MASTERS IN MANAGEMENT (MIM)

MASTERS FINAL WORK

DISSERTATION

FASHION FORWARD AI: EXPLORING CONSUMER PURCHASE INTENTION IN THE ERA OF ARTIFICIAL INTELLIGENCE

SOFIA ALEXANDRA COELHO PARREIRA

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SOFIA ALEXANDRA COELHO PARREIRA

JURY:

PRESIDENT: PROF. JOSÉ MANUEL CRISTÓVÃO VERÍSSIMO

RAPPORTEUR: PROF. WINNIE NG PICOTO

SUPERVISOR: PROF. JOANNA KRYWALSKI DA SILVEIRA SANTIAGO

MARCH - 2024

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ABSTRACT

Artificial Intelligence is one of the most pertinent topics in today's landscape. Due to its recent emergence and uncertainty about all its potential applications, there is a shortage of studies specially addressing consumers' purchasing intentions in the fashion industry. Many consumers in the sector express reservations and concerns about technological advancements, Therefore, this study, aims to comprehend the impact on the purchasing intentions of consumers who have already bought fashion products online.

The methodology employed in this study is quantitative, utilizing a questionnaire distributed across various social networks and encouraging its sharing within participants' contact networks. This resulted in a non-probabilistic convenience and snowball sampling. Out of the 390 responses obtained, only 331 were considered valid, excluding those who had not made online fashion purchases.

This study contributes academically by raising awareness about artificial intelligence in the fashion industry, offering insights for those unfamiliar with the topic and paving the way for further research. In a business context, it holds relevance for brands, emphasizing the need to understand AI's potential impact and allowing them to implement informed strategies to address concerns and leverage its positive aspects.

Lastly, this study provided deeper understanding of the factors that can influence customer satisfaction and attitude. Furthermore, it analyzed the impact of these factors on the potential intention to purchase fashion items. It is noteworthy that this study contributed to the analysis of factors that had not been explored collectively until now.

Keywords: Fashion, Artificial Intelligence, Purchase Intention, Consumer Satisfaction, Consumer Attitude, Technology Attitude

RESUMO

A Inteligência Artificial é um dos temas mais relevantes da atualidade. No entanto, devido à sua natureza recente e à incerteza sobre todas as suas potenciais aplicações, há uma escassez de estudos abordando especificamente a intenção de compra dos consumidores na indústria da moda. Muitos consumidores nesse setor demonstram reservas e preocupações em relação ao avanço tecnológico. Portanto, este estudo visa compreender o impacto nas intenções de compra de consumidores que já adquiriram produtos de moda online.

A metodologia adotada neste estudo é quantitativa, utilizando um questionário distribuído em várias redes sociais, incentivando a sua partilha nas redes de contactos dos participantes. Resultando numa amostragem não probabilística por conveniência e em bola de neve. Das 390 respostas obtidas, apenas 331 foram consideradas válidas, excluindo aqueles que não realizaram compras online de artigos de moda.

Este estudo contribui academicamente ao sensibilizar para a inteligência artificial na indústria da moda, oferecendo perceções a quem não está familiarizado com o tema e abrindo caminho para investigações adicionais. Num contexto empresarial, é relevante para as marcas, destacando a necessidade de compreender o impacto potencial da IA e permitindo a implementação de estratégias informadas para abordar preocupações e tirar partido dos seus aspetos positivos.

Por último, este estudo proporcionou uma compreensão mais aprofundada dos fatores que podem influenciar a satisfação e a atitude do cliente. Além disso, analisou o impacto desses fatores na intenção potencial de compra de itens de moda. É de salientar que este estudo contribuiu para a análise de fatores que não tinham sido explorados em conjunto até agora.

Palavras-Chave: Moda, Inteligência Artificial, Intenção de compra, satisfação do consumidor, Atitude do consumir, Atitude tecnológica

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CHAPTER 1 - INTRODUCTION

1.1. Academic and Business Relevance

As the number of internet users continues to rise steadily, being 5.35 billion users as of January 2024 (Petrosyan,2024), it is now estimated between 59.9% and 68.3% of the global population is connected online (Duarte, 2023). Aligned with the growth of internet users, the number of digital buyers is growing over the past few years, this is because of how convenient it is to shop online. According to analysis conducted by Instituto Nacional de Estatistica (INE), in 2022, approximately 43% of Portuguese have made online purchases, with a notable emphasis on apparel transactions.

Artificial Intelligence (AI) is not intended to replace humans, instead, its purpose is to augment human capabilities and contributions. It is causing a revolution in the fashion industry, influencing various aspects from design and production to shipping, marketing, and sales (Tiwari & Tomar, 2023). AI's impact is evident in apparel designing, here it aids fashion manufacturers in better understanding consumer desires and creating improved garments. Virtual Merchandising utilizes AI to assist consumers in predicting how a piece of clothing will look and fit on them, while Visual Search enables users to find stores that sell the desired products by using just one picture or screenshot (Tiwari & Tomar, 2023).

AI introduces essential tools for marketing, including recommendation systems and virtual styling assistants, facilitating pattern recognition, and enhancing the ability to predict online purchases (Rathore, 2017). In essence, AI is not a replacement but a transformative force that collaborates with human ingenuity to elevate and reshape the landscape of fashion industry.

Considering this it is essential to address sustainability and ethical practices in the realm of fashion, a concern that resonates strongly with consumers who are increasingly mindful of the environmental impact of fashion production and seek transparency. For a significant number of consumers, it is paramount that brands demonstrate a commitment to environmental responsibility and ethical principles. Consequently, fashion brands have introduced concepts such as the "circular economy", "eco design", and have actively promoted textile recycling (Rathore, 2017). This trend is anticipated to significantly contribute to the achievement of Sustainability Development Goals (SDG's), particularly SDG number twelve, which aims to establish sustainability consumption and production patterns. By 2030, the objective is to curtail waste generation through prevention, reduction, recycling, and reuse, Additionally, there is a push for companies to embrace sustainable practices and incorporate sustainability reporting, integrating, relevant information into their reporting cycles (The Global Goals, 2024).

1.2. Objectives of the Investigation

Artificial Intelligence is becoming an increasingly discussed topic, however, there remains limited understanding of its potential impact on the Fashion industry and consumers purchase intention. Shopping motivation, a pivotal aspect influencing consumer decision-making, has been a central focus in behavioral research. The online shopping environment is evolving rapidly, propelled by enhanced consumer interactivity facilitated by new technologies (Kim & Eastin, 2011).

This study aims to untangle the intriguing complexities surrounding the intersection of AI and the Fashion industry to understand how this can influence consumers' Purchase Intention. Particularly, it is intended to bring the insights and better understanding into the following inquires:

1. Which factors shape consumers' attitude toward AI?
2. To what extent does AI mold and influence consumer purchase intention within the realm of Fashion?
3. Which factors influence consumers' satisfaction in the field of Fashion?

The Fashion industry is highly competitive and this study, as mentioned before, has its purpose to analyze how can AI impact consumers' Purchase Intention with the use of AI in one of the biggest industries in the world.

1.3. Structure of the Document

This document is composed of six chapters. Chapter one initiates with a brief introduction to the principal subjects of the study, Fashion and Artificial Intelligence. Emphasis is placed on the Academic and Business Relevance and the Objective of the Investigation. Chapter two is dedicated to important Literature Review related to the study delving into topics such as The Growth of Artificial Intelligence, its diverse applications, the Customer Behavior and Technology, and a comprehensive analysis of the variables inherent in the adopted models (Technology Acceptance Model and the Trivedi and Trivedi model). Subsequently, Chapter three articulates the Structure of the Conceptual model. Chapter four, the Methodology, explains the Study design, Sample Selection and the Data Collection Instruments and Procedures. The crux of the study resides in the final two chapter. Chapter five undertakes an incisive analysis of acquired data, presenting results, while the concluding chapter encapsulates key findings, delineates inherent limitations, and proffers insightful recommendations for prospective research studies.

CHAPTER 2 – LITERATURE REVIEW

2.1 The Growth of Artificial Intelligence

While Artificial Intelligence is not a novel subject, its prominence in discussions has noticeably increased in recent years, this is transforming the way people interact, communicate, live, learn, and work (Chiu et al, 2021). Even though there is no real definition of AI, it can be defined as the science and engineering of making intelligent machines (McCarthy, 2007). The idea of using computers to simulate intelligent behavior and critical thinking was initially articulated by Alan Turing in 1950, Ramesh et al. (2004). AI originated as a basic set on computational coding and has progressed over numerous decades to incorporate more sophisticated algorithms, achieving capabilities comparable to the human brain. AI incorporates various subjects such as Machine Learning, Deep Learning, and Computer Vision (Kaul et al., 2020). In 1966, a significant milestone was achieved with the creation of the first mobile robot capable of interpreting instructions. This development made a crucial advancement, enabling the robot to process more, indicate commands and execute corresponding actions (Kuipers et al., 2017). Computing power was significantly improved in the 2000's with the availability of larger datasets.

The term "Artificial Intelligence" is often lead to think only about automated robots who serve humans. However, AI applies to any kind of machine that is able to think like a human and is particularly helpful for repetitive tasks (Verma et al. 2021). The emergence of this new topic prompts reflections on novel ethical and legal concerns related to AI applications. The main issue is on understanding how all the data collected is analyzed, wondering if it is biased or the transparency of such analyses (Holmes et al. 2021).

