the residuals do not correspond to a normal distribution. In addition, the mean value should be approximately 0, and the standard deviation should be around 1.

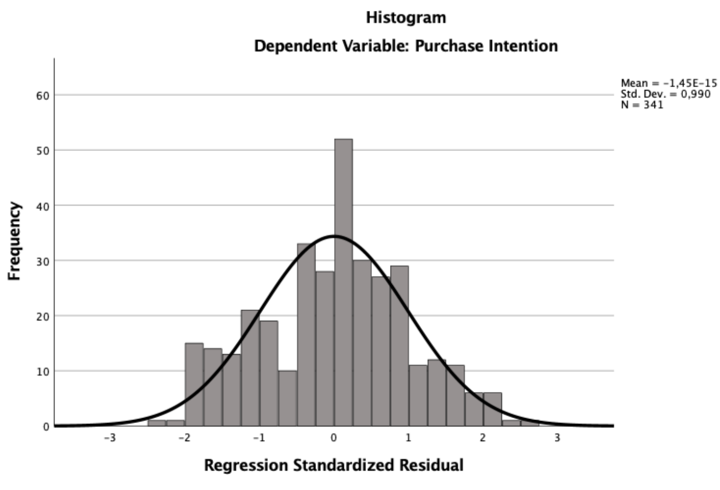


Figure 4.2.: Histogram – Distribution of the residuals
Source: Own elaboration using SPSS

The P-P plot illustrates the expected commutative probability versus the observed commutative probability. Thus, if a normal distribution exists, the data must lie precisely on the diagonal highlighted in the plot. By observing Figure 4.3., it is perceptible that there are data that are far from the diagonal, and this indicates that it is not a normal distribution, so the assumption fails.

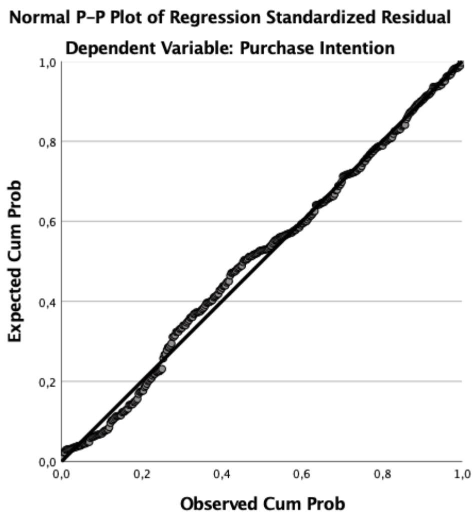


Figure 4.3.: P-Plot – Distribution of the residuals
Source: Own elaboration using SPSS

Linear Independence (No Multicollinearity)

Multicollinearity is, by definition, a strong linear relationship between the explanatory variables. However, it is necessary to analyze the Tolerance and VIF (Variance Inflator Factor) through the collinearity statistics to ensure no multicollinearity. For there to be no multicollinearity, the Tolerance value must be above 0.1, and the VIF value has to be below 10. By observing Table 4.12., it is possible to conclude that the Tolerance values are all above 0.1 and the VIF values are below 10. This way, it is possible to affirm that there is no multicollinearity, that is, there is no linear relationship between the explanatory variables, and, therefore, this assumption holds.

Table 4.12.: Collinearity Statistics

	Collinearity Statistics	
	Tolerance	VIF
Enjoyment	0,299	3,348
Ease of use	0,479	2,088
Service Quality	0,171	5,848
Trust	0,327	3,059
Need For Human Interaction	0,580	1,724

Convenience	0,281	3,561
Intention To Use	0,336	2,977

Source: Own elaboration using data obtained through SPSS

Correlation of the residual terms

To perform multiple regression analysis, there must be independent of residuals. Table 4.13 shows the SPSS analysis, the Durbin-Watson value is close to 2, indicating no correlation between the residuals. Thus, the assumption holds.

Table 4.13.: Model Summary of Dependent Variable: Purchase Intention

R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
.282[a]	0,080	0,060	1,54996	1,896

Source: Own elaboration using data obtained through SPSS

Multiple linear regression analysis only provides a sample characterization since not all assumptions are held. Thus, a generalization to the population cannot be made. Thus, the model cannot be used for inference.

4.3.2. Multiple Regression –Enjoyment, Ease of Use, and Service Quality as independent, Trust as dependent variables

From the constructs that make up the conceptual model, it is necessary to determine which variables occupy each role: the independent and dependent variables. To test hypotheses H1a), H2a), and H3a), that is, Enjoyment, Ease of Use and Service Quality positively affect Trust, it was defined that Enjoyment, Ease of Use and Service Quality are the independent variables and that Trust is the dependent variable.

Calculating the following adjusted regression equation from the regression coefficients is possible.

$$\boldsymbol{T} = 0{,}836 + 0{,}175\ x\ \boldsymbol{E} + 0{,}173\ x\ \boldsymbol{EOU} + 0{,}459\ x\ \boldsymbol{SQ} + \varepsilon \qquad (2)$$

Both Enjoyment (Sig =0,000 < 0,050), Ease of use (Sig =0,000 < 0,050), and Service Quality (Sig =0,000 < 0,050), show a linear correlation with trust, i.e., they are significant and, therefore, are suitable for prediction.

Thus, the three variables mentioned above are predictors of the Trust variable. Therefore, one can see that Enjoyment has a regression coefficient of 0,175 (SE=0,049); this means that when Enjoyment increases, Trust increases by 0.175. The same is true for Ease of Use, which has a regression coefficient of 0.173, meaning that for each increase in Ease of Use, Trust increases by 0.173 (SE=0,048). Finally, the Service Quality variable has the highest regression coefficient, which is 0.459 (SE=0,054). Therefore, as with the previous variables, each time Service Quality increases, Trust will increase by 0.459. It is also important to note that the 95% confidence interval of Enjoyment, Ease of Use, and Service Quality is greater than 0, which means that it contains only positive values, meaning that the effect of the independent variables is always positive.

Thus, hypotheses H1a), H2a), and H3a) are supported by the mentioned results, meaning that Enjoyment, Ease of Use, and Service Quality positively influence Trust.

Table 4.14: Coefficients of the Multiple Regression, Trust as Dependent Variable

		Unstandardized Coefficients			95,0% Confidence Interval for B	
		B	Std. Error	Sig.	Lower Bound	Upper Bound
Dependent Variable: **Trust**	(Constant)	0,836	0,165	0,000	0,511	1,161
	Enjoyment	0,175	0,049	0,000	0,079	0,271
	Ease of use	0,173	0,048	0,000	0,079	0,267
	Service Quality	0,459	0,054	0,000	0,353	0,566

Source: Own elaboration using data obtained through SPSS

4.3.3. Multiple Regression – Enjoyment, Ease of Use, and Service Quality as independent, Need for Human Interaction as dependent variables

To verify if Enjoyment, Ease of Use and Service Quality positively affect Need for Human Interaction (H1b), H2b) and H3b)), it was defined that Service Quality, Enjoyment, and Ease of Use are the independent variables and Need for Human Interaction is the dependent variable. Then, using the linear regression coefficients present in Table 4.15., it is possible to construct the linear regression equation:

$$\boldsymbol{NFHI} = 7{,}814 - 0{,}274\ x\ \boldsymbol{E} - 0{,}057\ x\ \boldsymbol{EOU} - 0{,}256\ x\ \boldsymbol{SQ} + \varepsilon \tag{3}$$

Both Enjoyment (Sig =0,000 < 0,050), and Service Quality (Sig =0,000 < 0,050), show a linear correlation with Need for Human Interaction, i.e., they are significant and, therefore, are suitable for prediction. The same is not valid for the Ease of Use variable, since Sig=0,340 > 0.050, which means that hypothesis H2b) is rejected.

Consequently, Enjoyment and Service Quality are predictors of Need for Human Interaction. However, if one looks at the regression coefficients, it is observable that they are negative, indicating that they negatively affect Need for Human Interaction. So, Enjoyment has a regression coefficient of -0,274 (SE=0,061); this means that when Enjoyment increases, Need for Human Interaction decreases by 0,274. The same is true for Service Quality, which has a regression coefficient of -0,256 (SE=0,068), lower than the previous one, meaning that each increase in Service Quality leads to a decrease of 0,256 in Purchase Intention. It is also important to note that the 95% confidence interval of Enjoyment and Service Quality is lower than 0, which means that it contains only negative values and, consequently, the effect that both Enjoyment and Service Quality have a consistently negative effect on Need for Human Interaction

Thus, no hypothesis is supported by the results since H2b) is rejected because Sig is higher than 0,05, and the values of the regression coefficients reject H1b) and H3b).

Table 4.15.: Coefficients of the Multiple Regression, Need for Human Interaction as Dependent Variable

		Unstandardized Coefficients			95,0% Confidence Interval for B	
		B	Std. Error	Sig.	Lower Bound	Upper Bound
Dependent Variable: **Need For Human Interaction**	(Constant)	7,814	0,208	0,000	7,405	8,223
	Enjoyment	-0,274	0,061	0,000	-0,395	-0,154
	Ease of use	-0,057	0,060	0,340	-0,176	0,061
	Service Quality	-0,256	0,068	0,000	-0,390	-0,121

Source: Own elaboration using data obtained through SPSS

4.3.4. Multiple Regression – Enjoyment, Ease of Use, and Service Quality as independent, Convenience as dependent variables

To verify if Enjoyment, Ease of Use and Service Quality positively affect Convenience (H1c), H2c) and H3c)), it was defined that Enjoyment, Ease of Use and Service Quality are the independent variables and that Convenience is the dependent variable. Thus, the regression equation is as follows, based on the regression coefficients in Table 4.16.:

$$\boldsymbol{C} = 0{,}882 + 0{,}049\ x\ \boldsymbol{E} +\ 0{,}140\ x\ \boldsymbol{EOU} + 0{,}551\ x\ \boldsymbol{SQ} +\ \varepsilon \qquad (4)$$

Both Ease of use (Sig =0,001 < 0,050), and Service Quality (Sig =0,000 < 0,050), show a linear correlation with Convenience, i.e., they are significant and, therefore, are suitable for prediction. The same is not valid for the Enjoyment variable, since Sig=0.241 > 0.050, which means that hypothesis H1c) is rejected.

