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The Customer Value Proposition of Fashion Brands in the Digital Era

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Abstract (English)

The purpose of this thesis is to examine the influence of place and promotion elements of the marketing mix on consumers' online purchase intentions, with a comparative focus on the fast fashion and luxury fashion industry. This study builds upon existing literature on Customer Value Proposition (CVP) within the fast fashion and luxury fashion industries to identify key dimensions shaping consumer preferences. Based on existing research, the CVP of fast fashion brands is primarily driven by economic customer value, whereas the CVP of luxury brands is centered on symbolic, emotional, and social customer value. Employing a Choice-Based Conjoint (CBC) analysis, this study draws on data from a sample of 165 participants recruited through a snowball sampling technique. Moreover, gender, age, and income are included as control variables to assess differences across demographic groups. The findings indicate that digital marketing strategies, online selection, free standard deliveries, and free and convenient return policies create a higher online purchase intention among fast fashion consumers than luxury fashion consumers. This study contributes to the understanding of how digital marketing strategies and omnichannel business models influence online consumer behavior, providing actionable insights for developing effective marketing strategies for target customers. Fast fashion brands should prioritize enhancing their e-commerce platforms by offering price promotions, free shipping, and convenient return policies, whereas luxury fashion brands should focus on integrating online shops with physical stores to create a seamless shopping experience.

Keywords: Digital Transformation, Customer Value Proposition, Fashion Industry, Fast Fashion, Luxury Fashion, Conjoint Analysis, Online Purchase Intention

Abstract (Deutsch)

Im Rahmen dieser Studie wird untersucht, wie die Elemente der Distributionspolitik und Kommunikationspolitik des Marketing-Mix die Online-Kaufabsichten von Kund/innen in der Fast-Fashion-Branche im Vergleich zur Luxusmodebranche beeinflussen. Diese Studie stützt sich auf bestehende Literatur zur Customer Value Proposition (CVP) innerhalb der Fast-Fashion- und Luxusmodebranche, um die wichtigsten Einflussfaktoren auf die Verbraucherpräferenzen zu verstehen. Basierend auf bestehender Forschung wird die CVP von Fast-Fashion-Marken hauptsächlich durch ökonomischen Kundenwert bestimmt, während das Nutzenversprechen von Luxusmarken in ihrem symbolischen, emotionalen und sozialen Kundenwert liegt. Mithilfe einer Choice-Based Conjoint (CBC)-Analyse basiert diese Untersuchung auf Daten einer Stichprobe von 165 Teilnehmer/innen, die mittels Schneeball-Sampling gewonnen wurden. Darüber hinaus werden Geschlecht, Alter und Einkommen als Kontrollvariablen einbezogen, um Unterschiede zwischen demografischen Gruppen zu analysieren. Die Ergebnisse zeigen, dass digitale Marketingstrategien, Online-Entscheidungsoptionen, kostenlose Standardlieferungen sowie kostenfreie und bequeme Rückgabemöglichkeiten die Online-Kaufabsicht von Fast-Fashion-Konsumenten stärker erhöhen als die von Luxusmode-Konsumenten. Diese Studie trägt zum Verständnis bei, wie digitale Marketingstrategien und Omnichannel-Geschäftsmodelle die Online-Kaufpräferenzen beeinflussen und liefert umsetzbare Erkenntnisse zur Entwicklung effektiver Marketingstrategien für Zielkunden. Fast-Fashion-Marken sollen die Optimierung ihrer E-Commerce-Plattformen priorisieren, insbesondere durch Preisaktionen, kostenlose Lieferungen und benutzerfreundliche Rückgaberichtlinien. Luxusmodemarken hingegen sollen sich auf die Integration von Online-Shops und physischen Geschäften konzentrieren, um ein nahtloses Einkaufserlebnis zu schaffen.

Schlüsselwörter: Digitale Transformation, Nutenversprechen, Modebranche, Fast Fashion, Luxusmode, Conjoint Analyse, Online-Kaufabsichten

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List of Abbreviations

AI	Artificial Intelligence
AIC	Akaike Information Criterion
AR	Augmented Reality
BIC	Bayesian Information Criterion
CBC	Choice-Based Conjoint
CV	Customer Value
CVP	Customer Value Proposition
GDN	Google Display Network
GLM	Generalized Linear Models
HB	Hierarchical Bayes
RFC	Randomized First Choice
RQ	Research Question
RTB	Real-Time Bidding
SE	Standard Error
SEA	Search Engine Advertising
SEO	Search Engine Optimization
UI	User Interface
UX	User Experience
VP	Value Proposition

1. Introduction

Marked by globalization, digitalization, technological innovations, and the demand for sustainable practices, the fashion industry is impacted by significant transformations and is facing intense competition (Bertola and Teunissen, 2018). Digitalization plays an important role in reshaping the fashion industry and the way fashion brands design, market, and sell their products (Kotler et al., 2022). It leads to changes in consumer preferences and needs, and customer value is becoming more important in explaining consumer behavior, attracting potential customers, and establishing a competitive advantage (Berman, 2012). Digitalization transforms the fashion industry by leveraging sociocultural trends and integrating new technologies to deliver customer value (Gellweiler and Krishnamurthi, 2020). The rise of online platforms creates new opportunities for fashion brands to connect with customers, increase their market share, and build closer relationships with their target groups (Cabigiosu, 2020).

Understanding customer needs is essential for brands to create value for their customers. Buyers wish for all their needs to be satisfied at once, and it is the company's objective to prioritize which needs are the most important to fulfill. This understanding enables a firm to allocate its resources optimally, thereby generating the greatest value for the customer (Kotri, 2006). The concept of value was first discussed in 1960 as a fundamental aspect of marketing strategy (McCarthy, 1960). Porter (1985) takes a customer-centric approach and acknowledges the importance of customer value in creating a competitive advantage. The fashion industry requires unique strategies compared to other industries, as fashion brands operate on emotion, image, and perception. As a result, the customer value proposition (CVP) has an important role in enabling brands to establish themselves in the market (Salsabilla and Mirzanti, 2022), influence consumer preferences, product choices, and repurchase intentions (Cronin et al., 2000), and is essential to a firm's success (Osterwalder et al., 2014).

To understand how specific elements of the marketing mix, most impacted by digitalization, influence customers' online purchase intentions in the fast fashion industry compared to the luxury fashion industry, this research employs conjoint analysis to evaluate consumer preferences, focusing on the promotion and place factors.

The CVP of fast fashion brands is primarily based economic customer value, driven by affordability (Gomes de Oliveira et al., 2022). The luxury fashion industry, on the other hand, is characterized by its symbolic CVP through its brand image elements, such as exclusivity, scarcity, rarity, heritage, and cultural influence (Amatulli et al., 2016; McGowan et al., 2018).

Investment in digital marketing is growing, and digital marketing strategies help increase brand awareness and brand reputation while enabling businesses to reach large numbers of current or potential customers (Aiolfi and Sabbadin, 2019; Rathore, 2021).

As online shopping continues to grow, brands are adopting omnichannel strategies to create a convenient and improved shopping experience. This approach allows customers to transition effortlessly between different channels (Lazaris and Vrechopoulos, 2014), and provides benefits such as convenient delivery and return policies (Cabigiosu, 2020).

Marketing specialists refer to a conjoint analysis as a relevant method for gaining insights into customers' preferences, needs, and trade-offs (Klemm and Kaufman, 2024; Kotri, 2006). A conjoint analysis is a survey-based quantitative research technique and helps understand the relative importance of different attributes influencing the purchase decision-making of consumers (Orme, 2014). In this study, conjoint analysis is used to determine the impact of various factors related to digitalization, such as promotion types, selection channels, delivery policies, and return policies, on purchase channel preferences for fast fashion and luxury fashion consumers.

The thesis is structured into two main sections: a theoretical part and an empirical part. The theoretical section presents a comprehensive literature review, examining existing research on the evolution of CVP, the role of the marketing mix in CPV creation, and the impact of digital transformation on the fashion industry. This literature review includes books, scholarly articles from academic journals, statistical data, and reports from management consulting firms. Based on the literature, the research gap is identified, and the research question and hypotheses are proposed.

In the following sections, the methodology is outlined, detailing the research method, data collection techniques, survey design, and analysis method used. The purpose of the research is to identify differences between the fast fashion and luxury fashion industries. Respondents were presented with two CBC (Choice-Based Conjoint) analysis scenarios: one for fast fashion and another for luxury fashion. In these scenarios, respondents were asked to imagine real-life situations of buying either fast fashion or luxury fashion items. They were presented with a series of choice scenarios and asked to select their preferred option from a set of alternatives. Each alternative included a combination of attributes and levels that reflect consumer preferences (Johnson and Orme, 2003).

Subsequently, the results of the CBC analyses are presented, followed by an in-depth discussion of the findings to offer potential explanations for the varying importance of specific attributes. Furthermore, the limitations of the study are outlined, and recommendations for future research are provided. The thesis concludes with a summary of the key findings and their implications for managerial practice.

The findings of this study hold significant value for both the fast fashion and luxury fashion industries in the context of digital transformation. A comparative analysis of the two sectors could explain how digitalization influences consumer shopping behavior in each industry, providing insights into how digital marketing strategies and omnichannel business models influence shopping behavior. Demographic variables, including gender, age, and income, are controlled to examine their influence on purchase channel preferences. This study also makes a scientific contribution in helping brands in tailoring strategies that more effectively align with their target groups offering superior value on specific elements that matter most to their customers (Anderson et al., 2006).

2. Literature Review

This chapter summarizes the key literature on Customer Value Proposition (CVP), beginning with a general overview, including its evolution over time and the role of the marketing mix in CVP creation. It then explores CVP in the fashion industry by comparing fast fashion with luxury fashion. Finally, the chapter examines the impact of digital transformation on the fashion industry, focusing on the promotion and place elements of the marketing mix.

2.1 General Overview of CVP

2.1.1 Evolution of CVP

The term “customer value” (CV) was first introduced by Lanning and Michaels (1988), who argued that businesses place too much focus on products rather than on customer needs. This early definition of a CV emphasizes balancing the benefits provided with the total costs of a product. The authors argue that customers choose products they perceive as offering greater benefits relative to their costs, and businesses achieve a competitive advantage by providing superior value to their customers. Superior value is achieved by offering distinct advantages and providing greater benefits or satisfaction to consumers compared to alternatives available in the market. The focus lies on reorienting the business system entirely around the customer and the benefits offered.

Previous research seeks to determine distinct types of customer values based on consumer needs. In order for organizations to create and deliver value to customers, it is essential to understand customer needs and preferences as a first step in creating value (McCarthy, 1960).

Customer needs and wants can be categorized as hedonic or utilitarian benefits (Holbrook and Hirschman, 1982). Utilitarian needs fulfill practical and functional requirements, addressing necessities (e.g., a car with antilock brakes). In contrast, hedonic benefits are driven by pleasure, aesthetics, and emotional satisfaction, often associated with positive experiences (e.g., a car with a panoramic sunroof) (Babin et al., 1994). Research demonstrates that hedonic experiences significantly improve customer loyalty (resulting in re-purchase intention and willingness to recommend products or services) and customer satisfaction (the alignment between expectations and reality) more effectively than utilitarian benefits (Chitturi et al., 2008; Purwanto and Sunjoto, 2015).

Park et al. (1986) introduce a normative framework for selecting, implementing, and controlling the brand image based on consumer needs. The authors identify three distinct consumer needs: functional, symbolic, and experiential. Functional needs motivate consumers to seek products that solve or prevent problems related to consumption (e.g., lawnmowers fulfill functional needs). Symbolic needs refer to the desire for products that enhance self-image, reinforce social roles, or support ego-identification (e.g., driving a sports car can fulfill a symbolic need). Experiential needs involve the desire for products that provide sensory enjoyment, variety, or intellectual stimulation (e.g., food can fulfill an experiential need).

Kambil et al. (1996) introduce another classification of customer needs, categorizing them into four types:

- Basic needs: essential to customers
- Expected needs: commonly provided by competitors
- Desired needs: preferred by customers
- Unanticipated needs: valued by customers, though not explicitly requested

Introducing unanticipated product attributes that customers appreciate significantly increases a company's competitive standing.

M. Lanning (1998) develops the concept of costumer value, focusing on the desirability that a customer assigns to a product or service based on their perception and experience, rather than its actual monetary cost. Customers often do not assess product values and costs accurately, as they make decisions based on personal perceptions of value. Organizations create and deliver value to customers in ways that enhance profitability by pricing products based on customers' perceived value, defined by the overall worth that customers attribute to a product or service, rather than focusing on cost or competition.

Further research distinguishes between the customer value (CV), customer value proposition (CVP) and value proposition (VP). A CV is customer-focused and is defined as “a customer's perceived preference for and evaluation of product attributes, attribute performances, and consequences arising from use that facilitate (or block) achieving the customer's goals and purposes in use situations” (Woodruff, 1997, p.142). The concept of CVP is a specific statement explaining CV and is defined as a “strategic tool that is used by a company to communicate how it aims to provide value to customer” (Payne, Frow, and Eggert 2017, p. 467). Osterwalder et al. (2014) take a business-centric approach and develop a framework for businesses to create their VP by identifying the customer profile. A VP highlights the company’s core value offerings and “describes the benefits customers can expect from your products and services” (Osterwalder et al. 2014, p. 6). This process involves creating a value map that outlines how products can deliver value to identified customers by achieving a fit between a company’s offerings and customer needs.

The term CVP is closely related to a unique selling proposition (USP), and it is important to distinguish between the two. A USP differentiates products from its competitors through unique offerings such as lower costs, higher quality, or being the first-ever product of its kind, and is often interpreted as a branding tool. On the other hand, a CVP focuses on very specific benefits directly related to the purchase of a product or service (Dennis, 2018). When creating a USP, it is important to define a benefit that clearly differentiates the organization's entire position in the market (Miremadi, 2010).

Holbrook (2006) proposes a typology framework that categorizes customer value based on different motivations behind consumer behavior. The author identifies two distinct dimensions through which customer value is created: extrinsic value (the quality or efficiency of a product) versus intrinsic value (the way customers experience a product), and self-oriented value (where the product benefits the consumer directly) versus other-oriented value (where the product is valued for its effect on others). These two dimensions create the following customer values types:

- Economic CV (extrinsic, self-oriented): Efficiency and quality that help achieve personal goals (e.g., fuel efficiency, high-quality electronics).
- Social CV (extrinsic, other-oriented): Consumption that enhances status or influences others' perceptions (e.g., wearing luxury brands).
- Hedonic CV (intrinsic, self-oriented): Personal enjoyment derived from experiences (e.g., leisure activities, art, entertainment).
- Altruistic CV (intrinsic, other-oriented): Ethical or selfless consumption that benefits others (e.g., charity, sustainable choices).

Limitations to Holbrook (2006) frameworks have been recognized, as the focus on motivations (intrinsic or extrinsic) and orientation (self or other-oriented) does not fully capture the complexity of the customer value construct and may be less applicable to business-to business contexts (Smith et al., 2007).

Anderson (2006) describes how value can be delivered to customers and argues that organizations need to craft a compelling CVP. The study identifies three approaches to developing a CVP:

- All benefits approach: Identifies all potential benefits believed to bring value to targeted customers. However, it risks inefficiency by claiming advantages for benefits that provide no real value, emphasizing that more is not always better.
- Favorable points of difference: Takes competition into consideration and focuses on differentiating from competitors by offering benefits superior to the next best

alternative. However, it does not guarantee that these differences hold real value for customers.

- Resonating focus: Emphasizes offering superior value on specific elements that matter most to target customers and communicating these in a way that demonstrates an understanding of their needs.

Rintamäki et al. (2007) identify the CVP in the retailing industry by establishing a link between CV and competitive advantage. The authors introduce a structured approach to identifying CVP through three stages: (1) identifying the core dimensions of CV that motivate customers, (2) developing CVP based on the identified dimensions, and (3) evaluating the CVP's potential to generate competitive advantage. The four key dimensions of CVPs in retailing identified are:

- Economic CVP: Defined by the monetary worth of a product relative to competitive offerings, focusing on affordability and cost-effectiveness.
- Functional CVP: Defined by the convenience related to selecting the right product with minimal time, physical, and cognitive effort.
- Emotional CVP: Defined by hedonic shopping motivations such as scents, sounds, tastes, or tactile stimuli (e.g., in-store experiences).
- Symbolic CVP: Defined by the meaning and emotional response that a product evokes, such as self-expression and identity.

The authors emphasize the importance of combining CV dimensions to create customer value propositions and aligning the company's resources with customer needs to gain a competitive advantage.

In the following subchapter, the role that marketing plays in identifying, capturing, and providing customer value is examined.

2.1.2 The Role of Marketing Mix in CVP Creation

Webster (2002) provides a guide for businesses aiming to define, develop, and deliver customer value and emphasizes the importance of a market-oriented approach to achieve a competitive advantage. According to Kumar and Reinartz (2016) for an organization to develop its customer value, it needs to implement an effective marketing strategy.

Marketing is defined as "an activity, set of institutions, and processes for creating, communicating, delivering, and exchanging offerings that have value for customers, clients, partners, and society at large" (Armstrong et al., 2014). Its core focus lies in crafting and delivering distinctive value to potential customers to secure a competitive advantage (Londhe, 2014). A marketing strategy outlines which target customers an organization serves and how it delivers value to these customers. All marketing decisions are based on what consumers need and want (Wu and Li, 2017).

For an effective marketing strategy to be implemented, an organization should conduct market research, gather and analyze data to gain insights into customer behavior and market trends, identify distinct customer groups, and tailor products and services to meet the specific needs of each segment. Businesses should then create products that align with customer requirements and market demands, identify opportunities to differentiate products, develop pricing strategies that balance profitability and customer value, gather and analyze customer feedback, improve products and services, and, finally, align the entire organization with a focus on delivering customer value (Lanning and Michaels, 1988). Market segmentation divides the market into separate groups of consumers with similar needs and can be behavioral, demographic, psychographic, or geographic in nature (Keller, 2013)

A marketing strategy is implemented through the marketing mix of 4Ps (Armstrong et al., 2014). McCarthy (1960) first introduces the concept of the marketing mix by providing a structured approach to marketing management and planning: the Marketing Theory of 4Ps. This model became widely adopted by marketers as a foundational tool for developing marketing strategies and managing marketing activities (Khan, 2014). The marketing mix is an essential component of marketing theory and strategy development and is used by organizations to impact the purchasing behavior and decisions of their target audiences (Constantinides, 2006). The four variables are designed to influence consumer demand and provide a suitable framework for exploring consumer behavior (Menon and Sigurdsson 2016).

The Product element refers to the market offering that the buyer acquires through purchase. The main characteristics of products include quality, brand, functionality, packaging, variety, design, features, sizes, and add-ons (McCarthy, 1960).

Price is another element of the marketing mix, and it directly impacts profitability of firms . Factors such as cost, competition, and demand determine the prices (McCarthy, 1960). The pricing strategy should align with the target market's perception of value and it can include additional charges for delivery, warranties, and other related expenses (Khan, 2014).

The Place element refers to the distribution strategy starting from product manufacturing and ending to the consumer’s location. The distribution strategy ensures that customers can easily access and purchase the products or services in the most convenient way (Constantinides, 2006).

The *Promotion* element is important for communicating a brand's value proposition and includes activities such as advertising, sales promotions, direct marketing, direct mail, and personal selling. Different promotional methods are tailored to various marketing channels and target groups. The main goal is to get attention, hold interest, arouse desire, and prompt a specific action from consumers (Khan, 2014).

By blending all the marketing mix elements into a marketing strategy, an organization can create, deliver, and communicate the intended value to its target customers (Armstrong et al., 2014). Organizations that deliver a value proposition with *resonating focus* and integrate a superior customer value proposition into the few elements of the marketing mix that are the most important to consumers, can cultivate brand loyalty and distinguish themselves in a competitive market (Londhe, 2014).

2.2 The CVP in the Fashion Industry

2.2.1 Overview of the Fashion Industry

Fashion is defined as "the clothing industry and that of related accessories (shoes, bags, jewelry, etc.), that is closely linked with the sociocultural spirit of the times, that markets products for which design, aesthetics, and style are of primary importance for the consumer" (Kotler et al., 2022, p. 1).