2.2. The Applications of Artificial Intelligence

Artificial Intelligence is applicable in numerous areas. For instance, medicine, which over the last five decades, has undergone significant evolution. The emergence of machine learning and deep learning has broadened the scope of application of Artificial Intelligence in medicine. Instead of relying only on algorithmic approaches, it has paved the way for personalized medicine. This may enhance diagnostic accuracy, streaming provider workflow and clinical operations, enabling more effective disease and therapeutic (Kaul et al., 2020).

Apart from its applications in medicine, AI can have a substantial impact on education. It holds significant potential to enhance various aspects such as learning, teaching, educational administration, and assessment. The ability of AI to enhance personalization, tailoring experiences to individual needs, and providing immediate feedback stands out as a pivotal factor. Additionally, the capability for machine-supported queries anywhere and anytime further underscores the transformative potential of AI in education (Chiu et al., 2021).

Also, the automotive industry is expected to undergo significant changes with the advent of the AI revolution. It is anticipated that the accident rate will decrease as AI reduces reliance on human input, and AI programming must possess the capability to surpass human judgement (Teoh & Kidd, 2017).

Finally, AI is making a significant impact on the fashion industry. According to Tiwara and Tomar (2023), the future applications of AI in fashion are promising. For instance, AI can enhance apparel design precision, leading to improved manufacturing processes, Virtual merchandising allows consumers to predict how clothing will fit them accurately. Visual search capabilities enable more effective exploration of personal style and preferences, avoiding the overwhelming number of results often seen in conventional online searches. Aias facilitates personalizes product recommendations. Designers are increasingly incorporating AI to create.

2.3. Customer Behavior and Technology

The rising adoption of new technologies in retail has led to a shift in consumer shopping behaviors and expectations. A modern consumer, utilizing multiple devices and screens, has emerged, characterized by being well-informed and seeking brands that offer omnichannel experiences. Studies indicate that omnichannel consumers are becoming increasingly prevalent on a global scale (Schlager & Maas, 2013). Customers anticipate a consistent, uniform, and integrated service or experience, regardless of the channel they choose. They are inclined to transition seamlessly between various channels – be it a traditional store, online platform, or mobile app- based on their preferences, current circumstances, the time of the day, or the product category (Cook, 2014; Piotrowicz & Cuthbertson, 2014). The omni shopper is no longer merely accessing a single channel, instead, they are consistently present in one or multiple channels simultaneously, leveraging the capabilities provided by technology and mobility. These contemporary shoppers prefer utilizing their personal devices to conduct searches, compare products, seek advice, or explore cost-effective alternatives throughout their shopping journey. This approach allows them to harness the advantages offered by each channel effectively (Yurova et al., 2017).

Personal innovativeness emerges as the most potent predictor of Purchase Intention within the omnichannel context, as demonstrated in the analysis by Juaneda-Ayensa et al. (2016). According to their findings, omni shoppers actively seek new technology, aiming to experiment with it and early adopters among their family and friends. Additionally, this research underscores the significance of effort and performance expectancy in elucidating attitude and purchase intention. (Juaneda-Ayensa et al., 2016). These factors positively influence behavior intention, aligning with well-established findings in the literature (Childers et al., 2001). Moreover, the study conducted by Juaneda-Ayensa et al. (2016), also shows that the acceptance and use of technology are more aligned with a novel experiential approach associated with an individual's innovativeness profile rather than a hedonic one. In other words, the focus is on the excitement of discovering how something works, rather than the anticipated enjoyment based on prior experiences.

Retailers should not only strategically determine which technologies to invest in but also consider how to foster their acceptance. The acceptance of technology proves to be a crucial predictor of Purchase Intention. Specifically, when implementing in-store technology, the emphasis should be on creating a fresh, integrated customer experience. This involves employing practical, enjoyable, and interesting technology to ensure that innovative customers perceive new omnichannel stores as facilitating and expediting their shopping journey (Juaneda-Ayensa et al. 2016).

2.4. Technology Acceptance Model

This study involves the implementation of the two models. The Technology Acceptance Model (TAM) is a theoretical framework extensively applied in the realm of information systems and technology adoption. Initially introduced by Fred Davis in 1989, it was subsequently expanded by Venkatesh and Davis in 2000. Moreover, they developed additional derivative models between 2003 and 2017, as indicated in the references. The TAM has been employed to evaluate consumer attitudes and acceptance across various domains, such as online mass-customization technology (Lee et al., 2011), wearable fitness technology (Lunney et. al., 2016), and smart in-store technology applications in retailing (Kim et. al., 2016).

2.4.1 Perceived Usefulness

Perceived usefulness is a fundamental element in TAM, represents the extent to which a person believes that using a particular system or technology would enhance their performance or simplify tasks (Davis, 1989). Liang et al. (2020) highlighted the significance of perceived usefulness in shaping consumers' attitudes toward AI. However, similar findings were made with Williams et al. (2014), in their article on "Consumers' Intention to Use E-readers".

Perceived usefulness is positively impacted by perceived ease of use, as, under similar conditions, the more user-friendly a technology is, the more valuable it tends to be (Lee et al., 2012). In other words, when consumers perceive a product as beneficial, they are inclined to be cognitive, driven by reason, and focused on achieving specific goals to enhance their tasks performance (Babin et. al, 1994; Dhar & Wertenbronch, 2000). In this sense, if consumers perceive that AI is useful in the fashion industry, with innovations such as virtual merchandising their attitude will positively be influenced.

This study aims to evaluate consumers' willingness to purchase online fashion products with the use of Artificial Intelligence. In this sense, we propose:

H1: Perceived usefulness in online fashion brands will positively influence consumers' attitude toward AI.

2.4.2. Perceived Ease of Use

As outlined by Davis (1989), TAM places significance on ease of use and perceived usefulness as crucial indicators, shaping consumers' perceptions of technology. Davis (1989) specifically defined perceived ease of use as "The degree to which a person believes that using a particular system would be free of effort" (p. 320). The author suggested that consumers who believe that a product may be easy to use are probably going to adopt a favorable utilitarian attitude toward its usage.

In this context, it is plausible that consumers will embrace the use of AI in fashion if they perceive it to be "easy to use". For that reason, we propose:

H2: Ease of use in online fashion brands will influence positively consumers' attitude toward AI.

2.4.3. Performance Risk

According to Davis (1989), ease of use and perceived usefulness are important indicators for the TAM model. However, the original model has been redefined and performance risk has become an important indicator.

Spreng and Olshavsky (1992) have divided perceived performance into two concepts: "Perceptual performance" and "Evaluative Performance". The first one stands for the beliefs that the consumer hold, while the second one involves a comparison between the consumers perception and the actual outcome of the product. Another conceptualization is the one given by Grewal et al. (1994, p. 145): "the possibility that the product will not function as expected and/or will not provide the desired benefits."

For this reason, if consumers perceived a higher risk in online fashion products, their attitude towards AI, will be negatively influenced. We propose the following:

H3: Performance risk will not influence positively consumers' attitude toward AI in online fashion brands.

2.4.4. Technology Attitudes

Technology has been increasing in a rapid way, and although this study focuses on online fashion brands, it is important to notice that companies have adapted in-store technologies, improved customers' experience and decreasing costs (McKenzie et al., 2018).

Peoples' beliefs are different, and for that reason, they will embrace technology in different ways (Agarwal and prasad, 1998; Devaraj et. al, 2008). Technology Readiness (TR) is an important characteristic, relevant to the acceptance of technology. TR is defined by the mental pre-existing state and the perception of using new technology (Lin et al., 2007). Lin and Hsieh (2006) also indicated that technology can trigger positive and negative feelings.

Some authors say that technology can cause anxiety and will negatively impact their online shopping experience (Kim & Forsythe, 2009), while others have concluded that attitudes toward technology can trigger favorable attitudes or willingness to adopt a technological product (Curran, Meuter, & Surprenant, 2003). For these reasons, the following hypotheses is proposed:

H4: Consumers attitudes toward technology will positively influence their attitudes on purchasing in online fashion brands.

2.4.5. Attitude toward AI

Perceived Usefulness, Ease of Use, and Technology Attitudes have a positive impact on consumers' Attitude toward AI, whereas Performance Risk negatively influences consumers' Attitude towards AI (Liang et al. 2020). Despite these general trends individuals have different attitudes regarding AI, with some expressing concerns that might lead to job displacement as it replaces various human tasks (Winick, 2018), on the other hand, there are individuals who are open to using AI without fear, as they perceive it to be beneficial (Lichtenthaler, 2019). On this matter Lichtenthaler (2018b) also concluded that even though human work may start to be substituted there will be more important benefits from it.

There are several authors (e.g. Belleau et. al., 2007; Wu, et al., 2016) that prove that the purchase intention is influenced on consumers' attitude, so, for that reason, if consumers have a positive attitude towards AI in online fashion brands, they will be more likely to purchase those products. Accordingly, it is proposed:

H5: Positive attitudes towards AI in online fashion brands influence positively consumers' purchase intention.

2.5. Trivedi and Trivedi's Model

Trivedi and Trivedi's (2018) model also utilized, serving as a theoretical framework that aims to understand and forecast consumers' intentions to make a purchase. This model is employed in marketing and consumer behavior research to explore the factors that influence individuals' decision-making processes leading up to a purchase. The purchase intention is considered a crucial precursor to actual purchasing behavior. While various models and theories exist within the realm of Purchase Intention, a common approach involves examining the impact of multiple factors on a consumer's intention to buy.

