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Artificial Intelligence in Marketing: Enhancing Brand Loyalty through AI-Powered Personalization Campaigns, in the fashion industry

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This dissertation marks the end of a significant journey, representing great effort and dedication that has paved the way for new opportunities. As this is a major milestone, I would like to express my gratitude to my parents and sister, who have consistently supported and motivated me to persevere, even when the path seemed impossible.

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ABSTRACT

In an increasingly technological context, artificial intelligence tools are progressively playing a leading role in the business context, through the automation of processes and identification of patterns. The first phase of the research consists of an extensive analysis of the existing literature, seeking to provide the latest information on the evolution of artificial intelligence, and brand relationships, including brand loyalty, self-brand connection and emotional connection.

The empirical study utilised a quantitative methodology involving a questionnaire constructed based on insights from writers in the relevant literature on the subject issues, all scales were scientifically validated. The questionnaire counted with the participation of 253 respondents. The study tested a conceptual model examining the relationship between emotional connection, AI-driven personalization, self-brand connection and online brand consumer engagement, as well as the relationship between online brand consumer engagement and brand loyalty.

The study revealed that brand loyalty and customer relationships can be strengthened through marketing strategies that create an emotional connection. Brands representing consumers' self-identity increase engagement and make customers less likely to switch to competitors. It also highlights the importance of online experiences and the use of AI to personalize campaigns, strengthening customer relationships. However, balancing personalization with data privacy concerns is essential to ensure long-term success.

Keywords: Artificial Intelligence, Brand Loyalty, Brand Engagement, Direct Marketing, Fashion Industry

JEL classification system: M31 (Marketing and Advertising – Marketing), M37 (Marketing and Advertising – Advertising)

RESUMO

Num contexto cada vez mais tecnológico, as ferramentas de inteligência artificial têm vindo a ganhar relevo no contexto empresarial, através da automatização de processos e da identificação de padrões. A primeira fase da pesquisa consiste numa análise extensiva da literatura existente, fornecendo as informações mais recentes sobre a evolução da inteligência artificial e as relações de marca, incluindo lealdade à marca, conexão com a marca e conexão emocional.

O estudo empírico utilizou uma metodologia quantitativa com base num questionário construído a partir da literatura relevante sobre os temas em questão, sendo todas as escalas cientificamente validadas. O questionário contou com a participação de 253 respondentes. O estudo testou um modelo conceitual que examinou a relação entre conexão emocional, personalização orientada por IA, conexão com a própria marca e engajamento do consumidor com a marca online, bem como a relação entre engajamento do consumidor com a marca online e fidelidade à marca.

O estudo revelou que a lealdade à marca e as relações com os clientes podem ser fortalecidas através de estratégias de marketing que criem uma conexão emocional. As marcas que representam a autoidentidade dos consumidores aumentam o envolvimento e fazem com que os clientes sejam menos propensos a mudar para concorrentes. O estudo também destaca a importância das experiências online e da utilização da IA para personalizar campanhas, fortalecendo as relações com os clientes. No entanto, é essencial equilibrar a personalização com as preocupações sobre a privacidade dos dados para garantir o sucesso a longo prazo.

Keywords: Artificial Intelligence, Brand Loyalty, Brand Engagement, Direct Marketing, Fashion Industry

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1. Introduction

The rapid advancement of artificial intelligence (AI) in the last decade has profoundly transformed sectors, with marketing appearing as a primary beneficiary of this technological revolution (Vlačić et al., 2021). The capacity of AI to analyze extensive data sets, automate procedures, and provide tailored customer experiences has generated unparalleled potential for organizations to strategically improve customer connections and engagement. As AI tools become more embedded in corporate operations, a crucial issue emerges: how can companies use AI-driven tactics to foster brand loyalty in a changing digital marketplace?

Direct marketing has undergone substantial development owing to the use of AI technology. Email marketing, a fundamental element of digital marketing, remains a very successful medium, producing over $10 billion in yearly sales (Statista, 2023). Although email marketing is extensively used, its efficacy differs markedly across certain demographic segments. In 2022, 25% of American customers expressed a propensity to buy upon receipt of an email newsletter; however, younger demographics, especially U.S. Gen Z consumers, showed less reaction to these marketing efforts (Statista, 2023). This indicates the need for more advanced, AI-driven customization tactics to reconcile client preferences with marketing results.

The AI sector is concurrently undergoing exponential expansion. Projections indicate that the global AI industry will expand from $241.8 billion in 2023 to around $740 billion by 2030 (Statista, 2023), underscoring its significant impact across several industries, including healthcare and marketing. The use of AI is anticipated to enhance operational efficiency and improve customer interaction quality, potentially reshaping labour markets by reallocating people to more productive, value-added positions (Statista, 2023). An exemplary illustration of AI's potential in marketing is seen in industry leaders such as Apple, whose brand devotion transcends product attributes or competitive prices. Apple's devoted client base is primarily influenced by its congruence with customers' fundamental values and emotional ties to the company (Sinek, 2009). In a competitive and economically volatile landscape, establishing strong emotional connections and trust with consumers is essential, especially as firms contend with price pressures and evolving consumer expectations.

This dissertation aims to investigate how AI-driven customization tactics might improve brand loyalty in the fashion business. This study will examine the function of AI in developing customized marketing strategies that connect with customers, enhance engagement, and ultimately promote enduring loyalty. This research investigates the convergence of AI technology, emotional branding, and customer behaviour to provide insights into how companies may maintain a competitive edge in a swiftly evolving digital environment.

1.1. Theme and Research Aim

"*Artificial Intelligence in Marketing: Enhancing Brand Loyalty through AI-Powered Personalization Campaigns, in the Fashion Industry*" is the theme of the present study, and pretends to understand how AI can be used in direct marketing campaigns to increase brand loyalty. This study further intends to examine how brands can benefit from the integration of AI-driven personalization in online campaigns and to what extent it will impact brand engagement and loyalty. The research focused on the variables analyzed, leading to the comparison between different constructs. To properly conduct this study, primary data were collected, allowing an in-depth analysis of the relationship between online engagement and consumer brand loyalty.

In the initial stage, the study seeks to comprehend the development of AI, particularly in the context of business, associated with marketing. The study pretends to understand how the implementation of this technological tool can bring benefits to managers and brands. Secondly, the study aims to examine the responses of all participants to an online questionnaire. The goal is to understand how consumers perceive the value of AI in online campaigns and to identify the most important variables that make them connect with their favourite fashion brand, ultimately enhancing brand loyalty.

Therefore, the study provides insights that enable to answer the following research questions:

(i) *How can AI-driven personalization be best used in developing direct campaigns, in the fashion industry, to enhance brand loyalty?*

(ii) *How do AI-Driven personalization direct marketing campaigns impact brand loyalty and engagement, in the fashion industry?*

(iii) *How can online Brand engagement enhance brand loyalty, using AI-Driven personalization direct marketing campaigns?*

1.2. Objectives and Motivation

Through my master’s program and course projects, I have realized how crucial it is to build strong ties between brands and clients. Customers must be made to feel that by acquiring a product or service from a certain brand, they are supporting the brand’s identity. Throughout several projects, I have prioritized customer loyalty development over short-term product sales techniques to turn them into devoted followers of the brand. Effectively communicating the “Why” behind a brand’s offering—rather than just the “What”—is a crucial but sometimes disregarded part of the marketing process. I now realize that the safest way to guarantee a brand's long-term success is to cultivate brand loyalty. It is not, however, an easily attained objective; to understand why consumers, associate with a brand and how we may successfully express our message to enhance this loyalty, we must do comprehensive research. Inspired by these realizations, I set out to investigate brand loyalty in further detail to understand how companies might strengthen it via a thorough comprehension of their target market and the driving forces behind brand loyalty. I started a comprehensive research project because of the ongoing global technological revolution, the rise and development of technologies like artificial intelligence (AI), virtual reality (VR), and augmented reality (AR), as well as the changing business paradigms connected to these innovations. After a thorough analysis of pertinent literature, I saw a special chance to use AI as a tactical instrument to strengthen the previously described brand loyalty. I can now see a way to maximize long-term brand performance because of the relationship between two crucial areas: artificial intelligence (AI) and brand loyalty. This insight has also made me think about other relevant aspects, such as the idea of brand love. The idea that these two ideas may be used to further the objectives of upcoming companies excited me. It dealt with brand loyalty, how businesses can identify the needs of their customers, and how artificial intelligence (AI) is driving and improving this industry. This investigation covers current AI systems as well as the continuous, methodical development of AI technology. In addition, my goal is to determine the degree to which direct marketing efforts and customer incentives might work together to influence the choice of a certain brand’s product. The goal is to make sure that these incentives not only persist but also gain momentum over time while considering the preservation of the essential elements that characterize brand loyalty.

1.3. Dissertation Structure

The present dissertation is composed of six main chapters, introduction, literature review, conceptual model and hypothesis, methodology, results, and conclusion, as illustrated in Figure 1. The first chapter is the introduction, which will introduce the research topic, objectives, and motivations. The second chapter is the literature review that provides a research foundation in order to understand the main concepts in the study. The third chapter discusses the conceptual model and research hypotheses. The fourth chapter, methodology, explains the research design, data collection and analysis methods, and the treatment of the data. The next chapter is Results, where the analysis and discussion of the collected data will be presented. The last chapter is Conclusion, where all the main theoretical conclusions and managerial implications are summarized, limitations are identified, and future research is encouraged.

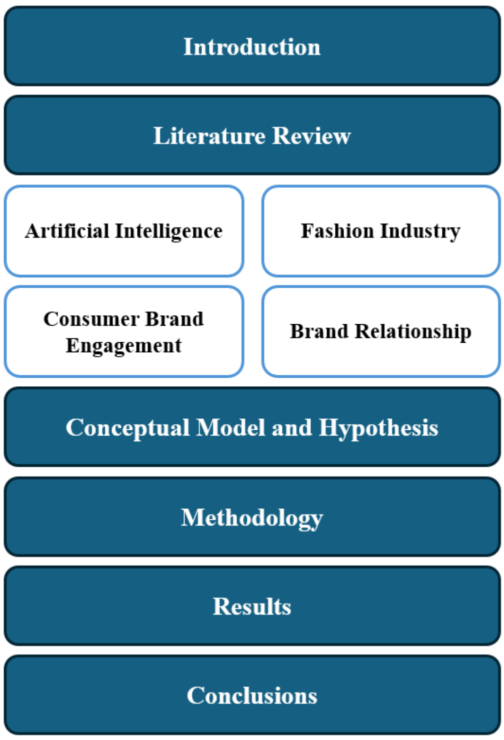

Figure 1: Dissertation´s Structure
Source: Author´s Elaboration

2. Literature Review

2.1. Artificial Intelligence

2.1.1. Definition

Defining the term intelligence may prove to be difficult. This is because each science provides a different definition. Likewise, there are so many different and varied interpretations and definitions of artificial intelligence (AI), and defining it may be difficult since recent studies indicate that AI doesn't have a concrete definition, nevertheless, according to (Kaplan & Haenlein, 2019) AI can be referred to as the ability of a system to analyse external information, identify patterns, and learn from them to generate information that can be used to achieve specific results.

2.1.2. Evolution of Artificial Intelligence in Marketing

The evolution of AI has been driven by significant technological advancements, profoundly affecting various industries. Today´s widely used memory-constrained AI systems have an increased capacity to gain knowledge from the past, allowing AI to automate routine tasks to employ machine learning for advanced insights (Kaplan & Haenlein, 2019). AI has revolutionized business processes, particularly in marketing. Recently AI has gained prominence as a critical tool for enhancing operational efficiency and driving innovation across industries (Davenport et al., 2020).