Historically, the fashion industry has experienced significant transformations and has been impacted by industrialization, globalization, digitalization, and societal development (Bertola and Teunissen, 2018). Modern fashion started in the nineteenth century in Paris and the city became the center of luxury fashion and haute couture, representing the highest level of fashion design, with individually crafted pieces worn by a small number of wealthy individuals. Paris then started setting global fashion trends, influencing styles worldwide (Monseau, 2023).

In the twentieth century, the rise of ready-to-wear collections made fashion more accessible, and the success of the fashion industry depended on industrialization and the mass production of standardized styles. Starting in 1999, fashion shows became public events, changing the mindset of fashion-conscious consumers. This shift increased demand for variety and exclusive, runway-inspired designs. Fashion retailers began expanding their product lines to offer trendy styles, contributing to the growth of fast fashion and globalization led to shifting of production to countries with lower labor costs (Bhardwaj and Fairhurst, 2010).

In the 21 century, the fashion market is divided into three dimensions: mass, premium, and high-end. The mass level includes fast fashion brands and at the other end of the spectrum lie luxury fashion brands. In the middle are premium brands, where luxury meets mass distribution with pieces of good quality and distinctive design (Kotler et al., 2022). The concepts of “fast fashion” and “luxury” create a dichotomy in the fashion industry, serving different consumer needs.

The fast fashion industry popularizes the “see now, buy now” trend, offering stylish and trendy items, as well as basic apparel at affordable prices (Tartaglione and Antonucci, 2013). A fast fashion system adopts an economies-of-scale strategy and quickly responds to rapidly changing fashion trends and consumer preferences. Fast fashion brands adopt a “quick fashion” process, quickly delivering fashion trends from runways to consumers. This short speed-to-market strategy encourages consumers to check new collections frequently and purchase multiple items (Bhardwaj and Fairhurst, 2010).

Globalization influences the way consumers purchase fashion items and shifts consumer mentality, creating impatience for new styles and trends. However, this shift raises concerns about the environmental and ethical implications of fast fashion, including its contribution to textile waste and labor exploitation (Cole and Deihl, 2015). Due to the growing emphasis on sustainability in consumer culture, fast fashion faces criticism for its rapid production practices and negative impact on the environment, as it encourages mass consumption and disposability (Gomes de Oliveira et al., 2022). This critique contributes to the rise of the "slow" fashion trend, promoting sustainability through low-speed production, use of natural materials, and small-batch manufacturing. The goal is to reduces resource consumption, minimizes waste, and improves labor conditions (Jung and Jin, 2016). As a result, high-end premium brands strive for “timeless elegance” in design and manufacturing to maintain cultural relevance over longer periods (Drew and Sinclair, 2015).

The luxury fashion industry, on the other hand, is characterized by its symbolic customer value through its brand image elements, such as exclusivity, scarcity, rarity, heritage, and cultural influence (Amatulli et al., 2016; McGowan et al., 2018). Luxury brands offer unique styles, exceptional craftsmanship, and high-quality products in limited distribution at premium prices. The luxury fashion industry is accompanied by personalized service, giving the buyer a sense of privilege (Kapferer and Bastien, 2009). For luxury items, price acts as an informational signal, indicating prestige (Menon and Sigurdsson, 2016). The relationship between luxury brands and consumers is often emotional, created through memorable and enjoyable purchase experiences, shared values, and associations with brand personality and mission.

Despite the differences between the fast fashion and luxury industries, both segments influence and intersect with each other. Luxury brands sometimes adopt quicker production cycles, while fast fashion brands occasionally introduce premium lines (Amatulli et al., 2016). Luxury fashion items, once seen as exclusive, are now affordable by of many consumers, leading to the growth of luxury fashion market (Monseau, 2023).

2.2.2 The CVP in Fast Fashion and Luxury Fashion Industry

Wang (2024) analyzes the marketing strategies of fast fashion and luxury brands using the 4Ps framework, comparing Zara and Prada. Zara, a leading Spanish fast fashion brand under the Inditex Group, has grown into one of the world's most competitive fast fashion brands. Zara's product offering is based on trendy styles and basic items for men, women, and children. The brand is known for its quick turnaround and fast-paced collection cycle, releasing new designs up to 24 times a year and motivating consumers to check out new collections frequently. Zara adjusts its prices based on regional markets and positions itself as a high-end fast fashion brand, increasing its average product price each year. Zara relies on digital marketing through its website and social media. The fast fashion retailer invests only a small percentage of revenue in advertising, preferring to invest in securing premium retail locations. Zara adopts an omnichannel strategy with retail stores located in high-traffic shopping areas, and its efficient logistics network ensures global delivery within 48 hours. The brand appeals to young consumers with its fast production, low prices, and strong social media presence.

Prada is a luxury fashion brand founded in Milan and its status as the official supplier to the Italian royal family helped establish its prestigious positioning in the high-end luxury market. Prada is known for blending tradition with modernity, combining classic elegance with new designs. The brand offers a wide range of luxury items, including clothing, accessories, and jewelry, and maintains a strong brand identity through exclusive design elements, such as its inverted triangle logo, which reinforces the brand recognition. Positioned in the high-end market, Prada maintains stable pricing and rarely offers discounts to preserve its luxury image. In terms of promotion, Prada leverages celebrity endorsements, particularly K-pop idols, to appeal to younger audiences. The brand adopts an omnichannel strategy with both online and offline sales channels. Its physical stores are strategically located in luxury shopping districts across more than 70 countries, as well as in selected international airports (Wang, 2024).

As research shows, customer value is achieved by examining customers' perceived value, defined as the overall worth that customers attribute to a product, which positively influences purchase decisions (Ilmi et al., 2023). To build brand loyalty and encourage purchases, firms need to understand customers' needs, desires, and expectations (Rintamäki, 2016).

The customer value of fast fashion brands primarily stems from their economic CV, motivated by affordability. Additionally, fast fashion lead to an emotional and social CV, as fast fashion items often resemble luxury items in terms of style, while remaining widely accessible (Gomes de Oliveira et al., 2022). Moreover, fast fashion provides functional CV through features like comfortable fabrics and easy-care materials (Tartaglione and Antonucci, 2013).

Ostovan and Khalili Nasr (2022) explore the dimensions of customer value in the luxury market, identifying experiential, symbolic, and functional CV as key factors influencing purchase intentions. Luxury fashion brands are associated with symbolic CV, as they embody intangible elements such as name, history, reputation, scarcity, rarity, and craftsmanship (Pozzoli et al., 2022). Additionally, luxury brands serve as symbols of wealth, success, and social status, affirming their role in creating social CV (Phau and Prendergast, 2000). Rudawska et al. (2018) examine the sources of CV for luxury secondhand and vintage fashion, identifying four key dimensions. These include economic CV (e.g. benefits in terms of price), functional CV (benefits in terms of utility, quality, and uniqueness of the item), individual CV (benefits related to personal identity, hedonism, and materialism), and social CV (benefits in terms of social status or prestige).

The following subchapter provides an overview of digital transformation within the fashion sector and its impact on consumer decision-making process.

2.3 Digital Transformation in the Fashion Industry

Digital transformation motivates fashion brands to rethink their business models and encourages innovation by levering digital technologies to achieve their goals (Bertola and Teunissen, 2018). To succeed in the digital era, fashion brands must create distinct CVPs and embrace digital innovations (Aiolfi and Sabbadin, 2019; Gellweiler and Krishnamurthi, 2020).

Gradillas and Thomas (2025) define digitalization as the "transformation of the socioeconomic environment through processes of digital artifact adoption, application, and utilization" (Gradillas and Thomas, 2025, p.113). The authors definition on digitalization encompasses both social and economic aspects, emphasizing the adoption and application of digital artifacts (e.g., software programs, digital platforms, technological tools). This process drives innovation and helps firms remain competitive.

Jin and Shin (2021) emphasize that developing innovative business models that address consumers' unmet needs is more important than merely adopting specific technologies. Russo et al. (2023) highlight the importance of maintaining control over digital resources, including technology, policies, and competencies, to help fashion brands sustain a competitive advantage.

Grewal et al. (2021) propose the "Strategic Wheel of Retailing" framework to help retailers adapt to new technologies. This framework focuses on key areas of strategic decision-making, including technology, retail location and supply chain management, product, pricing, and promotion.

Technologies such as Artificial Intelligence (AI), Blockchain, Cloud Computing, Big Data Analytics, and Augmented Reality (AR) enhance business performance in the fashion industry and help retailers more effectively meet customer needs (Jin and Shin, 2021). Advances in technology impact every aspect of the industry, from design and manufacturing to sales, services, and marketing strategies (Berman, 2012).

Digital transformation processes can have a significant impact on fashion industry. By leveraging digital technologies, fashion retailers can improve their operational efficiency, reduce costs, and increase customer satisfaction (Rathore, 2021). Digital technologies create opportunities to dematerialize supply chains and foster innovation in processes, products, and services (Casciani et al., 2022).

E-commerce revolution enables customers to buy products through online shops, mobile apps, and marketplaces (McCormick et al., 2014). ”Electronic commerce” or “E-commerce”, also known as “electronic business” and ”electronic markets” involves any economic activity conducted online (Wigand, 1997). E-commerce becomes an essential tool for retailers in fashion, allowing them to reach consumers directly through their own online shops or mobile applications, as well as marketplaces and online department stores (Rodríguez and Fernández, 2017). Brands can use digital tools to automate and enhance product development, such as designing items with software like 3D modeling and CAD. These approaches enable innovative product creation using big data, networks, and forecasting analysis (Nobile et al., 2021).

Artificial intelligence (AI) technologies are increasingly being used in the fashion industry to improve customer experiences and business operations. AI allows brands to predict consumer needs and wants, thereby avoiding the production of unwanted products and reducing fabric waste. Additionally, AI helps predict sales forecasts and manage purchasing and production levels. AI chatbots are virtual assistants that utilize utilizing machine learning algorithms to offer personalized customer experience in multiple languages. Chatbots provide personalized interactions, including customized product suggestions, order tracking, and customer support. Luxury fashion brands, such as Louis Vuitton and Gucci, are adopting AI chatbots to offer product recommendations to shoppers (Mishra et al., 2025; Tam and Lung, 2025).

Product customization allows customers to personalize items based on individual preferences. Technologies are leveraged to meet consumer demand by delivering hyper-personalized products and services at scale. For example, the sports brand Nike allows customers to personalize their shoes online by selecting various fabric and color options. Similarly, Levi's, a brand specializing in jeans, offers customization by allowing customers to choose unique combinations of patterns, washes, and other details. Additionally, 3D body scanning technology enables precise size and fit customization. This approach reduces material waste, unsold inventory, and the imbalance between demand and supply, contributing to environmental sustainability (Jin and Shin, 2021). Product customization enhances satisfaction and shopping experiences for consumers (Lee and Park, 2009).

Online shopping allows consumers to easily compare prices and take advantage of online promotions and discounts (Aiolfi and Sabbadin, 2019). Heim (2022) highlights that price transparency can help prevent price manipulation and allow consumers to make informed decisions. Prices may also include additional costs such as shipping fees and return expenses. Retailers adopt various shipping cost strategies, including charging fees, offering free shipping or no shipping costs for orders exceeding a certain basket value. Research indicates that free offers are associated with higher customer value and increased demand (Frischmann et al., 2012). Non-monetary costs, such as the time spent purchasing a product and perceived risks, can influence price perception (Woodall, 2003). Consumers often correlate the perceived quality with the pricing of a product (Chi and Kilduff, 2011).

In the following subchapter, a more in-depth analysis will be provided on how digital transformation impacts the promotion and place elements of the marketing mix of 4Ps in the fashion industry, as research indicates that these elements are the most impacted by digitalization.

2.3.1 The Promotion Element of the Marketing Mix

Through digital marketing strategies brands can reach out to potential customers, maintain relationships with current customers, and increase sales (Rathore, 2021). Digital marketing allows businesses to refine their advertising strategies and target potential customers regardless of their geographic location (Bertola and Teunissen, 2018). Digital marketing consists of various strategies and channels, including search engine optimization (SEO), search engine advertising (SEA), display marketing, content marketing, e-commerce marketing, e-mail marketing, affiliate marketing, social media marketing, and influencer marketing (Peter and Dalla Vecchia, 2021). Digital marketing increases brand awareness and brand reputation while enabling businesses to reach large numbers of current or potential customers (Aiolfi and Sabbadin, 2019).

Search engine optimization (SEO) and Search engine advertising (SEA)

Consumers use search engines like Google or Bing to find specific products or information by entering search queries. SEO is a digital marketing tool that enables "a website to appear in top result lists of a search engine for some certain keywords" (Yalçın and Köse, 2010, p. 488). SEO involves techniques such as keyword research, content optimization, and on-page and off-page optimization (Panchal et al., 2021). Research shows that SEO is an effective method for attracting customers in fashion e-commerce, requiring minimal investment while providing direct access through search engines without relying on paid advertisements (Erdmann et al., 2022). Well-established brands tend to have a better SEO performance due to the impact of search algorithms and strong brand recognition (Chen and Sénéchal, 2023).

In contrast, SEA consists of paid advertising campaigns that enable retailers to secure top positions or highlighted placements in search results. These advertisements appear based on specific keywords that users enter in search engines, with advertisers being charged based on different models, such as Pay-per-click or Pay-to-Action models (Panchal et al., 2021). Unlike SEO, which involves organic rankings (non-sponsored links), SEA advertisements are paid sponsored ads that help brands position themselves higher in search results (Kobylanski, 2012).

Display Advertising

Display advertising is another important type of online marketing strategy. The role of display advertising is to promote a brand on third party webpages through paid advertisements. Display advertising allows brands to be visible on digital platforms such as: e-commerce platforms (e.g., Amazon), social media platforms (e.g. Instagram), content platforms (e.g. YouTube or Netflix), and service platforms (e.g. Airbnb). Unlike SEO and SEA, which display ads based on specific keywords, display advertising targets audiences based on factors such as geography, device type, interests, and demographics. This enables retailers to target specific customer groups that are more likely to make purchases (Derave et al., 2021). For example, the luxury brand Louis Vuitton implemented display promotions on the International New York Times homepage to target users who have great potential to identify with the brand (Tam and Lung, 2025).

One of the most common platforms for display advertising is the Google Display Network (GDN), which offers an inventory of more than 2 million websites, videos, and apps where advertisements can appear (Booth and Koberg, 2012; Ahmad et al., 2024). This type of marketing captures the attention of potential consumers and enhances brand awareness (Ištvanić et al., 2017). Real-Time Bidding (RTB) has revolutionized display marketing and allows advertisers to buy individual ad impressions in real time as users visit a website, enabling precise user targeting and automated ad transactions (Wang et al., 2017).

Content marketing

Content marketing strategies involve publishing informative, interactive, and entertaining content online, which fosters customer engagement and leads to increased sales (Ling et al., 2024). Content marketing takes the form of articles, pictures, videos, infographics, on websites, blogs, and social platforms, providing informative content to internet users. Content platforms can include YouTube, Spotify, and other social media networks such as Instagram or Facebook (Derave et al., 2021). The purpose of content marketing is to offer relevant information about the brand, attract and retain an audience, and encourage engagement through likes, shares, and comments (Peter and Dalla Vecchia, 2021).

E-mail marketing

E-mail marketing is a direct form of communication targeting customers who provide their e-mail addresses and agree to receive commercial e-mails (Hartemo, 2016). E-mail marketing is defined “as a targeted sending of commercial and non-commercial messages to a detailed list of receivers respectively e-mail addresses” (Hudák et al., 2017, p. 342).

Through e-mail marketing, fashion retailers can deliver personalized messages, which research shows to enhance customer experience and positively affect sales performance, while simultaneously reaching a broad audience (Nobile and Cantoni, 2023). E-mail marketing is among the most popular direct marketing communication tools utilized by retailers to reach consumers leading to increased sales (Goic et al., 2021). E-mail marketing requires low execution costs and achieves relatively high response rates (Ištvanić et al., 2017). For example, the luxury retailer, Gucci, implements personalized marketing strategies, such as targeted email newsletters and recommendations based on customers’ browsing and purchasing behavior (Tam and Lung, 2025). The luxury brand, Chanel, provides e-mail subscribers with access to a series of videos about new product launches (Liu, 2023).

E-mail marketing is also facing criticism, as it could be negatively perceived as a firm’s attempt to manipulate choices and control purchasing decisions, leading to customer resistance (Vafainia et al., 2019).

Affiliate marketing

Affiliate marketing involves partnerships with organizations or websites, where affiliates promote products and receive commission fees for sales generated through third-party platforms (Peter and Dalla Vecchia, 2021). In the fashion industry, influencers, fashion bloggers, and other affiliates promote fashion brands or products on websites and social media platforms, earning a commission for driving sales or traffic to the brand’s website through affiliate links (Pedroni, 2023). The Shopee Affiliate Program is an example of a platform that connects advertisers (e.g., YouTube creators, TikTok users) with publishers (e.g., fashion brands), significantly influencing consumer buying interest through content, campaigns, and promotional offers (Augustin et al., 2022).

Social media marketing

Social media has revolutionized the way people interact with each other and enables fashion brands to connect with a broader audience, making it essential for capturing and retaining customer attention (Rathore, 2021). Social media channels are defined as ”a group of internet-based applications allowing both the creation and exchange of user-generated content, for example, blogs, collaborative projects, social networking (e.g. Facebook)” (Barnes, 2013, p. 201).

Social media allows for information to travel more freely and quickly (Aiolfi and Sabbadin, 2019). Through social media, fashion brands interact directly with consumers, offering behind-the-scenes content, address comments, and host Q&A sessions. These activities allow brands to gather feedback and adapt their product development and marketing strategies (Nobile et al., 2021). Social media enables brands to manage customer relationships, deliver brand content, and meet customers' transparency needs more effectively (McKinsey & Company, 2019). Research shows that perceived emotional value positively influences Instagram users' purchase decisions for fashion items (Sosanuy et al., 2021).

Gucci is an example of a luxury brand that maintains a strong social media presence with millions of followers, creating engaging content tailored to its audience, displaying exclusive glimpses of fashion shows and behind-the-scenes looks. Additionally, the brand allows customers to purchase products directly through Instagram via the shoppable posts functionality (Tam and Lung, 2025).

H&M, a globally recognized fast fashion retailer, uses its social media platforms to promote seasonal updates and campaigns, share information about new products, and engage consumers with relatable content, thereby increasing consumer engagement and brand recognition (Wei, 2024).

Social media has become one of the most influential advertising tools and communication platforms in the fashion industry, promoting fashion trends and societal values. However, it also raises concerns about data privacy, mental health, and misinformation. The future of social media is headed toward more personalized experiences and targeted advertising practices, driven by AI, which will enhance user experiences. Personalization is taking shape through AI recommendations, allowing users to engage with content tailored to their interests, resulting in more relevant and less intrusive advertisements, thus increasing engagement and satisfaction. E-commerce on social media is becoming more personalized, with product recommendations based on past purchases, browsing history, and social interactions. Additionally, AI-powered virtual shopping assistants are assisting users in finding items that match their preferences, sizes, and styles (Vavrová, 2024).

Influencer marketing

Digital influencers become an important part of the marketing strategy of fashion brands, influencing purchase intention of consumers. Social media influencers are “third-party actors who have established a significant number of relevant relationships with a specific quality to and influence on organizational stakeholders through content production, content distribution, interaction, and personal appearance on the social web” (Borchers, 2021, p.17).

Influencers showcase personal styles, drive trends, and even evolve into brands themselves (Gomes et al., 2022). Influencers help brands maintain audience interest across various communication channels (Vazquez et al., 2020). Social media platforms like Instagram or TikTok have become central in defining fashion trends and influencers play an important role in connecting brands with consumers (Gupta et al., 2024). For instance, the luxury brand Chanel collaborates with prominent social figures, such as the French actress Marion Cotillard, to serve as brand ambassadors and the face of new collections, while also acting as influencers (Liu, 2023). Louis Vuitton adopts influencer marketing as a key promotional strategy and has featured high-profile celebrities such as Madonna and Angelina Jolie in its advertising campaigns over the years (Tam and Lung, 2025).