According to Delone and McLean (2003), the Purchase Intention has three quality dimensions that determine success. The three dimensions are Information Quality (INFQ), System Quality (SYSQ), and Service Quality (SERQ). Engel et al. (1995) covered various aspects of consumer behavior, including decision-making processes leading to purchase intention. On their side, Hair et al. (2014) offered insights into multivariate analysis techniques in their textbook, commonly applied in the examination of purchase intention. Kim et al. (2011) delved into the dimensions influencing online purchasing intention, shedding light on the role of hedonic motivation. Additionally, Hill et al. (1975), through their work in social psychology, contributed to understanding attitudes, intentions, and behavior concerning purchase intention.

2.5.1. Information, System and Service Quality

In the Trivedi and Trivedi's (2018) model, the variables of Information, System, and Service Quality play crucial roles. Given that online shopping lacks the tangible and sensory aspects present in traditional retail stores, consumers heavily rely on the information presented on websites for their judgements. To address this limitation, online sellers facilitate consumer decision-making by enabling product evaluations to be shared online. This approach provides indirect experiences of the product and generates valuable information to guide purchase Intention decisions (Park et al., 2007). The effectiveness of online consumer reviews is further enhanced when sellers develop systems for recommending relevant reviews to both highly and minimally engaged consumers. This ensures that the impact of online reviews becomes more persuasive in influencing purchase intentions (Park et al., 2007).

In their study, Trivedi and Trivedi (2018) have mentioned that the younger generation want apps that are easy to use and give relevant information. For this reason, it is important that marketers can provide customized information, service, and system performance so that it can lead to a higher satisfaction. We created the following hypothesis regarding the online fashion brands:

H6: Information quality in online fashion brands will influence positively consumers' Satisfaction.

H7: System quality in online fashion brands will influence positively consumers' Satisfaction.

H8: Service quality in online fashion brands will influence positively consumers' Satisfaction.

2.5.2. Satisfaction

Consumer satisfaction is crucial for the success of any business, characterized as the assessment made by consumers regarding a product or service in relation to their needs and expectations (Oliver, 1980). Zeithaml et al. (1996) investigated the role of satisfaction in motivating Purchase Intention (PI) for an online portal, revealing that satisfaction consumers were more likely to make purchases through the portal. Wu et al. (2009) emphasized that the success of the m-commerce industry depends on the consumers' regular and long-term intention to use the platform. Chong (2013) noted that m-commerce users may lack consistency in their actions and might not return if dissatisfied. However, their satisfaction level plays a crucial role in determining the consistency of shopping through mobile devices.

Utilizing natural language processing and machine learning, AI-driven chatbots and virtual assistant tools can understand customer queries and provide informed responses, thereby enhancing customer satisfaction and fostering loyalty (Rathore, 2017). This heightened level of personalization contributes to customer satisfaction, builds brand loyalty, and ultimately drives sales. For this reason, it is proposed:

H9: Satisfaction with online fashion brands will positively influence consumers' Purchase Intention.

CHAPTER 3 - CONCEPTUAL MODEL

The conceptual model of this study is formed by two distinctive models, aimed to answer the research questions.

With the growing development of technology, and its integration in users' private and professional life, a decision regarding its acceptance or rejection remains an open question, for that reason, with the interest of addressing this question has resulted in the developed of the Technology Acceptance Model. This model is dominant in investigations factors affecting users' acceptance of technology. The first model used in this study was TAM as addressed in the study of Liang et al. (2020), with the goal of studying the implementation of AI in Fashion to understand consumers' attitudes and Purchase Intention in Fashion Brands. Perceived Usefulness, Perceived Ease of Use and Technology Attitudes positively influence consumers' attitude toward AI, in contrast, Performance Risk negatively influence consumers' Attitude toward AI. The Purchase Intention is influenced by consumers' Attitude Toward AI, which have a positive impact.

In addition, the Trivedi and Trivedi's (2018) model was used with the aim of analyzing the consumers' Purchase Intention, described as the judgment of whether he or she will consider purchasing an available and advertised product in the near future. Through this model it is possible to access the acceptance of a product or a service in the market. Figure 1 presents the proposed model developed on the base of both mentioned studies.

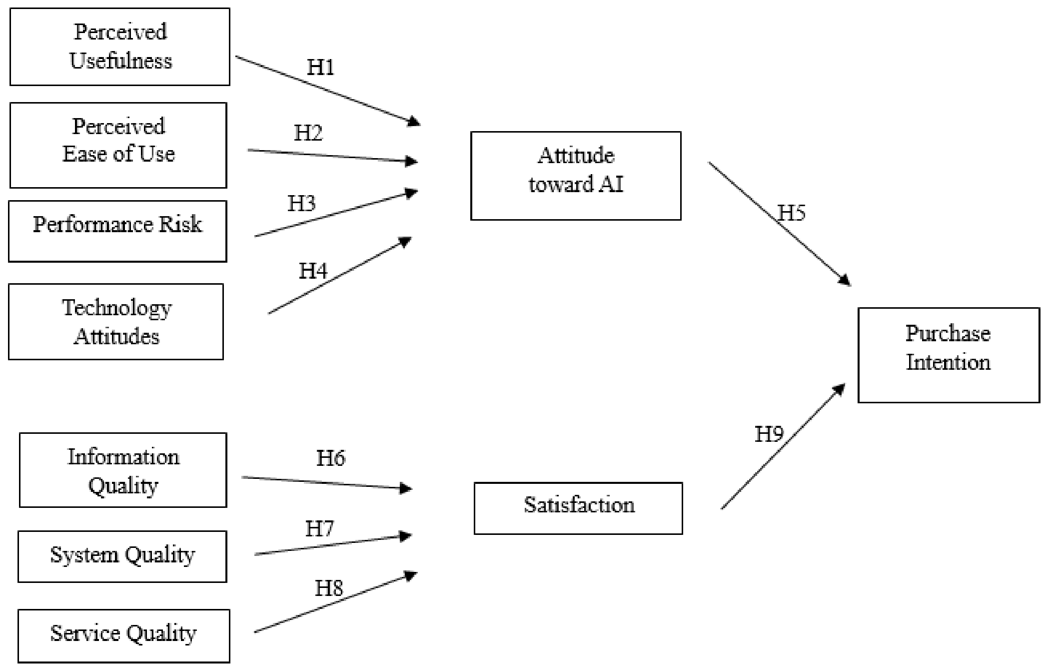

Figure 1. Conceptual Model
Source: Own elaboration based on Liang et al. (2020) TAM and Trivedi and Trivedi's (2018) model

CHAPTER 4 - METHODOLOGY

The primary goal of this study is to answer the research questions induced earlier. Within this chapter, we unfold the details of the methodology, providing a detailed account of the strategic plan that guided the research process to effectively address and answer the posed questions.

4.1. Study Design

This study was based on the philosophy of positivism, delving into the cause-and-effect relationships, and exploring the quantitative realm through statistical hypothesis testing. Guided by the deductive method, the aim was to affirm or refine existing theories, adding a dynamic layer to understanding (Saunders et al., 2009).

The methodological choice was the mono-method of quantitative research, we navigate the intricate landscape of AI in fashion brands, scrutinizing the relationships between variables through meticulous data collection and statistical analysis (Saunders et al., 2019). The strategy utilized was the survey by questionnaire, a choice not only for its simplicity in control, coding, and analysis but also for its cost-effective ability to gather a wealth of responses (Nunan et al., 2020; Saunders et al., 2019).

This study had a short period of time to be answered, for that reason the time horizon is cross-sectional (Saunders et al.,2019).

4.2. Sample Selection

The study focused on the population that has purchased online fashion products, such as apparel, makeup, accessories, shoes, or any other fashion category. Recognizing the impracticality of studying the entire population, we strategically gathered data from a representative sample, a methodology aligned with best practices in research (Saunders et al., 2019).

The sampling technique opted to study was the non-probability convenience. This method, swift and cost-effective, allowed to select individuals based on their availability and accessibility. While it facilitated a rapid data collection process, it is essential to note that, being a non-probability-sample, its finding cannot be statistically projected to the entire population.

Adding to this, we kickstarted the survey by encouraging the initial participants who have completed the survey to refer others in their circles who shared the criteria of having an online Fashion product purchase. This snowball sampling technique (Nunan et al.,2020; Saunders et al., 2019) allowed to expand the reach of the survey and tap into diverse perspectives.

4.3. Data Collection Instruments and Procedures

The questionnaire aimed to test the proposed hypothesis and answer the research questions, structured into five distinctive sections, as it is shown in the annex A of this study.

The first segment served as filter question, determining whether respondents have done any online fashion purchase. If the answer was affirmative, the questionnaire proceeds to subsequent sections, otherwise it skipped to the end. All questions were mandatory, ensuring respondents complete each section before advancing to the next.

In the questionnaire's second segment, four general questions were incorporated to gain insight into consumers' preferences in the realm of Fashion. The final section delves into socio-demographic details, encompassing geographic location, academic level, occupation, and other personal information. It is worth nothing that these questions employ diverse levels of measurement, some are categorized, while others are evenly spaced within an interval.

To measure the variables under investigation, sections three and four of the questionnaires were dedicated to the models supporting this study, namely the TAM and Trivedi and Trivedi (2018) model, this can be found in the annex B. All questions were structured using seven-point Linkert-type scales, initially in English, and subsequently translated to Portuguese align seamlessly with the language and context of this study. The variable "Attitude toward AI" was originally formulated on a distinct scale. For the sake of maintaining uniformity thought the questionnaire, it underwent adaption to a Linkert-type scale.