In the marketing field, AI initially focused on automating repetitive tasks, in areas such as email marketing and managing chatbots (Davenport et al., 2020). However, recent advancements have expanded its role to include data-driven insights, enabling businesses to make more strategic decisions in areas such as customer segmentation, targeting, and personalized marketing (Kaplan & Haenlein, 2019). By leveraging AI, companies are now able to move beyond simple automation to create hyper-personalized experiences, which cater to individual customer preferences in real-time (Kaplan & Haenlein, 2019). AI most significant contribution to marketing is its ability to deliver personalized experiences. AI analyses customer data through machine learning algorithms, refining segmentation, targeting, and positioning (STP) strategies (Verma et al., 2021). This allows marketers to identify high-value customer segments with greater precision, offering more relevant product recommendations (Chen et al., 2020; Simester, 2020). AI-driven marketing analytics solutions may assess the effectiveness of a product design in relation to changing consumer preferences, hence improving overall customer happiness (Dekimpe, 2020). In addition to customisation, AI is essential for enhancing pricing tactics. Utilizing machine learning algorithms, particularly Bayesian models, marketers may adjust pricing dynamically in response to fluctuations in market circumstances and consumer demand. This real-time pricing strategy enables organizations to sustain a competitive advantage, especially in fast-changing sectors like fashion, where trends and customer value expectations are always shifting (Bauer & Jannach, 2018).

As AI technology advances, its influence within the marketing domain is anticipated to grow even further. Future advancements in the “Theory of Mind” and self-aware AI hold the potential to deepen customer relationships by enabling systems to understand and predict not only consumer preferences but also emotions and desires (Kaplan & Haenlein, 2019). By utilizing extensive databases of consumer information and preferences, AI has the potential to enable tailored marketing. With this capacity, AI can apply preference wights to product qualities through patterns of customers (Verma et al., 2021). Moreover, AI-driven customer relationship management (CRM) tools will continue to enhance brand loyalty by providing personalized customer service and real-time responses to individual needs (Verma et al., 2021). Understanding how AI influences marketing outcomes is key to comprehending its impact on consumer-brand relationships, including brand loyalty.

2.1.3. Consumer Perceptions and Adoption of Artificial Intelligence

Customers frequently demand that artificial intelligence (AI) satisfy extremely high standards (Gray, 2017). The qualities of the work at hand greatly impact whether AI is used (Davenport et al., 2020). Consumer perceptions of AI are influenced by the specific task and the level of trust individuals have in AI systems. Research suggests that when tasks require subjective judgment or emotional intuition, such as selecting fashion items for personal expression, consumers are more reluctant to adopt AI systems (Castelo, 2019; (Davenport et al., 2020). Contrarily, AI systems are more readily accepted for more objective tasks such as price comparison or purchase tracking. This variation in consumer trust is further compounded by privacy concerns, particularly around the storage and repurposing of personal data (Wilson, 2018). Fashion consumers, in particular, may be hesitant to allow AI systems to influence their purchasing decisions when brand image or personal identity is at stake. According to (Davenport et al., 2020), the three main reasons for data privacy concerns are data remaining accessible for longer periods, data being repurposed and repackaged for uses other than its original purpose, and data about one person in the dataset may unintentionally contain information about other individuals.

The adoption of AI is significantly influenced by customer attributes. In this case, two crucial aspects are considered: the impression of risk is increased when a decision's results are substantial (Bettman, 1973). Customer's acceptance of AI is negatively correlated with how much it contributes to their sense of self (Davenport et al., 2020). People often claim ownership of the results of their consumption decisions as the prominence of the activity inside the customer's self-concept grows (Davenport et al., 2020). It's critical to strike a balance between privacy concerns and the benefits of customized offers and suggestions (Davenport et al., 2020). In order to ensure a balance between privacy and data value, it is essential to use data anonymization methods such as generalization, suppression, distortion, swapping, and masking. (A Comparative Study of Data Anonymization Techniques, 2019). These techniques eliminate or conceal personally identifiable information (PII), reducing the danger of unauthorized disclosure, while enabling organizations to extract insights from the data (A Comparative Study of Data Anonymization Techniques, 2019). K-anonymity guarantees that individual data points are indistinguishable from one another, hence complicating re-identification efforts. These anonymization methods safeguard user privacy, enabling data-driven customisation without jeopardizing sensitive information. It is crucial to use a suitable approach according to the data and its intended application to preserve both privacy and utility (A Comparative Study of Data Anonymization Techniques, 2019).

2.2. Fashion Industry

2.2.1. Fashion Recommendation Systems

Recommendation systems have historically been designed for certain disciplines, such as films, literature, and music. Prominent online platforms, like Amazon (Linden et al., 2003), Netflix (Koren, 2009), Google (Das et al., 2007), and Facebook (Shapira et al., 2013), have effectively incorporated recommendation algorithms into their business frameworks. These systems are characterized in several ways, illustrating their complexity and breadth of applications (Chakraborty et al., 2021). Rashid et al. (2002)

characterize recommendation systems as decision-support instruments intended to aid users in traversing complex information landscapes. Schafer, Konstan, and Riedl (1999) characterize recommendation systems as essential e-commerce tools that enhance product searches by using user preferences and selections to provide tailored recommendations. Consequently, these technologies are essential for mitigating information overload and improving the user experience.

Fashion recommendation systems have become essential for improving the online shopping experience by tackling the intricacies of customer behaviour and the extensive product information in the fashion sector. Utilizing sophisticated algorithms, these systems evaluate client preferences, historical behaviours, and product characteristics to provide tailored suggestions that facilitate decision-making in a data-rich context (Hwangbo et al., 2018). A substantial amount of study has investigated many methodologies for fashion suggestions, showing their ability to enhance consumer pleasure and promote corporate success. For example, Quanping (2015) incorporates essential fashion qualities, like style, colour, material, and seasonality, into a collaborative filtering algorithm to provide more precise and relevant suggestions. Additionally, some models, such as the functional tensor factorization method introduced by Hu et al. (2015), emphasize the recommendation of product sets instead of singular items, hence improving the contextual pertinence of the suggestions. Additional innovations encompass interactive multimedia systems that provide virtual fitting experiences in physical retail environments, exemplified by the smart mirror system proposed by Chao et al. (2009), and multimedia mining methodologies, as described by Tu and Dong (2010), which assist customers in identifying their optimal fashion products. The emergence of fashion recommendation algorithms has transformed e-commerce by providing customized purchasing experiences that correspond to consumer tastes, therefore enhancing customer engagement and fostering commercial growth.

2.3. Consumer Brand Engagement

The concept of "engagement" has been explored across various academic fields including psychology, sociology, political science, and organisational behaviour (Ilić, 2008). Consumer brand engagement (CBE) plays a central role in establishing the relationship between the consumer and the brand (Brodie, Ilic, Juric, & Hollebeek, 2013). In marketing, the term consumer brand engagement (CBE) has gained prominence as a way to understand the deep, ongoing interactions between consumers and brands that extend beyond interactions (Brodie et al., 2011) . Consumer brand engagement is closely linked to the field of relationship marketing, where the focus shifts from transactional exchanges to building deeper, long-lasting relationships with consumers (Rosado-Pinto et al., 2020). Numerous experts have attempted to formulate a definitive definition of consumer brand involvement, however have so far been unsuccessful (Rosado-Pinto et al., 2020). Numerous theories have been suggested to explain CBE.

Hollebeek, (2011a) defines consumer brand engagement as the extent of a customer´s cognitive (which reflects the level of attention and thought consumers put into interacting with a brand), emotional (which pertains to the feelings of attachment or emotional connection that consumers form with a brand) and behavioural (which encompasses the actions consumers take that demonstrate their involvement with a brand) investment in a brand. This multidimensional construct represents a psychological state that reflects how consumers interact with brands. Besides Hollebeek, (2011a) several models have been proposed to explain consumer engagement. For example, Vivek, Beatty, and Morgan (2012) intend that engagement refers to the depth of an individual's involvement in, and emotional connection to, an organization's products, services, or initiatives. It reflects both the intensity and quality of their participation, as well as the strength of their affinity with the organization's value proposition. Similarly, Verhoef, Reinartz, and Krafft (2010) describe CBE as behavioural manifestations that go beyond transactions, while Bijmolt et al. (2010) argue that different forms of engagement arise at various stages of the customer lifecycle.

In the last ten years, consumer brand engagement (CBE) has been more important in marketing literature, especially as a crucial factor influencing customer purchasing behaviour and brand loyalty. Researchers contend that consumer brand engagement (CBE) is essential for predicting customer loyalty and fostering lasting brand relationships (Bowden, 2009; Hollebeek, 2011). Research indicates that consumer engagement offers valuable insights into consumer behaviour, enabling predictions about outcomes such as customer satisfaction, loyalty, and advocacy (Prentice et al., 2019). The growing focus on CBE stems from the recognition that meaningful brand experiences foster lasting psychological connections with consumers, hence strengthening brand loyalty (Hapsari et al., 2016a; Vivek et al., 2012). Consumer engagement behaviours include actions that extend beyond just transactions, including word-of-mouth (WoM), blogging, composing reviews, and assisting other consumers (Rosado-Pinto et al., 2020; van Doorn et al., 2010). Consumer brand engagement is affected by cognitive, emotional, and behavioural traits, as well as social relationships and co-creation. These acts reinforce the connection between consumers and corporations, creating an engaged community that actively contributes to a brand's success. By facilitating interactive and co-creative experiences, firms may cultivate strong emotional and psychological connections with consumers, hence enhancing brand loyalty and customer retention (Rosado-Pinto et al., 2020). Effective client brand involvement yields several beneficial business outcomes. Engaged consumers are more likely to make repeat purchases, demonstrate lasting loyalty, and serve as brand advocates (Hapsari et al., 2016b; Vivek et al., 2014). Brands that successfully engage their customers often attain increased client retention, heightened purchase frequency, and improved brand equity.

2.3.1. Online Consumer Brand Engagement

The emergence of digital technology has revolutionized brand engagement with clients, generating novel chances for connection. Online consumer brand engagement (OCBE) denotes the active participation, contact, and involvement of consumers with a brand via online platforms (Baldus et al., 2015). Digital channels, including social media, online forums, and e-commerce sites, provide unique potential for businesses to enhance interaction with their audience (Baldus et al., 2015b). Numerous corporations are allocating resources to online brand communities as a tactic to enhance customer interactions. These communities provide a platform for customers to engage with the brand, give feedback, debate goods, and participate in brand-related events and promotions (Beukeboom et al., 2015). Each brand community often has a distinct goal, including customer support and the cultivation of belonging and loyalty among users (Baldus et al., 2015b). A fundamental aspect of these communities is user-generated content (UGC), which lacks a unified definition due to its evolving characteristics (Christodoulides, Jevon, & Bonhomme, 2012). Christodoulides et al. (2012) define user-generated content (UGC) as material that meets three fundamental criteria: it is publicly accessible through transmission channels, it exhibits a level of creative effort, and it is produced independently, without adherence to professional standards or practices.

Malthouse et al. (2016) underscore the importance of user-generated content (UGC) in brand engagement, suggesting that it allows customers to actively participate in the creation of brand narratives by expressing their goals. This co-creation strategy fosters a more profound psychological connection with the brand and enhances consumer engagement. Thus, UGC fosters brand loyalty and encourages repeat purchasing behaviours, driven by the consumer's heightened alignment with the company's values and objectives (Malthouse et al., 2016).