However, managing communication through fragmented digital sources like social media and influencers remains a challenge. Oversaturation of information reduces the sense of scarcity needed for value creation for luxury brands (Pozzoli et al., 2022). Consumers grow dissatisfied with excessive sponsored content and seek authenticity and relatability in influencers. Statistics show that younger generations lose attention within 1.3 seconds of viewing an advertisement (McKinsey & Company, 2019).

Consumers prefer influencers who inspire and entertain, encouraging brands to collaborate more closely with influencers and integrate brand values into their content styles (McKinsey & Company, 2024). The oversaturation of online advertisements has led to the emergence of micro-influencers, who, while less popular than macro-influencers, achieve higher engagement rates by offering authentic and reliable content (Vavrová, 2024).

Tiwari et al. (2023) highlights the growing importance of influencer marketing in the fashion industry, indicating that perceived trust (the personal belief that obligations will be fulfilled) positively influences attitudes toward fashion influencers, which in turn has a positive association with purchase intentions.

In conclusion, studies confirm that digital marketing significantly improves brand image, trust, and awareness, positively influencing purchasing decisions (Ilmi et al., 2023). Research shows that social media marketing, influencer marketing, and e-mail marketing are the most effective digital marketing strategies in enhancing brand awareness, purchase intention, and customer experience (Nuseir et al., 2023). Research identifies key success factors, including a strong online presence, targeted advertising, and personalized communication with customers. Social media platforms are crucial for customer engagement, while content marketing and SEO are effective tactics (Hermayanto, 2023).

2.3.2 The Place Element of the Marketing Mix

Different customers have different shopping preferences: some value the convenience and broader selection of online shopping, while others prefer traditional stores where they can physically inspect products. Integrating online shops and physical stores creates opportunities for brands to offer diverse services and address different customer segments (Lazaris and Vrechopoulos, 2014).

Omnichannel Retailing

The rise of e-commerce leads businesses to adopt an omnichannel business model, which integrates physical and online channels into a seamless customer experience. This approach allows brands to maintain a consistent brand image and interact with customers in a holistic way. For example, a customer might see an advertisement on social media, research the product online, visit a store to see the product, and make the purchase via a mobile app (Barnes, 2013).

E-commerce platforms provide customer benefits in terms of convenience, product availability, accessible customer service (through virtual assistants) (Chaffey and Ellis-Chadwick, 2019), as well as automated communication (via price alerts and in-stock notifications) and individual recommendations, based on personal fashion styles (Reinartz et al., 2019). Customers gain access to a wide selection of products available anytime and anywhere without investing resources in visiting physical stores (Blázquez, 2014). Buyers can easily compare products, read customer reviews, and enjoy an improved quality of choice. Online shopping also help consumers minimize the adverse effects of product unavailability in physical stores (Aiolfi and Sabbadin, 2019).

Through online shops, fashion brands can establish brand loyalty and enhance brand awareness (Bertola and Teunissen, 2018). To meet customer expectations, brands must ensure an integrated experience across all touchpoints. Inconsistencies between online shops and physical stores, such as differences in pricing or product assortments, can lead to customer dissatisfaction (Lazaris and Vrechopoulos, 2014). Adopting an omnichannel business model, rather than focusing on in-store or online channels, leads to an overall increase in sales. Mobile channels, in particular, increase purchase frequency and total spending amount (Timoumi et al., 2022).

Consumer satisfaction is enhanced through the development of user experience (UX) and user interface (UI) in online shops. A well-implemented user interface enables customers to easily navigate the website and interact with products. This includes visual design, micro-interactions, and graphical elements. UX stands for usability and other components related to experience using the online platform. Factors such as website design, user-friendly navigation, service quality, website security, and product availability enhance the overall consumer experience and increase purchase intentions (Watulingas, 2020).

User-generated content and product experiences also positively influence consumer behavior while online shopping. Previous buyers share their looks by posting photographs of themselves in styled settings, positively leading to emotional and relational experience, and increasing purchase intentions (Vazquez et al., 2020). However, online stores face significant challenges, including risks of identity theft, payment fraud, security breaches, and cyberattacks. Businesses must protect customers’ personal and financial data to maintain trust and loyalty (Lazaris and Vrechopoulos, 2014).

Physical stores remain an important part of the customer's shopping journey. By enhancing the store atmosphere through design, layout, ambiance, and service, brands can positively influence the customer experience (Blázquez, 2014). An omnichannel approach can enhance CV by providing additional services, multiple touchpoints, and a seamless, uninterrupted experience (Aiolfi and Sabbadin, 2019).

Delivery Policy

Omni-channel integration enables customers to access a wide range of products, ordering options, delivery services, and return policies, including options like buy online, pick up in-store (Truong, 2020).

Digital technologies allow brands to track inventory availability, digitize order processes, deliveries and return logistics (Russo et al., 2023). Consumer preferences are influenced by factors such as delivery cost, speed, and pickup location proximity, with different segments having different preferences. Fashion-conscious consumers, who see fashion as a significant aspect in their lives prefer in-store pickups, while frequent shoppers prefer home deliveries (Ma et al., 2024).

During the online shopping process, consumers search for, compare, order, and return items, while being driven by different motivations and perceived risks. Through qualitative analysis of 21 semi-structured interviews, Sutinen et al. (2022) identify activities within e-commerce context that consumers engage in in order to reduce economic risk or functional risk. Economic risk can be reduced by waiting for the right time to make a purchase in order to buy certain products at a lower price, or by comparing prices and delivery times across different online stores. The study shows that interviewees preferred online stores that did not charge delivery fees, with the purchasing process often being abandoned when a delivery fee appeared during the payment phase. Functional risk can be reduced by comparing products on different sites, checking the product in an offline store before ordering it online, or ordering multiple alternatives to ensure at least one product is suitable.

Vasić et al. (2021) show that online consumer satisfaction directly depends on logistic services, such as delivery time, shipping costs, delivery reliability, product quality and condition after delivery, return policy, and information quality. Luxury shoppers have higher expectations for their delivery experience compared to non-luxury shoppers, expecting fast and convenient deliveries (Liu, 2023).

Uzir et al. (2021) explore the impact of home delivery service quality and customer perceived value, indicating a significant improvement in customer satisfaction. Key factors driving satisfaction include on-time delivery, high service standards, positive perceived value, and trust in service providers.

Jara et al. (2024) examine the "click and collect" system by analyzing the key factors that maximize customer value. Findings show that customer relationship, the website design (e.g. quality of images), and the pickup station are the most important factors creating value for customers. In a "click and collect" purchase type where consumers buy online and pick up their package in-store or at a warehouse. The click and collect system provides consumers with greater flexibility, is more cost-effective as it saves on shipping fees, and contributes to sustainability (Cotarelo et al., 2024).

Return Policy

Returns are posing a challenge in the fashion industry, as the return rates are higher for purchases made online than in-store. Stöcker et al. (2021) estimate return rate in the fashion sector to be at 50%. Sellers face costs related to restocking and reprocessing, while buyers must manage reshipping, all of which contribute to environmental impact. To reduce return rates and enhance the shopping experience, sellers can improve product presentations by including 360° images, video demonstrations, and detailed size information.

Customers often struggle to assess product quality, size, or fit without physical interaction, resulting in dissatisfaction and a high return rate. To address this issue, many brands embrace in-store returns for online purchases to decrease return rates and reduce transportation costs (Aiolfi and Sabbadin, 2019). Customers also engage in comparing return policies to find the most convenient policy (Sutinen et al., 2022).

Yang et al. (2022) study the potential of AI applications in improving return rates, maximizing reselling, and reducing inventory issues such as overstock or shortages. AI technologies, such as virtual fitting tools (online fashion consultants that use AI to analyze consumer preferences) and chatbots (AI tools that enhance consumer engagement and provide higher-quality service and product fit information), enhance the shopping experience, increase purchase probabilities, and lower return rates in online retail.

To examine the impact of return policies on customer value and purchase behavior, return policies are categorized as either lenient or strict. Lenient return policies are characterized by three key factors: the time allowed for returns, the effort required to complete the return process, and the cost of refunds (Posselt et al., 2008). A lenient return policy is a customer-oriented approach that simplifies and adds flexibility to the return process. It often includes extended return time frames, fewer restrictions on reasons for returns, and a simplified process with little to no cost for the customer. Strict return policies, on the other hand, require consumers to pay for return shipping fees and any additional tariff costs (Shao et al., 2021).

A lenient return policy increases consumers perceive quality and perceived risk, ultimately increasing their purchase intention. Allowing consumers to easily return products if they are dissatisfied reduces their perceived risk. This effect is even more pronounced when the product is shipped from domestic warehouses or lacks a traceability code. Research indicate that consumers prioritize return policies more when prices and perceived risks are higher. However, although lenient return policies increase sales and customer satisfaction, they lead to higher return rates and higher costs for retailers (Rokonuzzaman et al., 2021).

Rintamäki et al. (2021) differentiate return policies based on whether returns are planned or unplanned. Planned returns occur when consumers intentionally order multiple items with the intention of returning some. These returns are associated with high satisfaction and customer loyalty, but may be unprofitable for retailers. Unplanned returns happen when consumers do not initially intend to return items. The study finds that customers evaluate return processes based on factors such as monetary costs, convenience, stress, and guilt. A positive return experience leads to higher overall satisfaction. The authors suggest that optimizing the return process is crucial for customer retention. Retailers should focus on reducing stress and inconvenience, particularly for unplanned returners, to improve customer loyalty. Effective returns management benefits both businesses and consumers by minimizing waste and unnecessary returns.

2.4 Research Question and Formulation of Hypotheses

With consumer preferences changing in today's digital world and increasing competition, customer value becomes more important in explaining consumer behavior (Kumar and Reinartz, 2016). Previous literature studies the evolution of the concept of CV. The fundamental focus lies in reorienting the business system entirely around the customer and the benefits offered (Lanning and Michaels, 1988). A business provides that value through its product, manufacturing, distribution, service, and price and finally communicates the value through sales messages, advertising, and promotion (Osterwalder et al., 2014; Dennis, 2018; Payne et al., 2020).

Digitalization plays an important role in reshaping the fashion industry and the way fashion brands design, market, and sell their products (Pozzoli et al., 2022). Digital technologies help business models innovation, creating new distribution channels and new ways to create and deliver value to customer segments (Matarazzo et al., 2021).

Hardabkhadze et al. (2023) explore the stages of digitalization in the fashion industry, providing a guide on how technologies can be integrated with core organizations and processes. Previous research examines how digitalization has impacted the fashion industry, from the dematerialization of supply chains (Casciani et al., 2022) to the enhancement of customer engagement through digital tools and value creation achieved by innovating products and promotional strategies (Sanz-Lopez et al., 2024). Price promotions have a significant impact on consumers' purchasing intention (Zhang et al., 2017), and an omnichannel strategy in the fashion industry can enhance customer value by providing additional services, multiple touchpoints, and a seamless, uninterrupted experience (Aiolfi and Sabbadin, 2019).

However, it is important to distinguish between fast fashion and luxury fashion industries, as they represent different CVPs and the effect on consumer behavior will be different (Hsin Chang and Wang, 2011). Previous studies focus on the impact of digitalization on either the fashion or luxury industry individually, or the fashion industry as a whole, but they rarely provide a comparative analysis between the two (Casciani et al., 2022).

The customer value of fast fashion brands lies in its economic CVP, motivated by affordability (Gomes de Oliveira et al., 2022). The luxury fashion industry, on the other hand, is characterized by its symbolic CVP through its brand image elements, such as exclusivity, scarcity, rarity, heritage, and cultural influence (Amatulli et al., 2016; McGowan et al., 2018). Ostovan and Khalili Nasr (2022) examine the dimensions of customer value in the luxury market and show that experiential, symbolic, and functional CVP are representative factors that influence purchase intentions. Many luxury retailers have not fully embraced digital transformation. While luxury brands gradually increase their digital marketing spending to attract customers, they face challenges in balancing innovation with their core brand value, such as exclusivity and scarcity (Liu, 2023).

A comparative study of both industries could explain how digitalization affects shopping behavior in each sector and provide deeper insights into how online and in-store preferences are influenced by factors such as digital marketing strategies and omnichannel business models. This could help fashion brands tailor strategies that better align with their target groups and offer superior value on specific elements that matter most to their customers (Anderson et al., 2006). Hence, the research question of this study is:

RQ: How do place and promotion elements of the marketing mix influence customers' online purchase intentions in the fast fashion industry compared to the luxury fashion industry?

Formulation of Hypotheses

Purchase Intention

Purchase intention is defined as “advancing a planned decision to purchase particular goods in the future” (Hasibuan and Nuraeni, 2023, p.82). Su et al. (2019) examines factors influencing consumers' purchase intentions using an integrated customer model approach and shows that functional, emotional, and social values are important antecedents affecting consumers' purchase intentions. Kumar et al. (2009) found that effective factors, such as emotional value, have a stronger influence on purchase intention for global brands than cognitive factors.

Past research shows that purchase intention can be influenced by various factors in today digital world. Gu and Wu (2019) explain customers’ online purchasing intention and found that perceived behavioral control has the strongest influence. Perceived behavior control refers to an individual's assessment of the factors that might “facilitate or inhibit the performance of a behavior” (Pavlou and Fygenson, 2006, p. 177). Furthermore, the research shows that frequent internet users, demonstrate positive attitudes toward online shopping.

Previous research suggest that technology factors (e.g. security, privacy, usability), shopping factors (e.g. convenience, trust, delivery policy), and product factors (product quality, functionality, assortment, variety) are important factors influencing purchase intention (Schaupp and Belanger, 2005; Bai et al., 2008; Chen et al., 2010). Watulingas (2020) shows that user experience (UX) has a positive and significant impact on purchase intention.

Sarin and Sharm (2023) shows that social media marketing activities have a significant impact on brand consciousness and brand trust, which in turn also have a significant impact on purchase intention of consumers. Odoom (2022) highlights the complex role of personalized ads in digital marketing and their significant impact on purchase intention.

Tiwari et al. (2023) studies the impact of fashion influencer measures on consumers' purchase intentions, indicating that perceived trust (the personal belief that obligations will be fulfilled) positively influences attitudes toward fashion influencers, which in turn has a positive association with purchase intentions.

Promotion

Within the marketing mix, digital marketing strategies play a central role in the promotional element. Digital marketing allows brands to directly communicate with potential customers regardless of their geographical location and includes: SEO, SEA, display marketing, content marketing, e-commerce marketing, e-mail marketing, affiliate marketing, to social media marketing, and influencer marketing (Peter and Dalla Vecchia, 2021).

As we know from research, the promotional aspect is an important part in enabling fashion brands to refine their targeting and directly communicate with potential customers (Kotler et al., 2021). Fast fashion products have short life cycles and fast fashion brands adopt a “quick fashion” process, quickly delivering trendy and affordable items to consumers (Bhardwaj and Fairhurst, 2010). The customer value of fast fashion brands lies in its economic CVP and through online promotions fast fashion brands can make customers aware of online promotions and new collections leading to increased sales (Gomes de Oliveira et al., 2022; Wang, 2024).

On the other hand, the CVP for luxury brand lies in its symbolism: a well-known brand identity and brand awareness, a sense of prestige and association with a high status (Phau and Prendergast, 2000). Social media allows luxury brands to maintain a consistent brand image and interact with customer in a holistic way (Barnes, 2013), which is relevant for creating a symbolic, emotional and social CVP (Ilmi et al., 2023).

Research shows that digital marketing strategies are relevant in both industries. E-mail marketing is a type of online advertising that is adopted by both luxury and fashion brands and allows them to maintain relationships and sustain brand loyalty (Ištvanić et al., 2017). Social media has a great impact on shaping consumer behavior in the fashion industry (Barnes, 2013) and influencers have become a powerful voice in the fashion industries influencing purchase intention (Gomes et al., 2022). Display advertising allows retailers to promote their products on other webpages and to target specific customer groups that are more likely to make purchases (Booth and Koberg, 2012). Odoom (2022) highlights the complex role of personalized ads in digital marketing and their significant impact on purchase intention.

On the other hand, as the CVP of fast fashion brands lies in economic value and, through online platforms, consumers can benefit from price promotions, which have a significant impact on consumers’ purchase intention (Zhang et al., 2017).

Therefore, we expect digital marketing strategies to create a higher online purchase intention among fast fashion consumers than luxury fashion consumers.

H_1	Digital marketing strategies create a higher online purchase intention among fast fashion consumers than luxury fashion consumers.

Place

With digital transformation, fashion brands are adding new touch-points channels to interact with customers in every step of the customer journey. Through online platforms, fast fashion consumers can benefit from convenience, speed, and access to a wide variety of options (Aiolfi and Sabbadin, 2019). Therefore, it is expected that in the fast fashion sector, online product selection offers greater customer value due to the availability of trendy and diverse options at affordable prices leading to a high online purchase intention. During online shopping, customers can easily compare prices, use online promotions and discounts, leading to an improved economic CVP representative to fast fashion brands (Aiolfi and Sabbadin, 2019).

Customer of luxury fashion can also benefit from access to exclusive or limited items through online platforms (Liu et al., 2013). For consumers of luxury fashion, an in-store experience leads to the creation of emotional CV, as the relationship between luxury brands and consumers is often emotional through the creation of memorable and enjoyable experiences during the purchase process (Phau and Prendergast, 2000). Therefore, we except, in the luxury fashion sector, in-store purchases offers greater customer value due to the shopping experience, aesthetic appeal of stores and exceptional customer service. An in-store experience is essential for creating the emotional CVP representative to luxury brands (Blázquez, 2014). Therefore, it is expected that online selection leads to a higher online purchase intention among fast fashion consumers compared to luxury fashion consumers, for whom physical stores remain an important shopping channel.

H_2	Online selection creates a higher online purchase intention among fast fashion consumers than luxury fashion consumers.

The Role of Delivery Policy

Rokonuzzaman et al. (2021) empathize that a lenient return policy increases consumers purchase intention.

The customer value in the fast fashion industry lies in its economic CVP, therefore consumers will want to have the most benefits relative to their costs, which can also include additional charges for delivery, returns, and other related expenses (Chaffey and Ellis-Chadwick, 2019; Tartaglione and Antonucci, 2013). Research shows that free shipping is associated with a higher customer value and increase in demand (Frischmann et al., 2012).

On the other hand, the customer value of luxury brands lies in its intangible elements such as exclusivity, symbolism, and brand image (McGowan et al., 2018) and for buyers of luxury, price serves as an informational stimulus (Menon and Sigurdsson, 2016).

H_3	Free standard deliveries create a higher online purchase intention among fast fashion consumers than luxury fashion consumers.

The Role of Return Policy

Similar to the implications associated with delivery policies, we expect that consumers of fast fashion prefer free and convenient return options, such as in-store return or postal drop-offs, whereas free returns hold less significance for luxury fashion buyers.

H_4	Free and convenient returns create a higher online purchase intention among fast fashion consumers than luxury fashion consumers.

3. Methodology

This chapter presents the research methodology used to explore how the promotion and place elements of the marketing mix influence customer's online purchase intention in the fast fashion industry compared to the luxury fashion industry. It provides an overview of the research method, including data collection methods, survey design, and experimental design.

3.1 Research Method

In this study, a conjoint analysis is used to evaluate consumer preferences by simulating real-world decision-making scenarios and determine which attributes are most important to customers by adopting the principle of utility maximization (Kumar and Reinartz, 2016). As defined by Broome (1991, p.3), utility is "the value of a function that represents a person's preferences".

Utility cannot be measured or observed directly, so the main task in measuring customer value is to examine the associated underlying attributes and benefits and their connection to the overall perceived value. A conjoint analysis is a de-compositional technique that measures preferences for attributes and is used to determine the customer perceived value. While a compositional method starts with a set of selected attributes to determine the overall value, a de-compositional method begins by measuring observed preferences and uses them to infer underlying utilities (Kumar and Reinartz, 2016).