Prior to launching the questionnaire on various platforms, a meticulous pre-test was conducted. Subsequently, a select group of individuals also participated in testing, thoroughly examining the questionnaire for any potential gaps. Following this comprehensive double-test phase, the finalized questionnaire was officially launched on December 27, 2023.

The questionnaire was built upon Qualtrics, and shared in different social media platforms, including WhatsApp, Instagram, and Facebook, collecting a total of 390 responses, however only 331 were consider valid (only individuals that have made an online Fashion purchase were considered for this study). This data was analyzed with the aid of the software SmartPLS.

CHAPTER 5– ANALYSIS AND RESULTS

Within this chapter, there will be a comprehensive presentation of topics such as the Sample Characterization, the Measurement Model Assessment, Discriminant Validity, Collinearity, Model Fit, and the Hypothesis testing.

5.1. Sample Characterization

With a total of 390 responses, out of which 331 were deemed valid, representing individuals who have made online fashion purchases. Within these 331 responses, 55.9% of respondents have identified themselves as female and 43.8% as male. The age spectrum exhibited a broad distribution, notably featuring a significant response from individuals aged 55 to 64, constituting 29.9%. The age brackets of 18 to 24 and 45 to 54 also made noteworthy contributions, collectively accounting for 24.17% of the responses. Occupationally, a diverse landscape emerged – 50.8% identified as employed, 9.1 % as students, 10.3% as working students, 12.4% as self-employed, and 10.3% as retired. Financial resilience echoed in the responses, with 1.2% citing difficulties, while a majority (53.17%) expressed comfort with their financial situations.

This multifaceted insight predominantly emanated from Portuguese residents, comprising 94.9% of the respondents.

In the realm of fashion preferences, 53.47% expressed a predilection for physical stores, while a substantial 31.72% remained indifferent to the medium, be it physical or online. Unveiling the digital landscape, mobile phones emerged as the preferred platform for online Fashion purchases at 54.38%, closely followed by computers at 38.67%.

The annex D shows the sample characterization with more detail.

5.2. Measurement Model Assessment

To analyze the Purchase Intention of Fashion consumers', Partial Least Squares Structural Equation modeling (PLS-SEM) was employed, utilizing the SmartPLS 4 software.

The Structural Equation Modelling facilitates the measurement of variables through indicators. The method offers advantages in exploring construct visibility and simplifying research, enabling researchers to assess the relationship between indicators and variables to test hypotheses (Urban & Mayerl, 2013). Notably, this approach the use of a smaller sample size and the distributional assumptions are not essential (Fuchs, 2011). According to Shackman (2013), further underscores that explanatory research benefits from the enhanced statistical power of PLS in detecting statistically significant relationships compared to other model types.

5.2.1. Reliability and Validity

The initial step in evaluating the reflective measurement model, as estimated by PLS-SEM, involves assessing the extent to which each indicator's variance is accounted by its corresponding construct (Sarstedt et al., 2021). It is recommended for indicator loadings to exceed 0.708, indicating that the construct elucidates more than 50% of the indicator's variance (Hulland, 1999). The indicator "SysQual3" displayed an outer loading of 0.409, falling below the 0.5 threshold and as a result, it has been excluded from further analysis. Table I presents the outer loading, incorporating item that were subsequently eliminated for the remaining analysis.

The second step in evaluating the reflective measurement model involves scrutinizing its internal consistency reliability. While Cronbach's alpha is a commonly used measure for this purpose, it has a significant limitation – assuming all indicator loadings are the same in the population. Therefore, in PLS-SEM, one of the primary measures employed is composite Reliability (rho_c) (Joreskog, 1971). Higher values of Composite Reliability indicate greater levels of reliability. However, acknowledging that Cronbach's alpha can be too conservative and

Composite Reliability too liberal, Dijkstra (2014) proposed an alternative, the reliability coefficient rho_a. Irrespective of the reliability indicator used, values should ideally exceed 0.7. Upon reviewing the table above (table I.), it is evident that all these indicators consistently meet this criterion.

The subsequent step involves evaluating the convergent validity of each construct using the Average Variance Extracted (AVE) metric. The minimum acceptable threshold for AVE is 0.50. Hence, any value equal to or greater than 0.5 explains that the construct elucidates 50 percent or more of the indicators' variance (Hair et. al, 2022). As shown in table I, all AVE values surpass 0.5, affirming the convergent validity of the constructs.

Table I. Reliability and Validity

Variable	Item	Outer loading	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Attitude	Attitude1	0.909	0.959	0.959	0.969	0.861
	Attitude2	0.947				
	Attitude3	0.950				
	Attitude4	0.951				
	Attitude5	0.880				
InfoQual	InfoQual1	0.788	0.812	0.820	0.890	0.729
	InfoQual2	0.920				
	InfoQual3	0.849				
PercEase	PercEase1	0.649	0.918	0.935	0.937	0.716
	PercEase2	0.791				
	PercEase3	0.897				
	PercEase4	0.907				
	PercEase5	0.905				
	PercEase6	0.896				
PercUse	PercUse1	0.751	0.934	0.948	0.948	0.751
	PercUse2	0.891				
	PercUse3	0.907				
	PercUse4	0.918				
	PercUse5	0.866				
	PercUse6	0.857				
PerfRisk	PerfRisk1	0.998	0.898	1.028	0.863	0.683
	PerfRisk2	0.719				
	PerfRisk3	0.732				
PurchInten	PurchInten1	0.942	0.923	0.926	0.952	0.868
	PurchInten2	0.964				
	PurchInten3	0.886				
Satisf	Satisf1	0.503	0.723	0.861	0.841	0.652
	Satisf2	0.929				
	Satisf3	0.917				
ServQual	ServQual1	0.904	0.866	0.881	0.909	0.715
	ServQual2	0.862				
	ServQual3	0.867				
	ServQual4	0.740				
SysQual	SysQual1	0.879	0.814	0.819	0.889	0.729
	SysQual2	0.852				
	SysQual3	0.409				
	SysQual4	0.809				
TechAtt	TechAtt1	0.858	0.825	0.839	0.895	0.739
	TechAtt2	0.825				
	TechAtt3	0.895				

Source: SmartPLS

5.2.2. Discriminant Validity

Discriminant validity measures the degree to which a construct is empirically from other constructs in the structural model. While Fornell-Larcker criterion and cross-loading are conventional methods for assessing this validity, Henseler et al. (2015) suggested that these approaches may yield lower outputs. Therefore, it is recommended to employ the Heterotrait-Monotrait (HTMT) ratio, which could provide a more robust outcome.

The Fornell-Larcker criterion evaluates the shared variance between all model constructs, and it should not exceed their respective AVE´s values (Henseler et al, 2015). This criterion is met, as illustrated in table II.

Table II. Fornell and Larcker Criterion

	Attitude toward AI	Ease of Use	Information Quality	Perceived Usefulness	Performance Risk	Purchase Intention	Satisfaction	Service Quality	System Quality	Technology Attidude
Attitude toward AI	**0.928**									
Ease of Use	0.794	**0.846**								
Information Quality	0.266	0.303	**0.854**							
Perceived Usefulness	0.408	0.468	0.401	**0.867**						
Performance Risk	-0.065	-0.026	-0.097	0.050	**0.827**					
Purchase Intention	0.258	0.294	0.546	0.328	-0.084	**0.932**				
Satisfaction	0.293	0.377	0.597	0.500	-0.040	0.723	**0.808**			
Service Quality	0.210	0.252	0.561	0.333	-0.106	0.466	0.659	**0.846**		
System Quality	0.292	0.303	0.669	0.378	-0.095	0.674	0.675	0.601	**0.761**	
Technology Attidude	0.762	0.749	0.316	0.475	-0.057	0.233	0.378	0.321	0.293	**0.860**

Source: SmartPLS

The cross-loadings show that all indicators exhibit a higher correlation with their respective construct than with any other constructs (table III).