OBCE is crucial in promoting online consumer involvement. Consistent favourable and gratifying online experiences with a brand lead customers to enhance their purchase frequency, provide feedback, and promote the company via testimonials and referrals (Kumar & Pansari, 2016a). These interactions not only strengthen the consumer's connection with the brand but also augment the brand's exposure and reach via organic channels, such as social media and word-of-mouth (Kumar & Pansari, 2016a). Emotional engagement is a vital result of online brand connection, with brand attachment serving as a primary catalyst for electronic word-of-mouth (e-WOM). (Loureiro et al., 2017) When customers establish an emotional connection to a brand, they are more inclined to disseminate their favourable experiences to others, so enhancing the company's reputation and exposure via electronic word-of-mouth (Loureiro et al., 2017). Multiple elements influence the emergence of OCBE, including as consumer happiness, engagement, and social identity within brand communities (Baldus et al., 2015b; Hollebeek et al., 2014; Kumar & Pansari, 2016a). Content consumers are more inclined to stay involved with the brand, while significant engagement and identification with a brand community foster more participation in online interactions (Baldus et al., 2015b; Hollebeek et al., 2014). These factors are crucial in fostering a devoted and involved consumer base. OCBE provides substantial commercial advantages, such as enhanced brand loyalty, improved use of goods or services, and a greater frequency of customer recommendations (Loureiro et al., 2017) Engaged consumers not only exhibit a propensity for repeat purchases but also facilitate brand development by disseminating material and endorsing the business to others. This degree of interaction is essential for businesses seeking to augment their market share and bolster client retention (Kumar & Pansari, 2016a). Brands have to consider OBCE as an adjunct approach to conventional engagement initiatives. Through the facilitation of online interactions, dissemination of product information, and promotion of content sharing, companies may engage both current and prospective consumers who connect with the brand digitally (Fernandes & Moreira, 2019). This comprehensive engagement approach fosters a bigger, more devoted consumer base, enhancing both customer acquisition and retention.

2.4. Brand Relationship

2.4.1. Brand Loyalty

Brand loyalty is the tendency of customers to consistently acquire items or services from a certain brand over an extended period. It may emerge as behavioural loyalty, when customers regularly choose a brand with which they identify, leading to a pattern of recurrent purchases. Emotional loyalty, conversely, is propelled by a profound commitment or affiliation to the brand. This kind of loyalty indicates a pronounced affinity for a certain brand, driven by favourable experiences and emotional connections (van der Westhuizen, 2018). Although recurrent purchase behaviour is often linked to brand loyalty, emotional commitment transcends simple transactional ties. Emotional loyalty is defined as a deep affiliation with the brand, leading customers to persist in their preference for it despite rival alternatives (van der Westhuizen, 2018). This emotional connection fosters enduring loyalty.

The brand experience is essential in fostering loyalty. Positive interactions with a brand create emotional ties that encourage repeat purchases. Brands that offer memorable experiences, especially online, can enhance customer satisfaction and foster loyalty (Schmitt et al., 2015). Trust is a key element in fostering brand loyalty. Brands that consistently fulfil their promises and uphold a strong, credible reputation are more likely to build a loyal customer base (Chaudhuri & Holbrook, 2001; He et al., 2012). Trust supports consumer retention and creates a channel for emotional connection, which leads to deeper loyalty (van der Westhuizen, 2018). Consumers tend to form lasting relationships with businesses that resonate with their self-identity. According to the self-verification hypothesis, individuals seek to maintain consistency in their self-concept through feedback and interactions with brands (van der Westhuizen, 2018). Establishing a strong self-brand connection reinforces positive attitudes and nurtures long-term loyalty (Escalas and Battman, 2003). Consumer brand engagement (CBE) is increasingly recognized as a crucial factor in building emotionally loyal customers (Hollebeek et al., 2014) Kandampully et al., 2015). Research shows that brands that foster higher levels of engagement are more likely to create positive attitudes, leading to increased loyalty (Hollebeek, 2011b). By offering meaningful experiences, brands build long-lasting emotional connections that transcend transactional interactions, solidifying loyalty and future purchase intentions (Brodie et al., 2011; Dwivedi, 2015). In today´s digital era, social media plays an influential role in shaping brand loyalty. Research shows that positive engagement on online platforms fosters loyalty by encouraging active participation and interaction with the brand (Fernandes & Moreira, 2019). Brands that establish meaningful digital relationships with consumers are more likely to retain loyal customers. However, while CBE on digital platforms is often associated with loyalty, the relationship remains underexplored, and further research is needed to fully understand its impact (So et al., 2016a).

Cultivating brand loyalty by emotional connections, trust, and engagement provides notable benefits, including enhanced customer retention, more advocacy, and less price sensitivity. However, while the link between CBE and brand loyalty is evident, further studies are required to understand the long-term effects of digital engagement strategies on brand loyalty (Dessart et al., 2015). Brands that effectively manage customer emotions and engagement are more likely to enjoy sustained competitive advantage in the marketplace.

2.4.2. Self-brand connection

Self-brand connection may be defined as the bond formed between a brand and a customer, in which the consumer uses the brand to communicate their identity to others or themselves. Consumers often participate in the construction of their self-identities and personal images (Dwivedi, 2015). Self-brand connection is related to consumers' self-identity. Consumers often acquire certain brand items to articulate their self-identification, establishing a link between their personal identity and the brands they interact with. This establishes a brand-user connection in which users incorporate the brand’s values and characteristics into their self-concept, therefore reinforcing both their own identity and external perceptions (Escalas, 2004; Escalas & Bettman, 2003). Brands are not just about the products they sell; often, they are linked to a symbol that creates connections and emotional bonds with consumers. This association allows people to shape their identity by purchasing branded products. People may choose items from specific brands to fit into a social group, express their individuality, or create a personal symbol (Dwivedi et al., 2015; Escalas, 2004). Escalas (2004), indicates that a brand's and its consumers' relationship may be formed through several strategies since people utilize brand connections to bolster their self-esteem. This allows consumers to articulate their personality and traverse various life phases. This relationship may enhance brand loyalty, rendering customers less inclined to switch to comparable items from rival brands during market shifts such as price reductions or promotional displays. Comprehending the significance of establishing robust connections between customers and the company is essential for cultivating genuine interactions (Escalas & Bettman, 2003). This will allow brands to gain an advantage, as it will be difficult for competitors to replicate this link (Escalas & Bettman, 2003). Brands that create a relatable story are seen more favourably by customers and are more likely to influence purchase choices than brands that have little or no personal connection with the consumer (Escalas, 2004; Ren et al., 2012).

2.4.3. Emotional Connection

Consumers are inherently emotional beings, and every interaction they have with a brand triggers a corresponding emotional response (Boakye et al., 2023). These responses, whether positive or negative, significantly impact their overall perception of the brand and future purchasing behaviours (Martin et al., 2008). While consumers strive for positive experiences, avoiding negative ones remains an equally strong motivator in their decision-making process (Martin et al., 2008). Positive emotional interactions between consumers and brands foster satisfaction and significantly influence long-term loyalty (Boakye et al., 2023; Qin et al., 2017). Negative experiences, on the other hand, can lead to dissatisfaction and brand abandonment. Research shows that as consumers experience satisfaction in their relationships with brands, their emotional state directly influences their behavioural intent (Boakye et al., 2023). Positive emotions act as the bridge connecting consumers to brands, motivating them to maintain ongoing relationships (Wang, 2017; Zhao et al., 2018). This emotional satisfaction not only strengthens loyalty but also plays a key role in driving repeat purchases.

Brands that develop strategies focused on eliciting emotions see a corresponding increase in market share and overall performance (Boakye et al., 2023) By fostering emotional connections, brands not only strengthen customer loyalty but also enhance behaviours such as repeat purchases and advocacy. This emotional loyalty creates a sustainable competitive advantage, as customers are more likely to remain committed to brands that align with their emotional needs.

In the current competitive business environment, cultivating emotional connections with customers has become essential for fostering brand loyalty and improving digital performance. Emotional tactics transcend the simple cultivation of favourable consumer attitudes or actions; they engender profound involvement by addressing emotional needs and establishing personal relationships (Straker & Wrigley, 2016). According to Belk (1988) and Richins (1997), assets and items imbued with personal significance act as symbolic extensions of the self, hence enhancing emotional connections. The significance of technology in influencing consumer experiences within digital interaction is crucial. Straker and Wrigley (2016) assert that the creation and ongoing development of emotional experiences across digital platforms is intricate, necessitating the organization to manage both the varied expectations of consumers and its message and values. Khan (2012) and Mattila (2001) claim that the establishment of emotionally resonant interactions is crucial for nurturing long-term consumer loyalty since memorable and emotionally powerful experiences cultivate trust and promote favourable sentiments towards the business. Emotional investments have concrete financial results. Park and Kim (2014) indicate that consumers who recognise a company's dedication to digital interaction are more inclined to share favourable experiences and become committed supporters. Consequently, using emotional methods in digital platforms improves customer pleasure and fosters growth by strengthening customer connections, leading to increased brand loyalty and sustained profitability. Businesses must integrate creativity, emotional intelligence, and strategic digital engagement to create significant consumer relationships that enhance online performance and promote sustainable success (Straker & Wrigley, 2016).

3. Conceptual Model and Hypotheses

3.1. Conceptual Model

Studies regarding the effect of emotional connection (EC) on brand loyalty (BL), others the connection between self-brand connections (SBC) on online brand consumer engagement (OBCE) have been done over the years. Some studies highlight the benefits of using AI-driven personalization on online engagement to understand how brands can benefit from it. However, to date, no studies have focused on how these variables influence online engagement, such as direct marketing campaigns, and how this engagement can enhance brand loyalty. Additionally, there is no specific scientific evidence of the relationship between loyalty and AI-driven personalization campaigns in this category.

The conceptual model presented is based on the information studied in the previous chapter. The concept was created to study how emotional connection and self-brand connection variables can be utilized to aid AI-driven personalization in creating personalized direct marketing campaigns. This, in turn, can increase online engagement between consumers and brands and enhance consumer loyalty towards the brand.

3.2. Research Hypothesis

Once the final conceptual model is defined, hypotheses can be formulated and tested to confirm acceptance or rejection. This information will be obtained after analysing the data collected in the previously constructed questionnaire:

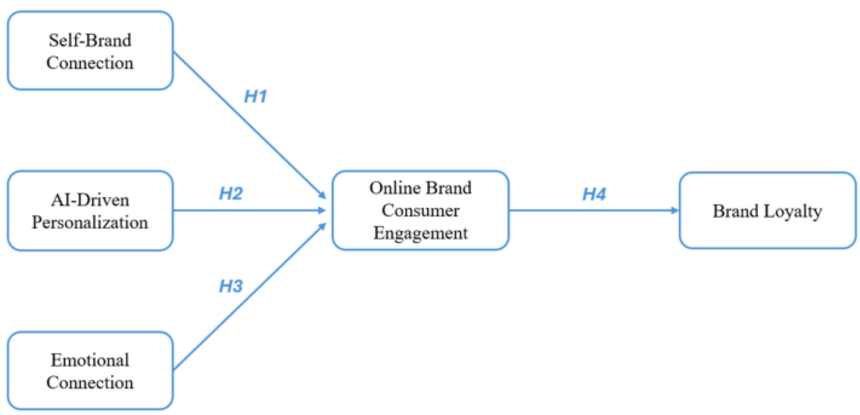

Figure 2: Conceptual Model
Source: Author´s Elaboration

Self-brand connection provides better interaction between consumers and brands making it essential for fashion brands to promote a more profound engagement with brand-related products (Escalas & Bettman, 2003). When consumers have a personal connection to a brand they are more inclined to engage in brand online campaigns, perceiving it as an extension of their self (Dwivedi et al., 2015). According to this the first hypothesis in the study is:

H1: Self-brand connection positively impacts online brand consumer engagement

According to Verma et al. (2021) AI-driven personalization enhances the online brand experience since it can deliver tailored recommendations based on individual customer data, therefore, employing AI for customized direct marketing campaigns allows brands to gain advantages, being more effective when targeting certain consumer segments, enhancing interactions with customers and brands (Chen et al., 2020). Consequently, the hypothesis was proposed:

H2: AI-Driven Personalization positively impacts online brand consumer engagement

Emotional connections between customers and companies are crucial for engagement, as people tend to engage more with brands that elicit good feelings and satisfaction (Ofori, 2020). Brands that effectively establish an emotional connection with their customers might encourage more engagement, including feedback, social media interactions (Chen et al., 2020).Therefore, the subsequent hypothesis may be articulated:

H3: Emotional Connection positively impacts online brand consumer engagement

Enhanced online consumer engagement with a company fosters greater brand loyalty since customers who regularly interact with a brand are more inclined to establish enduring connections, make repeat purchases, and advocate for the brand to others (Loureiro et al., 2017) Engaged consumers typically develop a favourable view of the brand, fostering enduring loyalty and advocacy (Kumar & Pansari, 2016b). Based on this information, the last hypothesis is:

H4: Online brand consumer engagement positively impacts brand loyalty

4. Methodology

4.1. Theoretical Approach

Following the literature review study, the authors present different perspectives on the variables in the study. To tackle the study issues it was vital to apply the correct technique, hence a deductive method was adopted, which consists of a search for the concept of professional under different theories testing these definitions on a sample of people using a structured questionnaire and testing if other groups have equal perceptions of how companies can better use artificial intelligence in direct marketing campaigns to enhance brand loyalty.