Research identifies other approaches for uncovering underlying utilities from customer preferences and values, including surveys, auctions, and field experiments (Kumar and Reinartz, 2016). One type of survey approach is the VALUEMAP model, where participants in an empirical study are asked whether the perceived value is better, the same, or worse than expected. This approach provides insights into the overall perceived value (Sinha and Desarbo, 1998). In auction methodologies, consumers indicate their willingness to pay and their reservation price range (Wang et al., 2007). A field experiment may allow consumers maximum control over the price they pay, enabling them to choose the amount they are willing to pay. This method offers insights into individual levels of value perception (Kim et al., 2009).

A conjoint analysis is a survey-based quantitative research technique and allows researchers "to understand how buyers make complex purchase decisions, to estimate preferences, and to predict buyer behavior" (Orme 2014, p.30). Conjoint analysis was first introduced by Luce and Tukey (1964) in the *Journal of Mathematical Psychology* and has since become the most widely used marketing research method for analyzing consumer preferences and trade-offs (Green et al., 2001). Research shows that compared to other commonly used methods for identifying customer needs, conjoint analysis determines more reliable and accurate results (Kotri, 2006).

In this study, a Choice-Based Conjoint (CBC) analysis is conducted using Sawtooth Software, a platform that provides advanced analytics and software tools for studying consumer preferences. In a CBC analysis, respondents are presented with a series of choice scenarios and asked to select their preferred option from a set of alternatives. Each alternative includes a combination of attributes and levels, reflecting consumer preferences (Johnson and Orme, 2003). Unlike other methods that assess the importance of attributes individually, conjoint analysis replicates real-world decision-making situations. Here, customers rank various alternatives and select the one offering the most value, guided by personal preferences for different attributes of each option (Kotri, 2006). According to Green et al. (2001) preference and likelihood of purchase are often used as measures.

3.2 Attributes and Levels

In a CBC analysis, attributes and their associated levels are used to evaluate consumer preferences. Attributes should influence consumers' utility, help differentiate between competitive offerings in the market, and represent measurable aspects (Eggers et al., 2022).

It is necessary to select the most relevant product attributes and their respective levels that correspond to customers' most important needs and preferences (Kotri 2006). In a CBC study implemented using Sawtooth Software, it is recommended to include between five and ten attributes, with no more than five levels for each. Attributes should be independent in meaning, and levels should be concise, concrete, and mutually exclusive. Attributes can be nominal (e.g., color, brand), ordinal (e.g., delivery), or quantitative, where numeric values are associated (e.g., price or time) (Sawtooth Software, 2002).

The selection of attributes and levels for this study is based on information obtained from current literature on customer value and digital transformation in the fashion industry, as well as prior research using conjoint analysis to determine consumer buying behavior in the fashion industry. Studies that use conjoint analysis to determine purchase intention in the digital era guide the selection of appropriate attributes for this research.

To examine how customers trade off attributes and which attributes influence their purchase decisions and preferences when selecting fashion products, the most common attributes used in past research include **brand and style** (North and Vos, 2002; Jegethesan et al., 2012), **color** (Le et al., 2019), **country of origin** (Jin et al., 2010), **quality** (Birtwistle et al., 1998; Jin et al., 2010), **price** (Birtwistle et al., 1998; Bumin, 2024; Jegethesan et al., 2012;

Jin et al., 2010; Le et al., 2019; North and Vos, 2002). Wang et al. (2022) studies the preferred product attributes for sustainable outdoor apparel, Bumin (2024) is looking at consumer preferences in sustainable fashion consumption and Fuchs and Hovemann (2022) studies consumer preferences for outdoor sporting goods, showing that functional product attributes as well as social sustainability are the most important attributes for purchase choices.

Previous research uses conjoint analysis in the context of digitalization in retailing, Kjeldsen et al. (2023) study the relative impact of QR codes in an omnichannel shopping environment on purchase intention and Carl et al. (2023) evaluate consumer preferences and segmentation regarding firms' Corporate Digital Responsibility, such as data privacy and security activities. Chen et al. (2010) examine the relationship between website attributes and consumer purchase intentions and finds that trust, security measures (like encryption) and user-friendly interfaces are important attributes to influencing purchase intentions.

Schaupp and Belanger (2005) explores key factors influencing online consumer satisfaction by examining technology, shopping, and product-related attributes. Results show that the three most important attributes to consumers for online satisfaction are privacy, merchandising, and convenience, followed by trust, delivery, usability, product customization, product quality, and security.

Puspaningrum (2023) uses a conjoint analysis to measure consumer preferences for the marketing promotion mix (advertising, sales promotion, and direct marketing) for foam matter products and determine the most effective promotion combination.

Menon and Sigurdsson (2016) analyzes social media importance in consumer purchase situations and shows an inverse relationship between price and utility, meaning the higher the price, the lower the corresponding utility. A similar trend has been observed to shipping costs.

Nguyen et al. (2019) explores how online shoppers value different delivery attributes (such as delivery speed, delivery date, and delivery fees) when choosing a delivery option. The findings from conjoint analysis show that delivery fees are the most important factor for consumers followed by non-price attributes. The study also identifies significant consumer preferences between different gender and income groups.

Kaur and Kumar (2021), through a conjoint analysis, study consumers preferences for different marketing attributes in social media networks influencing consumer purchase decisions. Findings shows that price was the primary factor driving online shopping decisions, followed by warranty, delivery charges, photo displays, order channels, and sizes available.

Price

The first attribute is Price and is included to assess whether the contribution of other attributes to the online purchase intention differ across different price levels. It is recommended to limit price levels to fewer than five, as fewer levels reduce the risk of measurement errors (Sawtooth Software, 2002). For this study, three price levels are chosen based on average estimations of observed prices in the fast fashion and luxury product industries (see Table 1). In 2025, the fast fashion retailer Zara offers a coat for €79.95, a dress for €49.95, and a top for €15.95 (Zara, 2025). In 2025, the luxury fashion retailer Prada prices a top at €1,200, a bag at €2,200, and a pair of sunglasses at €390 (Prada, 2025).

Table 1
Attribute Price and Levels

Attribute	Level for Fast Fashion	Level for Luxury Fashion
Price	€ 25	€ 500
	€ 50	€ 1,000
	€ 75	€ 2,000

Promotion

H_1 tests compares how digital marketing strategies influence online purchase intention among fast fashion consumers and luxury fashion consumers. Digital marketing consists of various strategies, including SEO, SEA, display marketing, content marketing, e-commerce marketing, e-mail marketing, affiliate marketing, social media marketing, and influencer marketing, that enable brands to communicate directly with potential customers regardless of geographical location (Peter and Dalla Vecchia, 2021).

Social media has become one of the most influential advertising tools and communication platforms in the fashion industry, promoting fashion trends and societal values, and influencing consumer behavior (Menon and Sigurdsson, 2016; Pantano et al., 2019; Chu and Seock, 2020; Vavrová, 2024). In practice, we see that every known brand has their own social media account on platforms such as Facebook and Instagram. For example, in February 2025, Chanel, the luxury fashion house has a total number of followers of 60.M on Instagram and 6,656 posts (@Chanelofficial, 2025), and the fast fashion retailer Zara has a total of 62.2M followers and 4,849 posts (@Zara, 2025).

Fashion influencers play an important role in connecting brands, influencing consumers' preferences (Gomes et al., 2022).

Some examples of well-established fashion influencers who focus on promoting luxury fashion items include Chiara Ferragni, with 28.9 million followers (@chiaraferragni, 2025), and Leonie Hanne with 4.8M followers on Instagram (@leoniehanne, 2025).

E-mail marketing is one of the most popular direct marketing communication tools used by retailers to reach consumers, leading to increased sales (Goic et al., 2021). In practice, it is common for every fashion brand to have the option to subscribe to receive an e-mail newsletter. For example, Zara allows customers to select interests and receive the latest news and trends each week (Zara, 2025).

Display advertising is also included as an important level, as it can be more effective in building brand awareness than other types of online promotions (Derave et al., 2021).

SEO, SEA, and content marketing were not included in the conjoint analysis, as the aim was to focus on the most important digital marketing strategies that have been more extensively researched and influence consumer preferences. SEO and SEA are strategies that drive organic and paid traffic to online retailers (Baye et al., 2016), while content marketing plays a role in providing relevant information about the brand to consumers, aiming to attract and retain an audience (Peter and Dalla Vecchia, 2021). Furthermore, a large number of levels could overwhelm respondents with too much information, leading them to resort to simplification strategies (Sawtooth Software, 2002).

Table 2 provides an overview of the levels chosen for promotion types.

Table 2
Attribute Promotion and Levels

Attribute	**Level**
Promotion	social media
	influencer
	e-mail newsletter
	display advertising

Place

H_2 tests whether online platforms create a higher online purchase intention among fast fashion consumers than luxury fashion consumers.

To determine whether an omnichannel experience influences customers' purchase intentions, two distinct attributes are defined: one representing selection platforms (see Table 3), where customers gather information about products and prices, and the other representing purchase channels (see Table 4), which refer to the locations where the final sale is made (Aiolfi and Sabbadin, 2019).

Table 3
Attribute Selection and Levels

Attribute	**Level**
Selection	in-store
	online selection

Table 4
Attribute Purchase and Levels

Attribute	**Level**
Purchase	in-store
	online purchase

Delivery Policy

H_3 examines whether delivery policies create a higher online purchase intention among fast fashion consumers and luxury fashion consumers. For example, in 2025, the fast fashion retailer Zara Austria provides free standard delivery to a home address or postal drop-off location for orders above €50, with delivery within 3–5 days after dispatch. For items on sale or orders below €50, standard delivery costs €5.95. Express delivery, which takes 1–2 days, is available for an additional fee of €9.95 (Zara, 2025).

Similarly, in 2025, the luxury brand Dior Austria offers free standard delivery within 3–4 days, while express delivery within 1–2 days is available for an additional fee of €9.95. Morning delivery is offered for a fee of €12.95. For orders exceeding €1,300, delivery is free, whether standard or express (Dior, 2025).

Table 6 provides an overview of the delivery attributes and their respective levels for online purchases. In-store delivery for in-store purchases is excluded, as the study uses an alternative-specific design to assess "delivery policy" and "return policy" for in-store purchases (see Subchapter 4.4 for more details).

Table 5
Attribute Delivery Policy and Levels

Attribute	**Level**
Delivery Policy	free standard
	paid standard
	paid express

Return Policy

H_4 explores whether return policy create a higher online purchase intention among fast fashion consumers and luxury fashion consumers. In Europe, retailers are required to offer a standard 14-day refund policy from the date of delivery (European Union, 2025). However, other retailers, such as Zara, allow returns up to 30 days from the date of receipt. Zara provides free in-store returns, but for postal drop-off returns, a €2.95 fee is deducted from the refund (Zara, 2025). Louis Vuitton, as a luxury brand, offers free in-store returns at a location chosen by the customer (Louis Vuitton, 2025).

Table 6
Attribute Return Policy and Levels

Attribute	**Level**
Return Policy	free postal drop-off return
	paid postal drop-off
	in-store

Control Variables

To ensure the internal validity of study, potential extraneous variables influencing consumer behavior in the fashion industries in the digital era, beyond the primary variables of interest are controlled (Kaya, 2015). Internal validity refers to the process of ensuring "results of investigations are attributable to the expected relationships among the identified variables" (Taylor, 2013, p.11). Demographic factors are shown in previous studies to influence online purchase intention (Law and Ng, 2016; Bhat et al., 2021; Alfanur and Kadono, 2022).

The Impact of Gender

Gender is included as a control variable, as research shows that woman put more importance on emotional value compared to men (Rudawska et al., 2018). Females are more influenced by security, economic reasons, convenience and social influence (Alfanur and Kadono, 2022). Additionally, woman generally show lower intentions to shop for fashion products online compared to men (Nirmala and Dewi, 2011).

The Impact of Age

Age is another control variable. With the baby boomer generation transitioning out of the typical luxury consumer demographic, millennials and Gen-Z exhibit distinct spending habits, including a decrease in brand loyalty (McGowan et al., 2018). Younger consumers spend significantly less time on purchase decisions compared to older consumers and expect brands to resonate with their individual values (D'Arpizio and Levato, 2016).

Furthermore, younger generations spend more time active on digital devices than older generations (McKinsey & Company, 2024). Younger consumers are more influenced by convenience and perceived website quality, while older consumers are influenced by economic factor, security, and social influence (Alfanur and Kadono, 2022). Online purchase intentions among younger consumers are largely influenced by social media usage (Gu and Wu, 2019).

The Impact of Income

Income is another control variable, as luxury fashion brands often target affluent customers willing to spend more on high-quality, exclusive products, while fast fashion brands focus on price-conscious and impulse shoppers (Amatulli et al., 2016). Research indicates that higher-income consumers perceive functional and symbolic value as more important compared to lower-income consumers (Rudawska et al., 2018).

3.3 Survey Design and Implementation

The choice-based analysis was conducted through an online survey, collecting data over a period of three weeks, from November 4th to November 24th, 2024. The survey questionnaire is designed using Sawtooth Software’s Lighthouse Studio and made available online to respondents via the Online Survey Link[1]. As Sawtooth Software's hosting service is available only for a limited time, the survey is no longer accessible at this link.

A pilot study was conducted with seven respondents prior to publishing the survey to ensure that participants clearly understood the tasks and to collect additional feedback. Based on the positive feedback received, no changes were necessary, and the survey questionnaire was published. The seven respondents were included in the final survey as well.

The identification of the target population is essential to this study, as it focuses on digitalization. For this research, it is crucial that the targeted individuals have internet access and are familiar with digital tools. Participants are recruited through social media platforms, and a snowball sampling method is employed, where initial respondents refer to other individuals who meet the research criteria. Snowball sampling is a popular method in qualitative research and enables the collection of a significant number of participants (Parker et al., 2019).

The survey begins with a brief introduction that outlines the research scope, assures respondents of anonymity and confidentiality, and provides an estimated completion time. To gather insights into participants' shopping behavior in the digital era for fast fashion and luxury categories, the survey includes questions about shopping frequency, preferred

[1] Online Survey Link: https://fashiononline.sawtoothsoftware.com/cgi-bin/ciwweb.pl?hid_studyname=CVP_Fashion_Online&hid_pagenum=1.

purchasing channels for fast fashion and luxury items, spending habits, the proportion of spending through online versus offline channels, and frequency of social media usage.

To differentiate online purchase intentions between the fast fashion and luxury fashion industries, two distinct CBC analyses are presented: the first for the fast fashion scenario, followed by the second for the luxury fashion scenario. In both scenarios, participants are provided with a brief explanation of the respective fashion industry and are asked to imagine real-life buying situations of fashion products while completing the survey. Additionally, they are informed about the purpose of the questionnaire and what is expected of them. In both scenarios, the participants were given four different options to choose their favorite from. The attribute levels offered to the respondents were varied randomly. Participants are then asked to select their preferred option from a set of alternatives. If none of the alternatives meet their preferences, they can indicate this by selecting the "None" option. The attributes in both scenarios remain the same, with price levels adjusted to reflect each industry.

Table 7 presents the attributes and corresponding levels used, including a column with questionnaire information that was provided to respondents while completing the survey to help them better understand the requirements. The study concludes with a section of demographic questions designed to understand how age, gender and income levels influence shopping behavior. The complete survey questionnaire is provided in Appendix A.

Table 7
Attributes and Levels

	Fast-Fashion		Luxury Fashion	
Questionnaire information	Attribute	Level	Attribute	Level
price	*Price*	€ 25 € 50 € 75	*Price*	€ 500 € 1,000 € 2,000
the brand is advertised through	*Promotion*	social media Influencer e-mail newsletter display advertising	*Promotion*	social media Influencer e-mail newsletter display advertising
you are looking for the product	*Selection*	in-store online selection	*Selection*	in-store online selection
you are buying	*Purchase*	in-store online purchase	*Purchase*	in-store online purchase
delivery policy	*Delivery Policy*	free standard paid standard paid express	*Delivery Policy*	free standard paid standard paid express
return policy	*Return Policy*	free postal drop-off paid postal drop-off in-store	*Return Policy*	free postal drop-off paid postal drop-off in-store

3.4 Experimental Design

In conjoint experiments respondents make choices from several sets of alternatives, simulating real-life scenarios (Haaijer et al., 2001). The experimental design defines the design of the choice experiment, including task generation methods and ensuring that the survey tests the hypotheses effectively and minimizes biases. A CBC analysis consists of a series of questions, commonly referred to as "tasks". These tasks include a set of choices, known as concepts, which incorporate all attributes from which respondents select the option that corresponds to their highest-utility concept (Discrete Choice) (Johnson and Orme, 2003).

Each of the two CBC analyses in this study includes seven choice tasks. Every task includes four alternatives from which respondents can choose, including a "none" option. A random design strategy is employed, allowing the algorithm to determine the combination of attribute levels for each task. Alternatively, a fixed design could be used, where all respondents complete the same version of the questionnaire. Fixed designs enhance efficiency in measuring main effects and specific interactions, while random designs provide robustness in estimating all effects (Sawtooth Software, 2024).

The questionnaire comprises three hundred different task combinations, ensuring that each respondent receives a unique version. This approach reduces order bias and learning effects (North and Vos, 2002).

Sawtooth Software (2024) allows the selection of different random task generation methods:

1. Complete Enumeration: Considers concepts with minimal overlap and balanced attribute level combinations, ensuring that attribute levels are displayed as few times as possible within a single task.
2. Shortcut: Creates profiles using the least-used attribute levels from prior responses, minimizing overlap.
3. Random: Generates random samples from all possible combinations, allowing overlaps but preventing duplicates within a choice set. No two identical concepts can appear within the same task.
4. Balanced Overlap: Strikes a balance between complete enumeration and random methods, maintaining efficiency for main effects while improving accuracy in estimating interaction effects.

The Balanced Overlap method is chosen for its efficiency and enhanced accuracy in estimating interactions, ensuring no single attribute level has an unfair advantage or disadvantage.

The system also allows for the prohibition of specific combinations of attribute levels from appearing together (within-concept prohibitions) or the prevention of certain concepts from being compared with others (across-concept prohibitions). However, prohibitions are generally discouraged because they can result in imprecise utility estimates and higher standard deviations (Sawtooth Software, 2024).

An alternative approach involves specifying alternative-specific designs, where conditional attributes are displayed only in conjunction with particular levels of a primary attribute. In this study, the primary attribute is 'type of purchase,' and the conditional attributes are 'delivery policy' and 'return policy,' which are displayed only for the 'online' level of 'type of purchase' and left blank for the 'in-store' level.

Sawtooth Software (2024) recommends running a Test Design report based on the planned sample size to evaluate the efficiency and ensure the study can accurately estimate attribute effects and part-worth utilities. After running a Test Design with an alternative approach, simulating three hundred dummy respondent answers and a 5% selection rate for the "None" option, the study produces statistically significant results, with the warning that interaction effects between attributes with alternative-specific rules cannot be estimated. This limitation must be considered during discussion of the analysis results.