Table III. Indicator Items Cross Loadings

	Attitude Toward AI	Information Quality	Perceived Ease of Use	Perceived Usefulness	Performance Risk	Purchase Intention	Satisfaction	Service Quality	System Quality	Technology Attitude
Attitude1	**0.909**	0.209	0.749	0.398	-0.037	0.211	0.249	0.207	0.242	0.712
Attitude2	**0.947**	0.244	0.742	0.360	-0.090	0.245	0.278	0.183	0.265	0.694
Attitude3	**0.950**	0.288	0.742	0.404	-0.053	0.276	0.299	0.213	0.301	0.682
Attitude4	**0.951**	0.242	0.732	0.346	-0.060	0.232	0.243	0.165	0.250	0.713
Attitude5	**0.880**	0.249	0.716	0.386	-0.061	0.230	0.290	0.207	0.276	0.732
InfoQual1	0.245	**0.788**	0.303	0.329	-0.057	0.536	0.485	0.340	0.587	0.232
InfoQual2	0.244	**0.920**	0.253	0.337	-0.104	0.481	0.552	0.520	0.584	0.307
InfoQual3	0.191	**0.849**	0.221	0.364	-0.084	0.382	0.489	0.573	0.551	0.266
PercEase1	0.476	0.264	**0.649**	0.389	-0.094	0.212	0.316	0.298	0.269	0.460
PercEase2	0.583	0.203	**0.791**	0.372	0.063	0.227	0.334	0.181	0.234	0.547
PercEase3	0.697	0.202	**0.897**	0.388	-0.048	0.173	0.240	0.178	0.173	0.676
PercEase4	0.755	0.282	**0.907**	0.433	0.009	0.260	0.343	0.211	0.254	0.716
PercEase5	0.705	0.278	**0.905**	0.403	-0.018	0.297	0.345	0.214	0.280	0.677
PercEase6	0.761	0.309	**0.896**	0.404	-0.052	0.318	0.350	0.231	0.303	0.685
PercUse1	0.231	0.321	0.323	**0.751**	0.055	0.283	0.446	0.314	0.318	0.330
PercUse2	0.318	0.342	0.396	**0.891**	0.048	0.302	0.458	0.306	0.334	0.377
PercUse3	0.403	0.345	0.450	**0.907**	0.030	0.281	0.433	0.288	0.326	0.448
PercUse4	0.406	0.390	0.442	**0.918**	-0.031	0.340	0.468	0.300	0.386	0.457
PercUse5	0.358	0.337	0.410	**0.866**	0.090	0.223	0.376	0.264	0.274	0.428
PercUse6	0.363	0.350	0.391	**0.857**	0.085	0.284	0.441	0.282	0.369	0.405
PerfRisk1	-0.066	-0.096	-0.027	0.044	**0.998**	-0.084	-0.043	-0.106	-0.102	-0.057
PerfRisk2	0.005	-0.096	0.040	0.063	**0.719**	-0.060	-0.033	-0.142	-0.039	-0.015
PerfRisk3	-0.008	-0.089	0.029	0.102	**0.732**	-0.063	-0.013	-0.120	-0.023	-0.023
PurchInten1	0.221	0.504	0.257	0.325	-0.036	**0.942**	0.686	0.410	0.665	0.177
PurchInten2	0.227	0.519	0.271	0.314	-0.048	**0.964**	0.697	0.431	0.652	0.196
PurchInten3	0.274	0.501	0.297	0.276	-0.156	**0.886**	0.637	0.464	0.595	0.284
Satisf1	0.216	0.242	0.292	0.325	0.075	0.246	**0.502**	0.314	0.233	0.277
Satisf2	0.221	0.582	0.292	0.399	-0.066	0.732	**0.929**	0.622	0.663	0.296
Satisf3	0.296	0.541	0.367	0.499	-0.045	0.647	**0.917**	0.600	0.635	0.370
ServQual1	0.209	0.520	0.225	0.298	-0.093	0.457	0.632	**0.904**	0.583	0.316
ServQual2	0.158	0.461	0.198	0.268	-0.058	0.394	0.550	**0.862**	0.510	0.247
ServQual3	0.210	0.534	0.255	0.324	-0.136	0.407	0.575	**0.867**	0.536	0.294
ServQual4	0.122	0.363	0.169	0.230	-0.067	0.303	0.453	**0.740**	0.395	0.218
SysQual1	0.263	0.625	0.263	0.333	-0.097	0.618	0.603	0.520	**0.887**	0.284
SysQual2	0.235	0.551	0.260	0.346	-0.116	0.572	0.605	0.567	**0.855**	0.214
SysQual4	0.238	0.542	0.231	0.304	-0.036	0.563	0.530	0.456	**0.818**	0.229
TechAtt1	0.712	0.347	0.697	0.425	-0.040	0.255	0.353	0.302	0.333	**0.858**
TechAtt2	0.539	0.190	0.545	0.379	-0.015	0.107	0.258	0.241	0.152	**0.825**
TechAtt3	0.692	0.260	0.672	0.417	-0.086	0.218	0.351	0.279	0.228	**0.895**

Source: SmartPLS

For the HTMT criteria, it is noteworthy that all the obtained values are below the recommended threshold of 0.85 (Henseler, 2015). All methods confirm the discriminant validity, as shown in table IV.

Table IV. Indicator Items HTMT

	Attitude toward AI	Ease of Use	Information Quality	Perceived Usefulness	Performance Risk	Purchase Intention	Satisfaction	Service Quality	System Quality	Technology Attidude
Attitude toward AI										
Ease of Use	**0.838**									
Information	0.301	**0.354**								
Perceived U	0.423	0.506	**0.462**							
Performance	0.038	0.072	0.130	**0.090**						
Purchase Int	0.275	0.320	0.632	0.355	**0.085**					
Satisfaction	0.366	0.492	0.740	0.625	0.107	**0.827**				
Service Qual	0.227	0.290	0.662	0.374	0.150	0.518	**0.803**			
System Qual	0.344	0.376	0.828	0.427	0.092	0.767	0.829	**0.713**		
Technology	0.846	0.847	0.376	0.534	0.058	0.260	0.503	0.374	**0.371**	

Source: SmartPLS

5.2.3. Collinearity Validity

It is evident from the following table, table V., that there is collinearity validity, as the inner Variance Inflation Factor (VIF) is lower than 5. The outer VIF is presented in the annex C.

Table V. Inner model VIF

	VIF
Attitude toward AI -> Purchase Intention	1.094
Ease of Use -> Attitude toward AI	2.369
Information Quality -> Satisfaction	1.956
Perceived Usefulness -> Attitude toward AI	1.350
Performance Risk -> Attitude toward AI	1.011
Satisfaction -> Purchase Intention	1.094
Service Quality -> Satisfaction	1.692
System Quality -> Satisfaction	2.114
Technology Attidude -> Attitude toward AI	2.402

Source: SmartPLS

5.3. The Structural Model

To evaluate the structural model, it is necessary to analyze the coefficient of determination (R^2) of the endogenous constructs and the significance of the path coefficients, as despite below in figure 2.

The R^2 coefficient, ranging from 0 to 1, signifies the explanatory power, with higher values indicating greater explanatory power. As a general guideline, an R^2 value of 0.75 can be considered substantial, 0.50 moderate, and 0.25 weak (Hair, Ringle & Sarstedt, 2011). The coefficient of determination is a function of the number of predictor constructs, the greater the number of predictor constructs, the higher the R^2.

The significance level of the path coefficient will be analyzed in 5.4 (hypotheses testing) with the bootstrapping procedure.

Figure 2. PLS Algorithm Model
Source: SmartPLS

To analyze the model Fit criteria, the Standardized Root Mean Square Residual (SRMR) was employed. SRMR is calculated as the square root of the sum of the squared differences between model-implied and the empirical correlation matrix, representing the Euclidean distance between two matrices. A perfect fit is indicated by an SRMR value of 0. However, studies have demonstrated that even a correctly specified model can yield SRMR values of 0.06 and higher (Henseler et al., 2014). Thus, a more appropriate cut-off value of 0.08, as proposed by Hu and Bentler (1999), is considered. As observed in table VI., the SRMR is 0.055 indicating an acceptable fit.

Table VI. Model Fit

	Saturated model	**Estimated model**
SRMR	0.055	0.066
d_ULS	2.490	3.564
d_G	1.153	1.216
Chi-square	2139.587	2219.531
NFI	0.822	0.815
	R-square	**R-square adjusted**
Attitude toward AI	0.695	0.691
Purchase Intention	0.525	0.522
Satisfaction	0.569	0.565

Source: SmartPLS

5.4. Hypotheses Testing: Bootstrapping

PLS-SEM employs a nonparametric bootstrap procedure to test the significance of estimated path coefficients. The significance assessment builds on bootstrapping standard errors as a basis for calculating *t*-values of path coefficients or alternatively confidence intervals. A path coefficient is considered significant at the 5% level if the value zero does not fall within the 95% confidence interval (Aguirre-Urreta & Ronkko, 2018). Bootstrap analysis with 5000 interactions of resampling was utilized to calculate t-values, the hypotheses were accepted as statistically significant if the t-value exceeded the critical value (t-value > 1.96) and p-value was less than 0.05 (Henseler et al., 2016). The path coefficient led to the acceptance of six out of the nine presented hypotheses, as indicated in table VII. The last column in the table reflects the decision on each Hypothesis, denoting whether it is "supported" or "Not Supported" based on the predetermined significance level.

Table VII. Summary of hypothesis testing

Hypothesis	**Relationship**	**Path Coefficient**	**t-value**	**p-value**	**Decision**
H1	Perceived Usefulness -> Attitude toward AI	-0.011	0.265	0.791	*Not supported*
H2	Ease of Use -> Attitude toward AI	0.512	9.606	0.000	*Supported*
H3	Performance Risk -> Attitude toward AI	-0.030	0.705	0.481	*Not supported*
H4	Technology Attidude -> Attitude toward AI	0.382	7.084	0.000	*Supported*
H5	Attitude toward AI -> Purchase Intention	0.050	1.218	0.223	*Not supported*
H6	Information Quality -> Satisfaction	0.156	2.555	0.011	*Supported*
H7	System Quality -> Satisfaction	0.363	5.860	0.000	*Supported*
H8	Service Quality -> Satisfaction	0.352	6.773	0.000	*Supported*
H9	Satisfaction -> Purchase Intention	0.709	17.830	0.000	*Supported*

Source: SmartPLS

5.5. Discussion of Results

The influence on the Attitude toward AI was substantiated solely by “Ease of Use” and “Technology Attitude”. Hypotheses H2 and H4 demonstrated p-values of 0.000 and 0.000, along with t-values surpassing 1.96. Consequently, the outcomes demonstrate that consumers’ Technology Attitude and Ease of Use in online fashion brands positively impact consumers’ attitude toward AI, aligning with findings from previous studies conducted by Liang et al. (2020), Kim et al. (2017), and Li and Huang (2009). These studies have also evidenced that Perceived Usefulness (H1) and Performance Risk (H3) employ positive and negative impacts (respectively) on consumers’ attitudes toward AI. However, these relationships could not be confirmed in the present study, as H1 and H3 exhibited p-values of 0.791 and 0.481, with t-values falling below 1.96. Hypothesis H5 lacked support, registering a p-value of 0.223 and a t-value of 1.218, both outside the accepted threshold. Nevertheless, various researchers (e.g., Belleau et al., 2007; Liand et al., 2020; Lee & Chang, 2011; Li & Huang,2009) have established that Positive Attitudes toward AI significantly influence consumers’ Purchase Intention.