Considering that this study intends to understand what variables influence consumer loyalty after engaging in direct marketing campaigns, it was decided that the survey would be conducted using a quantitative approach, which determined this to be the most relevant method for the research. Firstly the quantitative method allows to reach a larger and more diverse audience in a shorter period, providing insights from consumers with different cultures and behavioural differences. Regarding statistical analysis, the quantitative method leads to a more objective approach and minimises subjectivity in result interpretation, since scientific scales restrict all responses.

The questionnaire was distributed online, through social networks that generated a snowball effect and questionnaire exchange platforms, such as SurveyCircle, to reach as many respondents as possible. The main target audience was people who were interested in the fashion industry and who simultaneously interacted with direct marketing campaigns. All data obtained from the questionnaire results were analysed in SPSS, which helped to conclude.

4.2. Questionnaire

4.2.1. Development and Data Collection

The questionnaire was produced using the Qualtrics platform and was composed of a total of thirty-four questions, four demographic multiple questions and thirty questions with a 7-point Likert Scale. The questionnaire aimed to reach a minimum of two hundred respondents. The questionnaire took about five to ten minutes to complete and was available from the 8th of June to the 10th of August.

Before reaching the final version of the questionnaire a pilot test was conducted, it involved the participation of ten volunteers and was distributed individually via the WhatsApp application. The pilot test attempted to analyse the survey flow and establish whether it was excessively long, preventing future respondents from quitting it without finishing, among other concerns. The feedback provided by these volunteers was fundamental to creating the final version. Based on the input, three major concerns were found during the pilot test. First, respondents believed there was a poor link between sections, which caused uncertainty. Second, some questions had incorrect phrase structure, which was promptly fixed. Finally, they remarked that certain scales appeared identical as if they were continually answering the same question. The final version of the questionnaire consisted firstly of two brief introductions, the first explicitly identifies the topic of the study and specifies that all information gathered would be kept secret. The second paragraph presented an overview of the study's main objectives and the importance of studying this topic and answering the research questions proposed. After these two introductions, participants were then shown a third section focusing on artificial intelligence. The objective was to explore the connection between participants and artificial intelligence and understand how they perceive its potential benefits in developing direct marketing campaigns. The fourth component desired to comprehend the consumer-brand relationship, attempting to uncover what motivates people to be loyal and the fundamental aspects that build a connection, driving them to prefer their favourite fashion brand over others. The points examined in this component were brand loyalty, self-brand connection, and emotional connection. The fifth component focused on respondents' online interactions with the brand, namely direct marketing initiatives. The final component of the questionnaire was designed to obtain demographic information from responders. By dividing the population into comparable groups, it becomes easier to analyse specific subgroups and establish tailored data. In this part, respondents were presented with four demographic questions: age, gender, education, and country of residence.

The major dissemination channels for the questionnaire were social media and the questionnaire-sharing site Survey Circle. Initially, the questionnaire was distributed via social media platforms such as Instagram, Facebook, and Reddit. During the early period of dispersion, it is possible to identify that the population was largely Portuguese. To expand the number of responders and get a more thorough and varied sample, the questionnaire was made available on the Survey Circle website, the questionnaire was made available to everyone, and since it is a worldwide platform, correspondents from all over the world were able to contribute, resulting in a more comprehensive understanding of the study.

4.2.2. Variables and Measures

The conceptual model showed a set of variables that had a relationship between them, which varied from positive to negative. A 7-point Likert scale was utilised (1=Strongly disagree and 7=Strongly Agree). In this model, Online Brand Customer Engagement (OBCE) is the dependent variable; Brand Loyalty is the mediating variable. The independent variables are Self-Brand Connection, AI-driven Personalization, and Emotional Connection. The scales used for measuring the variables were adapted from antecedent studies to allow respondents to specify their preferred brand in the fashion industry. Each scale utilised has been scientifically validated and had as the main criteria to be published in journals ranked Q1 and Q2 in Scimago. Self-brand connection was measured using five items adapted from two studies Hollebeek et al. (2014) and van der Westhuizen (2018). AI-driven personalization was assessed using eight items. Two of these aimed to study the “Attitude” and “Experience” between respondents and artificial intelligence, while the remainder sought to understand how respondents perceived the value of using AI in marketing campaigns, all of the items were adapted from Lim & Zhang (2022). Emotional connection was measured using five items adapted from the journal article Ellison et al. (2007). Following Siu et al. (2023) Online Brand Consumer Engagement (OBCE) was measured using six items. Brand Loyalty considered the main variable to be measured in the study had six stages adapted from Sohaib & Han (2023), Cheng & Jiang (2022) and Goyal & Verma (2024)

Variables	Scales Author	Nº of Items
Self-Brand Connection	(Hollebeek, L. D., Glynn, M. S., & Brodie, R. J. 2014) & (Van Der Westhuizen, L. 2018)	5
Ai-Driven Personalization	(Lim, J. S., & Zhang, J. 2022)	8
Emotional Connection	(Ellison, N. B., Steinfield, C., & Lampe, C. 2007)	5
OBCE	(Lai, G. W. F., Zhang, T. J., & Yeung, R. S. M. (2023)	6
Brand Loyalty	(Sohaib, M., & Han, H. 2023) & (Cheng, Y., & Jiang, H. 2021) & (Goyal, A., & Verma, P. 2022)	6

Table 1: Variables, Scale´s Authors, and Number of Items
Source: Author´s Elaboration

4.2.3. Sample Characteristics

Following data collection, a descriptive analysis of the findings was carried out using IBM SPSS Statistics software. Table X shows the qualitative data that were this study's subject. A total of 253 respondents completed the online questionnaire. In the sample, we observed that most respondents identified as female 68,78% (174), while approximately 29,64% (75) identified as male. Only a small portion of the respondents identified as "Other" sex, making up 1,58% (4).

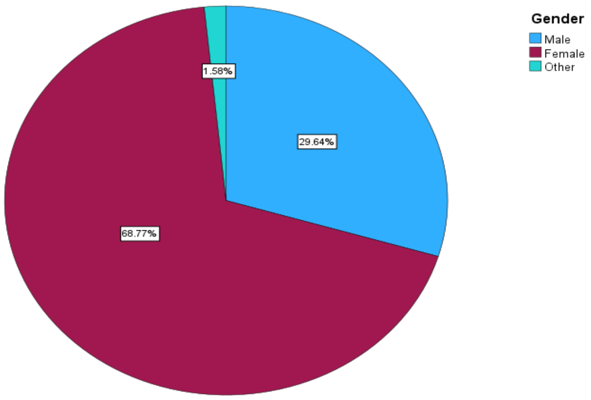

Figure 3: Gender Distribution
Source: Author´s Elaboration

In a sample open to the general public, the options for academic qualifications varied significantly, with respondents indicating "high school," "bachelor's degree," "master's degree," and "PhD" as an answer. There is a notable connection between the majority having at least a bachelor's degree and possessing significant experience with AI. The results showed that the majority, 52,17% (132), hold a master's degree. In contrast, only 2,77% (7) have a PhD degree, 11,86% (30) have a high school diploma, and the smallest percentage, approximately 33,20% (84), hold a bachelor´s.

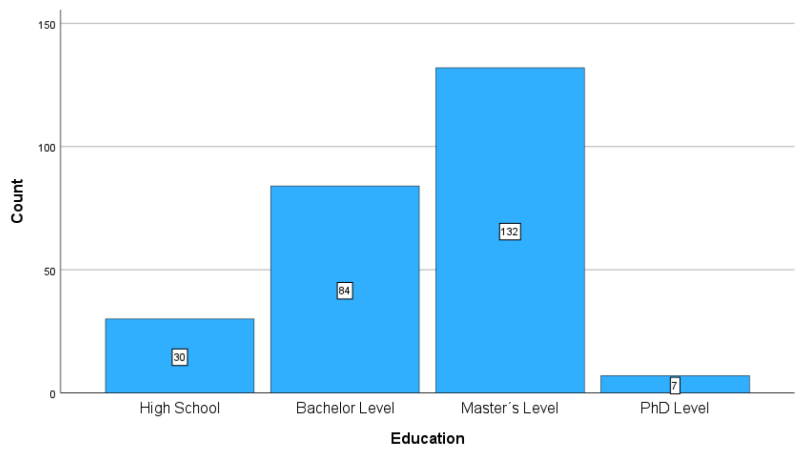

Figure 4: Education Distribution
Source: Author´s Elaboration

To facilitate a more detailed demographic analysis and better understand the different perspectives and experiences with AI, age intervals were created in the questionnaire. The intervals ranged from 18 to over 35 years. Following the analysis, it was evident that the study population was relatively young. Most respondents, 47,43% (120), were aged between 18 and 24 years. Additionally, 31,62% (80) were aged between 25 and 30 years, 6,32% (16) were aged between 31 and 35 years, and a minority, 14,62% (37), were over 35 years old.

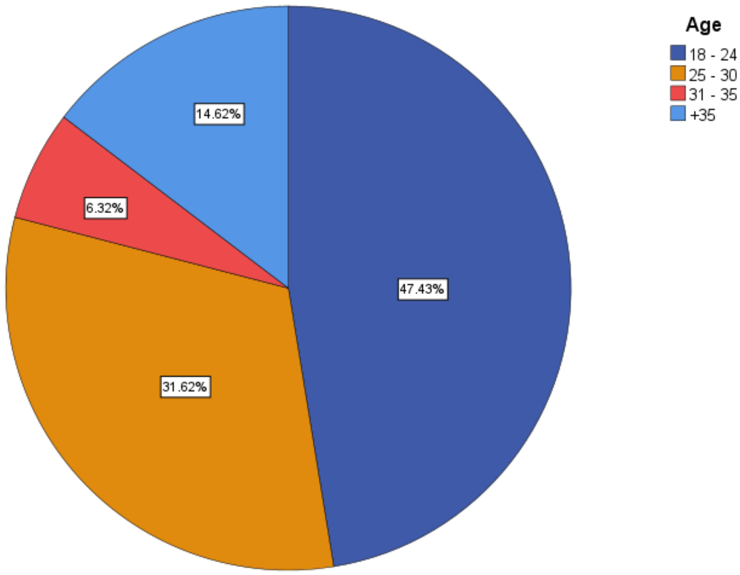

Figure 5: Age Distribution
Source: Author´s Elaboration

As previously mentioned, this study involved an open population, and considering the methods used to share the questionnaire online, we observed a wide variety of responses in the nationality variable. The study reached five continents and included participants from thirty-one different nationalities. Among the nationalities collected, the most represented were Portuguese, with 38% (95) of respondents, this information can be attributed to the fact that the questionnaire was conducted majorly in Portugal, followed by the United Kingdom of Great Britain with 27% (68), and finally the United States of America with 8% (20). In terms of geographical distance, the study reached Australia with 6% (14).