Therefore, Ease of Use and Service Quality are predictors of the Convenience variable. Therefore, Ease of Use has a regression coefficient of 0,140 (SE=0,041); this means that when Ease of use increases, Convenience increases by 0,140. The same goes for Service Quality, which has a regression coefficient of 0,551 (SE=0,046), meaning that for each increase in Service Quality, Convenience increases by 0,551. By looking at the 95% confidence interval of Ease of Use, and Service Quality, it can be concluded that it is greater than 0, which means that it contains only positive values, meaning that the effect of the independent variables is permanently positive.

According to the results, hypotheses H2c) - *Ease of Use has a positive effect on Convenience* - and H3c) - *Service Quality has a positive effect on Convenience* - are supported. On the other hand, H1c) - *Enjoyment has a positive effect on Convenience.* - is rejected.

Table 4.16.: Coefficients of the Multiple Regression, Convenience as Dependent Variable

		Unstandardized Coefficients			95,0% Confidence Interval for B	
		B	Std. Error	Sig.	Lower Bound	Upper Bound
Dependent Variable: **Convenience**	(Constant)	0,882	0,141	0,000	0,606	1,158
	Enjoyment	0,049	0,041	0,241	-0,033	0,130
	Ease of use	0,140	0,041	0,001	0,060	0,219
	Service Quality	0,551	0,046	0,000	0,461	0,642

Source: Own elaboration using data obtained through SPSS

4.3.5. Multiple Regression – Trust, Need for Human Interaction, and Convenience as independent, Intention to Use as dependent variables

It is essential to understand how Trust, Need for Human Interaction, and Convenience affect Intention to Use. Therefore, to test hypotheses H4, H5, and H6, a linear regression analysis was performed where Trust, Need for Human Interaction, and Convenience are independent variables and Intention to Use is the dependent variable.

Thus, the regression equation is as follows, based on the regression coefficients in Table 4.17.:

$$ITU = 1{,}809 + 0{,}314\, x\, \boldsymbol{T} - 0{,}155\, x\, \boldsymbol{NFHI} + 0{,}468\, x\, \boldsymbol{C} + \varepsilon \quad (5)$$

Trust (Sig = 0,000 < 0,050), Need for Human Interaction (Sig = 0,001< 0,050) and Convenience (Sig = 0,000 < 0,050), show a linear correlation with Intention to Use, i.e., they are significant and, therefore, are suitable for prediction.

Consequently, the three variables mentioned above are predictors of Intention to Use. Therefore, Trust has a regression coefficient of 0,314 (SE=0,054); this means that when Trust increases, Intention to Use increases by 0,314. The same is true for Convenience, which has a regression coefficient of 0,468 (SE=0,061), meaning that for each increase in Convenience, Intention to Use increases by 0,468. It is also important to note that the 95% confidence interval of Trust and Convenience is greater than 0, which means that it contains only positive values, meaning that the effect of the independent variables is always positive.

As for the variable Need for Human Interaction, as said before, it is a predictor of Intention to Use. However, its effect on this is negative since the coefficient is – 0,155 (SE=0,045). Thus, it can be concluded that every time the Need for Human interaction increases, the Intention to Use decreases by 0.155. When looking at the 95% confidence interval of the Need for Human Interaction variable, the values are always negative, thus concluding that the effect of Need for Human Interaction on Intent to Use is always negative.

Thus, it can be concluded that the results support H4 and H6 are supported. However, the same is not valid for H5 since Need for Human Interaction, although it affects Intention to Use, it affects it negatively and not positively.

Table 4.17.: Coefficients of the Multiple Regression, Intention to Use as Dependent Variable

		Unstandardized Coefficients			95,0% Confidence Interval for B	
		B	Std. Error	Sig.	Lower Bound	Upper Bound
Dependent Variable: **Intention to Use**	(Constant)	1,809	0,398	0,000	1,026	2,593
	Trust	0,314	0,054	0,000	0,208	0,420
	Need For Human Interaction	-0,155	0,045	0,001	-0,244	-0,066
	Convenience	0,468	0,061	0,000	0,348	0,589

Source: Own elaboration using data obtained through SPSS

4.3.6. Linear Regression – Intention to Use as independent and Purchase Intention as dependent variables

To test the last proposed hypothesis, H7: *Intention to Use positively affects Purchase Intention*, it was defined that Intention to Use would be the independent variable and Purchase Intention would be the dependent variable. Using the linear regression coefficients present in Table 4.18., it is possible to construct the linear regression equation:

$$\boldsymbol{PI} = 2{,}919 + 0{,}174\ x\ \boldsymbol{ITU} + \varepsilon \tag{6}$$

Observing the table, the Sig. of Intention to Use is equal to 0,002, which is smaller than 0,050, meaning that Intention to Use is significant, i.e., that it has a linear correction with Purchase Intention and, consequently, is appropriate for prediction.

Intention to Use, being a predictor of Purchase Intention, has a regression coefficient of 0,174, which means that each increase in Intention to Use leads to an increase of 0,174 (SE=0,055) in Purchase Intention. By looking at the 95% confidence interval of Intention to Use, it can be concluded that it is greater than 0, which means that it contains only positive values, meaning that the effect of Intention to Use is constantly positive.

Thus, the results support H7, which means that Intention to Use positively affects Purchase Intention.

Table 4.18.: Coefficients of the Multiple Regression, Purchase Intention as Dependent Variable

		Unstandardized Coefficients			95,0% Confidence Interval for B	
		B	Std. Error	Sig.	Lower Bound	Upper Bound
Dependent Variable: **Purchase Intention**	(Constant)	2,919	0,235	0,000	2,456	3,381
	Intention To Use	0,174	0,055	0,002	0,067	0,282

Source: Own elaboration using data obtained through SPSS

The following Table summarizes all the hypotheses under study and which ones were validated.

Table 4.19.: Hypothesis and Validation

Hypothesis	***Validated?***
H1a. *Enjoyment has a positive effect on Trust.*	*Yes*
H1b. *Enjoyment has a positive effect on Need for Human Interaction.*	*No**
H1c. *Enjoyment has a positive effect on Convenience.*	*No*
H2a. *Ease of Use has a positive effect on Trust.*	*Yes*
H2b. *Ease of Use has a positive effect on Need for Human Interaction.*	*No*
H2c. *Ease of Use has a positive effect on Convenience.*	*Yes*
H3a. *Service Quality has a positive effect on Trust.*	*Yes*
H3b. *Service Quality has a negative effect on Need for Human Interaction.*	*No**
H3c. *Service Quality has a positive effect on Convenience.*	*Yes*
H4. *Trust has a positive effect on Intention to Use.*	*Yes*
H5. *Need for Human Interaction has a positive effect on Intention to Use.*	*No**
H6. *Convenience has a positive effect on Intention to Use.*	*Yes*
H7: *Intention to Use positively affects Purchase Intention*	*Yes*

Source: Own elaboration

* Has a negative effect

5. Conclusions and Implications

Artificial Intelligence is a reality and will change the paradigm in many sectors and can help businesses to improve their processes significantly (Davenport et al., 2020). Many brands, including Luxury brands, have already implemented systems with Artificial Intelligence in their business, such as Gucci, Hugo Boss, or Tommy Hilfiger (Deloitte, 2020).

Some researchers (e.g., Song & Kim, 2022) have already studied the likelihood of customers sharing their information with Robots or even accepting such services in stores, but this research is still limited. However, little research still addresses how well AI systems are accepted in physical stores by consumers and how this will impact Purchase Intention.

This section is intended to review the objectives of this research and, through this, summarize the results obtained in this dissertation. This will be done based on the conclusions drawn from the literature review and the results obtained through the empirical research. Thus, this chapter aims to compile the conclusions obtained regarding the increase in Purchase Intention through the variables implicit in the designed model: Enjoyment, Ease of Use, Service Quality, Trust, Need for Human Interaction, and Intent to Use. Thus, the relations obtained among the variables will be analyzed in detail. In this way, the theoretical contribution of the study will be provided, as well as the implications that these conclusions may have in the management.

5.1. Theoretical Contribution

This study refers to 79.18% of women, mostly between 45 and 64 years old, followed by 55-64 years old, and mostly living in Portugal.

The results show that customers tend to think using a Service incorporating AI will not be an enjoyable experience ($\bar{x}$ = 3,8710). However, the results show that Enjoyment affects Trust, a crucial point for adopting robots/virtual assistants. Furthermore, it is also evidenced that the more enjoyable an experience, the less the Need for Human Interaction. The results support what had been said by Chuah and Yu (2021), who evidenced that emotions are a relationship facilitator, in this case, between the customer and the robot/virtual assistant.

This study shows that there is still some reluctance about the quality of this kind of system ($\bar{x}$ =3,8109). The respondents' uncertainty regarding the service quality of an IA Service agrees with what was mentioned in the study by Chiang and Trimi (2020). However, it was realized that Service Quality becomes very impactful in increasing trust and Convenience and decreasing the Need for Interaction with store staff. This uncertainty may condition the Intention to Use an AI service to purchase a product.