Consumers’ Satisfaction with Purchasing Fashion products was examined through three hypotheses, all of which found support in this study. Information Quality (H6), System Quality (H7), and Service Quality (H8) all yielded a p-value of 0.000, below the critical value of 0.05, along with t-values exceeding 1.96, with values of 2.555, 5.860, and 6.773, respectively. With these substantiated hypotheses, it can be concluded that Information, System, and Service Quality exert a positive influence on consumers’ Satisfaction. This lends support to Hypotheses H9, which was also validated in this study, indicating that satisfaction positively impacts consumers’ Purchase Intention.

CHAPTER 6– CONCLUSIONS, LIMITATIONS AND SUGGESTIONS FOR FUTURE RESEARCH

The last chapter aims to present the main conclusions of this study identifying limitations, and suggestions for future research.

6.1. Conclusions

This study was designed within the current trend of artificial intelligence, specifically in the realm of fashion, as there is still limited knowledge about the intersection of these two topics. Although open to participants of various nationalities, it received a higher response rate from the Portuguese community. The primary objective was to explore the factors influencing attitudes toward AI and customer satisfaction, as well as how these factors impact purchase intentions in fashion brands. The study aimed to contribute to a deeper understanding of how fashion companies can enhance their strategies in the era of artificial intelligence. Consequently, based on the obtained results, it is evident that the primary objectives were successfully accomplished, allowing for the resolution of the three research questions posed in the introduction.

To address the first question, “Which factors shape consumers’ attitude toward AI?”, this study reveals that both “Perceived Ease of Use” and “Technology Attitude” play roles in shaping consumers’ attitude toward AI. Nevertheless, it is essential to highlight that “perceived ease of use” emerges as the predominant factor influencing consumers’ attitude toward AI in this study. This finding aligns with the insights provided by Liang et al. (2020), they suggest that perceived usefulness and performance risk are additional factors that contribute to shaping attitudes toward AI. However, it is important to note that within the specific context of the fashion industry, this study did not yield conclusive evidence to support the impact of perceived usefulness and performance risk.

In response to the second question, “To what extend does AI mold and influence consumer purchase intention within the realm of fashion?” conclusive insights regarding the impact of AI on purchase intention were challenging to derive. This limitation may stem from participants’ potential lack of information about artificial intelligence and its future implications. Despite this, supporting evidence from Liang et al. (2020) underscores the importance of ongoing studies to explore the nuanced ways in which AI can influence purchase intentions, particularly within the dynamic landscape of the fashion industry.

Regarding the third question, “Which factors influence consumers’ satisfaction in the field of Fashion?” this study underscores the pivotal roles of system quality, service quality, and information quality in determining consumer satisfaction. Notably, system and service quality exhibit a more substantial impact. Furthermore, the study establishes a direct link between consumer satisfaction and purchase intention, affirming that satisfied consumers are more likely to express an intention to make a purchase.

The contributions of this study extend both academically and in business context. Academically, it raises awareness about artificial intelligence, particularly within the fashion industry, providing valuable insights for those previously unacquainted with the topic and paving the way for further research. From a business perspective, the study holds relevance for brands, emphasizing the need to comprehend the potential impact of AI on their operations. Understanding the factors that evoke apprehension in consumers allows brands to implement informed strategies to address concerns and leverage the positive aspects of AI integration.

6.2. Limitations of the Study

This study acknowledges several limitations that should be taken into account for future research endeavors. Firstly, the time horizon adopted was cross-sectional, primarily due to constraints in time and inherent aspects of the chosen theme. Therefore, for subsequent research, a longitudinal study is recommended to capture the dynamics over time. Additionally, the use of a non-probability sampling technique implies that the sample may not be fully representative of the entire population, limiting the generalizability of the results. It is suggested that future studies incorporate interviews or focus groups to enhance the depth of understanding. Lastly, despite the growing prominence of AI, there is still limited information available about its day-to-day impact, highlighting the need for further exploration in this area.

6.3. Suggestions for Future Research

For future research, a qualitative approach, employing focus groups or interviews, is recommended as a primary suggestion. Exploring the relationship between Purchase Intention and sociodemographic variables, such as studying a specific generation, could provide valuable insights. Shifting the focus to the industry side rather than the consumer side is another intriguing avenue, particularly examining how AI can influence the production processes of Fashion brands. Additionally, a targeted analysis of Personalization in Fashion products would be valuable to understand its impact on Purchase Intention.

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ANNEXES

Annex A - Questionnaire

O presente questionário tem a finalidade de **estudar o impacto da Inteligência Artificial (IA) na área da moda.**

Este estudo, faz parte da minha dissertação de Mestrado que estou a frequentar no ISEG - Instituto Superior de Economia e Gestão, da Universidade de Lisboa.

A duração do questionário é de aproximadamente 10 minutos, será totalmente anónimo e os dados obtidos, serão tratados com confidencialidade.

As questões finais, de caráter sociodemográfico, são absolutamente anónimas, não sendo possível a identificação dos participantes.

Agradeço desde já o tempo prestado pela sua colaboração. Alguma dúvida ou esclarecimento adicional, queira por favor entrar em contacto comigo:

Sofia Parreira

sofiaacparreira@aln.iseg.ulisboa.pt

ISEG Lisbon School of Economics & Management
Universidade de Lisboa

1. Alguma vez comprou online um artigo de moda (ex: roupa, maquilhagem, acessórios, calçado, etc...)?

- ◯ Sim
- ◯ Não

2. Onde efetua/efetuou as suas compras online? (é possível escolher mais do que uma opção)

- ☐ Loja e-commerce
- ☐ Redes Sociais
- ☐ Plataforma com vários vendedores (ex: Amazon, AliExpress, ebay, Vinted, etc...)
- ☐ outro

3. Prefiro comprar artigos de moda (escolha apenas uma opção):

- ◯ Em lojas fisicas
- ◯ Online
- ◯ Não tenho preferência

4. Qual o equipamento que mais usa nas compras online? (escolha apenas uma opção)

- ◯ Computador
- ◯ Telemóvel
- ◯ Tablet
- ◯ Outro

5. Qual a categoria de produtos de moda que costuma comprar online? (é possível escolher mais do que uma opção)

- ☐ Roupa
- ☐ Roupa desportiva
- ☐ Maquilhagem
- ☐ Acessórios
- ☐ Calçado
- ☐ outra

6. As seguintes frases são relacionadas com a **sua experiência** em lojas de moda online.
Numa escola de 1 a 7, sendo 1 - concordo plenamente e 7 - discordo plenamente, qual o nível de concordância das seguintes afirmações.

	1 - Concordo plenamente	2 - Concordo	3 - Concordo um pouco	4 - Neutro	5 - Discordo um pouco	6 - Discordo	7 - Discordo plenamente
Lojas de moda online, fornecem-me os artigos que necessito.	○	○	○	○	○	○	○
Lojas de moda online fornecem informações suficientes para que eu possa comprar.	○	○	○	○	○	○	○
A informação fornecida pelas lojas de moda online é útil em relação às minhas questões/ problemas.	○	○	○	○	○	○	○

7. As frase abaixo são relacionadas com a **facilidade de compra** em lojas online.
Numa escola de 1 a 7, sendo 1 - concordo plenamente e 7 - discordo plenamente, qual o nível de concordância das seguintes afirmações.

	1 - Concordo plenamente	2 - Concordo	3 - Concordo um pouco	4 - Neutro	5 - Discordo um pouco	6 - Discordo	7 - Discordo plenamente
Acho fácil tornar-me hábil no uso de lojas de moda online.	○	○	○	○	○	○	○
Acredito que as lojas de moda online são fáceis de usar.	○	○	○	○	○	○	○
Usar lojas de moda online requer pouco esforço mental.	○	○	○	○	○	○	○
Usar lojas de moda online é conveniente.	○	○	○	○	○	○	○

8. As seguintes afirmações são relacionadas com a **qualidade do serviço** prestado por lojas online.
Numa escola de 1 a 7, sendo 1 - concordo plenamente e 7 - discordo plenamente, qual o nível de concordância das seguintes afirmações.

	1 - Concordo plenamente	2 - Concordo	3 - Concordo um pouco	4 - Neutro	5 - Discordo um pouco	6 - Discordo	7 - Discordo plenamente
Estou satisfeito/a com o apoio ao cliente nas lojas de moda online.	○	○	○	○	○	○	○
Estou satisfeito/a com o serviço pós-venda das lojas de moda online.	○	○	○	○	○	○	○
As lojas de moda online conseguem perceber os meus pedidos e problemas	○	○	○	○	○	○	○
As lojas de moda online respondem aos meus pedidos suficientemente rápido.	○	○	○	○	○	○	○

9. As seguintes afirmações são relacionadas com a **comunicação** das lojas de moda online.
Numa escola de 1 a 7, sendo 1 - concordo plenamente e 7 - discordo plenamente, qual o nível de concordância das seguintes afirmações.