5. RESULTS

5.1. Data Treatment

Initially, the data collected in the questionnaires were exported from the Qualtrics platform as an SPSS file. All data collected were later imported into IBM SPSS Statistics 29 software for descriptive analysis, multiple regression analysis, and simple regression analysis. Subsequently, the type of variable measure of each item under study was identified. The item's gender, location and education were identified as nominal variables. Age was the only item considered as an ordinal variable. All remaining items in the study measured with a 7-point Likert scale were identified as scale variables.

5.2. Descriptive Statistics

The next section includes a descriptive analysis of all variables present in the study. The analysis was carried out using SPSS Statistics 29. The mean, standard deviation, skewness, and kurtosis values were computed in the descriptive analysis.

5.2.1. AI-Driven Personalization

The variable AI-driven personalization was studied using eight items, presented on a 7-point Likert scale adopted by Lim & Zhang (2022). Table 2 displays the mean values, standard deviation, skewness, and kurtosis factor. AI_4 – "*Find products that interest me*" had the highest mean value at 5.45, which suggests that respondents strongly agree that AI should be used to find products that personally interest them. In contrast AI_8 "*I feel the online recommendations delivers products should be based on my specific actions*" and AI_5 "*Help me discover trending products*" presented the lowest media with a value of 5.02, AI_5 also presents the highest standard deviation of 1.454. The average of all the items in the study was above 5, respondents have a very positive relationship with AI and see it as a useful tool in direct marketing campaigns.

The construct AI-driven personalization, represents the relationship between respondents and AI and its usage in direct marketing was calculated by computing the items AI_1, AI_2, AI_3, AI_4, AI_5, AI_6, AI_7 and AI_8. AI-driven personalization has a mean value of 5.2436 and a standard deviation of 0.85247. The mean value is more than one value higher than the middle value in the Likert Scale from 1 to 7, indicating that AI-driven personalization positively impacts respondents' relationship with AI utilization. Considering that the skewness value of -0.847 and the kurtosis value of 1.116 are within the interval [-2;2], as shown in Table 2, we are dealing with a symmetric and normal distribution.

Table 2: Descriptive Statistics for AI

		Mean	Std. Deviation	Skewness		Kurtosis	
		Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
AI_1	Attitude toward AI	**5.28**	**1.240**	**-1.084**	**.153**	**1.649**	**.305**
AI_2	Experience toward AI	**5.30**	**1.078**	**-.786**	**.153**	**1.319**	**.305**
AI_3	Find personally relevant products based on my interests	**5.32**	**1.226**	**-1.236**	**.153**	**1.877**	**.305**
AI_4	Find products that interest me	**5.45**	**1.206**	**-1.191**	**.153**	**1.670**	**.305**
AI_5	Help me discover trending products	**5.02**	**1.454**	**-.846**	**.153**	**.133**	**.305**
AI_6	Find relevant products fast and easily	**5.49**	**1.160**	**-1.046**	**.153**	**1.485**	**.305**
AI_7	Online products responses related to my earlier inputs	**5.06**	**1.335**	**-.823**	**.153**	**.327**	**.305**
AI_8	I feel the online recommendations delivers products should be based on my specific actions	**5.02**	**1.329**	**-.650**	**.153**	**.179**	**.305**
	ConstructAI	**5.2436**	**.85247**	**-.874**	**.153**	**1.116**	**.305**

5.2.2. Brand Loyalty

The variable brand loyalty was studied using six items, presented on a 7-point Likert scale adopted by Cheng & Jiang (2022), Goyal & Verma (2024) and Sohaib & Han (2023). Table 3 displays the mean values, standard deviation, skewness, and kurtosis factor. BL_4 – "*I intend to keep purchasing products from my favourite brand*" had the highest mean value at 5.40, which suggests that respondents intensely agree that they intend to keep purchasing products from their favourite fashion brand. In contrast BL_3 "*I would not buy other brand if my favourite brand is available at store*" presented the lowest mean with a value of 3.83 and the highest standard deviation of 1.853. The average of all the items in the study was 4.7246.

The construct brand loyalty, representing the loyalty between respondents and their favourite fashion brand, was calculated by computing the items BL_1, BL_2, BL_3, BL_4, BL_5 and BL_6. Brand loyalty has a mean value of 4.7246 and a standard deviation of 1.06798. The mean value is more than one value higher than the middle value in the Likert Scale from 1 to 7, indicating that the variable brand loyalty influences respondents' relationship with their favourite fashion brand. Considering that the skewness value of -.181 and the kurtosis value of -.190 are within the interval [-2;2], as shown in Table 3, we are dealing with a symmetric and normal distribution.

Table 3: Descriptive Statistics for BL

		Mean	Std. Deviation	Skewness		Kurtosis	
		Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
BL_1	I consider myself loyal to my favourite brand	**4.42**	**1.512**	**-.362**	**.153**	**-.564**	**.305**
BL_2	My favourite brand would be my first choice	**4.99**	**1.367**	**-.655**	**.153**	**.057**	**.305**
BL_3	I would not buy other brand if my favourite brand is available at store	**3.83**	**1.853**	**.147**	**.153**	**-1.183**	**.305**
BL_4	I intend to keep purchasing products from my favourite brand	**5.40**	**1.212**	**-.904**	**.153**	**.976**	**.305**
BL_5	I will expand using other products of my favourite brand	**5.08**	**1.217**	**-.772**	**.153**	**.689**	**.305**
BL_6	I am willing to pay more for my favourite brand	**4.62**	**1.568**	**-.457**	**.153**	**-.538**	**.305**
BL		**4.7246**	**1.06798**	**-.190**	**.153**	**-.181**	**.305**

5.2.3. Self-brand Connection

The variable self-brand connection was studied using five items, presented on a 7-point Likert scale adopted by Hollebeek et al. (2014) and van der Westhuizen (2018). Table 4 displays the mean values, standard deviation, skewness, and kurtosis factor. SBC_2 – "*I can identify with my favourite brand*" had the highest mean value at 4.68, which suggests that respondents intensely agree that they identify with the actions and products of their favourite fashion brand. In contrast, SBC_5 "*I use my favourite brand to communicate who I am to other people*" presented the lowest mean with a value of 4.11 and the highest standard deviation of 1.757.

The construct self-brand connection, representing the connection between respondents and their favourite fashion brand, was calculated by computing the items SBC_1, SBC_2, SBC_3, SBC_4 and SBC_5. Self-brand connection has a mean value of 4.3281 and a standard deviation of 1.39831. The mean value is more than one value higher than the middle value in the Likert Scale from 1 to 7, indicating that the variable self-brand connection influences respondents' relationship with their favourite fashion brand. Considering that the skewness value of -.181 and the kurtosis value of -.190 are within the interval [-2;2], as shown in Table 4, we are dealing with a symmetric and normal distribution.

Table 4: Descriptive Statistics for SBC

		Mean	Std. Deviation	Skewness		Kurtosis	
		Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
SBC_1	My favourite brand reflects who I am	**4.40**	**1.634**	**-.555**	**.153**	**-.502**	**.305**
SBC_2	I can identify with my favourite brand	**4.68**	**1.426**	**-.686**	**.153**	**-.037**	**.305**
SBC_3	I feel a personal connection with my favourite brand	**4.17**	**1.632**	**-.165**	**.153**	**-.820**	**.305**
SBC_4	I use my favourite brand to reflect who I consider myself to be	**4.28**	**1.673**	**-.375**	**.153**	**-.890**	**.305**
SBC_5	I use my favourite brand to communicate who I am to other people	**4.11**	**1.757**	**-.176**	**.153**	**-.992**	**.305**
SBC		**4.3281**	**1.39831**	**-.437**	**.153**	**-.378**	**.305**

5.2.4. Emotional Connection

The variable emotional connection was studied using five items, presented on a 7-point Likert scale adopted by Ellison et al. (2007). Table 5 displays the mean values, standard deviation, skewness, and kurtosis factor. EC_4 – "*I would be sorry if my favourite brand shut down"* had the highest mean value at 5.37, which suggests that the shutdown of respondents' favourite brand would affect them. In contrast EC_2 "*I feel out of touch when I haven't used my favourite brand for a while*" presented the lowest mean with a value of 3.08. EC_3 has the highest standard deviation of 1.788.

The construct emotional connection, representing the emotional connection between respondents and their favourite fashion brand, was calculated by computing the items EC_1, EC_2, EC_3, EC_4 and EC_5. Emotional connection has a mean value of 4.0609 and a standard deviation of 1.32901. The mean value is more than one value higher than the middle value in the Likert Scale from 1 to 7, indicating that the variable emotional connection influences respondents' relationship with their favourite fashion brand. Considering that the skewness value of -.011 and the kurtosis value of -.479 are within the interval [-2;2], as shown in Table 5, we are dealing with a symmetric and normal distribution.

Table 5: Descriptive Statistics for EC

		Mean	Std. Deviation	Skewness		Kurtosis	
		Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
EC_1	My favourite brand has become part of my daily routine	**3.87**	**1.724**	**-.064**	**.153**	**-1.081**	**.305**
EC_2	I feel out of touch when I haven't used my favourite brand for a while	**3.08**	**1.769**	**.634**	**.153**	**-.723**	**.305**
EC_3	I feel I am part of my favourite brand community	**3.38**	**1.788**	**.281**	**.153**	**-1.027**	**.305**
EC_4	I would be sorry if my favourite brand shut down	**5.37**	**1.495**	**-1.258**	**.153**	**1.268**	**.305**
EC_5	I am proud to tell people I use my favourite brand	**4.60**	**1.634**	**-.529**	**.153**	**-.357**	**.305**
EC		**4.0609**	**1.32901**	**-.011**	**.153**	**-.479**	**.305**

5.2.5. Online Brand Consumer Engagement

The variable online brand consumer engagement was studied using six items, presented on a 7-point Likert scale adopted by Siu et al. (2023). Table 6 displays the mean values, standard deviation, skewness, and kurtosis factor. OBCE_2 – "*I feel very positive when I am engaging with my favourite brand online"* had the highest mean value at 4.60, which suggests that respondents intensely agree that they intend to keep purchasing products from their favourite fashion brand. In contrast, OCBE_5 "*I spend much time engaging with my favourite brand online compared with other category brands*" presented the lowest mean with a value of 3.70 and the highest standard deviation of 1.870.

The construct online consumer brand engagement, representing the online engagement between respondents and their favourite fashion brand, was calculated by computing the items OCBE_1, OCBE_2, OCBE_3, OCBE_4, OCBE_5 and OCBE_6. Online consumer brand engagement has a mean value of 4.2971 and a standard deviation of 1.27480. The mean value is more than one value higher than the middle value in the Likert Scale from 1 to 7, indicating that the variable online brand consumer engagement influences respondents' relationship with their favourite fashion brand. Considering that the skewness value of -.393 and the kurtosis value of .010 are within the interval [-2;2], as shown in Table 6, we are dealing with a symmetric and normal distribution.

Table 6: Descriptive Statistics for OCBE

		Mean	Std. Deviation	Skewness		Kurtosis	
		Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
OCBE_1	Engagement activities online get me to think about my favourite brand	**4.32**	**1.585**	**-.393**	**.153**	**-.532**	**.305**
OCBE_2	I feel very positive when I am engaging with my favourite brand online	**4.60**	**1.331**	**-.630**	**.153**	**.533**	**.305**
OCBE_3	I feel good when I am engaging with my favourite brand online	**4.58**	**1.397**	**-.543**	**.153**	**.152**	**.305**
OCBE_4	I am proud to engage online with my favourite brand	**4.29**	**1.491**	**-.352**	**.153**	**-.171**	**.305**
OCBE_5	I spend much time engaging with my favourite brand online compared with other category brands	**3.70**	**1.870**	**-.046**	**.153**	**-1.196**	**.305**
OCBE_6	Whenever I am engaging this category online, I usually engage with my favourite brand	**4.30**	**1.612**	**-.474**	**.153**	**-.565**	**.305**
OCBE		**4.2971**	**1.27480**	**-.393**	**.153**	**.010**	**.305**

5.3. Exploratory Data Analysis

This chapter presents an exploratory data analysis consisting of reliability and validity analysis, single and multiple regression analysis tests.