This study also shows that respondents tend to find it easy to learn how to use these types of services and their subsequent use ($\bar{x}$ = 4,5293). Ease of use proved to be impactful in increasing Trust and convenience for the customer. Thus, what Davis et al. (1989) said is supported by this study since it will impact both Trust and Convenience (since it allows doing the same task with less effort and time), which positively influences the Intention to Use.

Trust becomes crucial in AI's acceptance and adoption process, as Siau and Wang (2018). Consequently, it also becomes essential for improving the entire customer experience, as it is present from the beginning to the end of the journey. As proposed, Enjoyment, Ease of Use, and Service Quality positively impact customer trust in each AI system. Thus, the results support what would have been said by Chuah & Yu (2021) and Rincon et al. (2019), who state that Enjoyment, a state related to emotions, is a facilitator for building a good relationship between the customer and AI systems, promoting Trust.

It should be noted that Service Quality is the factor that most strongly impacts trust, indicating that a service perceived as high quality creates a greater sense of trust on the part of the customer. Thus, these systems must ensure that they give the customer the possibility to make the most correct and informed decisions by combining excellent functional and design factors, as studied by Ameen et al. (2021).

A system can be considered convenient, from the customer's point of view, when it allows them to perform a particular task with the least possible time and effort (Ameen et al., 2021). This study supports that Ease of Use positively impacts convenience. This result is in line with what was proposed by Davis et al. (1989) when they stated that Ease of Use could decrease the effort with which the customer accomplishes a task.

Once again, Service Quality has the most significant impact on Convenience for the customer, i.e., the more a service is perceived as high quality, the more convenient it tends to be for the customer. Furthermore, by increasing the functional and technical quality (Grönroos, 1984) and ensuring that the five dimensions of service quality are ensured (Berry et al., 1988; Parasuraman, 2000), it offers customers benefits compared to the traditional buying process, namely in terms of better recommendation systems or creating a disruptive and innovative experience, besides allowing him to do everything he needs to buy a product in a single system with the certainty that he is making the right decision.

Contrary to what was proposed, Enjoyment was not proven to affect Convenience positively. Thus, this result does not support what is proposed by Chang et al. (2013), who state that if the process is more pleasurable for the customer, he tends to take more advantage of that process, such as doing a task more effectively and efficiently, saving time and effort. This may be related to convenience being interconnected with the most functional part of this service, not being connected to the emotional part of the established relationship.

Need for Human Interaction is a crucial variable in this study since, for most customers, human contact is a very relevant factor in the buying process because they believe that a person can offer another type of service that an AI service is not able to provide (Ashfaq et al., 2020; Song & Kim, 2022). The results show that Enjoyment and Service Quality affect the Need for Human Interaction. However, through the analysis of the results, it is concluded that these two variables have a negative impact on the Need for Human Interaction, which indicates that both a more enjoyable service and a higher quality decrease the customer's need to communicate with a store assistant. This result was expectable since all the variables mentioned are advantages for the customer. The Enjoyment provides a more pleasurable journey (Chang et al., 2013) which will most likely be a much more fun experience than what the customer is used to with a store assistant and the Service quality, being composed of features that provide an informed, accurate and effective response to the customer (Song & Kim, 2022) avoids having to resort to the store staff to require some help. Contrary to what was expected, Ease of Use is not a Predictor of Need for Human Interaction, which means that although a system may be easy to use, it does not mean that a customer will have more or less need to interact with a store assistant.

The present study shows that Trust, Need for Human Interaction, and Convenience are predictors of Intention to Use. However, only Trust and Convenience positively affect the Intention to Use, with particular emphasis on Convenience, which most strongly affects Intention to Use (B= 0,468). Therefore, the idea that an AI system is reliable must be fostered. This can be done, as said before, through a transparent process that allows the customer to understand the mechanism of these services (Siau & Wang, 2018) and, consequently, to realize that the more they trust their data in these systems, the better their experience will be (Song & Kim, 2021), because it will allow them to make correct and right decisions, i.e., choosing the clothes or accessories that best suit them, thus increasing their intention to use it. Nevertheless, beyond that, both fostering trust and increasing the customer's perception of convenience should be seen as a whole so that they can work together. If a customer perceives that using a specific service will bring him more convenience, i.e., allow him to better perform his task with less effort and time (Chang et al., 2013), his intention to use it tends to increase. The Intention to Use it increases even more if he trusts that using these services will bring him benefits and that the system, by having the ability to handle his data, will allow him to make better and more informed decisions (Song & Kim, 2022).

Need for Human Interaction proved to be a crucial variable in this dissertation. Descriptive Analysis concluded that the respondents still give considerable importance to human contact ($\bar{x}$ = 5.52). The results showed that Need for Human Interaction negatively impacted the Intention to Use AI systems. Consumers continue to believe that humans (which, applied to the context of this dissertation, will be the store assistants) have impossible capabilities for any AI System to replace (Ashfaq et al., 2020; Song et al., 2022). Thus, it is already expected that this consumer need would affect their intention to use these services in stores. It is thus necessary to consider this need when implementing these services in stores and promoting their adoption (Ashfaq et al., 2020). Thus, a gradual implementation of these systems should be considered, and they must work together with the human factor in the stores and not as a replacement. This factor becomes even more critical when talking about luxury brands. The relationship between these brands and their customers must be based on proximity and customization (Chevalier & Mazzalovo, 2008; Fionda & Moore, 2009). Customers of Luxury Fashion brands want high-quality products, with all that this implies. However, they also want a treatment of excellence and exclusivity, which differentiates this type of brand from the rest (Vigneron & Johnson, 2004). Thus, if customers believe that an AI service cannot offer them what they want, the need for human contact becomes even more imperative.

In conclusion, the results show that Intention to Use leads to higher Purchase Intention. Thus, the results support what would have been said by Ng et al. (2022), which indicates that a higher Use Intention leads to a specific behavior, which in this case, consists of Purchase Intention.

5.2. Managerial Contribution

The emergence of new technologies completely transforms the customer journey and, consequently, the customer experience, providing retailers with new strategic and tactical opportunities or improving already implemented processes. Before investing, more and more, in developing services that incorporate AI, deploying or promoting them, it is necessary to gauge how likely customers are to adopt them (Kim et al., 2017), even more so when it comes to high involvement products, as is the case of Luxury pieces.

For these virtual assistants to become more appealing to the customer, companies need to create a fun customer experience, and there is room for that. Today, customers still do not perceive using a robot/virtual assistant as relaxing or enjoyable, but this paradigm has to change. Creating interactive systems where the customer can have fun and be entertained by the system is an excellent way to improve customer experience. However, it should also be noted that Enjoyment does not influence Convenience, which indicates that brands will have to ensure that these systems are enjoyable to use but that this factor does not affect whether or not they become convenient for the customer. Therefore, it must be ensured that the services maintain a high quality to increase convenience and not only strongly. Thus, for Luxury brands to offer high-quality and user-friendly service, which have proven to be indicators that increase customer Convenience, the systems must always be actualized and have an interface that is easy to use and understand. To increase service quality, incorporating virtual reality into these systems would be a powerful weapon for brands. This would give customers a sense of how a clothing or accessory would look on their bodies. This would be a way to increase the idea that luxury brands are associated with innovation and creativity.

Applied to the Luxury Fashion context, one must remember that customers have stereotypes associated with this genre of products, namely high quality, high price, high status, and an experience elevated to excellence. Therefore, implementing these new AI systems must align with what a customer expects from a luxury brand. In this way, luxury fashion brands, characterized by a personalized and unique customer experience, must ensure that the systems they use continue to deliver an equal or better customer experience than the customer already used to. Thus, customers must perceive the system used as high quality, which means it must be objective and assertive. Thus, brands will need to leverage a large amount of customer data to offer each customer a unique experience tailored to their needs. In this way, companies must ensure that they have the necessary information to show the customer the most appropriate pieces, considering their tastes, size, and body shape, so that when the system suggests pieces to customers, they can be sure that a particular piece is ideal for them. This allows the customer to be more confident in the whole new experience, to need less and less the help of a store assistant (with the caveat that they remain indispensable), and will bring more convenience to the customer, as it saves effort, time and facilitates the whole process, by compiling all the processes into a single AI system (robots or virtual assistants).

Through what was concluded, it is possible to realize that respondents still have concerns about what these services can offer them, doubting their quality and the benefits they can bring. Thus, brands need to teach the customer and demonstrate how these services work and the benefits they can bring to his life and improve his experience. Luxury brands, even fashion brands, have many opportunities to show their customers how Artificial Intelligence can be an ally for them. Large luxury brands can use their runway shows, magazines, social media, or stores to perform this demonstration. This can also be a lever to increase further the idea of exclusivity, innovation, and creativity, which are hallmarks of this brand.

In order to implement this type of technology in stores, the communication of the stores has to emphasize the benefits, i.e., how much customers´ experience can be improved. Thus, the communication of the brands must highlight these benefits, mitigating some uncertainties that customers may have regarding the use of these services (Moore et al., 2022), in addition to helping the customer understand how these services work, as mentioned above.

To combat the need customers have to interact with a store assistant, virtual robots/assistants must work with the store staff. In other words, these systems cannot be implemented as a replacement for in-store assistants but rather as an aid to providing a better and more unique customer experience. As shown in this study, the Need for Human Interaction is very relevant for customers, so these systems will have to work as a support to the store assistants, i.e., as a tool that allows access to data much more quickly, facilitating the entire shopping process, because all previously separate processes may be compiled into a single service.