	1 - Concordo plenamente	2 - Concordo	3 - Concordo um pouco	4 - Neutro	5 - Discordo um pouco	6 - Discordo	7 - Discordo plenamente
O serviço das lojas de moda online é frequentemente personalizado para mim.	○	○	○	○	○	○	○
As lojas de moda online tratam-me como um/a cliente único/a e individual	○	○	○	○	○	○	○
Quando comunico com lojas de moda online, muitas vezes sou abordado/a pelo meu nome	○	○	○	○	○	○	○

10. As frases abaixo são relacionadas com a **probabilidade de compra** nas lojas de moda online.
Numa escola de 1 a 7, sendo 1 - concordo plenamente e 7 - discordo plenamente, qual o nível de concordância das seguintes afirmações.

	1 - Concordo plenamente	2 - Concordo	3 - Concordo um pouco	4 - Neutro	5 - Discordo um pouco	6 - Discordo	7 - Discordo plenamente
É muito provável que compre artigos em lojas de moda online no futuro.	○	○	○	○	○	○	○
Considero que a probabilidade de comprar em lojas de moda online é grande.	○	○	○	○	○	○	○
A minha vontade de comprar em lojas de moda online é alta.	○	○	○	○	○	○	○

11. As seguintes frases são relacionadas com a sua **satisfação** nas lojas de moda online.
Numa escola de 1 a 7, sendo 1 - concordo plenamente e 7 - discordo plenamente, qual o nível de concordância das seguintes afirmações.

	1 - Concordo plenamente	2 - Concordo	3 - Concordo um pouco	4 - Neutro	5 - Discordo um pouco	6 - Discordo	7 - Discordo plenamente
Ao fazer compras em lojas de moda online, sinto que estou a explorar um "novo mundo".	○	○	○	○	○	○	○
Estou satisfeito/a com a experiência do uso de lojas de moda online.	○	○	○	○	○	○	○
As lojas de moda online fazem um bom trabalho ao satisfazer as minhas necessidades.	○	○	○	○	○	○	○

12. Tendo em conta a aplicação do **sistema de recomendação** nas lojas online qual é a sua concordância com as seguintes frases (1 - concordo plenamente, 7 - discordo plenamente)

	1 - Concordo plenamente	2 - Concordo	3 - Concordo um pouco	4 - Neutro	5 - Discordo um pouco	6 - Discordo	7 - Discordo plenamente
O sistema de recomendação permite-me a escolha de artigos de forma mais rápida	○	○	○	○	○	○	○
O sistema de recomendação melhora o meu desempenho na escolha de artigos que são tendência.	○	○	○	○	○	○	○
O sistema de recomendação aumenta a eficiência na escolha de artigos que são tendência.	○	○	○	○	○	○	○
O sistema de recomendação melhora a minha eficácia na escolha de artigos de moda em tendência.	○	○	○	○	○	○	○
O sistema de recomendação faz com que seja mais simples a escolha dos artigos de moda	○	○	○	○	○	○	○
O sistema de recomendação é útil para escolher os artigos de moda que são tendência	○	○	○	○	○	○	○

13. Tendo em conta a **aplicação das ferramentas de IA** nas lojas online qual é a sua concordância com as seguintes frases (1 - concordo plenamente, 7 - discordo plenamente)

	1 - Concordo plenamente	2 - Concordo	3 - Concordo um pouco	4 - Neutro	5 - Discordo um pouco	6 - Discordo	7 - Discordo plenamente
A utilização de IA para potenciar a utilização de lojas online é uma tarefa fácil.	○	○	○	○	○	○	○
Seria mais fácil se conseguisse fazer com que o dispositivo de IA na moda realizasse as tarefas pretendidas.	○	○	○	○	○	○	○
A minha interação com lojas de moda online seria mais simples e percetível com a utilização de IA.	○	○	○	○	○	○	○
A interação com lojas online potenciadas por IA seria mais flexivel	○	○	○	○	○	○	○
Seria fácil tornar-me hábil a usar lojas de moda online potenciadas por IA	○	○	○	○	○	○	○
Penso que o comércio online potenciado por IA seria fácil de usar	○	○	○	○	○	○	○

14. Tendo em conta a **aplicação das ferramentas de IA** nas lojas online qual é a sua concordância com as seguintes frases (1 - concordo plenamente, 7 - discordo plenamente)

	1 - Concordo plenamente	2 - Concordo	3 - Concordo um pouco	4 - Neutro	5 - Discordo um pouco	6 - Discordo	7 - Discordo plenamente
Aplicação da IA trará soluções a muitos dos nossos problemas.	○	○	○	○	○	○	○
Com IA tudo é possível.	○	○	○	○	○	○	○
Sinto-me mais realizado/a pela utilização de IA.	○	○	○	○	○	○	○

15. Tendo em conta a **aplicação das ferramentas de IA** nas lojas online qual é a sua concordância com as seguintes frases (1 - concordo plenamente, 7 - discordo plenamente)

	1 - Concordo plenamente	2 - Concordo	3 - Concordo um pouco	4 - Neutro	5 - Discordo um pouco	6 - Discordo	7 - Discordo plenamente
Estou preocupado/a que o produto publicitado online não seja igual na vida real.	○	○	○	○	○	○	○
Tenho receio que o produto exposto online não assente/ funcione da maneira que espero.	○	○	○	○	○	○	○
Preocupa-me se o produto realmente resultará tão bem quanto espero.	○	○	○	○	○	○	○

16. Tendo em conta a **aplicação das ferramentas de IA** nas lojas online qual é a sua concordância com as seguintes frases (1 - concordo plenamente, 7 - discordo plenamente)

	1 - Concordo plenamente	2 - Concordo	3 - Concordo um pouco	4 - Neutro	5 - Discordo um pouco	6 - Discordo	7 - Discordo plenamente
É valioso usar IA nas lojas online de moda.	○	○	○	○	○	○	○
Sou a favor de usar IA nas lojas online de moda.	○	○	○	○	○	○	○
Concordo com o uso de IA nas lojas online de moda.	○	○	○	○	○	○	○
Acho benéfico o uso de IA nas lojas online de moda.	○	○	○	○	○	○	○
Gosto de usar IA nas lojas online de moda.	○	○	○	○	○	○	○

17. Moro atualmente:

- ○ Em Portugal
- ○ Outro país na Europa
- ○ Fora da Europa
- ○ Sou nómada digital
- ○ outra opção

18. Género:

- ○ Feminino
- ○ Masculino
- ○ Outro
- ○ Prefiro não responder

19. O último grau académico conlcuido foi:

- ○ até 1º ciclo do ensino básico (4º ano)
- ○ até 3º ciclo do ensino básico (9º ano)
- ○ Ensino secundário
- ○ Licenciatura / Bacharelato
- ○ Pós Graduação
- ○ Mestrado
- ○ Doutoramento
- ○ outro

20. Faixa etária

- ◯ menos de 18 anos
- ◯ 18 aos 24 anos
- ◯ 25 aos 34 anos
- ◯ 35 aos 44 anos
- ◯ 45 aos 54 anos
- ◯ 55 aos 64 anos
- ◯ 65 ou mais

21. Ocupação

- ◯ Estudante
- ◯ trabalhador Estudante
- ◯ Trabalhador por conta de outrem
- ◯ Trabalhador por conta própria
- ◯ Nómada digital
- ◯ Desempregado
- ◯ Reformado
- ◯ Outro