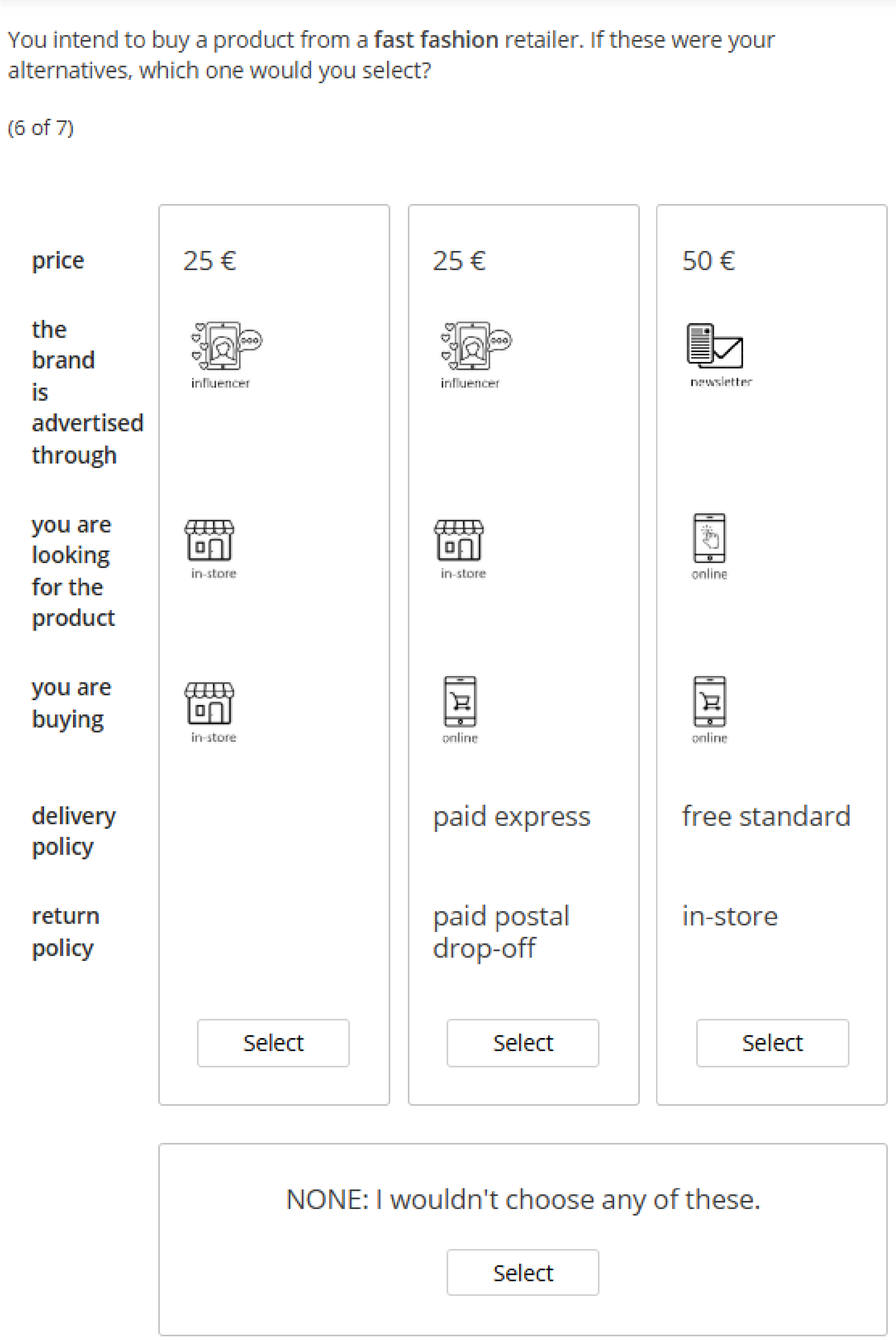
In this research, respondents were presented with two scenarios, one for fast fashion and another for luxury fashion. All respondents were presented first with the fast fashion scenario and they were asked to imagine real-life situations of buying fast fashion items. After completing the fast fashion scenario, respondents were presented with the luxury fashion scenario, in which they were asked to image real-life situation of buying luxury fashion items.

Throughout the questionnaire, small icons were used as visual cues to explain attribute labels, as they can quickly and concisely convey important information and enhance the user experience by increasing clarity, improving recognition, and reducing cognitive load (Caplin, 2001). However, a small text below the icons was also introduced, as research shows that people better understand the meaning of icons when accompanied by text (Jin et al., 2023).

Figure 1 illustrates an example choice set from the fast-fashion scenario (refer to Appendix B for the complete survey).

Figure 1

Example of a Choice Set



4. Results and Analysis

This chapter addresses descriptive statistics, attribute importance, part-worth utilities, and market simulations, which are then used to answer the hypotheses of the study. Sawtooth Software's Analysis Manager in Lighthouse Studio provides tools for analyzing and interpreting the collected data. Based on Orme and Chrazan (2017), CBC data is typically analyzed using Aggregate Logit, Counts, and a Hierarchical Bayes (HB) estimation. Once the part-worth utilities are estimated, the results can be applied in the Choice Simulator to create market simulations, allowing for the evaluation of market outcomes under different scenarios.

4.1 Test Design Report

Standard errors of attributes assess how precisely the design estimates utilities. Sawtooth Software (2024) recommends aiming for standard errors of 0.05 or smaller for main effect utilities and 0.10 or smaller for interaction effects or alternative-specific effects. Standard errors of attributes should be approximately equal. The standard error for the “none” option can be ignored, as it is just a constant that varies with the frequency of its selection. The Test Design Report in Lighthouse Studio 9.16.0 only shows standard errors for main effect and not for interaction effects or alternative-specific effects.

The Test Design report in Table 8 provides a summary of attributes and their respective standard errors. The standard errors for each level reveals that the precision of all levels meets or exceeds the recommended targets (<0.05) for main effects. The Test Design report is identical for both scenarios, fast fashion, and luxury fashion, since only the absolute value of the price attribute differs between them.

Table 8
Obtained Test Design Report

Attribute	Level	SE (standard error)
1	€25	0.03444
1	€50	0.03452
1	€75	0.03447
2	social media	0.04349
2	Influencer	0.04341
2	e-mail newsletter	0.04306
2	display advertising	0.04327
3	in-store	0.02395
3	online selection	0.02395
4	in-store	0.02491
4	online purchase	0.02491
5	free standard	0.04458
5	paid standard	0.04458
5	paid express	0.04443
6	free postal drop-off	0.04447
6	paid postal drop-off	0.04448
6	in-store	0.04449
	None	0.15602

Note. Results obtained from Lighthouse Studio 9.16.0

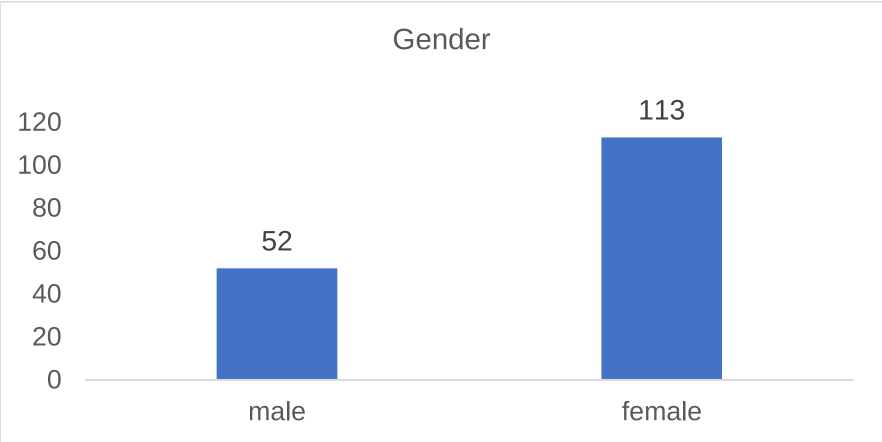
4.2 Descriptive Statistics

This subchapter provides an overview of the sample, the distribution of responses, and outlines the demographic breakdown. Before the analysis, survey data is downloaded from the web server. A total of 317 responses were collected, with 143 responses being incomplete, indicating that the survey was not finished for these responses. The remaining responses of 174 are fully completed.

The Data Management feature in Lighthouse Studio is then used to review the records for completed surveys and identify any respondents who should be removed, such as those who completed the survey unusually quickly (speeders). Respondents spend an average of 8 minutes and 36 seconds completing the entire survey, from the introduction page to the final page. Respondents who complete the survey in less than 3 minutes are excluded from the sample, as they are considered speeder. After removing the responses of nine participants who completed the survey too quickly, 165 completed questionnaires remain in the dataset.

Figure 2 indicates the distribution of the sample by gender, with 32% male and 68% female respondents. An imbalance in the sample can affect its representativeness and limit the generalizability of the findings. The results may not accurately reflect the entire population and could be skewed due to the overrepresentation of female respondents (Seale et al., 2004).

Figure 2
Distribution of Sample by Gender



To examine purchase intentions across different age groups, participants are asked to indicate their age category. Previous research serves as a reference for age classification, dividing age groups into generational categories and demonstrating that different generations exhibit distinct spending habits (D’Arpizio and Levato, 2016; McGowan et al., 2018; McKinsey & Company, 2024).

For this reason, the age groups presented to respondents match generational groups. The classification is based on Dimock (2019), where generations are defined as follows:

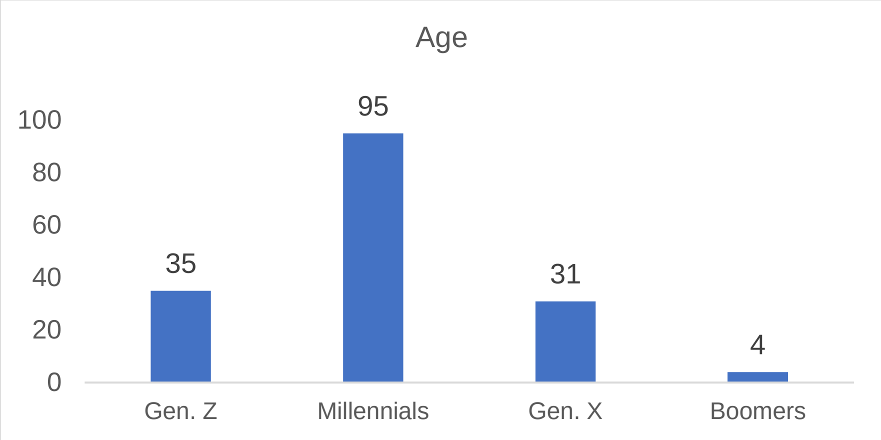
- Generation Z: Born between 1997 and 2012 (ages 12 to 27 in 2024)
- Millennials: Born between 1981 and 1996 (ages 28 to 43 in 2024)
- Generation X: Born between 1965 and 1980 (ages 44 to 59 in 2024)
- Boomers: Born between 1946 and 1964 (ages 60 to 78 in 2024)

For simplification purposes, Gen. Z is represented in the questionnaire as "27 or younger" Millennials as ages “28-43”. Gen. X as ages “44-59”, and Boomer are represented as "60 or older."

Figure 3 illustrates the distribution of the sample by generational group. Millennials account for 58% of the participants, followed by Gen Z at 21%, Gen X at 19%, and Boomers at 2%. The imbalance in age distribution may affect the representativeness and generalizability of the sample (Seale et al., 2004).

Figure 3

Distribution of Sample by Generation Group



Note. Age classification based on (Dimock, 2019)

Figure 4 shows the distribution of sample by income. The income levels are derived from Eurostat, the statistical office of the European Union, which provides data for analyzing and comparing various economic indicators. The income levels are based on the Euro area (EA-20, from 2023) consisting of the 20 European Union countries that have adopted the euro as their official currency.

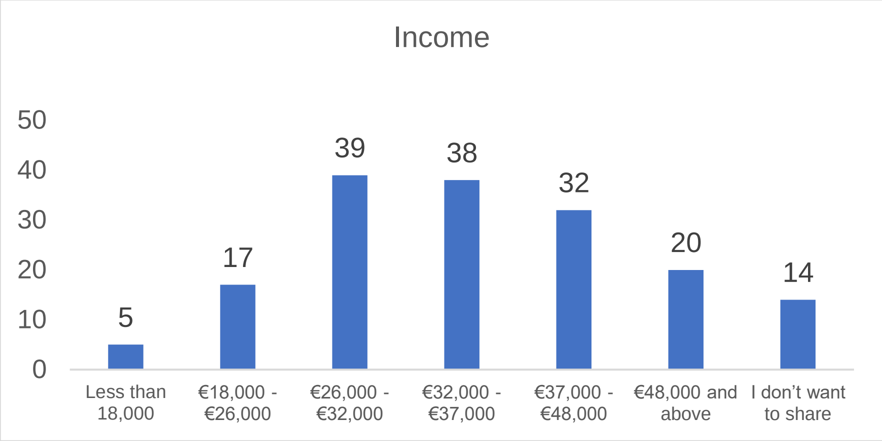
According to Eurostat (2024), the average annual net earnings in the Euro area are as follows:

A single person without children earning:

- 50% of the average earning: €18,383
- 80% of the average earning: €26,081
- 100% of the average earning: €31,149
- 125% of the average earning: €37,291
- 167% of the average earning: €47,348

For simplification and easier visualization in the survey, net income levels are rounded, providing clear and understandable ranges. The data shows a concentration of respondents in the middle-income ranges, followed by respondents with higher-than-average net income, and a drop in low net income ranges.

Figure 4
Distribution of Sample by Annual Net Income



Note. Income classification based on average annual net earnings from EA-20 (Eurostat, 2024)

Based on the information collected through the survey about participants' shopping behavior, the following conclusions are outlined:

Figure 5 illustrates the shopping frequency for fashion items among participants. Most respondents (62%) shop on a seasonal basis during specific times, such as the start of new seasons or special occasions. A considerable proportion (25%) shop monthly, indicating high engagement in regular shopping. Smaller groups shop bi-weekly or yearly (4% for each category). Only 3 participants (2%) shop weekly, and 4 participants (2%) report not shopping for fashion items at all.

Figure 5
Shopping Frequency Fashion

Figures 6 illustrate the respondents' preferred shopping channels for fast fashion. Most participants (62%) prefer to purchase fast fashion items online, while in-store shopping is less preferred (26%) for fast fashion items. A group of participants reports no specific preference for shopping channels (8%) and a portion (3%) does not purchase fast fashion items.

Figure 6
Fast Fashion Purchase

Figures 7 shows the respondents' preferred shopping channels for luxury fashion. In-store shopping is more preferred for luxury fashion items, with most participants (45%) selecting this channel. A smaller group (27%) prefers to purchase luxury items online. A significant portion (21%) does not purchase luxury fashion items. This aspect may raise concerns about the sample's representativeness for the purpose of this study. Additionally, a group of participants reports no specific preference for shopping channels (7%).

Figure 7
Luxury fashion Purchase

Figure 8 presents a breakdown of annual spending on fashion items. The most common spending range is €600–€1,000 per year, reported by 78 participants (47%). A smaller but significant group spends €1,000–€2,000 annually (28%).

Figure 8
Spending Amount

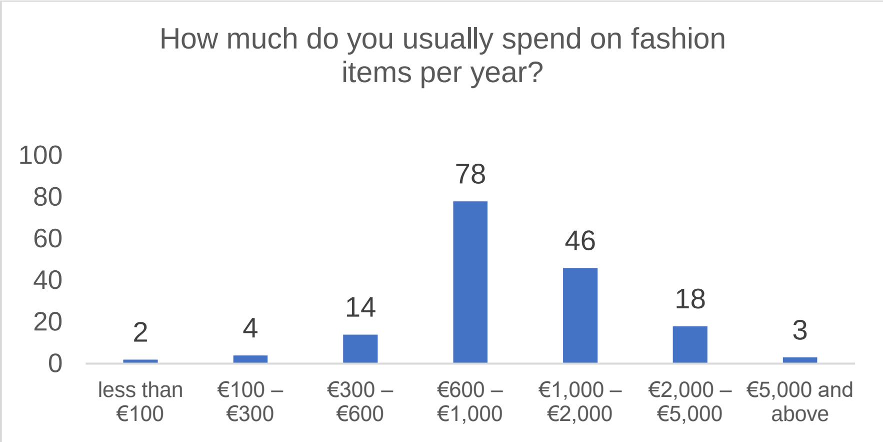


Figure 9 illustrates the proportions of spending online versus in-store. Most participants (61%) allocate 80% of their spending online and 20% in-store, while a smaller group (18%) split their spending equally between 50% online and 50% in-store.

Figure 9
Spending Habits

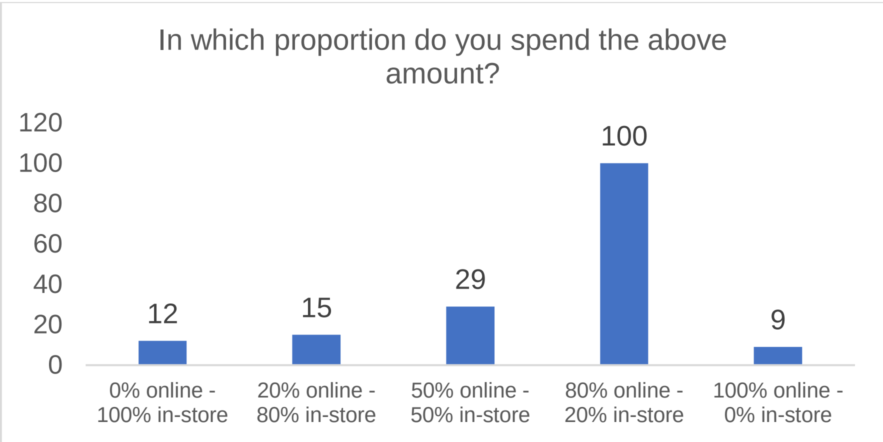
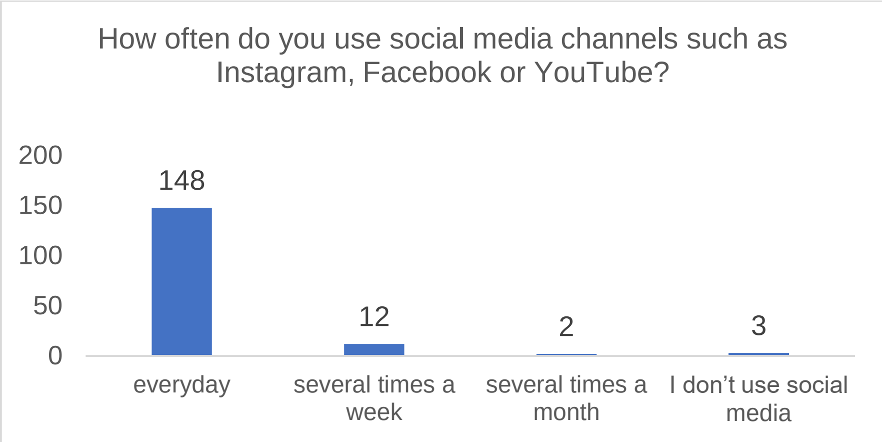


Figure 10 analyzes social media usage frequency, showing that most participants (90%) use social media daily. A smaller number of participants (7%) access social media several times a week. Only 3 participants (2%) report that they do not use social media.

igure 10
Social Media Usage



The Influence of Demographic Groups on the Likelihood of Online Purchases

A binomial logistic regression was performed using the glm() command in RStudio 2024.12.1 software to assess how demographic groups influence the likelihood of online purchases. Generalized linear models (GLM) are "a generalization of regular linear regression that allow for other link functions to map from linear model output to the dependent variable, and other error distributions to describe the residuals." (Fischetti, 2015, p.223). A binomial logistic regression is a type of GLM and is applied when the outcomes are binary, typically represented by 1s and 0s (Dunn and Smyth, 2018). To transpose the data into binomial form, data for all respondents is downloaded, and only the groups that stated a clear preference for a shopping channel are selected for analysis. A value of 1 indicates a preference for online shopping, and a value of 0 indicates a preference for in-store shopping.

For each variable, a null and an alternative hypothesis is defined. The null hypothesis states that the variable does not play a role in explaining the dependent variable, while the alternative hypothesis suggests that it does. P-values determines whether to reject the null hypothesis at significance levels and conclude that the variables contribute to explaining the model (Kronthaler and Zöllner, 2021).

Sawtooth Software recommends a sample size of at least n = 30 per population group to improve both individual and aggregate prediction accuracy (Sawtooth Software, 2019). For this reason, only the following variables with sample sizes greater than 30 are included in the binomial logistic regression analysis.

Table 9 presents an overview of the number of respondents in the fast fashion and luxury fashion scenarios, segmented by their stated preference for either online or in-store shopping. Individuals who reported no specific preference or indicated that they do not shop for fashion items were excluded from the analysis.

Table 9
Samples Demographic Groups in the Fast Fashion and Luxury Fashion Scenarios

Demographic group	**Fast Fashion Scenario**		**Luxury Fashion Scenario**	
	Sample	*Number of Respondents*	*Sample*	*Number of Respondents*
Gender	male	49	male	35
	female	97	female	85
Age	Gen. Z	31	Millennials	58
	Millennials	78	Gen. X	31
	Gen. X	33		
Income	less than €26,000	58	€26,000–€37,000	43
	€26,000–€37,000	48	€37,000 and above	35
	€37,000 and above	40		

Differences across Gender Segments

The summary of the glm() command used to fit Generalized Linear Models commonly used in R (Kronthaler and Zöllner, 2021), with gender as explanatory variables can be found in Table 10 for the fast fashion scenario and Table 11 for the luxury fashion scenario.