Luxury fashion brands can also use the information they collect from customers to understand what products are most in demand and meet those needs since they can compile the information of what customers are looking for and want in their closets. As a result, AI will allow fashion brands to predict trends, better understand their consumers' preferences, and thus manage their products more efficiently.

5.3. Limitations

It is necessary to keep in mind that all studies have their limitations and their boundaries. These limitations are often related to the methodology, the research method, or the cultural and demographic context in which the study was conducted.

One of the limitations of this study is related to the respondents' nationality. All but two of the respondents are of Portuguese nationality. This may influence the study since it focuses much on Portuguese culture and mentality. In addition, this impacts the study because cultures may have different opinions and a greater or lesser propensity to adopt these new systems than what was studied in this dissertation. Thus, it is not easy to use this study in any context other than the one in which it was conducted.

The research being quantitative is also a limitation. Considering that the subject of this dissertation is still abstract to most people, the numerical answers do not express opinions, doubts, or thoughts that the respondents might have. Thus, and despite the contextualization given in the survey, some doubts about the theme of this dissertation may not have been clarified, influencing the answers given.

Another limitation of this study was that it was applied to the luxury fashion context. Several factors influence people's propensity to buy (or not) these products, so the study being limited to the luxury context may have influenced the answers obtained.

5.4. Future Research

Future research could investigate this topic in other countries, and consequently in other cultures, to understand to what extent culture can influence adopting these systems in Luxury Fashion Retail.

It would also be essential to test other research methods allowing for more dialogue, where respondents could express their thoughts and opinions, thus providing a broader context. It would also be essential to include in the following research the demonstration of how these systems work so that future respondents have more knowledge of the subject and that their answers refer to a situation they have already experienced. In addition, future research could look at post-purchase scenarios, i.e., how people perceived the benefits and harms of using this service.

In addition, researchers can also address whether age influences the adoption of these services with embedded AI since younger generations have already been born into a digital world and have more significant contact with technology.

Given that the Need for Human Interaction was a crucial variable in this dissertation, it will be necessary to consider this variable in future research to gauge the extent to which this need will hinder the widespread implementation and subsequent adoption of these AI systems. Thus, it is also essential to include in future research whether workers can adopt these systems in their day-to-day jobs. Finally, it is crucial to understand whether workers are likely to work with these new systems, which are increasingly becoming a reality.

6. References

Aggarwal, P., Jun, S. Y., & Huh, J. H. (2011). Scarcity Messages. *Journal of Advertising*, *40*(3), 19–30. https://doi.org/10.2753/joa0091-3367400302

Alexander, N. (2009). Brand authentication: Creating and maintaining brand auras. *European Journal of Marketing*, *43*(3–4), 551–562. https://doi.org/10.1108/03090560910935578

Ameen, N., Tarhini, A., Reppel, A., & Anand, A. (2021). Customer experiences in the age of artificial intelligence. *Computers in Human Behavior*, *114*, 106548. https://doi.org/10.1016/j.chb.2020.106548

Ashfaq, M., Yun, J., Yu, S., & Loureiro, S. M. C. (2020). I, Chatbot: Modeling the determinants of users' satisfaction and continuance intention of AI-powered service agents. *Telematics and Informatics*, *54*, 101473. https://doi.org/10.1016/j.tele.2020.101473

Barro, S., & Davenport, T. H. (2019). People and machines: Partners in innovation. *MIT Sloan Management Review*, *60*(4), 22–28. https://www.proquest.com/scholarly-journals/people-machines-partners-innovation/docview/2273706424/se-2

Becker, K., Lee, J. W., & Nobre, H. M. (2018). The concept of luxury brands and the relationship between consumer and luxury brands. *Journal of Asian Finance, Economics and Business*, *5*(3), 51–63. https://doi.org/10.13106/jafeb.2018.vol5.no3.51

Belk, R. W. (1988). Possessions and the Extended Self. *Journal of Consumer Research*, *15*(2), 139–168. https://doi.org/10.1086/209154

Berry, L. L., Parasuraman, A., & Zeithaml, V. A. (1988). SERVQUAL: A multiple-item scale for measuring consumer perceptions of service quality. *Journal of Retailing*, *64*(1), 12–40. https://discovery.ebsco.com/c/2i6b6x/viewer/pdf/wk7nu2e34z

Berthon, P., Pitt, L., Parent, M., & Berthon, J. P. (2009). Aesthetics and ephemerality: Observing and preserving the luxury brand. *California Management Review*, *52*(1), 45–66. https://doi.org/10.1525/cmr.2009.52.1.45

Bhagat, R., Chauhan, V., & Bhagat, P. (2022). Investigating the impact of artificial intelligence on consumer's purchase intention in e-retailing. *Foresight*, *ahead-of-print*(ahead-of-print). https://doi.org/10.1108/FS-10-2021-0218

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

Brakus, J. J., Schmitt, B. H., & Zarantonello, L. (2009). Brand Experience: What Is It? How Is It Measured? Does It Affect Loyalty? *Journal of Marketing*, *73*(3), 52–68. https://doi.org/10.1509/jmkg.73.3.52

Byrnes, J. P., Miller, D. C., & Schafer, W. D. (1999). Gender differences in risk taking: A meta-analysis. *Psychological Bulletin*, *125*(3), 367–383. https://doi.org/10.1037/0033-2909.125.3.367

Castelo, N. (2019). *Blurring the line between human and machine: marketing artificial intelligence* [Doctoral Dissertation, Columbia University]. https://www.proquest.com/openview/2e35c7ff7c154b371f880ac9cd965aec/1?pq-origsite=gscholar&cbl=18750&diss=y

Castelo, N., & Ward, A. (2016). Political affiliation moderates attitudes towards artificial intelligence. *ACR North American Advances*, *44*, 723–723. http://www.acrwebsite.org/volumes/1022134/volumes/v44/NA-44

Chang, C. C., Liang, C., Yan, C. F., & Tseng, J. S. (2013). The Impact of College Students' Intrinsic and Extrinsic Motivation on Continuance Intention to Use English Mobile Learning Systems. *Asia-Pacific Education Researcher*, *22*(2), 181–192. https://doi.org/10.1007/s40299-012-0011-7

Chevalier, M., & Mazzalovo, G. (2008). *Luxury brand management: A world of privilege* (1st ed.). Wiley & Sons. https://books.google.pt/books?id=En7lK92AXo4C&lpg=PP8&ots=nYotU9Vnv9&dq=Chevalier%2C%20M.%20and%20Mazzalovo%2C%20G.%20(2008)%20Luxury%20Brand%20Management%3A%20A%20World%20of%20Privilege.%20Singapore%3A%20Wiley%20and%20Sons.%20&lr&hl=pt-PT&pg=PP11#v=onepage&q&f=false

Chiang, A. H., & Trimi, S. (2020). Impacts of service robots on service quality. *Service Business*, *14*(3), 439–459. https://doi.org/10.1007/s11628-020-00423-8

Choi, B., Lee, C., Lee, H., & Subramani, M. (2004). Effects of web retail service quality and product categories on consumer behavior: A research model and empirical exploration. *Proceedings of the Hawaii International Conference on System Sciences*, *37*, 2751–2760. https://doi.org/10.1109/hicss.2004.1265425

Choi, Y., Choi, M., Oh, M., & Kim, S. (2020). Service robots in hotels: understanding the service quality perceptions of human-robot interaction. *Journal of Hospitality Marketing and Management*, *29*(6), 613–635. https://doi.org/10.1080/19368623.2020.1703871

Christodoulides, G., Michaelidou, N., & Li, C. H. (2009). Measuring perceived brand luxury: An evaluation of the BLI scale. *Journal of Brand Management*, *16*(5–6), 395–405. https://doi.org/10.1057/bm.2008.49

Chuah, S. H.-W., & Yu, J. (2021). The future of service: The power of emotion in human-robot interaction. *Journal of Retailing and Consumer Services*, *61*, 102551. https://doi.org/10.1016/j.jretconser.2021.102551

Collier, J. E., & Bienstock, C. C. (2006). Measuring service quality in E-retailing. *Journal of Service Research*, *8*(3), 260–275. https://doi.org/10.1177/1094670505278867

Corritore, C. L., Kracher, B., & Wiedenbeck, S. (2003). On-line trust: Concepts, evolving themes, a model. *International Journal of Human Computer Studies*, *58*(6), 737–758. https://doi.org/10.1016/S1071-5819(03)00041-7

Cristini, H., Kauppinen-Räisänen, H., Barthod-Prothade, M., & Woodside, A. (2017). Toward a general theory of luxury: Advancing from workbench definitions and theoretical transformations. *Journal of Business Research*, *70*, 101–107. https://doi.org/10.1016/j.jbusres.2016.07.001

Dabholkar, P. A. (1994). Incorporating Choice into an Attitudinal Framework: Analyzing Models of Mental Comparison Processes. *Journal of Consumer Research*, *21*(1), 100–118. https://doi.org/10.1086/209385

Dabholkar, P. A. (1996). Consumer evaluations of new technology-based self-service options: An investigation of alternative models of service quality. *International Journal of Research in Marketing*, *13*(1), 29–51. https://doi.org/10.1016/0167-8116(95)00027-5

Dabholkar, P. A., & Bagozzi, R. P. (2002). An Attitudinal Model of Technology Based Self Service: Moderating Effects of Consumer Traits and Situational Factors. *Journal of the Academy of Marketing Science*, *30*(3), 184–201. https://doi.org/10.1177/009207030230300

Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science*, *48*(1), 24–42. https://doi.org/10.1007/s11747-019-00696-0