22. Com o rendimento do agregado familiar vivo :

- ◯ Muito confortável
- ◯ Confortável
- ◯ Razoável
- ◯ Com dificuldades

Annex B – Summary Table of Constructs

Variable Name	Reference	Original Scale	Code	Adapted Scale in English	Adapted Scale in Portuguese
Inf. Quality	Trivedi and Trivedi, 2018	Fashion m-commerce apps provide me with the precise information I need.	InfoQual1	Online Fashion brands provides me with the apparel I need.	Lojas de moda online, fornecem-me os artigos que necessito.
		Fashion m-commerce apps provide sufficient information to enable me to do my tasks.	InfoQual2	Online Fashion brands provides sufficient information to enable me to buy.	Lojas de moda online fornecem informações suficientes para que eu possa comprar.
		The information provided by fashion m-commerce apps is helpful regarding my questions or problems.	InfoQual3	The information provided by online fashion brands is helpful regarding my needs and wants.	A informação fornecida pelas lojas de moda online é útil em relação às minhas questões/ problemas.
System Quality	Trivedi and Trivedi, 2018	I find it easy to become skillful at using fashion m-commerce apps	SysQual1	I find it easy to become skillful at using online fashion brands	Acho fácil tornar-me hábil no uso de lojas de moda online
		I believe that fashion m-commerce apps are easy to use.	SysQual2	I believe that online fashion brands are easy to use.	Acredito que as lojas de moda online são fáceis de usar
		Using fashion m-commerce apps require very little mental effort.	SysQual3	Using online fashion brands requires very little mental effort.	Usar lojas online de moda requer pouco esforço mental.
		It is satisfying to use fashion m-commerce apps	SysQual4	It is satisfying to use online fashion brands	Usar lojas de moda online é conveniente
Service Quality	Trivedi and Trivedi, 2018	I am satisfied with the customer support provided by fashion m-commerce apps	ServQual1	ServQual2	Estou satisfeito/a com o apoio ao cliente nas lojas de moda online.
		I am satisfied with the after-sales service provided by fashion m-commerce apps.	ServQual2	I am satisfied with the after-sales service provided by online fashion brands.	Estou satisfeito/a com o serviço pós-venda de lojas de moda online.
		Fashion m-commerce apps understand my problems and requests.	ServQual3	Online Fashion brands understand my problems and requests.	As lojas de moda online conseguem perceber os meus pedidos e problemas
		Fashion m-commerce apps respond to my requests fast enough.	ServQual4	Online Fashion brands respond to my requests fast enough.	As lojas de moda online respondem aos meus pedidos suficientemente rápido.
Personalization	Trivedi and Trivedi, 2018	The services of fashion m-commerce apps are often personalized for me.	Personalization1	The online fashion services are often personalized for me	O serviço das lojas de moda online é frequentemente personalizados para mim
		The fashion m-commerce apps treat me as an individual unique customer.	Personalization2	The online fashion treats me as na individual unique customer	As lojas de moda online tratam-me como um/a cliente único/a e individual
		When communicating with the fashion m-commerce apps I am often addressed using my name.	Personalization3	When communicating whith online fashion businesses i am often addressed usign my name	Quando comunico com loja de moda online, muitas vezes sou abordado/a pelo meu nome
Purchase intention	Trivedi and Trivedi, 2018	My likelihood of purchasing apparel products from fashion m-commerce apps is high.	PurchInten1	My likelihood of purchasing apparel products from online fashion brands is high.	É muito provavel que compre artigos em lojas de moda online no futuro
		The probability that I would consider buying apparel through fashion m-commerce apps is high.	PurchInten2	The probability that I would consider buying apparel through online fashion is high.	Considero que a probabilidade de comprar em lojas de moda online é grande.
		My willingness to buy apparel through fashion m-commerce apps is high	PurchInten3	My willingness to buy apparel from online fashion brands is high	A minha vontade de comprar em lojas de moda online é alta.
Satisfaction	Trivedi and Trivedi, 2018	While shopping on fashion m-commerce apps i feel like i am exploring new worlds	Satisf1	Shopping in Fashion online stores, i feel that i am exploring a "new world"	Ao fazer compras em lojas de moda online, sinto que estou a explorar um "novo mundo"
		I am pleased with the experience of using fashion m-commerce apps	Satisf2	I am Satisfyed with the experience of using online Fashion stores	Estou satisfeito/a com a experiência do uso de lojas de moda online
		The fashion m-commerce apps do a good job of satisfying my needs	Satisf3	Online Fashion Brands make a good job because they satisfy my needs.	As lojas de moda online fazem um bom trabalho ao satisfazer as minhas necessidades

Variable Name	Reference	Original Scale	Code	Adapted Scale in English	Adapted Scale in Portuguese
Perceived Usefulness		Choose my outfit faster	PercUse1	AI will choose outfits faster than humans	O sistema de recomendação permite-me a escolha de artigos de forma mais rápida
		Improve my performance in choosing the most trendy	PercUse2	AI will improve the performance of choosing the most trendiest outfits	O sistema de recomendação melhora o meu desempenho na escolha de artigos que são tendência.
	Liang, Lee, and Workman, 2019	Increase my efficiency in choosing the most trendy outfit	PercUse3	AI will be more efficient in choosing the trendiest outfit	O sistema de recomendação aumenta a eficiência na esolha de artigos que são tendência
		Enhance my effectiveness in choosing the most trendy outfit	PercUse4	AI will enhance the effectiveness in choosing the tendiest outfits	O sistema de recomendação melhora a minha eficácia na esolha de artigos de moda que são tendência.
		Make it easier for me to pick out what to wear	PercUse5	AI will make it easier for humans to pick what to wear	O sistema de recomendação faz com que seja mais simples a escolha dos artigos de moda.
		Be useful for choosing the most trendy outfit	PercUse6	AI will be useful for choosing the most trendy outfits	O sistema de recomendação é útil para escolher os artigosde moda que são tendência.
Perceived ease of use		Learning to operate this device would be easy	PercEase1	Learning how to operate the devices would be easier	A utilização de IA para potenciar a utilização de lojas online é uma tarefa fácil.
		I think I would find it would be easy to get this device to do what I want it to do	PercEase2	It would be easier if I would get the device to do what I want it to do	Seria mais fácil se conseguisse fazer com que o dispositivo de IA na moda realizasse as tarefas pretendidas.
	Liang, Lee, and Workman, 2019	My interaction with this device would be clear and understandable	PercEase3	My interaction with the device would be clear and understandable	A minha interação com lojas de moda online seria mais simples e perceptivel com a utilização de IA.
		This device would be flexible to interact with	PercEase4	The device would be flexible to interact with	A interação com lojas online potenciadas por IA seria flexivel
		It would be easy to become skillful at using this device	PercEase5	It would be easy to become skillful at using the device	Seria fácil tornar-me hábil a usar lojas de moda online potenciadas por IA.
		I think this device would be easy to use	PercEase6	I think the online market with AI tools would be easy to use	Penso que o comercio online potenciado por IA seria fácil de usar.
Technology attitudes		Technology will provide solutions to many of our problems	TechAtt1	AI will provide solutions to many of our problems	Aplicação da IA trará soluções a muitos dos nossos problemas.
	Liang, Lee, and Workman, 2019	With technology anything is possible	TechAtt2	With AI anything is possible	Com IA tudo é possivel.
		I feel that I get more accomplished because of technology	TechAtt3	I feel that I get more accomplished because of technology	Sinto-me mais realizado/a pela utilização de IA.
Performance risk		I am concerned that the product advertised in the video is different from the actual product	PerfRisk1	I am concerned that the cloth advertised won´t be the same in real life	Estou preocupado/a que o produto publicitado online não seja igual na vida real
	Liang, Lee, and Workman, 2019	I am afraid that the product advertised in the video would not perform the way I expect	PerfRisk2	I am affraid that cloth shown online won´t look as good when i try them	Tenho receio que o produto exposto online não assente/funcione da maneira que espero.
		I am concerned about whether this product would really ‘‘perform’’ as well as it is supposed to	PerfRisk3	I am concerned about whether this product would really look as well as it is supposed to	Preocupa-me se o produto realmente resultará tão bem quanto espero.
Attitude Geral to Use/ Real Use		Valuable	Attitude1	Using AI in online Fashion brands is valuable	É valioso usar IA nas lojas online de moda.
		Favorable	Attitude2	I am favorable with the use of AI in online Fashion brands	Sou a favor de usar IA nas lojas online de moda.
	Liang, Lee, and Workman, 2019	Agreeable	Attitude3	I agree with the use of AI in online Fashion brands	Concordo com o uso de IA nas lojas online de moda.
		Beneficial	Attitude4	I think it is beneficial to use AI in online Fashion Brands	Acho benéfico o uso de IA nas lojas online de moda.
		Like	Attitude5	I like using AI in online Fashion brands	Gosto de usar IA nas lojas online de moda.

Annex C - Outer VIF

	VIF
Attitude1	3.772
Attitude2	8.715
Attitude3	8.587
Attitude4	7.068
Attitude5	3.109
InfoQual1	1.552
InfoQual2	2.737
InfoQual3	2.184
PercEase1	1.560
PercEase2	2.080
PercEase3	3.586
PercEase4	4.121
PercEase5	4.363
PercEase6	3.791
PercUse1	2.085
PercUse2	3.684
PercUse3	4.284
PercUse4	4.607
PercUse5	2.891
PercUse6	2.645
PerfRisk1	2.237
PerfRisk2	3.541
PerfRisk3	3.335
PurchInten1	5.813
PurchInten2	7.164
PurchInten3	2.520
Satisf1	1.128
Satisf2	2.441
Satisf3	2.423
ServQual1	2.983
ServQual2	2.634
ServQual3	2.270
ServQual4	1.625
SysQual1	2.092
SysQual2	1.824
SysQual3	1.096
SysQual4	1.678
TechAtt1	1.729
TechAtt2	1.875
TechAtt3	2.207

Annex D - Sociodemographic Characterization of the sample

Indicator	Answers	Absolute Frequency	Relative Frequency (%)
Gender	Female	185	55,89%
	Male	145	43,81%
	Other	1	0,30%
Age	<18	2	0,60%
	18 - 24	80	24,17%
	25 - 34	28	8,46%
	35 - 44	21	6,34%
	45 - 54	80	24,17%
	55 - 64	99	29,91%
	>65	21	6,34%
Academic level	9th Grade	8	2,42%
	High School	95	28,70%
	Bachelor´s Degree	136	41,09%
	Master´s Degree	46	13,90%
	Postgraduate	36	10,88%
	Doctorate	7	2,11%
	Other	3	0,91%
Ocupation	Student	30	9,06%
	Working Student	34	10,27%
	Employee	168	50,76%
	Self-employed	41	12,39%
	Digital nomad	1	0,30%
	Unemplyed	6	1,81%
	Retired	34	10,27%
	Other	17	5,14%
Financial Situation	Very confortabel	45	13,60%
	Confortable	176	53,17%
	Razoable	106	32,02%
	With Dificulties	4	1,21%
Residence	Portugal	314	94,86%
	Other country in Europe	8	2,42%
	Outside Europe	8	2,42%
	Other option	1	0,30%
Preference on buying Fashion products	Online Stores	49	14,80%
	Physical Stores	177	53,47%
	No preference	105	31,72%
Most online Fashion purchases are made through:	Mobile phone	180	54,38%
	Tablet	12	3,63%
	Computer	128	38,67%
	Other	11	3,32%