The dependent variable *Online Shopping Preference* is operationalized as a binary variable, where a value of 1 indicates respondents who show a clear preference for online shopping, and a value of 0 indicates those who prefer in-store shopping. The intercept represents the outcome for females. The results show statistically significant results for both coefficients in the fast fashion scenario, indicating that females are more likely to shop online than males. A predict() command is used to generate predictions based on previously built linear model and can be used to predict probabilities (Fischetti, 2015). In this case, there are 82% chances that females will shop online and 47% chances that male will shop for fast fashion items online.

The results in the luxury show statistically significant results for the intercept. The negative coefficient indicates that females are less likely to engage in shopping online. The probability of females engaging in online shopping lies at 37%.

In Generalized Linear Models, the null deviance measures how well the response variable is predicted by a model with only an intercept, while the residual deviance compares the fit of the current model to that of a saturated model (best case). A smaller residual deviance indicates a better model. The Akaike Information Criterion (AIC) balances goodness of fit with model complexity. A lower AIC indicates a better fitting model (Zuur et al., 2009).

Table 10

GLM Results for Gender and Online Shopping Preference in Fast Fashion

Coefficients:	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	1.55	0.27	5.80	0.00	***
Male	(1.67)	0.39	(4.27)	0.00	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 177.00 on 145 degrees of freedom

Residual deviance: 157.79 on 144 degrees of freedom

AIC: 161.79

Gender	Prob
Female	0.82
Male	0.47

Note. Results obtained from RStudio 2024.12.1

Table 11

GLM Results for Gender and Online Shopping Preference in Luxury Fashion

Coefficients:	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	- 0.50	0.22	(2.25)	0.02	*
Male	- 0.02	0.42	(0.05)	0.96	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 158.78 on 119 degrees of freedom

Residual deviance: 158.77 on 118 degrees of freedom

AIC: 162.77

Gender	Prob
Female	0.38
Male	0.37

Note. Results obtained from RStudio 2024.12.1

Differences across Age Segments

The logistic regression analysis of age as an explanatory variable in online shopping versus in-store shopping is presented in Table 12 for fast fashion and Table 13 for luxury fashion. In the fast fashion scenario, the results show statistically significant results for the reference group, which represents Millennials. After running a predict() command, the results indicate a 74% chances for Millennials to shop for fashion items online. Differences across age groups for the luxury fashion scenario are not statistically significant.

Table 12
GLM Results for Age and Online Shopping Preference in Fast Fashion

Coefficients:	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	1.04	0.24	4.28	0.00	***
age 44-59	(0.39)	0.44	(0.88)	0.38	
younger than 27	(0.15)	0.51	(0.30)	0.77	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)
Null deviance: 172.04 on 143 degrees of freedom
Residual deviance: 171.27 on 141 degrees of freedom
AIC: 177.27

Age	Prob
younger than 27	0.71
28-43	0.74
44-59	0.66

Note. Results obtained from RStudio 2024.12.1

Table 13
GLM Results for Age and Online Shopping Preference in Luxury Fashion

Coefficients:	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	(0.33)	0.24	(1.39)	0.17
Age44-59	(0.52)	0.46	(1.12)	0.26

(Dispersion parameter for binomial family taken to be 1)
Null deviance: 158.78 on 119 degrees of freedom
Residual deviance: 157.16 on 117 degrees of freedom
AIC: 163.16
Note. Results obtained from RStudio 2024.12.1

Differences across Income Segments

The logistic regression examining income levels influencing the likelihood of engaging in online shopping for the fast fashion and luxury fashion scenario can be found in Table 14 and Table 15.

Differences across age groups for the fast fashion scenario are not statistically significant. In the luxury fashion scenario, the income group *€37,000 and above* shows statistically significant results. The negative coefficient indicates a low likelihood of shopping online for this income group with a probability of 22%.

Table 14

GLM Results for Income and Online Shopping Preference in Fast Fashion

Coefficients:	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	0.51	0.30	1.71	0.09	.
€37,000 and above	0.08	0.49	0.16	0.88	
less than 26,000	0.83	0.44	1.89	0.06	.

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)
Null deviance: 163.37 on 133 degrees of freedom
Residual deviance: 159.15 on 131 degrees of freedom
AIC: 165.15

Note. Results obtained from RStudio 2024.12.1

Table 15

GLM Results for Income and Online Shopping Preference in Luxury Fashion

Coefficients:	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	0.1335	0.2988	0.447	0.65496	
€37,000 and above	-1.3863	0.5	-2.773	0.00556	**

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 108.70 on 80 degrees of freedom
Residual deviance: 100.32 on 79 degrees of freedom
AIC: 104.32

Income	Prob
€37,000 and above	0.22
€26,000 - €37,000	0.53

Note. Results obtained from RStudio 2024.12.1

The Influence of Spending Amount on the Likelihood of Online Purchases

A cross-tabulation was performed in RStudio 2024.12.1 to assess the relationship between annual spending amount and preferred shopping channel in the fast fashion and luxury fashion industries. Cross-tabulation is a statistical method used to display the frequency distribution of categorical variables against one another and to assess whether there is a relationship between those variables. A Chi-square test of independence was conducted to determine whether the observed relationship is statistically significant (Gianmarco, 2024).

The spending amount, based on respondents' self-reported annual expenditures, was categorized into a categorical variable with three levels: low (less than €1,000), medium (€1,000–€2,000), and high (€2,000 and above). The preferred shopping channel variable included three options: online, in-store, or no preference.

The results of the cross-tabulation in the fast fashion industry are presented in Table 16 and Table 17 for the luxury fashion industry. With a p-value greater than 0.05, the analysis concludes that there is no statistically significant relationship between spending and preferred shopping channel.

Table 16
Cross-tabulation Analysis for Spending Amount and Online Shopping Preference in Fast Fashion

	Purchase Channel Preference		
Spending	online	in-store	no preference
Low	51	28	6
medium	29	11	6
High	23	4	2

Pearson's Chi-squared test
X-squared = 5.7918, df = 4, p-value = 0.2152

Note. Results obtained from RStudio 2024.12.1

Table 17
Cross-tabulation Analysis for Spending Amount and Online Shopping Preference in Luxury Fashion

	Purchase Channel Preference		
spending	online	in-store	no preference
low	23	29	5
medium	13	28	4
high	9	18	2

Pearson's Chi-squared test
X-squared = 1.8976, df = 4, p-value = 0.7546

Note. Results obtained from RStudio 2024.12.1

4.3 Conjoint Analysis Results

4.3.1 Model Estimation and Fit

Aggregate Logit Analysis

Aggregate Logit analysis provides an estimation of summary utility weights and evaluates the significance of the overall model, attributes, levels, and interaction effects. T-tests are used to validate the significance between variables. A t-ratio with an absolute magnitudes greater than 1.96, provides at least 95% confidence that the coefficient is significantly different from zero (Sawtooth Software, 2024)

The chi-square test, developed by Pearson (1900) is used to evaluate the independence between variables or to determine how well a sample aligns with the expected distribution of a population (goodness of fit). The Chi-square statistic is calculated as twice the difference between the model fit and the null fit, known as the 2 log-likelihood test (Orme and Chrazan, 2017).

$$\text{Chi-square} = 2(LL_m - LL_n)$$

Where:

- LL_m is the log-likehood of this model (the fit provided by the estimated part-worths).
- LL_n is the log-likelihood of the null model (where all part-worth utilities are zero).

A chi-square test, calculated as 2×(Log-likelihood difference), assesses the significance of the improvement in fit from the null model to the estimated model (Orme and Chrazan, 2017). The fast fashion scenario shows a Chi-square value of 591.64, while the luxury fashion scenario has a Chi-square value of 633.34. Refer to Appendix B for the full summary of the two conjoint aggregate logit analyses for the fast fashion and luxury fashion scenarios.

The Akaike Information Criterion (AIC) balances the trade-off between the model fit and complexity. A lower AIC value for the luxury fashion scenario suggests a better model fit (Cavanaugh and Neath, 2019). The Bayesian Information Criterion (BIC), rooted in Bayesian probability, also balances model fit and complexity. A higher BIC indicates superior model performance for the luxury fashion scenario (Neath and Cavanaugh, 2012).

4.3.2 Counting Analysis

A counting analysis is a simple and straightforward descriptive method for calculation of the main effects and two-way interactions. A count analysis “calculates a proportion of "wins" for each level, based on how many times a concept including that level is chosen, divided by the number of times a concept including that level appeared in the choice task.” (Sawtooth Software, 2024, p.388).

A counting analysis is a basic, intuitive approach that provides insights into relative impact of attribute levels. The ratio for each attribute level reflects the relative attractiveness or importance of each level. Counts provide a Chi-Square statistic for each main and joint effect, indicating whether the proportions in the table differ significantly. The p-value indicates whether the observed results are statistically significant. If no prohibitions are included in the CBC, the count proportions closely correspond to conjoint utilities (Orme and Chrazan, 2017). However, when respondents have differing opinions, attributes may appear less important in aggregate analysis, even if individuals hold strong preferences. Sawtooth Software recommends determining attribute importance for more accurate results using HB analysis (Sawtooth Software, 2024).

Table 18 show the counts proportions of attribute levels. In the fast fashion scenario, the *selection*, *purchase*, and *delivery policy* attributes show statistically significant results. Online selection has been selected 35.1% of times it occurred. However, in-store purchases were chosen 43.6% of times, while online purchases were selected less frequently (20.8%). In terms of delivery policy, free standard delivery was chosen 40.8% times.

In the luxury fashion scenario, *price*, *selection*, *purchase*, *and delivery policy* attributes show statistically significant results. Price level of €500 was chosen 35% of times, followed by €1,000, which was chosen 29.1% times it was shown. Online options were selected 33.7% times over in-store selection (20.7%). In-store purchases remain dominant for luxury fashion, having being selected 46.2% of times. Similar to the fast fashion scenario, free delivery is was selected more often, though with less proportion (28.3%).

Table 18
Main Effects Estimation Using Counting Analysis

Fast Fashion		Luxury Fashion	
Price		***Price***	
	Total		Total
Total Respondents	165	Total Respondents	165
€ 25	0.31	€ 500	0.35
€ 50	0.273	€ 1,000	0.291
€ 75	0.289	€ 2,000	0.177
Within Att. Chi-Square	2.712	Within Att. Chi-Square	66.6
D.F.	2	D.F.	2
Significance	not sig	Significance	p < .01
Promotion		***Promotion***	
	Total		Total
Total Respondents	165	Total Respondents	165
social media	0.311	social media	0.284
Influencer	0.26	Influencer	0.268
e-mail newsletter	0.318	e-mail newsletter	0.278
display advertising	0.271	display advertising	0.258
Within Att. Chi-Square	7.474	Within Att. Chi-Square	1.22
D.F.	3	D.F.	3
Significance	not sig	Significance	not sig
Selection		***Selection***	
	Total		Total
Total Respondents	165	Total Respondents	165
in-store	0.23	in-store	0.207
online selection	0.351	online selection	0.337
Within Att. Chi-Square	43.69	Within Att. Chi-Square	53.647
D.F.	1	D.F.	1
Significance	p < .01	Significance	p < .01
Purchase		***Purchase***	
	Total		Total
Total Respondents	165	Total Respondents	165
in-store	0.436	in-store	0.462
online purchase	0.208	online purchase	0.165
Within Att. Chi-Square	142.967	Within Att. Chi-Square	260.194
D.F.	1	D.F.	1
Significance	p < .01	Significance	p < .01

Fast Fashion		Luxury Fashion	
Delivery policy		***Delivery policy***	
	Total		Total
Total Respondents	165	Total Respondents	165
free standard	0.408	free standard	0.283
paid standard	0.141	paid standard	0.149
paid express	0.078	paid express	0.063
Within Att. Chi-Square	216.498	Within Att. Chi-Square	110.073
D.F.	2	D.F.	2
Significance	p < .01	Significance	p < .01
Return policy		***Return policy***	
	Total		Total
Total Respondents	165	Total Respondents	165
free postal drop-off	0.218	free postal drop-off	0.163
paid postal drop-off	0.199	paid postal drop-off	0.154
in-store	0.207	in-store	0.176
Within Att. Chi-Square	0.671	Within Att. Chi-Square	1.128
D.F.	2	D.F.	2
Significance	not sig	Significance	not sig

Note. Results obtained from Analysis Manager of Lighthouse Studio 9.16.0

Interactions Effects

A counting analysis calculates significant interactions between variables demonstrating how one variable influences another. Interaction effects describe how the preference for one attribute level depends on the level of another attribute. If interaction effects are significant, main effects design can create biased estimates and reduce the accuracy of a main effect model (Sylcott et al., 2015).

Sawtooth Software (2024) recommends aiming for standard errors of 0.10 or smaller for interaction effects. In the fast fashion scenario (see Table 19), a significant interaction exists between *selection and purchase channels*. A significant number of consumers who consider in-store selection choose in-store purchases (45.1%), while online selection also interacts in-store purchases (42.1%).

Table 19

Fast Fashion Interactions Effects: selection x purchase

		Total
Total Respondents		165
in-store	in-store	0.451
in-store	online purchase	0.104
online selection	in-store	0.421
online selection	online purchase	0.311
Interaction Chi-Square		77.167
D.F.		1
Significance		$p < .01$

Note. Results obtained from Analysis Manager of Lighthouse Studio 9.16.0

In the luxury fashion scenario (see Table 20), a significant interaction exists *between price and delivery policy*. The highest interaction effect exists at price level €500 and free standard delivery (42.1%).

Table 20

Luxury Fashion Interactions effects: price x delivery policy

		Total
Total Respondents		165
€ 500	free standard	0.421
€ 500	paid standard	0.184
€ 500	paid express	0.052
€ 1,000	free standard	0.3
€ 1,000	paid standard	0.154
€ 1,000	paid express	0.072
€ 2,000	free standard	0.133
€ 2,000	paid standard	0.109
€ 2,000	paid express	0.063
Interaction Chi-Square		11.586
D.F.		4
Significance		$p < .05$

Note. Results obtained from Analysis Manager of Lighthouse Studio 9.16.0

A similar trend to the one observed in the fast fashion scenario is evident in the luxury fashion scenario with a significant interaction between *selection* and *purchase* attributes (see Table 21). A significant number of consumers who consider online selection choose in-store purchases (50.2%), while in-store selection also interacts in-store purchases (42.2%).

Table 21
Luxury Fashion Interactions Effects: selection x purchase

			Total
Total Respondents			165
	in-store	in-store	0.422
	in-store	online purchase	0.085
	online selection	in-store	0.502
	online selection	online purchase	0.243
Interaction Chi-Square			38.367
D.F.			1
Significance			$p < .01$

Note. Results obtained from Analysis Manager of Lighthouse Studio 9.16.0

4.3.3 The Hierarchical Bayes (HB) Analysis

As mentioned in the Sawtooth Software (2021) technical paper, a Hierarchical Bayes (HB) conjoint approach is a widely used method for estimating average utilities and it is recommended to use this type of analysis to compute attribute importances. A HB estimation for the final model will be then used within market simulation.

A HB analysis "borrows" data from all participants to generate estimates for each participant, even though the amount of data available may be not sufficient for individual analysis. Additionally, HB analysis accounts for variability in individual preferences and captures differences across respondents (Sawtooth Software, 2021). A HB method enables the analysis of part-worth values at an individual level, delivering stable and precise results even with limited sample sizes (Orme, 2014).

A HB report uses Zero-Centered Diffs method, meaning the sum of the utilities within each attribute is zero. These values are normalized, making it easier to compare attributes and interpret relative preferences. A part-worth score is given to each attribute, indicating whether it the attribute adds to a scenario's total worth or subtract from it (Sawtooth Software, 2024).

A HB model assesses utilities at the individual level and the estimated utility values can be both positive and negative. A high positive utility value for a specific level indicates that a respondent was more likely to choose a concept when that level was included. Conversely, a high negative utility value suggests that the respondent was less likely to select a concept if it contained that particular level. The higher the utility score, the more preferred the attribute level is. A negative value does not mean that it is undesirable for respondents, but only that it is less desirable than other levels within the attribute (Sawtooth Software, 2019).

This approach helps measure the contribution of each attribute level to the overall preference for a choice. Utilities are additive across attributes and should not be compared between attributes. Even if two levels from different attributes share the same part-worth value, it does not imply they are equally preferred. The part-worth values do not have an absolute meaning, rather, they are used to assess the impact of each level and compare across levels (Orme and Chrazan, 2017).

An overview of the part-worth utilities for the fast fashion and luxury fashion scenarios is presented in Table 22.

Fast Fashion

In the fast fashion scenario, the highest part-worth utility lies at the lowest price point of €25. Regarding promotional strategies, e-mail newsletters have the highest contribution to the utility, followed by social media. Both online selection and in-store purchases show positive utilities, as are the free standard delivery policy and the free postal drop-off return policy.

Luxury Fashion

In the luxury fashion scenario, the highest contribution to the utility lies at the lowest price point of €500. In terms of promotion, only social media shows a positive part-worth utility. Regarding omnichannel strategies, both online selection and in-store purchases are associated with positive utilities. Levels free standard delivery and free postal drop-off options show higher utility scores compared to the other levels within the respective attribute.

Table 22
Part-Worth Utilities based on Hierarchical Bayes Analysis

Fast Fashion		Luxury Fashion	
Label	Utility	Label	Utility
Price		***Price***	
€25	9.57	€500	37.7
€50	-14.23	€1,000	13.43
€75	4.66	€2,000	-51.13
Promotion		***Promotion***	
social media	6.98	social media	9.14
Influencers	-10.95	Influencers	-5.26
e-mail newsletter	10.3	e-mail newsletter	-2.77
display advertising	-6.34	display advertising	-1.11
Selection		***Selection***	
in-store	-24.46	in-store	-26.4
online selection	24.46	online selection	26.4
Purchase		***Purchase***	
in-store	52.84	in-store	59.96
online purchase	-52.84	online purchase	-59.96
Delivery Policy		***Delivery Policy***	
free standard	111.69	free standard	85.72
paid standard	-22.09	paid standard	2.01
paid express	-89.6	paid express	-87.73
Return Policy		***Return Policy***	
free postal drop-off	12.43	free postal drop-off	4.74
paid postal drop-off	-6.31	paid postal drop-off	-4.19
in-store	-6.12	in-store	-0.55
None	-12.82	None	16.38

Note. Results obtained from Analysis Manager of Lighthouse Studio 9.16.0

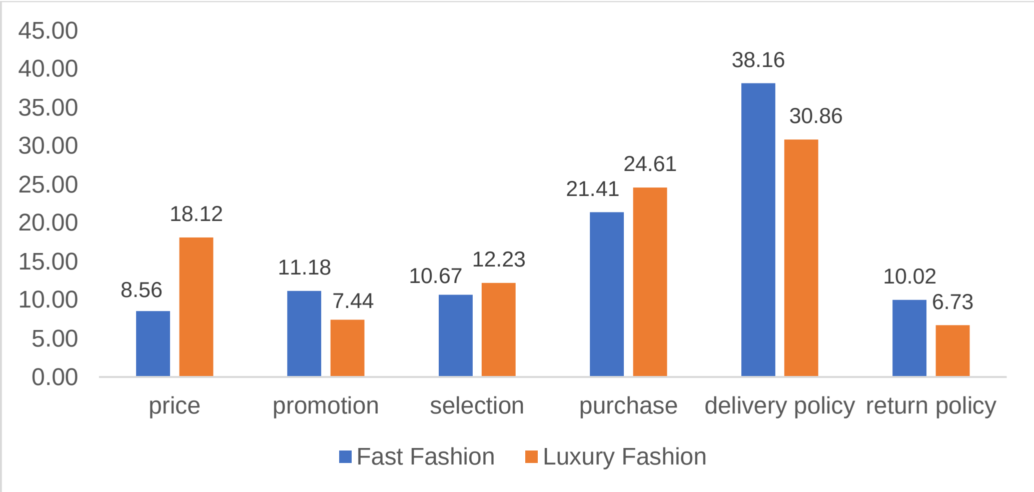
Average Importance Scores

In addition to the part-worth utilities, a HB analysis also computes the average importance score for each attribute, assessing the relative impact each attribute can have on the total utility. Averaged importance scores are calculated by dividing the utility range for an attribute by the total utility range across all attributes, then multiplying by 100. For instance, if an attribute scores 50, it indicates that it accounts for 50% of the overall preference (Orme, 2014)

Figure 11 shows the average important scores across all attributes in the fast fashion and luxury fashion scenarios. The most important attributes in both scenarios are delivery policy and purchase types, with delivery policy being more important in for fast fashion buyers and purchase type being more important for luxury fashion buyers. Price and selection channels are more important for luxury fashion consumers, while promotion types and return policies are more important for fast fashion buyers.