Davenport, T. H., & Kirby, J. (2016). Just how smart are smart machines? *MIT Sloan Management Review*, *57*(3), 21–25. http://mitsmr.com/1SPyBNL

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly: Management Information Systems*, *13*(3), 319–339. https://doi.org/10.2307/249008

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
Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1992). Extrinsic and Intrinsic Motivation to Use Computers in the Workplace. *Journal of Applied Social Psychology*, *22*(14), 1111–1132. https://doi.org/10.1111/j.1559-1816.1992.tb00945.x
De Bruyn, A., Viswanathan, V., Beh, Y. S., Brock, J. K.-U., & von Wangenheim, F. (2020). Artificial Intelligence and Marketing: Pitfalls and Opportunities. *Journal of Interactive Marketing*, *51*(1), 91–105. https://doi.org/10.1016/j.intmar.2020.04.007
Deloitte. (2020). *Global Powers of Luxury Goods 2020 The new age of fashion and luxury*. https://www2.deloitte.com/global/en/pages/consumer-business/articles/gx-cb-global-powers-of-luxury-goods.html
Deloitte. (2021). *Global Powers of Luxury Goods 2021: Breakthrough luxury Contents*. https://www2.deloitte.com/global/en/pages/consumer-business/articles/gx-cb-global-powers-of-luxury-goods.html
Deutsch, M. (1958). Trust and suspicion. *Journal of Conflict Resolution*, *2*(4), 265–279. https://doi.org/10.1177/002200275800200401
Dion, D., & Arnould, E. (2011). Retail Luxury Strategy: Assembling Charisma through Art and Magic. *Journal of Retailing*, *87*(4), 502–520. https://doi.org/10.1016/j.jretai.2011.09.001
Eastman, J. K., & Eastman, K. L. (2011). Perceptions Of Status Consumption And The Economy. *Journal of Business & Economics Research* , *9*(7), 9–20. https://doi.org/10.19030/jber.v9i7.4677
Fionda, A. M., & Moore, C. M. (2009). The anatomy of the luxury fashion brand. *Journal of Brand Management*, *16*(5–6), 347–363. https://doi.org/10.1057/bm.2008.45
Gil, L. A., Kwon, K. N., Good, L. K., & Johnson, L. W. (2012). Impact of self on attitudes toward luxury brands among teens. *Journal of Business Research*, *65*(10), 1425–1433. https://doi.org/10.1016/j.jbusres.2011.10.008
Grönroos, C. (1984). A Service Quality Model and its Marketing Implications. *European Journal of Marketing*, *18*(4), 36–44. https://doi.org/10.1108/EUM0000000004784
Gustafson, P. E. (1998). Gender differences in risk perception: Theoretical and methodological perspectives. *Risk Analysis*, *18*(6), 805–811. https://doi.org/10.1023/B:RIAN.0000005926.03250.c0
Han, Y. J., Nunes, J. C., & Drèze, X. (2010). Signaling Status with Luxury Goods: The Role of Brand Prominence. *Journal of Marketing*, *74*(4), 15–30. https://doi.org/10.1509/jmkg.74.4.15
Hengstler, M., Enkel, E., & Duelli, S. (2016). Applied artificial intelligence and trust-The case of autonomous vehicles and medical assistance devices. *Technological Forecasting and Social Change*, *105*, 105–120. https://doi.org/10.1016/j.techfore.2015.12.014
Hoeffler, S. (2003). Measuring Preferences for Really New Products. *Journal of Marketing Research*, *40*(4), 406–420. https://doi.org/10.1509/jmkr.40.4.406.19394
Hoyer, W. D., Kroschke, M., Schmitt, B., Kraume, K., & Shankar, V. (2020). Transforming the Customer Experience Through New Technologies. *Journal of Interactive Marketing*, *51*, 57–71. https://doi.org/10.1016/j.intmar.2020.04.001
Hsieh, S. H., & Lee, C. T. (2021). Hey Alexa: examining the effect of perceived socialness in usage intentions of AI assistant-enabled smart speaker. *Journal of Research in Interactive Marketing*, *15*(2), 267–294. https://doi.org/10.1108/JRIM-11-2019-0179
Huang, M. H., & Rust, R. T. (2018). Artificial Intelligence in Service. *Journal of Service Research*, *21*(2), 155–172. https://doi.org/10.1177/1094670517752459

Hubert, M., Blut, M., Brock, C., Backhaus, C., & Eberhardt, T. (2017). Acceptance of Smartphone-Based Mobile Shopping: Mobile Benefits, Customer Characteristics, Perceived Risks, and the Impact of Application Context. *Psychology and Marketing*, *34*(2), 175–194. https://doi.org/10.1002/mar.20982

Hung, K. peng, Chen, A. H., Peng, N., Hackley, C., Tiwsakul, R. A., & Chou, C. lun. (2011). Antecedents of luxury brand purchase intention. *Journal of Product and Brand Management*, *20*(6), 457–467. https://doi.org/10.1108/10610421111166603

Jackson, T. (2004). A contemporary analysis of global luxury brands. In C. Moore, M. Bruce, & G. Birtwistle (Eds.), *International Retail Marketing: A Case Study Approach* (pp. 155–168). Elsevier Butterworth-Heinemann.

Jang, W. E., Ko, Y. J., Morris, J. D., & Chang, Y. (2015). Scarcity Message Effects on Consumption Behavior: Limited Edition Product Considerations. *Psychology and Marketing*, *32*(10), 989–1001. https://doi.org/10.1002/mar.20836

Joshi, N. (2019, June 19). *7 Types Of Artificial Intelligence*. Forbes. https://www.forbes.com/sites/cognitiveworld/2019/06/19/7-types-of-artificial-intelligence/?sh=5fcaf6b6233e

Kapferer, J. N. (2008). *The new strategic brand management: Creating and sustaining brand equity long term*. Kogan Page Publishers. https://books.google.pt/books?id=8PoItiB7bicC&lpg=PR5&ots=ezXc8ywJUw&dq=Kapferer%2C%20J.%20N.%20(2008)%20The%20New%20Strategic%20Brand%20Management%3A%20Creating%20and%20Sustaining%20Brand%20Equity%20Long%20Term%2C%204th%20edn.%2C%20London%3A%20Kogan%20Page%20Limited.%20&lr&hl=pt-PT&pg=PA11#v=onepage&q&f=false

Kapferer, J. N. (2012). Abundant rarity: The key to luxury growth. *Business Horizons*, *55*(5), 453–462. https://doi.org/10.1016/j.bushor.2012.04.002

Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons*, *62*(1), 15–25. https://doi.org/10.1016/j.bushor.2018.08.004

Keller, K. L. (2002). Brand synthesis: The multidimensionality of brand knowledge. *Journal of Consumer Research*, *29*(4), 595–600. https://doi.org/10.1086/346254

Kim, H. Y., Lee, J. Y., Mun, J. M., & Johnson, K. K. P. (2017). Consumer adoption of smart in-store technology: assessing the predictive value of attitude versus beliefs in the technology acceptance model. *International Journal of Fashion Design, Technology and Education*, *10*(1), 26–36. https://doi.org/10.1080/17543266.2016.1177737

Ko, E., Costello, J. P., & Taylor, C. R. (2019). What is a luxury brand? A new definition and review of the literature. *Journal of Business Research*, *99*, 405–413. https://doi.org/10.1016/j.jbusres.2017.08.023

Kosinski, M., Stillwell, D., & Graepel, T. (2013). Private traits and attributes are predictable from digital records of human behavior. *Proceedings of the National Academy of Sciences of the United States of America*, *110*(15), 5802–5805. https://doi.org/10.1073/pnas.1218772110

Li, L. H., & Lai, C. Y. (2021). Comparing the Impact of Service Quality on Customers' Repurchase Intentions Based on Statistical Methods and Artificial Intelligence-Taking an Automotive Aftermarket (AM) Parts Sales Company as an Example. *Proceedings of the 2021 15th International Conference on Ubiquitous Information Management and Communication (IMCOM)*, 1–8. https://doi.org/10.1109/IMCOM51814.2021.9377415

Li, X., Hess, T. J., & Valacich, J. S. (2008). Why do we trust new technology? A study of initial trust formation with organizational information systems. *Journal of Strategic Information Systems*, *17*(1), 39–71. https://doi.org/10.1016/j.jsis.2008.01.001

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

Llamas, R., & Thomsen, T. U. (2016). The luxury of igniting change by giving: Transforming yourself while transforming others' lives. *Journal of Business Research*, *69*(1), 166–176. https://doi.org/10.1016/j.jbusres.2015.07.030

Loureiro, S. M. C., Guerreiro, J., & Tussyadiah, I. (2021). Artificial intelligence in business: State of the art and future research agenda. *Journal of Business Research*, *129*, 911–926. https://doi.org/10.1016/j.jbusres.2020.11.001

Lu, L., Cai, R., & Gursoy, D. (2019). Developing and validating a service robot integration willingness scale. *International Journal of Hospitality Management*, *80*, 36–51. https://doi.org/10.1016/j.ijhm.2019.01.005

Malodia, S., Islam, N., Kaur, P., & Dhir, A. (2022). Why Do People Use Artificial Intelligence (AI)-Enabled Voice Assistants? *IEEE Transactions on Engineering Management*, 1–15. https://doi.org/10.1109/TEM.2021.3117884

Mandel, N., Petrova, P. K., & Cialdini, R. B. (2006). Images of success and the preference for luxury brands. *Journal of Consumer Psychology*, *16*(1), 57–69. https://doi.org/10.1207/s15327663jcp1601_8