5.3.1. Reliability and Validity Analysis

Reliability and validity analysis aims to measure the quality of the sample under study. Both measure different points, but they end up being related. Reliability analysis measures the consistency of a measure, while validity analysis focuses on measuring the accuracy of a measure.

To test the reliability of the study, Cronbach's Alpha test was calculated, not only for all items in question but also for all constructs. Cronbach's alpha is a method of measuring reliability that compares the amount of shared variation among the items in an instrument to the total variance. The Cronbach's alpha test assumes values between 0 and 1. To obtain a reliable scale, the inter-item correlation should be high. Consequently, to obtain an excellent result, the values presented by Conbach's Alpha for a given construct must be above 0.9. If the value falls between 0.8 and 0.9, it indicates very good consistency. If it falls between 0.7 and 0.8, it denotes good consistency. Finally, values between 0.6 and 0.7 are considered acceptable.

Table 8 presents the results of the Cronbach's Alpha test for all constructs under study. All values presented are higher than 0.8, showing that there is high reliability and internal conciseness. The constructs stand out, are self-brand connection and online consumer brand engagement presenting values above 0.9, meaning that they have excellent results. The construct with the lowest value ends up being brand loyalty with 0.820, which is a very good result, AI-driven personalization with 0.832 and emotional connection with 0.848.

Table 7:Reability Analysis for all Variables

Main Construct	Cronbach´s Alpha
AI-Driven Personalization	0.832
Brand Loyalty	0.820
Self-Brand Connection	0.911
Emotional Connection	0.848
Online Consumer Brand Engagement	0.901

The Cronbach Alpha reliability test was also conducted for the six constructs as summated variables (table 9), resulting in a value of 0.818, indicating high reliability.

Table 8: Cronbach´s Alpha for all summated Constructs

Cronbach´s Alpha	Nº of Items
0.818	5

5.3.2. Single and Multiple Regression Analysis 5.3.2

The next chapter presents the single and multiple regression analysis, Its main purposes are to identify the connections among different constructs and to accurately test the previously presented conceptual model. The difference between the single and multiple regression analysis is the number of independent variables. In single regression analysis, there is a single independent variable, while in multiple regression there are at least two independent variables.

5.3.2.1. Assumption of the Multiple Regression 5.3.2.1

The theoretical model assumes a linear relationship between the independent and dependent variables in construction. The model uses "β" to represent the coefficient measuring the linear impact of the independent variable on the dependent variable. For the previously established conceptual model, it's possible to identify the following multiple regression:

Brand Loyalty *= β0 +β1×**Self-brand connection**+β2×**AI-driven personalization**+β3× **Emotional Connection**+β4×**Online Brand Consumer Engagement**+ ε*

5.3.2.2. Normality of the residuals 5.3.2.2

As per Figure 7, it is possible to understand that residuals are approximately randomly distributed along the 45º line, indicating that the assumption of normality is likely satisfied. Furthermore, from Figure 6, the histogram shows that the residuals closely follow a normal distribution. Therefore, the assumption of normally distributed residuals appears to hold in this case.

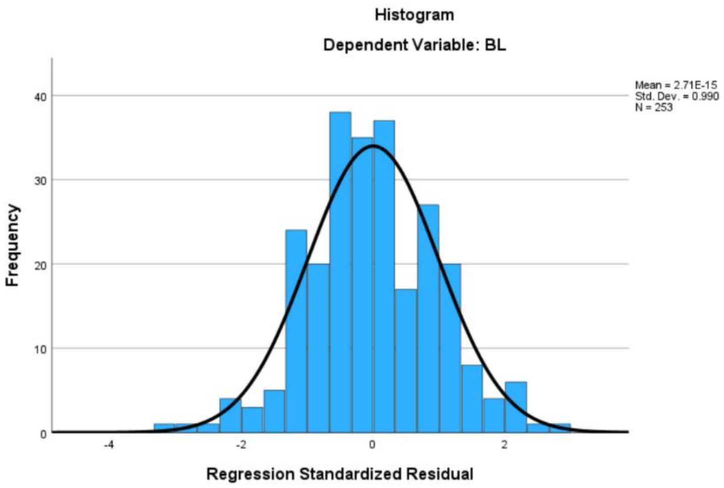

Figure 6: Histogram of the Distribution of the Residuals
Dependent Variable: Brand Loyalty
Source: Own Elaborations through SPSS Data

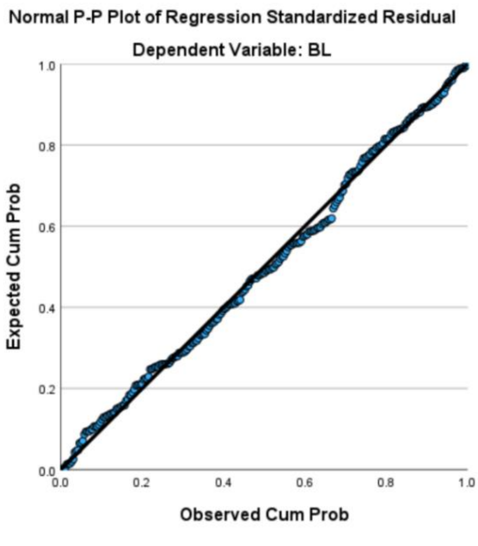

Figure 7: P-Plot - Distribution of the residuals
Source: Own Elaborations through SPSS Data

5.3.2.3. *Multiple Regression – SBC, AI and EC as independent variables and OBCE as dependent variable*

The impact of each variable was calculated using multiple regression analysis based on the conceptual model presented. The goal of the multiple regression was to determine whether the independent variables, affection, self-brand connection, AI-driven personalization, and emotional connection, positively affect the dependent variable online brand consumer engagement.

Table 9: Coefficients of the Multiple Regression, OBCE as Dependent Variable

MODEL	UNSTANDARDIZED COEFFICIENTS		STANDARDIZED COEFFICIENTS	SIG	R SQUARE
	B	STD. ERROR	B		
(Constant)	.037	.382		.097	.513
SBC	.177	.057	.194	.002	
AI	.289	.067	.193	<.001	
EC	.487	.060	.508	<.001	

Source: Own Elaboration through SPSS Data

From the table above and looking at the regression coefficients it is possible to write the adjusted regression equation:

$$\textbf{\textit{OBCE}} = .037 + .177 \times SBC + .289 \times AI + .487 \times EC + \varepsilon$$

The analysis shows that the independent variable self-brand connection positively affected online brand consumer engagement (β = .194, SIG = .003). The hypothesis 1 was accepted. AI-driven personalization positively affects online brand consumer engagement (β = 0.193, P = <.001). Hence, hypothesis 2 was accepted. Emotional connection positively impacted online brand consumer engagement (β = .508, SIG = <.001). Therefore, hypothesis 3 was accepted.

These results support the hypotheses:

H1: Self-brand connection positively impacts online brand consumer engagement

H2: AI-driven personalization positively impacts online brand consumer engagement

H3: Emotional connection positively impacts online brand consumer engagement

The R-squared value is 0.506, indicating that the variables in the model (SBC, AI, and EC) explain 50.6% of the variation in online brand consumer engagement (OBCE). This is considered a good value because ideally, the R-squared should be higher than 0.5.

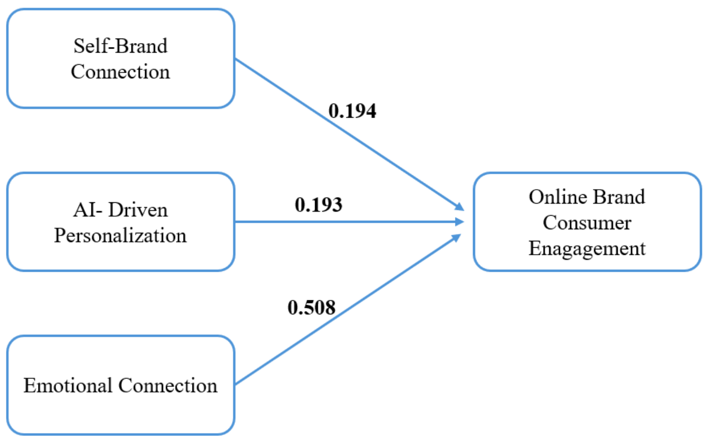

Figure 8: Regression Coefficients - OBCE as Dependent Variable
Source: Author´s Elaboration

5.3.2.4. Single Regression – OBCE as independent variable and BL as dependent variable

The present regression aims to determine if the constructs, online brand consumer engagement and brand trust positively impact the construct of brand loyalty.

Table 10: Single Regression - BL as Dependent Variable

MODEL	UNSTANDARDIZED COEFFICIENTS		STANDARDIZED COEFFICIENTS	SIG	R SQUARE
	B	STD. ERROR	B		
(Constant)	2.706	.196		<.001	.314
OBCE	.470	.044	.561	<.001	

According to the table above and looking at the regression coefficients it is possible to write the adjusted regression equation:

$$\boldsymbol{BL} = 2.706 + .470 \times OBCE + \varepsilon$$

According to the analysis, the construct of online brand consumer engagement positively impacts brand loyalty (β =.561, SIG = <.001). Hence hypothesis 4 was accepted.

These results support the hypotheses:

H4: Online brand consumer engagement positively impacts brand loyalty

Results show that the R-squared value is 0.314, meaning that the variables in the model (OBCE and BT) explain 31,4% of the variation in brand loyalty. This is considered a weak value. Ideally, the R-squared should be higher than 0.5.

Figure 9: Regression Coefficients - BL as Dependent Variable

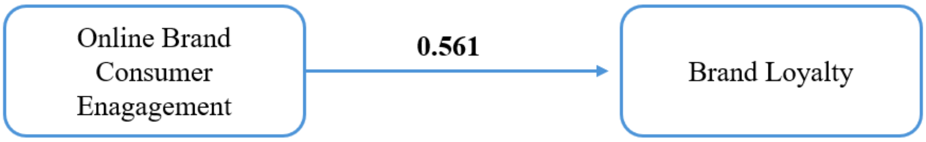

Table 11: List of Hypothesis and Validation

HYPOTHESIS	VALIDATED?
H1: *Self-brand connection positively impacts online brand consumer engagement*	**YES**
H2: *AI-driven personalization positively impacts online brand consumer engagement*	**YES**
H3: *Emotional connection positively impacts online brand consumer engagement*	**YES**
H4: *Online brand consumer engagement positively impacts brand loyalty*	**YES**

6. Conclusion

This study intended to evaluate the influence of selected variables on online brand consumer engagement and how it might enhance brand loyalty. A conceptual model was developed, incorporating pertinent constructs identified through a literature review. After that, the model was operationalized and assessed through an online survey. The model and the research hypotheses could be accepted, as the survey analysis demonstrated that the various measures for evaluating validity and reliability demonstrate their support. There are studies investigating how artificial intelligence can be used in online strategies in order to enhance brand loyalty, however, only a small percentage of them are focused on direct marketing campaigns. The study focused on the influence that the constructs of self-brand connection, AI-driven personalization, and emotional connection have on the online brand consumer engagement variable and consequently what impact this will have on the brand loyalty variable when it comes to direct marketing campaigns. This research enhances the literature by offering new insights into the interactions among these constructs.