Figure 11

Average Importance scores based on HB analysis



4.3.4 Market Simulation Results

As a final step in the analysis, the part-worth utilities derived from the HB estimation were applied to simulate shares of preference for constructed scenarios via the Choice Simulator of Lighthouse Studio 9.16.0. A market simulation is considered the most efficient method for maximizing the value of the data by borrowing information across respondents and converting raw conjoint (part-worth utilities) data into simulated market choices (Orme and Chrazan, 2017; Sawtooth Software, 2024).

Only looking at the average utilities and selecting the best levels doesn't account for heterogeneity. For example, some people prefer online shopping, while others prefer in-store purchases. A market simulation provides insights into how various attributes interact with each other. The predictions are interpreted as relative indications of preference rather than actual market share. By computing scenarios under different configurations, it can determine which offering is most preferred by consumers and analyze how changes in one attribute affect the shares of preference of (Orme, 2002).

A Randomized First Choice (RFC) simulation method was used to analyze the impact of various attributes on the preferred purchase chancel. A RFC method emerged as a superior simulation approach, addressing the limitations of traditional First Choice and Share of

Preference models by incorporating random variation into part-worths (Sawtooth Software, 2019). A RFC runs multiple iterations per respondent, adding random error to part-worth utilities in each round, thereby enhancing precision and accuracy in results (Orme and Huber, 2000).

In this study, simulations were conducted to explore the effects of various attributes on purchase channel preferences. The configurations for the simulations were based on the part-worth utilities with the highest scores, as determined by the HB estimation.

The Impact of Price on Purchase Channel Preference

A market simulation in the Choice Simulator of Lighthouse Studio 9.16.0 was configured to analyze whether the share of preferences for online vs. in-store purchases changes at different price points, while all other attribute levels are being kept constant.

Table 23 breaks down the share of preferences for fast fashion scenario, showing stable differences in share of preferences for purchase channels across price points within the simulated scenarios.

Table 23
The Impact of Price on Purchase Channel Preference in Fast Fashion

Fast Fashion			
	Share of Preference		
Price	Online Purchase	In-Store Purchase	None (No Purchase)
€ 25	49.4%	40.3%	10.3%
€ 50	47.5%	38.7%	13.8%
€ 75	49.1%	40.4%	10.5%

Note. Results obtained from Choice Simulator of Lighthouse Studio 9.16.0

Table 24 breaks down the share of preference in the luxury fashion market, indicating that in-store purchases remain dominant but decline with higher prices. A rise in opt-out share of preference ("None") at €2,000 (26.40%) suggests that higher prices decrease consumers' purchase intent.

Table 24
The Impact of Price on Purchase Channel Preference in Luxury Fashion

Luxury Fashion			
	Share of Preference		
Price	Online Purchase	In-Store Purchase	None (No Purchase)
€ 500	27.5%	62.1%	10.4%
€ 1,000	25.2%	60.6%	14.2%
€ 2,000	20.8%	52.8%	26.4%

Note. Results obtained from Choice Simulator of Lighthouse Studio 9.16.0

The Impact of Promotion on Purchase Channel Preference

A market simulation analysis examines how different digital marketing strategies (social media, influencer marketing, e-mail newsletters, and display advertising) influence shares of preference for purchase channel types, while all other attributes levels are being kept constant. The results show a similar share of preference across promotion types, with online purchases being more common among fast fashion buyers (see Table 25).

Table 25
The Impact of Promotion on Purchase Channel Preference in Fast Fashion

Fast Fashion			
	Share of Preference		
Promotion Type	Online Purchase	In-Store Purchase	None (No Purchase)
Social Media	47.8%	38.1%	14.1%
Influencer	46.3%	38.2%	15.5%
E-mail Newsletter	47.5%	38.7%	13.8%
Display Advertising	47.0%	38.4%	14.6%

Note. Results obtained from Choice Simulator of Lighthouse Studio 9.16.0

For the luxury fashion scenario (see Table 26), in-store purchases remain dominant across all promotion types. Social media (27.50%) and display advertising (27%) lead to a higher share of preference than other channels for online purchases, though the differences are minimal.

Table 26
The Impact of Promotion on Purchase Channel Preference in Luxury Fashion

Luxury Fashion			
	Share of Preference		
Promotion Type	Online Purchase	In-Store Purchase	None (No Purchase)
Social Media	27.5%	62.1%	10.4%
Influencer	26.1%	61.1%	12.8%
E-mail Newsletter	26.6%	61.5%	11.9%
Display Advertising	27.0%	61.7%	11.3%

Note. Results obtained from Choice Simulator of Lighthouse Studio 9.16.0

The Impact of Selection Channel on Purchase Channel Preference

The following simulation examines how the selection process (online selection vs. in-store selection) influences purchase channel share of preference, while keeping all other levels constant. In the fast fashion scenario (see Table 27), online selection leads to a higher share of preference for online purchases (47.5%) compared to in-store purchases (38.7%). Online purchases are the preferred type regardless of the selection channel.

The opt-out share of preference ("None") is higher for in-store selection (20.9%) compared to online selection (13.8%).

Table 27

The Impact of Selection Channel on Purchase Channel Preference in Fast Fashion

Fast Fashion			
	Share of Preference		
Selection Type	Online Purchase	In-Store Purchase	None (No Purchase)
Online Selection	47.5%	38.7%	13.8%
In-Store Selection	41.6%	37.5%	20.9%

Note. Results obtained from Choice Simulator of Lighthouse Studio 9.16.0

For consumers of luxury fashion (see Table 28), online selection leads to higher share of preference for online purchases (27.50%) compared to in-store selection (23.70%). In-store purchases remain the preferred channel regardless of selection type. The opt-out share of preference ("None") is higher for in-store selection (15.90%) than online selection (10.40%).

Table 28

The Impact of Selection Channel on Purchase Channel Preference in Luxury Fashion

Luxury Fashion			
	Share of Preference		
Selection Type	Online Purchase	In-Store Purchase	None (No Purchase)
Online Selection	27.5%	62.1%	10.4%
In-Store Selection	23.7%	60.3%	15.9%

Note. Results obtained from Choice Simulator of Lighthouse Studio 9.16.0

The Impact of Delivery Policy on Purchase Channel Preference

The market simulation explores how different delivery policies (free standard shipping, paid standard shipping, and paid express shipping) impact consumers' share of preference for online versus in-store purchases.

To determine whether the differences in shares of preference across delivery policies are statistically significant, Sawtooth recommends using the confidence intervals provided by the market simulator. Assuming the sample is representative of the population, there is 95% confidence that the true population lies within the estimated interval. When the confidence intervals for two alternatives do not overlap, it can be concluded with 95% confidence that a statistically significant difference in preference exists between them (Sawtooth Software, 2024). The market simulator shows no overlapping confidence intervals between online and in-store purchases in both the fast fashion and luxury fashion industries, indicating statistically significant differences in shares of preference. Refer to Appendix C for the full summary of the confidence intervals and respective standard errors.

In the fast fashion scenario (see Table 29), consumer’s share for preference for online purchases is higher when standard delivery is free (47.50%). However, once a shipping fee is introduced, the share of preference for online purchases drops, from 47.50% (free standard) to 11.90% (paid standard) and 5.70% (paid express). Paid shipping policies shift share of preference towards in-store purchases (70.20% for paid standard and 73.50% for paid express). Higher shipping costs also increase opt-out share of preference ("None"), with 20.80% of consumers choosing not to make a purchase.

Table 29
The Impact of Delivery Policy on Purchase Channel Preference in Fast Fashion

Fast Fashion	
Type of Purchase	Share of Preference
Online Purchases and Free Standard Delivery	47.5%
In-store Purchase	38.7%
None	13.8%
Online Purchases and Paid Standard Delivery	11.9%
In-store Purchase	70.2%
None	17.9%
Online Purchases and Paid Express Delivery	5.7%
In-store Purchase	73.5%
None	20.8%

Note. Results obtained from Choice Simulator of Lighthouse Studio 9.16.0

Table 30 shows the impact of delivery policy on purchase channels preference for luxury fashion consumers. Even with free shipping, consumers share of preference for in-store purchases (60.30%) is higher than online purchases (23.70%). Paid shipping discourages online purchases, dropping to 11.40% (paid standard) and just 5.30% (paid express). Paid express shipping results in the highest opt-out share of preference (24%).

Table 30
The Impact of Delivery Policy on Purchase Channel Preference in Luxury Fashion

Luxury Fashion	
Type of Purchase	Share of Preference
Online Purchases and Free Standard Delivery	23.7%
In-store Purchase	60.3%
None	15.9%
Online Purchases and Paid Standard Delivery	11.4%
In-store Purchase	68.6%
None	20.0%
Online Purchases and Paid Express Delivery	5.3%
In-store Purchase	70.7%
None	24.0%

Note. Results obtained from Choice Simulator of Lighthouse Studio 9.16.0

The Impact of Return Policy on Purchase Channel Preference

This market simulation explores how different return policies (free postal drop-off, paid postal drop-off, and in-store returns) influence the share of preference for purchase channels across the fast fashion and luxury fashion industries. In the luxury fashion scenario, the market simulator shows no overlapping confidence intervals between online and in-store purchases, indicating statistically significant differences in share of preference. In the fast fashion scenario, confidence interval overlaps lie between online purchases with paid postal drop-off and in-store purchases, as well as between online purchases with in-store returns and in-store purchases. These overlaps suggest no statistically significant differences in those cases. However, for online purchases with free postal drop-off versus in-store purchases, no overlap in confidence intervals is observed, indicating with 95% confidence, that a statistically significant difference in preference exists between these two channels. Refer to Appendix D for the full summary of the confidence intervals and respective standard errors.

For fast fashion consumers (Table 31), free postal drop-off return policy leads to a higher share of preference for online purchases (47.5%) than in-store purchases (38.7%).

Table 31
The Impact of Return Policy on Purchase Channel Preference in Fast Fashion

Fast Fashion

Type of Purchase	Share of Preference
Online Purchases and Free Postal Drop-Off	47.5%
In-store Purchase	38.7%
None	13.8%
Online Purchases and Paid Postal Drop-Off	39.8%
In-store Purchase	46.3%
None	13.9%
Online Purchases and In-Store Returns	41.1%
In-store Purchase	44.5%
None	14.3%

Note. Results obtained from Choice Simulator of Lighthouse Studio 9.16.0

For luxury fashion (see Table 32) even with free postal drop-offs, the share of preference for in-store purchases (60.3%) still higher than online purchases (23.7%). Paid postal returns reduce online shopping preference even more (20.40%) and increase in-store preference (62.4%).

Table 32

The Impact of Return Policy on Purchase Channel Preference in Luxury Fashion

Luxury Fashion	
Type of Purchase	Share of Preference
Online Purchases and Free Postal Drop-Off	23.7%
In-store Purchase	60.3%
None	15.9%
Online Purchases and Paid Postal Drop-Off	20.4%
In-store Purchase	62.4%
None	17.2%
Online Purchases and In-Store Returns	21.7%
In-store Purchase	62.0%
None	16.3%

Note. Results obtained from Choice Simulator of Lighthouse Studio 9.16.0

4.4 Socio-demographic Influences on Online Purchase Intention

The descriptive analysis explores socio-demographic differences, highlighting variations in purchase intentions across channels. The choice simulator of Lighthouse Studio 9.16.0 allows for segmentation variables with the conjoint part-worths. The choice simulator uses the part-worth utilities at the individual levels to investigate how purchase scenarios appeal to different groups of segments.

To identify significant differences between demographic groups, a two-tailed t-test and ANOVA are conducted in RStudio and the corresponding p-values are reported. If the p-value is smaller than 0.05, it indicates statistically significant differences between the means of different demographic groups. A two-tailed t-test is used when comparing two groups, while ANOVA, similarly to the t-test, is used to compare differences between mean estimates across more than two groups (Herzog et al., 2019).

Part-worth utility reports of individual respondents are used in the analysis to examine whether socio-demographic factors influence online purchase intention.

1. Gender

The sample includes 52 male respondents and 113 female respondents, representing the two gender groups under analysis. The results of the two-tailed t-test conducted in RStudio are as follows:

Fast Fashion Scenario

t = 0.16288, df = 79.081, p-value = 0.871
alternative hypothesis: true difference in means between group female and group male is not equal to 0
95 percent confidence interval: [-17.19, 20.25]
sample estimates:
mean in group female mean in group male
-52.35770 -53.88942

Luxury Fashion Scenario

t = 0.27096, df = 71.834, p-value = 0.7872
alternative hypothesis: true difference in means between group 1 and group 2 is not equal to 0
95 percent confidence interval: : [-18.67, 24.54]
sample estimates:
mean in group 1 mean in group 2
-57.95209 -60.88928

Since the p-values in both scenarios (0.871 for the fast fashion scenario and 0.7872 for the luxury fashion scenario) are greater than 0.05, there is no statistically significant difference in mean online purchase intention between female and male groups.

2. Age

The sample includes 35 Gen. Z respondents, 95 Millennials, and 31 Gen. X respondents, representing the three age groups under analysis. Age groups with fewer than 30 respondents are excluded from the analysis. The results of the ANOVA test conducted in RStudio are as follows:

Fast Fashion Scenario

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
as.factor(age)	2	8344	4172	1.719	0.183
Residuals	158	383538	2427		

Luxury Fashion Scenario

	Df	Sum Sq	Mean Sq	F value	Pr(>F)	
as.factor(age)	2	16678	8339	2.715	0.069	.
Residuals	158	485282	3071			

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

The results indicate no statistically significant findings in the fast fashion scenario, whereas the luxury fashion scenario demonstrates a statistically significant effect.

For the luxury fashion scenario, a market simulation of purchase channel preferences across age groups is presented in Table 33. In the luxury fashion scenario consumers' share of preference for in-store purchases is higher across all age groups. Older and younger generation have a higher share of preference for in-store purchases.

Table 33
Purchase Channel Preference by Age

	Share of Preference		
Label	online purchase	in-store purchase	None
Total	25.4%	64.5%	10.1%
Gen. Z	27.5%	66.3%	6.2%
Millennials	27.2%	59.9%	12.9%
Gen. X	18.4%	76.5%	5.0%

Note. Results obtained from Choice Simulator of Lighthouse Studio 9.16.0

3. *Income*

The sample includes 39 respondents from income group €26,000–€32,000, 38 respondents from income group €32,000–€37,000, and 32 respondents from income group €37,000–€48,000. Income groups with fewer than 30 respondents are excluded from the analysis. The results of the ANOVA test conducted in RStudio are as follows:

Fast Fashion Scenario

	Df	Sum Sq	Mean Sq	F value	Pr(>F)	
as.factor(income)	2	17952	8976	10.58	0.0001	***
Residuals	106	89958	849			

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Luxury Fashion Scenario

	Df	Sum Sq	Mean Sq	F value	Pr(>F)	
as.factor(income)	2	70488	35244	13.15	0.0000	***
Residuals	106	284107	2680			

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

The results indicate statistically significant differences in mean online purchase intention between income groups in both scenarios. The conjoint choice simulator results in Table 34 provide insights into purchase channel preferences for fast fashion and luxury fashion items, broken down by income.

In the fast fashion scenario, online shopping is the dominant purchase channel across all income groups, with the share of preference for online purchases increasing as income rises.

In the luxury fashion scenario, consumers' share of preference for in-store purchases is higher across all income groups, with the share of preferences increasing with higher incomes. High earners show the highest preference for in-store purchases, with a share of 77%. Compared to other income groups, lower-income groups are more likely to select the "None" option in both scenarios.

Table 34
Purchase Channel Preference by Income

	Share of Preference					
	Fast Fashion			Luxury Fashion		
Label	online purchase	in-store purchase	None	online purchase	in-store purchase	None
Total	49.4%	40.3%	10.3%	25.4%	64.5%	10.1%
€26,000–€32,000	41.4%	34.2%	24.4%	35.2%	41.3%	23.5%
€32,000–€37,000	50.8%	40.3%	8.9%	24.2%	67.5%	8.3%
€37,000–€48,000	55.1%	42.7%	2.2%	18.6%	77.0%	4.4%

Note. Results obtained from Choice Simulator of Lighthouse Studio 9.16.0

For a more detailed overview of average part-worth utilities and attribute importance of demographic sub-groups, a utility report can be found in Appendix E.

5 Discussion and Limitation of the Research

This study aims to explore how the promotion and place elements of the marketing mix influence customer's online purchase intention in the fast fashion industry compared to the luxury fashion industry.

5.1 Discussion of Results

The purpose of this research is to study how do place and promotion elements of the marketing mix influence customers' online purchase intentions in the fast fashion industry compared to the luxury fashion industry. Demographic variables are accounted as control variables for in the analysis of purchase channel preferences.

The Role of Price in Purchase Intention

Based on the counting analysis, the price attribute shows statistically significant effect for the luxury fashion scenario at the .01 significance level. In the luxury fashion scenario, the highest contribution to the utility lies at the lowest price point of €500. The market simulation shows that in-store purchases remain dominant but decline with higher prices, suggesting that increased prices reduce consumers' purchase intent across both channels. As research, shows luxury shoppers are driven by different motivational factors. Online luxury shoppers tend to be price-conscious, whereas in-store shoppers prioritize the overall shopping experience and personal interactions (Liu et al., 2013).

The results of the descriptive statistics indicate that the most common spending range is €600–€1,000 per year (47%), followed by €1,000–€2,000 annually (28%). The cross-tabulation analysis concludes that there is no statistically significant relationship between spending amount and the preferred shopping channel. However, most participants (61%) self-reported allocating 80% of their spending online and 20% in-store.

The Impact of Promotion on Purchase Channel Preference

Descriptive statistics highlight social media usage frequency among respondents, showing that most participants (90%) use social media daily. Social media allows fashion brands to maintain a consistent brand image and interact with customers in an holistic way (Barnes, 2013). Previous research shows that frequent internet users demonstrate positive attitudes toward online shopping (Gu and Wu, 2019) and social media marketing, influencer marketing, and e-mail marketing are effective digital marketing strategies in enhancing brand awareness, purchase intention, and customer experience (Gomes et al., 2022; Odoom, 2022; Nuseir et al., 2023).

The counting analysis shows no statistically significant main effects for the promotion levels. Among digital marketing strategies, email newsletters contribute the most to utility for fast fashion consumers, followed by social media. For luxury fashion consumers, only social media exhibits a positive part-worth utility. Furthermore, promotion attributes displays a lower average importance score compared to other attributes, although it is more relevant for fast fashion consumers.

The results of the market simulations highlight how different online marketing strategies influence consumers' purchasing decisions across online and in-store channels. The simulations reveal a similar share of preference across promotion types, with online purchases being more common among fast fashion buyers. In the luxury fashion scenario, in-store purchases remain dominant across all promotion types. Social media and display advertising show slightly higher shares of preference for online purchases, although the differences are minimal.

Through digital marketing strategies, luxury brands can maintain a consistent brand image (Barnes, 2013), which is essential for creating symbolic, emotional, and social CVPs (Ilmi et al., 2023). In contrast, fast fashion brands often rely on price promotions to establish economic CVPs that are characteristic of the segment and influence purchase intention (Zhang et al., 2017).

H_1	Digital marketing strategies create a higher online purchase intention among fast fashion consumers than luxury fashion consumers.	Accepted

The Impact of Selection Channel on Purchase Channel Preference

Different customers have different shopping preferences, some value the convenience and broader selection of online shopping, while others prefer traditional stores where they can physically inspect products (Lazaris and Vrechopoulos, 2014).