Martin, K. D., Borah, A., & Palmatier, R. W. (2017). Data privacy: Effects on customer and firm performance. *Journal of Marketing*, *81*(1), 36–58. https://doi.org/10.1509/jm.15.0497

Martin, K. D., & Murphy, P. E. (2017). The role of data privacy in marketing. *Journal of the Academy of Marketing Science*, *45*(2), 135–155. https://doi.org/10.1007/s11747-016-0495-4

Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An Integrative Model Of Organizational Trust. *Academy of Management Review*, *20*(3), 709–734. https://doi.org/10.5465/amr.1995.9508080335

McFerran, B., Aquino, K., & Tracy, J. L. (2014). Evidence for two facets of pride in consumption: Findings from luxury brands. *Journal of Consumer Psychology*, *24*(4), 455–471. https://doi.org/10.1016/j.jcps.2014.03.004

McKnight, D. H., Cummings, L. L., & Chervany, N. L. (1998). Initial trust formation in new organizational relationships. *Academy of Management Review*, *23*(3), 473–490. https://doi.org/10.5465/AMR.1998.926622

Moore, S., Bulmer, S., & Elms, J. (2022). The social significance of AI in retail on customer experience and shopping practices. *Journal of Retailing and Consumer Services*, *64*, 102755. https://doi.org/10.1016/j.jretconser.2021.102755

Mortelmans, D. (2005). Sign values in processes of distinction: The concept of luxury. *Semiotica*, *2005*(157), 497–520. https://doi.org/10.1515/semi.2005.2005.157.1-4.497

Ng, F. Z.-X., Yap, H.-Y., Tan, G. W.-H., Lo, P.-S., & Ooi, K.-B. (2022). Fashion shopping on the go: A Dual-stage predictive-analytics SEM-ANN analysis on usage behaviour, experience response and cross-category usage. *Journal of Retailing and Consumer Services*, *65*, 102851. https://doi.org/10.1016/j.jretconser.2021.102851

Nueno, J. L., & Quelch, J. A. (1998). The mass marketing of luxury. *Business Horizons*, *41*(6), 61–68. https://doi.org/10.1016/S0007-6813(98)90023-4

Osawa, H., Ema, A., Hattori, H., Akiya, N., Kanzaki, N., Kubo, A., Koyama, T., & Ichise, R. (2017). What is Real Risk and Benefit on Work with Robots? From the Analysis of a Robot Hotel. *Proceedings of the Companion of the 2017 ACM/IEEE International Conference on Human-Robot Interaction*, 241–242. https://doi.org/10.1145/3029798.3038312

Parasuraman, A. (2000). Technology Readiness Index (Tri): A Multiple-Item Scale to Measure Readiness to Embrace New Technologies. *Journal of Service Research*, *2*(4), 307–320. https://doi.org/10.1177/109467050024001

Parasuraman, A., Zeithaml, V. A., & Berry, L. L. (1994). Reassessment of Expectations as a Comparison Standard in Measuring Service Quality: Implications for Further Research. *Journal of Marketing*, *58*(1), 111–124. https://doi.org/10.1177/002224299405800109

Pavlou, P. A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model. *International Journal of Electronic Commerce*, *7*(3), 101–134. https://doi.org/10.1080/10864415.2003.11044275

Phau, I., & Prendergast, G. (2000). Consuming luxury brands: The relevance of the 'Rarity Principle.' *Journal of Brand Management*, *8*(2), 122–138. https://doi.org/10.1057/palgrave.bm.2540013

Popper, K. R. (1979). *Objective Knowledge: An Evolutionary Approach*. Oxford University Press.

Prentice, C., Dominique Lopes, S., & Wang, X. (2020). The impact of artificial intelligence and employee service quality on customer satisfaction and loyalty. *Journal of Hospitality Marketing & Management*, *29*(7), 739–756. https://doi.org/10.1080/19368623.2020.1722304

Rafailidis, D., & Manolopoulos, Y. (2019). Can Virtual Assistants Produce Recommendations? *Proceedings of the 9th International Conference on Web Intelligence, Mining and Semantics - WIMS2019*, 1–6. https://doi.org/10.1145/3326467.3326468

Rincon, J. A., Costa, A., Novais, P., Julian, V., & Carrascosa, C. (2019). A new emotional robot assistant that facilitates human interaction and persuasion. *Knowledge and Information Systems*, *60*(1), 363–383. https://doi.org/10.1007/s10115-018-1231-9

Shankar, V. (2018). How Artificial Intelligence (AI) is Reshaping Retailing. *Journal of Retailing*, *94*(4), vi–xi. https://doi.org/10.1016/S0022-4359(18)30076-9

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

Shum, H., He, X., & Li, D. (2018). From Eliza to XiaoIce: challenges and opportunities with social chatbots. *Frontiers of Information Technology & Electronic Engineering*, *19*(1), 10–26. https://doi.org/10.1631/FITEE.1700826

Siau, K., Sheng, H., Nah, F., & Davis, S. (2004). A qualitative investigation on consumer trust in mobile commerce. *International Journal of Electronic Business*, *2*(3), 283. https://doi.org/10.1504/IJEB.2004.005143

Siau, K., & Wang, W. (2018). Building trust in artificial intelligence, machine learning, and robotics. *Cutter Business Technology Journal*, *31*(2), 47–53. https://www.researchgate.net/profile/Keng-Siau-2/publication/324006061_Building_Trust_in_Artificial_Intelligence_Machine_Learning_and_Robotics/links/5ab8744baca2722b97cf9d33/Building-Trust-in-Artificial-Intelligence-Machine-Learning-and-Robotics.pdf

Song, C. S., & Kim, Y.-K. (2021). Predictors of consumers' willingness to share personal information with fashion sales robots. *Journal of Retailing and Consumer Services*, *63*, 102727. https://doi.org/10.1016/j.jretconser.2021.102727

Song, M., Xing, X., Duan, Y., Cohen, J., & Mou, J. (2022). Will artificial intelligence replace human customer service? The impact of communication quality and privacy risks on adoption intention. *Journal of Retailing and Consumer Services*, *66*, 102900. https://doi.org/10.1016/j.jretconser.2021.102900

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

Stigler, G. J., & Becker, G. S. (1977). De Gustibus Non Est Disputandum. *The American Economic Review*, *67*(2), 76–90. http://www.jstor.org/stable/1807222

Syam, N., & Sharma, A. (2018). Waiting for a sales renaissance in the fourth industrial revolution: Machine learning and artificial intelligence in sales research and practice. *Industrial Marketing Management*, *69*, 135–146. https://doi.org/10.1016/j.indmarman.2017.12.019

Tian, K. T., Bearden, W. O., & Hunter, G. L. (2001). Consumers' Need for Uniqueness: Scale Development and Validation. *Journal of Consumer Research*, *28*(1), 50–66. https://doi.org/10.1086/321947

Townsend, C., & Sood, S. (2012). Self-Affirmation through the Choice of Highly Aesthetic Products. *Journal of Consumer Research*, *39*(2), 415–428. https://doi.org/10.1086/663775

Tsai, S. (2005). Impact of Personal Orientation on Luxury-Brand Purchase Value: An International Investigation. *International Journal of Market Research*, *47*(4), 427–452. https://doi.org/10.1177/147078530504700403

Vakkuri, V., & Abrahamsson, P. (2018). The Key Concepts of Ethics of Artificial Intelligence. *2018 IEEE International Conference on Engineering, Technology and Innovation (ICE/ITMC)*, 1–6. https://doi.org/10.1109/ICE.2018.8436265

Veblen, T. (2009). *The theory of the leisure class* (M. Banta, Ed.). Oxford World's Classics.

Venkatesh, Thong, & Xu. (2012). Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology. *MIS Quarterly*, *36*(1), 157–178. https://doi.org/10.2307/41410412

Verhoef, P. C., Stephen, A. T., Kannan, P. K., Luo, X., Abhishek, V., Andrews, M., Bart, Y., Datta, H., Fong, N., Hoffman, D. L., Hu, M. M., Novak, T., Rand, W., & Zhang, Y. (2017). Consumer Connectivity in a Complex, Technology-enabled, and Mobile-oriented World with Smart Products. *Journal of Interactive Marketing*, *40*(1), 1–8. https://doi.org/10.1016/j.intmar.2017.06.001

Vigneron, F., & Johnson, L. W. (2004). Measuring perceptions of brand luxury. *Journal of Brand Management*, *11*(6), 484–506. https://doi.org/10.1057/palgrave.bm.2540194

Villasenor, J. (2019, January 3). *Artificial intelligence and bias: Four key challenges*. Brookings. https://www.brookings.edu/blog/techtank/2019/01/03/artificial-intelligence-and-bias-four-key-challenges/

Vo, A.-D., Nguyen, Q.-P., & Ock, C.-Y. (2018). Opinion–Aspect Relations in Cognizing Customer Feelings via Reviews. *IEEE Access*, *6*, 5415–5426. https://doi.org/10.1109/ACCESS.2018.2797224

Wang, E. S.-T., & Lin, R.-L. (2017). Perceived quality factors of location-based apps on trust, perceived privacy risk, and continuous usage intention. *Behaviour & Information Technology*, *36*(1), 2–10. https://doi.org/10.1080/0144929X.2016.1143033

Wang, X., Tajvidi, M., Lin, X., & Hajli, N. (2020). Towards an Ethical and Trustworthy Social Commerce Community for Brand Value Co-creation: A trust-Commitment Perspective. *Journal of Business Ethics*, *167*(1), 137–152. https://doi.org/10.1007/s10551-019-04182-z