The present section focuses on responding to the research questions proposed in the introduction of this dissertation in the form of theoretical and managerial contributions. The managerial contribution will address the general approach and core of this thesis. Furthermore, there will be a review of the limitations of the study and proposed opportunities for future research.

6.1. Theoretical Contribution

This study contributes to the current body of work on AI-driven customization, self-brand connection, emotional engagement, online consumer interaction, and brand loyalty. It integrates numerous significant theoretical principles in marketing, emphasizing the significance of artificial intelligence and brand partnerships. The research broadens our understanding of how AI might improve online marketing strategies by cultivating a more profound relationship with customers' self-image, therefore reinforcing brand loyalty.

Primarily this study aims to contribute to the understanding of how can AI-Driven personalization be best used in developing direct marketing campaigns, in the fashion industry, and enhancing brand loyalty. Literature reveals that AI plays a pivotal role in maintaining long-term loyalty by offering brands the ability to craft personalized marketing experiences that resonate with consumers´ preferences. According to Chen et al. (2020) and Verma et al. (2021), AI enhances customer segmentation and product targeting, ensuring that fashion brands can deliver relevant offers to consumers. This tailored approach strengthens the emotional and identity-based connection between the consumer and the brand, which is a key driver of brand loyalty. Research from Boakye et al. (2023) and Chaudhuri & Holbrook (2001) supports the idea that AI helps brands deliver highly personalized experiences that feel tailored to the individual´s preferences, leading consumers to develop affection and trust towards the brand, leading to repeat purchases and advocacy, by indicating that emotional connections are a critical driver of brand loyalty.

The empirical findings from this study indicate a positive relationship between AI-driven personalization and brand loyalty. The descriptive analysis revealed that respondents highly value the use of AI in direct marketing campaigns, particularly in "Finding personally relevant products" (X=5.32). The regression analysis further supports this, showing a significant impact of AI-driven personalization on online brand consumer engagement, which in turn strengthens brand loyalty ($p<.001$).

In conclusion, AI-driven personalization is a powerful tool for developing direct marketing campaigns in the fashion industry that enhance brand loyalty. By leveraging AI to deliver customized, relevant, and evolving content that aligns with individual consumer preferences, fashion brands can build deeper emotional and identity-based connections. This leads to higher levels of engagement, trust and repeat purchasing, all of which are crucial to ultimately enhance long-term brand loyalty.

Furthermore, the study supports the hypothesis that personalized direct marketing campaigns significantly impact online brand consumer engagement through AI-driven personalization, by integrating the concepts of self-brand connection and emotional connection. AI-driven personalization allows brands to deliver marketing campaigns that are finely tuned to each consumer´s preferences and history. By leveraging vast amounts of consumer data, AI can create hyper-personalized experiences. This relevance increases the likelihood of online engagement, as consumers are more inclined to interact with content directly to their preferences (Verma et al., 2021). AI´s ability to deliver highly tailored messages enhances the consumer´s perception that the brand aligns with their identity, thereby strengthening the self-brand connection. Dwivedi et al. (2015) suggest consumers who experience a strong self-brand connection are more likely to interact and advocate for the brand. Emotional engagement has measurable financial results, as Park and Kim (2014) indicate that customers who recognize a company's dedication to digital interactions are more inclined to share favorable experiences and develop loyalty as advocates. Consequently, using emotionally-driven techniques on digital platforms promotes customer pleasure and fosters growth by strengthening customer connections, eventually leading to increased brand loyalty and long-term profitability.

The empirical evidence confirms that both self-brand connection and emotional connection play significant roles in driving online engagement. The regression analysis shows that AI-driven personalization, when used to cater to both emotional and identity-based needs, positively influences online brand consumer engagement ($p<.001$). The analysis further highlights that emotional connection ($B=.508$, $p=.001$) and self-brand connection ($B=.194$, $p=.002$) are key factors contributing to increased consumer engagement. The data supports the idea that personalized campaigns are more effective when they target both the emotional and self-identity dimensions of consumer-brand relationships.

As has been shown, AI-driven personalization significantly enhances online brand consumer engagement by leveraging both self-brand connection and emotional connection. Through personalized direct marketing campaigns, AI can deliver content that resonates with both consumer's identities and emotional needs, leading to deeper and more sustained engagement. The integration of AI with self-brand connection and emotional connection creates a powerful synergy that drives consumers to interact more frequently and meaningfully with the brand resulting in stronger online engagement.

The results of this research substantiate the concept that brand loyalty may be forecasted by online consumer brand engagement (OCBE). The findings indicated a substantial direct relationship between these two constructs ($p < .001$). Although engagement patterns show marginal variations, brand loyalty often remains consistently elevated. The findings indicated a positive correlation among the following variables: OCBE_2 (“I experience a strong sense of positivity when interacting with my preferred brand online”) has a mean score of 4.60, BL_4 (“I plan to continue purchasing products from my preferred brand”) has a mean of 5.40, and BL_5 (“I will increase my utilization of other products from my preferred brand”) has a mean of 5.08. This indicates that customers who interact favourably online are more inclined to demonstrate brand loyalty. These results align with previous studies. Loureiro et al. (2017) cited brand loyalty as a possible result of online brand interaction, whilst Hollebeek (2011) highlighted that positive engagement cultivates enhanced brand loyalty. Furthermore, Dwivedi (2015) and Vivek et al. (2012) posited that robust connections established by consumer brand involvement might amplify loyalty intentions. Fernandes and Moreira (2019) observed that brand loyalty and associated effects are enhanced with active and favourable involvement. The study demonstrates that people with elevated online engagement are more prone to establish enduring relationships with businesses, leading to increased loyalty. This favourable correlation indicates that brand loyalty increases when people interact more with the business online. Consequently, fashion firms have to emphasize the development of direct online marketing strategies that cultivate significant ties with customers throughout their digital engagements.

In summary emotional connection, self-brand connection and AI-driven personalization have a positive impact on OBCE. Emotional connection and AI-driven personalization are the most impactful dimensions when it comes to OBCE, this means that these dimensions have a crucial role in building relationships between consumers and their favourite fashion brands. The analysis shows that even though the self-brand connection dimension has the least impact on OBCE, it still significantly influences it. This suggests that brands aligning their campaigns with consumers' identities fosters stronger engagement. The data also shows that OBCE has a moderate effect on brand loyalty, which implies that while engagement is important, additional factors may be required to fully strengthen a long-term relationship between fashion brands and consumers. Furthermore, the findings highlight the potential for AI-driven personalization to enhance bot engagement and loyalty.

Considering all of this, it can be stated that if individuals are influenced by personalized campaigns from fashion brands, their engagement levels with those brands will increase. This, in turn, will have a positive impact on brand loyalty when comparing the brand to others within the same category.

6.2. Managerial Contribution

The chapter on management contributions provides significant insights for marketing managers in the fashion sector, highlighting the need to augment brand loyalty and cultivate robust consumer connections. A strong connection between brands and customers may result in enhanced long-term sales, especially in a competitive landscape with many consumer choices. Therefore, managers must comprehensively comprehend customer behaviour to tailor brand experiences that successfully impact purchase choices.

In the current technology-driven environment, the digital presence of fashion firms is essential for engaging with consumers. The web channel functions as the principal medium connecting companies and customers, allowing them to display their products and convey their messages efficiently. Consequently, marketing managers have to emphasize the development of captivating online experiences using diverse direct marketing channels, such as Google Ads, email marketing, and social media advertising. The main aim of these initiatives should be to promote recurring engagements and strengthen favourable brand experiences.

Brands must acknowledge that their internet advertising should extend beyond just items and prices. Establishing a strong emotional connection between the brand and the customer is essential since a brand's worth transcends its physical products. Considering that customers often align with companies that mirror their self-identity, marketing strategies need to prioritize promoting concepts that embody this identity. By doing so, companies may enhance customer engagement and create a significant connection that enables consumers to integrate the brand's values and attributes into their self-concept. This link may markedly strengthen brand loyalty, rendering buyers less prone to transitioning to rival items, especially amongst market variations such as price decreases or promotional offers. This profound emotional bond offers a competitive edge that is hard for competitors to duplicate.

Managers should include lifestyle themes, narratives, customized messages, and emotional branding into their campaigns to foster this connection, rather than concentrating only on product qualities and cost. Moreover, synchronizing brand identity with customers' self-concept is essential. Marketing managers could harness emotional branding by using artificial intelligence (AI) to convey messages that elicit profound emotional reactions. Campaigns aimed at evoking positive emotions—such as gratitude or enthusiasm—can enhance customer engagement and foster brand loyalty.

AI-driven customization is essential for combining these elements. Its ability to analyze extensive data sets and discern trends facilitates the creation of highly tailored marketing campaigns derived from specific customer information. Preserving extensive customer data in loyalty accounts enables AI to develop customized marketing with individualized suggestions and communications. This proactive strategy improves engagement and cultivates loyalty.

It is essential to reconcile customers' privacy apprehensions related to AI use with the advantages of personalized offers and recommendations (Davenport et al., 2020). Brands should provide customers with explicit information on data protection procedures throughout the loyalty account signup process. Employing techniques like QR codes may guide customers to the brand's data protection policy websites, providing transparency (Bilro et al., 2018).

6.3. Limitations and Future Research

Regardless of the efforts to avoid bias, this study presents limitations. These limitations can lead to further opportunities to develop the topic from a different perspective. Hence, the interpretation of the results should take into account the limitations of this study.

The first limitation of the study is related to the sample size, consisting of 253 valid responses, which was considered small for the study. This was mainly due to the high number of incomplete responses and the lack of time and resources. This ended up limiting the generalizability of the study. As it was being published mainly in Portugal, this study naturally ended up having mostly Portuguese respondents, and the study ended up being more focused on Portuguese culture. Despite the presence of numerous nationalities, these ended up not having a significant number of respondents that could impact the variables. It is proposed that future research focus on a specific country or culture so that brands can understand how the perception of brand loyalty differs in a different context.

Moreover, adopting a quantitative approach produces conclusions derived from numerical data, thereby providing little insight into thoughts and behaviours, which may result in a deficiency of context. Future studies could use other research methodologies to get deeper insights into the ideas and behaviours of participants, contextualizing masstige for mobile businesses more comprehensively. It would be interesting if future researchers analysed the impact of other variables such as affection in online brand consumer engagement. Future research can also understand if online brand consumer engagement will positively impact consumers' purchase intention or consumer satisfaction. Furthermore, it is also possible to investigate whether the variable brand trust will positively impact brand loyalty.

Additionally, future research should focus on different industries in order to understand how it may influence this perception of loyalty. The automotive, retail and sports industries are some of the industries that are suggested for study. In addition, future research should focus on a specific type of direct marketing, such as email marketing or Google Ads, as these are common examples in everyday life.

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Appendix A – Online Survey

Welcome to the questionnaire designed for the thesis course unit as part of the Master´s Degree in Marketing at ISCTE - Business School. The purpose of this questionnaire is to find out how AI can be used in Direct Marketing Campaigns to increase brand loyalty. Completing the questionnaire should only take around 5 minutes or less of your time. All information and data collected will be treated as confidential and anonymous. The responses will undergo statistical processing and will be used solely for statistical analysis purposes.

Your participation is greatly appreciated, and your contribution is invaluable to the sucess of this academic research. Thank you for taking the time to participate.

→

The growth of direct marketing campaigns, has been significant, reflecting consumers' preference for personalized interactions. AI offers a solution to enhance brand loyalty through tailored campaigns. By analyzing vast amounts of data, AI enables marketers to understand individual preferences and behaviors. Through predictive analytics and recommendation engines, AI-driven campaigns can strengthen brand-consumer relationships.