Wang, Y., & Griskevicius, V. (2014). Conspicuous Consumption, Relationships, and Rivals: Women's Luxury Products as Signals to Other Women. *Journal of Consumer Research*, *40*(5), 834–854. https://doi.org/10.1086/673256

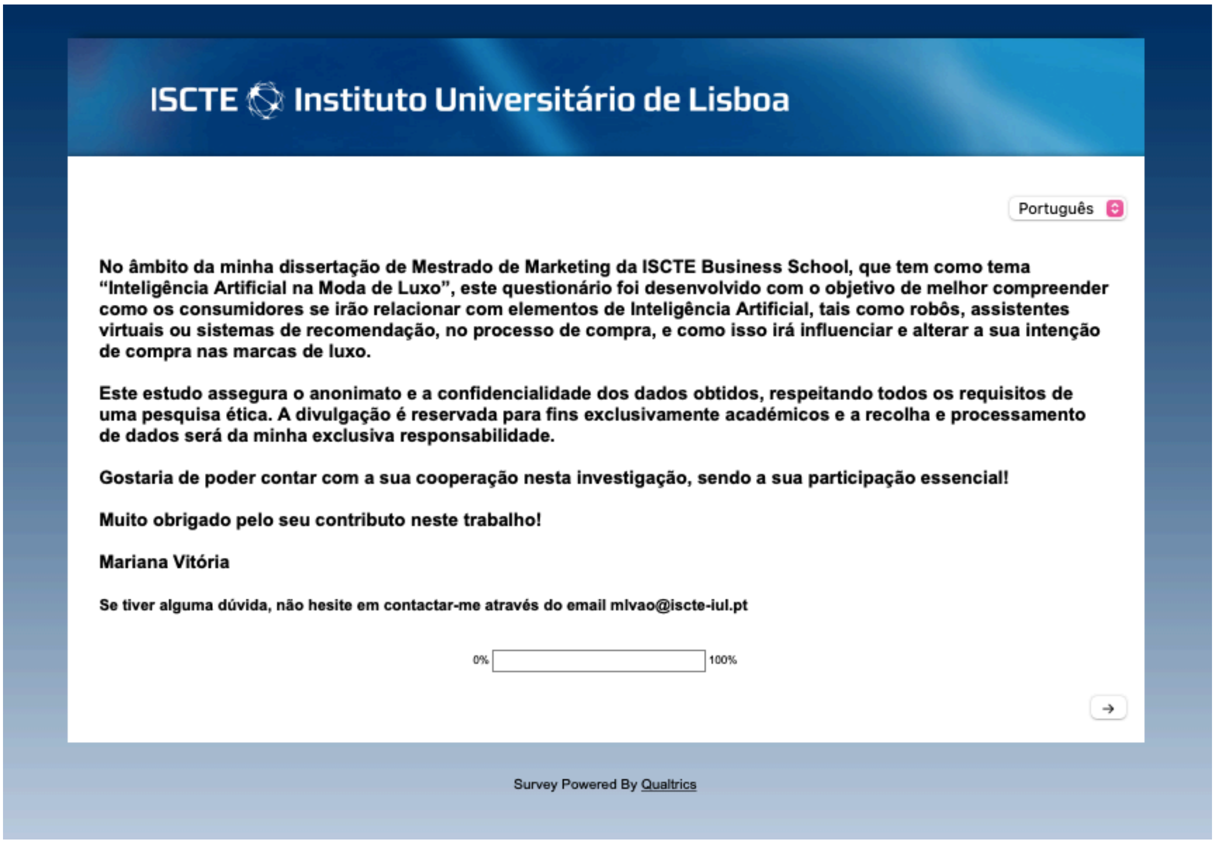
Wiedmann, K.-P., Hennigs, N., & Siebels, A. (2009). Value-based segmentation of luxury consumption behavior. *Psychology and Marketing*, *26*(7), 625–651. https://doi.org/10.1002/mar.20292

Wirtz, J., Patterson, P. G., Kunz, W. H., Gruber, T., Lu, V. N., Paluch, S., & Martins, A. (2018). Brave new world: service robots in the frontline. *Journal of Service Management*, *29*(5), 907–931. https://doi.org/10.1108/JOSM-04-2018-0119

Zhao, M., Hoeffler, S., & Dahl, D. W. (2012). Imagination Difficulty and New Product Evaluation. *Journal of Product Innovation Management*, *29*, 76–90. https://doi.org/10.1111/j.1540-5885.2012.00951.x

7. Appendices

Appendix A – Online Survey



ISCTE Instituto Universitário de Lisboa

Português

No âmbito da minha dissertação de Mestrado de Marketing da ISCTE Business School, que tem como tema "Inteligência Artificial na Moda de Luxo", este questionário foi desenvolvido com o objetivo de melhor compreender como os consumidores se irão relacionar com elementos de Inteligência Artificial, tais como robôs, assistentes virtuais ou sistemas de recomendação, no processo de compra, e como isso irá influenciar e alterar a sua intenção de compra nas marcas de luxo.

Este estudo assegura o anonimato e a confidencialidade dos dados obtidos, respeitando todos os requisitos de uma pesquisa ética. A divulgação é reservada para fins exclusivamente académicos e a recolha e processamento de dados será da minha exclusiva responsabilidade.

Gostaria de poder contar com a sua cooperação nesta investigação, sendo a sua participação essencial!

Muito obrigado pelo seu contributo neste trabalho!

Mariana Vitória

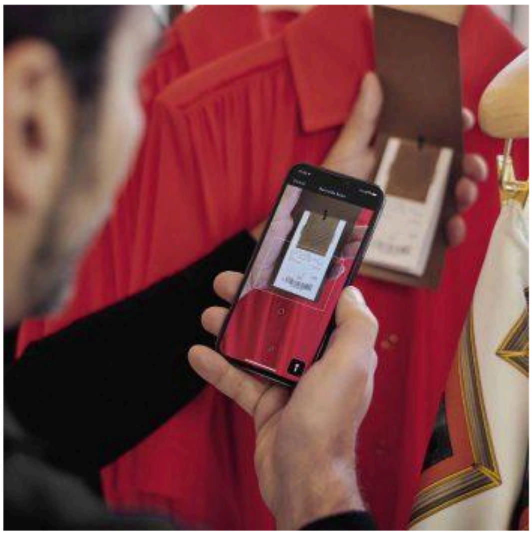
Se tiver alguma dúvida, não hesite em contactar-me através do email mlvao@iscte-iul.pt

0% 100%

Survey Powered By Qualtrics

Tenha em atenção as seguintes imagens e respetivas explicações.

Hoje em dia, já é possível ser atendido/a por um robô, num contexto de loja de roupa física. Este poderá ajudá-lo/a a escolher a peça ideal para si, tendo em conta as suas compras anteriores, combinações com peças que já tenha adquirido ou até mesmo as suas características físicas.



Os assistentes virtuais são criados com base em inteligência artificial e respondem por comandos de voz ou de texto. Podem ser utilizados em vários contextos, nomeadamente para ajuda da vida diária, exemplo disso são a Alexa ou o Google Home. No contexto de moda, estes assistentes virtuais têm a função de lhe recomendar peças, encontrar o conjunto perfeito para si, dar-lhe detalhes sobre determinado produto, tendo por base as suas preferências, compras anteriores, características físicas ou até mesmo fundamentando-se nas suas publicações/interações nas redes sociais. Para além disso, poderão servir de ferramenta de apoio aos assistentes de loja.

0% 100%

→

Português

Responda, por favor, consoante o seu nível de concordância com as seguintes frases. Tenha em atenção que terá de escolher um número entre 1 e 7, em que 1 significa "Discordo totalmente" e 7 significa "Concordo totalmente".

	1 - Discordo totalmente	2	3	4 - Não concordo nem discordo	5	6	7 - Concordo totalmente
Sentir-me-ia descontraído/a ao falar com robôs/assistentes virtuais.	○	○	○	○	○	○	○
Eu apreciaria a interação com robôs/assistentes virtuais.	○	○	○	○	○	○	○
Eu sentir-me-ia satisfeito/a ao ter uma conversa com robôs/assistentes virtuais.	○	○	○	○	○	○	○

	1 - Discordo totalmente	2	3	4 - Não concordo nem discordo	5	6	7 - Concordo totalmente
Aprender a utilizar um robô/assistente virtual seria fácil.	○	○	○	○	○	○	○
Seria fácil tornar-me habilidoso na utilização de um robô/assistente virtual.	○	○	○	○	○	○	○
A utilização de um robô/assistente virtual seria clara e compreensível.	○	○	○	○	○	○	○
Um robô/assistente virtual seria fácil de utilizar.	○	○	○	○	○	○	○

	1 - Discordo totalmente	2	3	4 - Não concordo nem discordo	5	6	7 - Concordo totalmente
A minha visão sobre os serviços que um robô/assistente virtual pode prestar é muito boa.	○	○	○	○	○	○	○
De uma forma geral, ficaria satisfeito com os serviços prestados por um robô/assistente virtual.	○	○	○	○	○	○	○
De uma forma geral, um robô/assistente virtual ajudaria a elevar a qualidade de serviço à excelência.	○	○	○	○	○	○	○
Considero que os serviços prestados pelo robô/assistente virtual iriam ao encontro das minhas expectativas sobre o que considero ser um bom atendimento.	○	○	○	○	○	○	○

	1 - Discordo totalmente	2	3	4 - Não concordo nem discordo	5	6	7 - Concordo totalmente
Um robô/assistente virtual parece-me ser confiável.	○	○	○	○	○	○	○
Um robô/assistente virtual parece-me ser credível.	○	○	○	○	○	○	○
Um conselho de um robô/assistente virtual parece-me ser fiável.	○	○	○	○	○	○	○

	1 - Discordo totalmente	2	3	4 - Não concordo nem discordo	5	6	7 - Concordo totalmente
O contacto humano torna o processo de compra mais agradável para mim.	○	○	○	○	○	○	○
É importante para mim ter um atendimento personalizado por parte do assistente de loja.	○	○	○	○	○	○	○
Eu gosto de comunicar com um assistente de loja.	○	○	○	○	○	○	○
Interagir com um robô/assistente virtual incomodar-me-ia mais do falar com um assistente de loja.	○	○	○	○	○	○	○

	1 - Discordo totalmente	2	3	4 - Não concordo nem discordo	5	6	7 - Concordo totalmente
Para me ajudar no processo de compra, ser-me-ia mais conveniente interagir com um robô/assistente virtual.	○	○	○	○	○	○	○
Utilizar um robô/assistente virtual permitir-me-ia fazer várias tarefas ao mesmo tempo.	○	○	○	○	○	○	○
Eu conseguiria automatizar todo o processo de compra ao utilizar um robô/assistente virtual.	○	○	○	○	○	○	○
Eu gosto da capacidade que um robô/assistente virtual teria em poupar-me tempo e esforço ao longo do processo de compra.	○	○	○	○	○	○	○
Interagir com um robô/assitente virtual seria fácil e compreensível.	○	○	○	○	○	○	○

0% 100%

→

Considerando o cenário em que terá possibilidade de interagir com um robô/assistente virtual, responda, por favor, consoante o seu nível de concordância com as seguintes frases. Tenha em atenção que terá de escolher um número entre 1 e 7, em que 1 significa "Discordo totalmente" e 7 significa "Concordo totalmente".

	1 - Discordo totalmente	2	3	4 - Não concordo nem discordo	5	6	7 - Concordo totalmente
Irei interagir com um robô/assistente virtual, regularmente, no futuro.	○	○	○	○	○	○	○
Irei interagir com um robô/assistente virtual, frequentemente, no futuro.	○	○	○	○	○	○	○
Irei recomendar a outras pessoas o uso de um robô/assistente virtual.	○	○	○	○	○	○	○

Responda, por favor, consoante o nível de probabilidade, às seguintes frases. Tenha em atenção que terá de escolher um número entre 1 e 7, em que 1 significa "Muito baixa" e 7 significa "Muito alta".

	1 - Muito baixa	2	3	4 - Neutro	5	6	7 - Muito alta
A minha vontade de comprar um produto de luxo.	○	○	○	○	○	○	○
A probabilidade de eu considerar comprar um produto de luxo.	○	○	○	○	○	○	○
A probabilidade de eu comprar um produto de luxo.	○	○	○	○	○	○	○

0% 100%

ISCTE Instituto Universitário de Lisboa

Português

Qual é o seu género?

- ○ Feminino
- ○ Masculino
- ○ Outro

Que idade tem? (Escolha o intervalo em que se insere).

- ○ Menos de 18 anos
- ○ 18-24
- ○ 25-34
- ○ 35-44
- ○ 45-54
- ○ 55-64
- ○ 65 ou mais

Atualmente, em que país reside?

0% 100%

Appendix B – List of Constructs, Items and Sources

Enjoyment	E1	I would feel relaxed when talking to robots/virtual assistants	(Song and Kim, 2021)
	E2	I would appreciate interaction with robots/virtual assistants	
	E3	I would feel satisfied having a conversation with robots/virtual assistants.	
Ease of Use	EOU1	Learning to use a robot/virtual assistant would be easy	
	EOU2	It would be easy to become skilled at using a robot/virtual assistant	
	EOU3	The use of a robot/virtual assistant would be clear and understandable	
	EOU4	A robot/virtual assistant would be easy to use	
Service Quality	SQ1	My view on the services that a robot/virtual assistant can provide is very good	
	SQ2	Overall, I would be satisfied with the services provided by a robot/virtual assistant	
	SQ3	Overall, a robot/virtual assistant would help to elevate the quality of service to excellence	
	SQ4	I believe that the services provided by the robot/virtual assistant would meet my expectations about what I consider to be good service	
Trust	T1	A robot/virtual assistant seems to me to be reliable	(Song and Kim, 2021)
	T2	A robot/virtual assistant seems to me to be credible	
	T3	Advice from a robot/virtual assistant seems to me to be reliable	
Need for Human Interaction	NFHI 1	Human contact makes the buying process more pleasant for me	(Song et al., 2022)
	NFHI 2	It is important for me to have personalized service from the store assistant	
	NFHI 3	I like to communicate with a shop assistant	
	NFHI 4	Interacting with a robot/virtual assistant would bother me more than talking to a store assistant	
Convenience	C1	To help me with the purchase process, it would be more convenient for me to interact with a robot/virtual assistant	(Malodia et al., 2021)
	C2	Using a robot/virtual assistant would allow me to multitask	
	C3	I could automate the entire purchase process using a robot/virtual assistant	
	C4	I like the ability of a robot/virtual assistant to save me time and effort throughout the purchase process	
	C5	Interacting with a robot/virtual assistant would be easy and understandable	

Intention to Use	ITU1	I will interact with a robot/virtual assistant on a regular basis in the future	(Hsieh & Lee, 2021)
	ITU2	I will interact with a robot/virtual assistant often in the future	
	ITU3	I will recommend to others the use of a robot/virtual assistant	
Purchase Intention	PI1	My desire to buy a luxury product	(Liang et al., 2020)
	PI2	The likelihood that I will consider buying a luxury product	
	PI3	The probability that I will buy a luxury product	

Appendix C – Model fit of Multiple Regression –Enjoyment, Ease of Use, and Service Quality as independent, Trust as dependent variables

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.805[a]	.648	.645	.91572

a. Predictors: (Constant), Service Quality, Ease of use, Enjoyment

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	520.375	3	173.458	206.857	.000[b]
	Residual	282.589	337	.839		
	Total	802.963	340			

a. Dependent Variable: Trust

b. Predictors: (Constant), Service Quality, Ease of use, Enjoyment

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			95,0% Confidence Interval for B	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound
1	(Constant)	.836	.165		5.059	.000	.511	1.161
	Enjoyment	.175	.049	.204	3.600	.000	.079	.271
	Ease of use	.173	.048	.162	3.630	.000	.079	.267
	Service Quality	.459	.054	.509	8.478	.000	.353	.566

a. Dependent Variable: Trust

Appendix D - Model fit of Multiple Regression – Enjoyment, Ease of Use, and Service Quality as independent, Need for Human Interaction as dependent variables

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.634[a]	.402	.396	1.15315

a. Predictors: (Constant), Service Quality, Ease of use, Enjoyment

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	300.711	3	100.237	75.380	.000[b]
	Residual	448.129	337	1.330		
	Total	748.841	340			

a. Dependent Variable: Need For Human Interaction

b. Predictors: (Constant), Service Quality, Ease of use, Enjoyment

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	7.814	.208		37.567	.000	7.405	8.223
	Enjoyment	-.274	.061	-.331	-4.485	.000	-.395	-.154
	Ease of use	-.057	.060	-.055	-.956	.340	-.176	.061
	Service Quality	-.256	.068	-.294	-3.747	.000	-.390	-.121

a. Dependent Variable: Need For Human Interaction

Appendix E - Model fit of Multiple Regression –Enjoyment, Ease of Use, and Service Quality as independent, Convenience as dependent variables

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.831[a]	.690	.687	.77900

a. Predictors: (Constant), Service Quality, Ease of use, Enjoyment

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	455.010	3	151.670	249.934	.000[b]
	Residual	204.505	337	.607		
	Total	659.516	340			

a. Dependent Variable: Convenience

b. Predictors: (Constant), Service Quality, Ease of use, Enjoyment

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	.882	.141		6.277	.000	.606	1.158
	Enjoyment	.049	.041	.062	1.175	.241	-.033	.130
	Ease of use	.140	.041	.144	3.437	.001	.060	.219
	Service Quality	.551	.046	.674	11.959	.000	.461	.642

a. Dependent Variable: Convenience

Appendix F – Model fit of Multiple Regression –Trust, Need for Human Interaction, and Convenience as independent, Intention to Use as dependent variables

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.774[a]	.599	.595	.99700

a. Predictors: (Constant), Convenience, Need For Human Interaction, Trust

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	499.445	3	166.482	167.487	.000[b]
	Residual	334.978	337	.994		
	Total	834.424	340			

a. Dependent Variable: IntentionToUse

b. Predictors: (Constant), Convenience, Need For Human Interaction, Trust

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	1.809	.398		4.541	.000	1.026	2.593
	Trust	.314	.054	.308	5.847	.000	.208	.420
	Need For Human Interaction	-.155	.045	-.147	-3.433	.001	-.244	-.066
	Convenience	.468	.061	.417	7.674	.000	.348	.589

a. Dependent Variable: IntentionToUse

Appendix G - Model fit of Multiple Regression – Intention to Use as independent, Purchase Intention as dependent variables

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.171[a]	.029	.026	1.57782

a. Predictors: (Constant), IntentionToUse

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	25.321	1	25.321	10.171	.002[b]
	Residual	843.943	339	2.490		
	Total	869.264	340			

a. Dependent Variable: Purchase Intention

b. Predictors: (Constant), IntentionToUse

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	2.919	.235		12.420	.000	2.456	3.381
	IntentionToUse	.174	.055	.171	3.189	.002	.067	.282

a. Dependent Variable: Purchase Intention