Therefore, I present this questionnaire where you will be asked to respond to the following statements by rating them on a scale from 1=Strongly Disagree to 7=Strongly Agree

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Given your experience with Artificial Intelligence (AI), would it be reasonable to assume that you hold a positive:

	1. Strongly Disagree	2. Disagree	3. Somewhat Disagree	4. Either Agree or Disagree	5. Somewhat Agree	6. Agree	7. Strongly Agree
Attitude toward AI	○	○	○	○	○	○	○
Experience toward AI	○	○	○	○	○	○	○

Considering the various applications of AI in the creation of direct marketing campaigns, which aspects would you personally find relevant for AI assistance:

	1. Strongly Disagree	2. Disagree	3. Somewhat Disagree	4. Either Agree or Disagree	5. Somewhat Agree	6. Agree	7. Strongly Agree
Find personally relevant products based on my interests	○	○	○	○	○	○	○
Find products that interest me	○	○	○	○	○	○	○
Help me discover trending products	○	○	○	○	○	○	○
Find related products fast and easily	○	○	○	○	○	○	○
Online products responses related to my earlier inputs	○	○	○	○	○	○	○
I feel the online recommendations delivers products should be based on my specific actions	○	○	○	○	○	○	○

→

To what extent do you agree or disagree with the following statements regarding your emotinal connection for your favourite fashion brand?

	1. Strongly Disagree	2. Disagree	3. Somewhat Disagree	4. Either Agree or Disagree	5. Somewhat Agree	6. Agree	7. Strongly Agree
My favourite brand has become part of my daily routine	○	○	○	○	○	○	○
I feel out of touch when I havent used my favourite brand for a while	○	○	○	○	○	○	○
I feel I am part of my favourite brand community	○	○	○	○	○	○	○
I would be sorry if my favourite brand shut down	○	○	○	○	○	○	○
I am proud to tell people I use my favourite brand	○	○	○	○	○	○	○

→

To what extent do you agree or disagree with the following statements regarding your loyalty for your favourite fashion brand?

	1. Strongly Disagree	2. Disagree	3. Somewhat Disagree	4. Either Agree or Disagree	5. Somewhat Agree	6. Agree	7. Strongly Agree
I consider myself loyal to my favourite brand	○	○	○	○	○	○	○
My favourite brand would be my first choice	○	○	○	○	○	○	○
I would not buy other brand if my favourite brand is available at store	○	○	○	○	○	○	○
I intend to keep purchasing products from my favourite brand	○	○	○	○	○	○	○
I will expand using other products of my favourite brand	○	○	○	○	○	○	○
I am willing to pay more for my favourite brand	○	○	○	○	○	○	○

To what extent do you agree or disagree with the following statements regarding your online engagement with your favourite fashion brand?

	1. Strongly Disagree	2. Disagree	3. Somewhat Disagree	4. Either Agree or Disagree	5. Somewhat Agree	6. Agree	7. Strongly Agree
Engagement activities online get me to think about my favourite brand	○	○	○	○	○	○	○
I feel very positive when I am engaging with my favourite brand online	○	○	○	○	○	○	○
I feel good when I am engaging with my favourite brand online	○	○	○	○	○	○	○
I am proud to engage online with my favourite brand	○	○	○	○	○	○	○
I spend much time engaging with my favourite brand online compared with other category brands	○	○	○	○	○	○	○
Whenever I am engaging this category online, I usually engage with my favourite brand	○	○	○	○	○	○	○

To what extent do you agree or disagree with the following statements regarding your self-brand connection for your favourite fashion brand?

	1. Strongly Disagree	2. Disagree	3. Somewhat Disagree	4. Either Agree or Disagree	5. Somewhat Agree	6. Agree	7. Strongly Agree
My favourite brand reflects who I am	○	○	○	○	○	○	○
I can identify with my favourite brand	○	○	○	○	○	○	○
I feel a personal connection with my favourite brand	○	○	○	○	○	○	○
I use my favourite brand to reflect who I consider myself to be	○	○	○	○	○	○	○
I use my favourite brand to communicate who I am to other people	○	○	○	○	○	○	○

Age

- 18 - 24
- 25 - 30
- 31 - 35
- +35

Gender

- Male
- Female
- Other

Education

- High School
- Bachelor Level
- Master´s Level
- PhD Level

In which country do you currently reside?

→

Appendix B – Constructs, Scales and Authors

Author	Construct	Code	Scales
(Hollebeek, L. D., Glynn, M. S., & Brodie, R. J. 2014) & (Van Der Westhuizen, L. 2018)	Self-brand Connection	SBC1	My favourite brand reflects who I am
		SBC2	I can identify with my favourite brand
		SBC3	I feel a personal connection with my favourite brand
		SBC4	I use my favourite brand to reflect who I consider myself to be
		SBC5	I use my favourite brand to communicate who I am to other people
(Ellison, N. B., Steinfield, C., & Lampe, C. 2007)	Emotional Connection	EC1	My favourite brand has become part of my daily routine
		EC2	I feel out of touch when I haven't used my favourite brand for a while
		EC3	I feel I am part of my favourite brand
		EC4	I would be sorry if my favourite brand shut down
		EC5	I am proud to tell people I use my favourite brand
(Lim, J. S., & Zhang, J. 2022)	AI-Driven Personalization	AI1	Attitude toward AI
		AI2	Experience toward AI
		AI3	Find personally relevant products based on my interests
		AI4	Find products that interest me
		AI5	Help me discover trending products
		AI6	Find related products fast and easily
		AI7	Online products responses related to my earlier inputs
		AI8	I feel the online recommendations delivers products should be based on my specific actions

(Lai, G. W. F., Zhang, T. J., & Yeung, R. S. M. (2023)	Online Brand Consumer Engagement	OBCE1	Engagement activities online get me to think about my favourite brand
		OBCE2	I feel very positive when I am engaging with my favourite brand online
		OBCE3	I feel good when I am engaging with my favourite brand online
		OBCE4	I am proud to engage online with my favourite
		OBCE5	I spend much time engaging with my favourite brand online compared with other category brands
		OBCE6	Whenever I am engaging this category online, I usually engage with my favourite brand
(Sohaib, M., & Han, H. 2023) & (Cheng, Y., & Jiang, H. 2021) & (Goyal, A., & Verma, P. 2022)	Brand Loyalty	BL1	I consider myself loyal to my favourite brand
		BL2	My favourite brand would be my first choice
		BL3	I would not buy other brand if my favourite brand is available at store
		BL4	I intend to keep purchasing products from my favourite brand
		BL5	I will expand using other products of my favourite brand
		BL6	I am willing to pay more for my favourite brand

Appendix C – Linear Regression Assumptions

BL as Dependent Variable:

VARIABLES ENTERED/REMOVED (A)

MODEL	Variables Entered	Variables Removed	Method
1	AI, SBC, OBCE, EC(B)		Enter

A: Dependent Variable: BL
B: All requested variables entered

MODEL SUMMARY (B)

MODEL	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.697(a)	.486	.477	.77214	2.222

A: Predictors: (Constant), AI, SBC, OBCE, EC
B: Dependent Variable: BL

ANOVA (A)

MODEL		Sum of Squares	df	Mean Square	F	Sig
	Regression	139.568	4	34.892	58.523	<.001(b)
1	Residual	147.859	248	.596		
	Total	287.428	252			

A: Dependent Variable
B: Predictors: (Constant), AI, SBC, OBCE, EC

COEFFICIENTS (A)

MODEL		Understandardized B	Coefficients Std.Error	Coefficients Std.Error Beta	t	Sig	Collinearity Tolerance	Statistics VIF
1	Constant	1.450	.327		4.437	<.001		
	SBC	.144	.049	.188	2.902	.004	.494	2.022
	EC	.330	.058	.410	5.728	<.001	.404	2.473
	OBCE	.121	.054	.144	2.226	.027	.494	2.023
	AI	.152	.060	.121	2.540	.012	.913	1.096

A: Dependent Variable BL

COLLINEARITY DIAGNOSTICS(A)

					Variance Proportions			
MODEL	**Dimension**	**Eigenvalue**	**Condition Index**	**Constant**	**SBC**	**EC**	**OBCE**	**AI**
1	1	4.841	1.000	.00	.00	.00	.00	.00
	2	.085	7.549	.06	.10	.10	.01	.09
	3	.037	11.514	.02	.56	.02	.56	.00
	4	.025	13.796	.02	.33	.86	.37	.00
	5	.012	19.871	.90	.01	.03	.05	.91

A: Dependent Variable: BL

RESIDUAL STATISTICS (A)

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	2.7265	6.6703	4.7246	.74421	253
Residual	-2.43725	2.12118	.00000	.76599	253
Std. Predicted Value	-2.685	2.614	.000	1.000	253
Std. Residual	-3.156	2.747	.000	.992	253

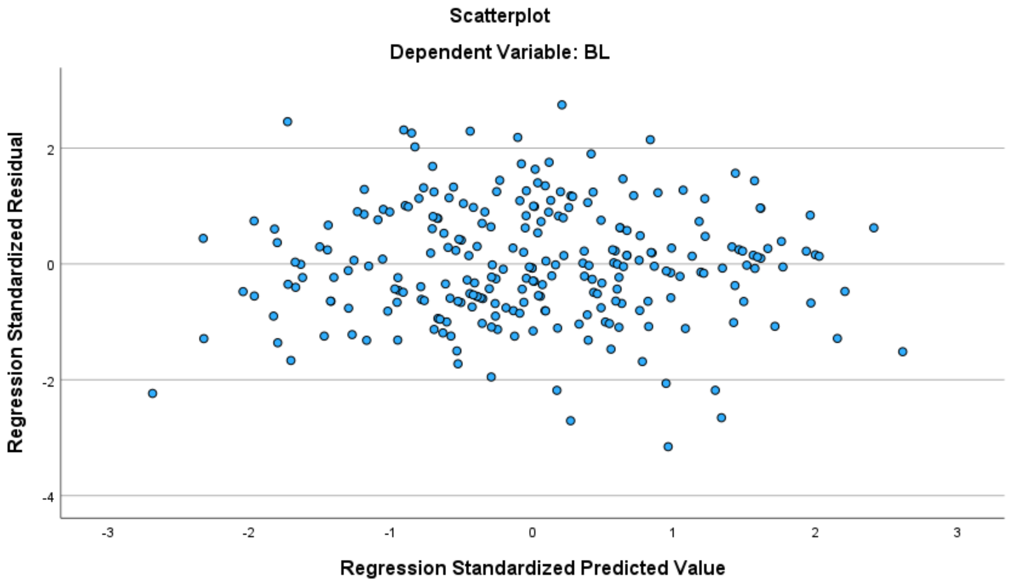
A: Dependent Variable BL

DESCRIPTIVE STATISTICS

	Mean	Std. Deviation	N
BL	4.7246	1.06798	253
SBC	4.3281	1.39831	253
EC	4.0609	1.32901	253
OBCE	4.2971	1.27480	253
AI	5.2436	.85247	253

CORRELATIONS

		BL	SBC	EC	OBCE	AI
Pearson Correlation	BL	1.000	.571	.654	.561	.240
	SBC	.571	1.000	.697	.572	.124
	EC	.654	.697	1.000	.669	.134
	OBCE	.561	.572	.669	1.000	.285
	AI	.240	.124	.134	.285	1.000
Sig. (1-Tailed)	BL	.	<.001	<.001	<.001	<.001
	SBC	.000	.	.000	.000	.025
	EC	.000	.000	.	.000	.017
	OBCE	.000	.000	.000	.	.000
	AI	.000	.025	.017	.000	.
N	BL	253	253	253	253	253
	SBC	253	253	253	253	253
	EC	253	253	253	253	253
	OBCE	253	253	253	253	253
	AI	253	253	253	253	253


Scatterplot
Dependent Variable: BL
Regression Standardized Residual
2
0
-2
-4
-3
-2
-1
0
1
2
3
Regression Standardized Predicted Value