E-commerce platforms provide customer benefits in terms of convenience and product availability (Chaffey et al., 2016), as well as individual recommendations based on personal fashion styles (Reinartz et al., 2019). Buyers can easily compare products, read customer reviews, and enjoy an improved quality of choice. Online shopping also helps consumers minimize the adverse effects of product unavailability in physical stores (Aiolfi & Sabbadin, 2019).

The counting analysis shows statistically significant effects at the .01 significance level for both selection and purchase channels across industries. In the fast fashion scenario, a significant interaction exists between selection and purchase channels. A significant number of consumers who consider in-store selection also choose in-store purchases, more so than those who consider online selection but purchase in-store. In the luxury fashion scenario, a significant number of consumers who consider online selection ultimately make in-store purchases.

An analysis of the part-worth utilities indicates that online selection and in-store purchases have the highest contribution to the utility. Moreover, selection and purchase attributes indicate higher importance scores among luxury fashion consumers compared to fast fashion consumers. Overall, selection and purchase attributes are less important than delivery policy in both industries.

The market simulation examines how the selection channel impacts purchase channel preference, while holding all other attribute levels constant. In the fast fashion scenario, online selection results in a higher consumers' share of preference for online purchases compared to in-store purchases. However, online purchases lead to a higher share of preference regardless of the selection channel. The results of the market simulation align with the descriptive statistics, indicating that most respondents (62%) prefer purchasing fast fashion items online, while in-store shopping is less preferred (26%). Furthermore, the majority of participants state that they allocate 80% of their spending online and 20% in-store.

As research indicates, the CVP of fast fashion brands lies in their economic value, driven by affordability (Gomes de Oliveira et al., 2022). E-commerce platforms allow consumers to easily compare prices and take advantage of online promotions and discounts (Aiolfi & Sabbadin, 2019), as well as benefit from automated communication, such as price alerts, which contribute to the creation of economic CVP representative of fast fashion brands (Reinartz et al., 2019).

On the other hand, the relationship between luxury brands and consumers is often emotional, created through memorable and enjoyable purchase experiences, shared values, and associations with brand personality and mission (Kapferer and Bastien, 2009). The results of the market simulation shows that for consumers of luxury fashion, in-store purchases remain the preferred purchase channel, regardless of the selection channel. The results align with the descriptive statistics, which indicate that consumers prefer in-store purchases over online purchases for luxury fashion items, with 45% selecting this channel.

Physical stores remain an important part of the customer's shopping journey. By enhancing the store atmosphere through design, layout, ambiance, and service, brands can positively influence the customer experience (Blázquez, 2014). An omnichannel approach can enhance customer value by providing additional services, multiple touchpoints, and a seamless, uninterrupted experience (Aiolfi and Sabbadin, 2019). Adopting an omnichannel business model, rather than focusing solely on in-store or online channels, leads to an overall increase in sales. Mobile channels, in particular, increase purchase frequency and total spending (Timoumi et al., 2022).

H_2	Online selection creates a higher online purchase intention among fast fashion consumers than luxury fashion consumers.	Accepted

The Impact of Delivery Policy on Purchase Channel Preference

The counting analysis shows statistically significant effects for delivery policy attribute at the .01 significance level across both industries. An analysis of the part-worth utilities indicates that free standard deliveries have the highest contribution to the utility. Furthermore, delivery policy is the most important attribute relative to other attributes in both fast fashion and luxury fashion scenarios.

The results align with previous research, where Nguyen et al. (2019) explore how online shoppers value different delivery attributes (such as delivery speed, delivery date, and delivery fees) when choosing a delivery option. The findings show that delivery fees are the most important attribute for consumers, followed by non-price attributes.

Research shows that a key attribute driving customer satisfaction includes on-time delivery (Uzir et al., 2021) and consumers prefer online stores that do not charge delivery fees, with the purchasing process often being abandoned when a delivery fee appears during the payment phase (Sutinen et al., 2022), the higher the shipping costs, the lower the corresponding utility (Menon and Sigurdsson, 2016).

The market simulation examines how delivery policy influences purchase channel preference, while holding all other attribute levels constant. The estimated differences in shares of preference between online and in-store purchases, based on 95% confidence intervals, indicate statistically significant effects. The results indicate that consumers' share of preference for online purchases is higher among fast fashion consumers when free standard delivery is offered. However, once a shipping fee is introduced, the preference for online purchases decreases, with consumers shifting towards in-store purchases. This suggests that consumers are more likely to visit physical stores than pay for delivery. For luxury consumers, the share of preference for in-store purchases remains higher than for online purchases, regardless of the delivery policy.

H_3	Free standard deliveries create a higher online purchase intention among fast fashion consumers than luxury fashion consumers.	accepted

The Impact of Return Policy on Purchase Channel Preference

Research indicate that a lenient return policy increases consumers perceive quality and perceived risk, ultimately increasing their purchase intention (Rokonuzzaman et al., 2021). Furthermore, free shipping is associated with a higher customer value and increase in demand (Frischmann et al., 2012).

The counting analysis does not reveal statistically significant results for the return policy attribute across both industries. Sawtooth Software recommends determining attribute importance for more accurate results using HB analysis (Sawtooth Software, 2024). An analysis of the part-worth utilities indicates that free postal drop-off has the highest contribution to utility, while other levels show negative part-worth utilities. Furthermore, an examination of the average importance scores shows that return policies are more important to fast fashion consumers than to luxury fashion consumers.

The market simulation indicates statistically significant effects at the 95% confidence interval for the differences between free postal drop-offs and in-store options across both scenarios. The results of the market simulations show that, in the fast fashion scenario, free postal drop-off return policies lead to a higher preference share for online purchases compared to in-store purchases.

For luxury fashion consumers, even with free postal drop-offs, the share of preference for in-store purchases remains higher than for online purchases. Paid postal returns further reduce the share of preference for online shopping, increasing the share of preference for in-store shopping.

H_4	Free and convenient returns create a higher online purchase intention among fast fashion consumers than luxury fashion consumers.	accepted

Demographic Differences in Purchase Channel Preferences

Market segmentation divides the market into separate groups of consumers with similar needs and can be behavioral, demographic, psychographic, or geographic in nature (Keller, 2013). A marketing strategy outlines which target customers an organization serves and how it delivers value to them (Wu and Li, 2017).

The results of the conjoint analysis show no statistically significant difference in mean online purchase intention between female and male groups. However, based on self-reported data, female participants show a higher preference for online purchases when buying fast fashion items, and a higher preference for in-store purchases when buying luxury fashion items

Among luxury fashion consumers, both older and younger generations have a higher share of preference for in-store purchases. However, the share of preference for online purchases is slightly higher among Gen Z compared to older generations (Boomers). As research shows, younger consumers spend significantly less time on purchase decisions than older consumers (D'Arpizio and Levato, 2016) and are more influenced by convenience (Alfanur and Kadono, 2022), which may lead to a higher online purchase intention. Based on self-reported data, Millennials show a higher preference for online purchases when buying fast fashion items.

Among fast fashion buyers, the preference for online purchases increases with rising income, whereas among luxury buyers, higher income is associated with a stronger preference for in-store purchases. These findings are consistent with self-reported data from the luxury fashion scenario, where high-income earners indicate a lower likelihood of shopping online. Research indicates that higher-income consumers perceive functional and symbolic value as more important than lower-income consumers (Rudawska et al., 2018), which may explain the higher share of preference for in-store purchases among high earners.

5.2 Limitations and Future Research

While the study provides valuable insights into purchase intentions in the evolving digitalization in the fast fashion and luxury fashion industries, several limitations should be acknowledged:

The conjoint analysis examines a predefined set of attributes. The chosen attributes and their associated levels are defined through an in-depth literature review and while a good overview can be gathered, other potentially relevant factors influencing online purchase intention, such as website design, user-friendly navigation, service quality, website security, and product availability (Chen et al., 2010; Watulingas, 2020), brand consciousness and brand trust (Sarin and Sharma, 2023), product quality, functionality, assortment, and variety (Schaupp and Belanger, 2005; Bai et al., 2008; Chen et al., 2010).

Researchers identified several problems with a CBC study that must be considered when analyzing the data. Scenarios might not be an ideal choice for a respondent and selection does not always reflect reality. Repetitive or similar scenarios lead to impatience and respondents tend to select scenarios very quickly (Johnson and Orme, 2007). Furthermore, conjoint market simulators can approximate share of preference under controlled conditions, assuming all relevant attributes have been measured, but fail to account for real-world factors that shape market shares (Orme, 2014).

From a statistical viewpoint, choice tasks are not a very efficient way to learn about preferences. Respondents evaluate multiple concepts, but only select the one that they prefer. This aspect limits the study of how strong that preference is relative to other task concepts. Showing more product concepts per screen increases the information content of each task, though it increases task difficulty (Sawtooth Software, 2014).

The study relies on a convenience sample of respondents, which may not represent the broader population. Typical sample sizes start at 100 or more respondents, though most conjoint analyses involve 300 to 1,000 respondents (Sawtooth Software, 2024). A sample size should not be below 75 respondents in a conjoint analysis (McCullough, 2002).

Furthermore, certain demographic groups, such as older individuals (60+) are underrepresented, limiting the findings across all consumer segment. Furthermore, the composition of the sample is skewed for many demographic characteristics, as females, millennials, and middle-income groups are overrepresented. An imbalance in the sample can affect its representativeness and limit the generalizability of the findings (Seale et al., 2004).

Shopping habits and preferences vary significantly across regions (Jin et al., 2010). The study uses a snowballing sample method and no information about the place of living is asked in the survey, which may not capture cultural and regional differences in consumer behavior globally.

Another limitation lies in potential biases leading to a misrepresentation of the population sample. Self-selection bias can occur, as respondents with a particular interest in fashion may have been more likely to participate. Furthermore, a response bias leads to respondents not providing accurate answers (Elston, 2021). Response bias is the observer's tendency to favor one response over others (Macmillan and Creelman, 1990). For example, respondents who favor online or in-store shopping, might not take into account other attributes presented and only select their preferred option.

An alternative approach was employed in the CBC analysis, which involved omitting information regarding delivery type and return policy for in-store purchases in the questionnaire. This approach was necessary to ensure that the scenarios accurately reflect real-life buying situations, where such attributes are not applicable to in-store purchases. Prior to the survey's publishing, a pilot study with seven respondents was conducted to confirm that participants clearly understood the tasks. For these respondents, the absence of this information did not lead to confusion and it was understood that in-store purchases do not involve delivery services or postal drop-off returns.

While the study investigates interactions between selection and purchase channels, it does not fully explore the complexity of omnichannel behaviors, such as how consumers switching between online and offline touchpoints during the shopping journey (Lazaris and Vrechopoulos, 2014).

Finally, the study focuses on two segments of the fashion industry lying at the opposite sides of the spectrum and does not take into account other segments in the fashion industry, such as premium or niche brands (Kotler et al., 2022).

Future Research Directions

To build upon the findings and address the limitations, future research can explore the following areas, such as expanding the sample size and collecting data from a more diverse and representative sample across different regions, age groups, and income levels to improve the significance of the results.

To provide a more holistic picture of consumer preferences, the conjoint analysis can be extended to include other attributes that might impact online purchase intention. Further research can also consider CVPs across different regions and cultures to identify differences.

Digitalization is continually evolving, and AI is becoming increasingly important in reshaping the fashion industry (Mishra et al., 2025). Future research should consider new emerging technologies involving AI impacting the digital transformation in the fashion industry.

By addressing these limitations and pursuing the outlined research directions, future studies can provide a more comprehensive understanding of consumer behavior in the digital era and implement effective strategies for both fast fashion and luxury fashion industries.

6 Conclusion

Digital transformation motivates fashion brands to rethink their business models and encourages innovation by leveraging digital technologies to achieve their goals (Bertola and Teunissen, 2018). Digital technologies create new distribution channels and new ways to create and deliver value to customer segments (Matarazzo et al., 2021).

The aim of this study is to investigate how specific elements of the marketing mix most impacted by digitalization, namely promotion and place, influence customers' online purchase intentions in the fast fashion industry and luxury fashion industry. As the fast fashion and luxury fashion industries represent different customer values, their effects on consumer shopping behavior will differ (Hsin Chang and Wang, 2011).

The results of the conjoint analysis show that changes in price have no impact on purchase channel preferences in the fast fashion industry, while in the luxury fashion scenario, higher prices reduce consumers' purchase intent across channels. However, price promotions have a significant impact on consumers' purchasing intentions (Zhang et al., 2017). Through digital marketing, fast fashion brands can make customers aware of online promotions and new collections, leading to increased sales (Wang, 2024), thereby influencing the online purchase intentions of fast fashion consumers.

Online shopping allows consumers to easily compare prices and take advantage of online promotions and discounts (Aiolfi and Sabbadin, 2019), leading to the creation of an economic CVP representative of fast fashion brands. The results of the conjoint analysis show that fast fashion consumers have a higher share of preference for online purchases, regardless of the selection channel.

Luxury fashion consumers, on the other hand, show a higher share of preference for in-store shopping, regardless of the selection channel, indicating that physical stores remain an important part of the customer's shopping journey. This aspect can be explained by the fact that the luxury fashion industry is accompanied by personalized service, which gives the buyer a sense of privilege (Kapferer and Bastien, 2009).

In the fast fashion scenario, free standard shipping increases the share of preference for online purchases. Paid shipping policies shift preference toward in-store purchases, indicating that consumers likely prefer visiting physical stores rather than paying for delivery. For luxury fashion consumers, even with free shipping, in-store shopping remains the preferred option. A "click-and-collect" system, in which consumers buy online and pick up their package in-store or at a warehouse, can offer greater flexibility and cost-effectiveness by reducing shipping fees (Cotarelo et al., 2024).

Return policies have minimal impact on purchase channel preferences. However, free and convenient returns create a higher online purchase intention among fast fashion consumers than luxury fashion consumers. Return policies are more important for fast fashion buyers than for luxury buyers, highlighting the importance of convenient return options for these customers.

In summary, this study aims to help fast fashion and luxury fashion brands construct the most effective marketing strategies for their target customers. Fast fashion brands should prioritize developing their e-commerce platforms to enhance convenience, product availability, and the user experience (UX) and user interface (UI) in online shops, as research shows these factors improve customer satisfaction (Chaffey and Ellis-Chadwick, 2019; Watulingas, 2020). They should also leverage digital marketing strategies to promote price promotions (Zhang et al., 2017).

Luxury brands should pay attention to the emerging segment of online luxury consumers and focus on integrating online shops with physical stores, creating opportunities to offer diverse services and address different customer segments.

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Appendices

Appendix A: Screenshots of the Questionnaire

Welcome!

Thank you for volunteering to participate in my research study!

Your insights are invaluable in helping us understand today's dynamic fashion world. As online shopping continues to grow, it's essential to learn more about how consumers like you engage with fashion brands, make purchasing decisions, and navigate the digital shopping experience.

I take the protection of your personal data as part of this survey very seriously. Your data is anonymous and analyzed in aggregated form, and is used solely for the purpose of this study. Your data is only collected and processed on the basis of legal provisions (section 2f, para. 5 of the Austrian research organisation act, Forschungsorganisationsgesetz, FOG).

This survey should take about 12 minutes to complete.

Next

How often do you shop for **fashion items** (clothing, shoes or accessories)?

- ◯ weekly
- ◯ bi-weekly
- ◯ monthly
- ◯ seasonally
- ◯ yearly
- ◯ I don't shop fashion

How do you prefer to buy **fast fashion** items?

- ◯ online
- ◯ in-store
- ◯ I don't have a preference
- ◯ I don't buy fast fashion items

How do you prefer to buy **luxury fashion** items?

- ◯ online
- ◯ in-store
- ◯ I don't have a preference
- ◯ I don't buy luxury fashion items

How much do you usually spend on **fashion items** per year?

- ◯ less than €100
- ◯ €100 – €300
- ◯ €300 – €600
- ◯ €600 – €1.000
- ◯ €1.000 – €2.000
- ◯ €2.000 – €5.000
- ◯ €5,000 and above

In which proportion do you spend the above amount?

- ◯ 0% online - 100% in-store
- ◯ 20% online - 80% in-store
- ◯ 50% online - 50% in-store
- ◯ 80% online - 20% in-store
- ◯ 100% online - 0% in-store

How often do you use social media channels such as Instagram, Facebook or YouTube?

- ◯ everyday
- ◯ several times a week
- ◯ several times a month
- ◯ I don't use social media

Back Next

Imagine you are considering buying fashion items from a **fast fashion** retailer of your preference. Some examples: it can be a T-shirt from Zara, a dress from Zalando, or shoes from ASOS. It is not important what you're buying or from which fast fashion retailer. We are interested in your preferences in terms of in-store vs. online shopping, delivery type, return policy, and the type of online promotion used by the brand.

In the next section, we ask you to select from a set of alternatives the most preferred one. Should no alternative offered in the set meet your preferences, you can indicate that by choosing the option "None".

Back Next

0% 100%

You intend to buy a product from a **fast fashion** retailer. If these were your alternatives, which one would you select?

(6 of 7)

price	25 €	25 €	50 €
the brand is advertised through	influencer	influencer	newsletter
you are looking for the product	in-store	in-store	online
you are buying	in-store	online	online
delivery policy		paid express	free standard
return policy		paid postal drop-off	in-store
	Select	Select	Select

NONE: I wouldn't choose any of these.

Select

Now imagine the scenario of buying fashion items from a **luxury fashion** retailer. Some examples: it can be a necklace from Cartier, a sweater from Dior, or a handbag from Chanel. Again, it is not important what you're buying or from which luxury fashion retailer.

We are interested in your preferences in terms of in-store vs. online shopping, delivery type, return policy, and the type of online promotion used by the brand.

Which option would select?

Back Next

0% 100%

You intend to buy a fashion item from a **luxury fashion** retailer. If these were your alternatives, which one would you select?

(3 of 7)

price	2.000 €	1.000 €	2.000 €
the brand is advertised through	brand's account	influencer	influencer
you are looking for the product	in-store	online	online
you are buying	in-store	in-store	online
delivery policy			free standard
return policy			free postal drop-off
	Select	Select	Select

NONE: I wouldn't choose any of these.

Select

Thank you for selecting your options.

Please indicate your age.

- ○ younger than 27
- ● 28-43
- ○ 44-59
- ○ 60 or older

Gender

- ○ male
- ● female
- ○ diverse
- ○ I prefer not to say

What was your total net income for the last calendar year?

- ○ Less than €18,000
- ○ €18,000 - €26.000
- ● €26,000 - €32.000
- ○ €32,000 - €37.000
- ○ €37,000 - €48.000
- ○ €48,000 and above
- ○ I don't want to share

Back Next

0% 100%

You have now reached the end of the questionnaire. If you have any questions about the content, purpose or research ethics of this survey, or if you are interested in the results of the study, please contact Daria Cocos at a01305521@unet.univie.ac.at.

I would like to thank you again for your time and effort!

0% 100%

Appendix B. Aggregate Logit Analysis

Fast Fashion Scenario

Log-likelihood for this model	-1305.35
Log-likelihood for null model	-1601.17
Difference	295.82
Percent Certainty	18.48
Akaike Info Criterion	2634.7
Consistent Akaike Info Criterion	2707.33
Bayesian Information Criterion	2695.33
Adjusted Bayesian Info Criterion	2657.21
Chi-Square	591.64
Relative Chi-Square	49.3

Note. Results obtained from Analysis Manager of Lighthouse Studio 9.16.0

Luxury Fashion Scenario

Log-likelihood for this model	-1284.5
Log-likelihood for null model	-1601.17
Difference	316.67
Percent Certainty	19.78
Akaike Info Criterion	2593
Consistent Akaike Info Criterion	2665.62
Bayesian Information Criterion	2653.62
Adjusted Bayesian Info Criterion	2615.5
Chi-Square	633.34
Relative Chi-Square	52.78

Note. Results obtained from Analysis Manager of Lighthouse Studio 9.16.0

Appendix C: Evaluating the Effect of Delivery Policies on Shares of Preference Using Confidence Intervals

Fast Fashion Scenario

Free standard shipping

Label	Shares of Preference	Std Error	Lower 95% CI	Upper 95% CI
online purchase	47.5%	1.9%	43.7%	51.3%
in-store purchase	38.7%	1.7%	35.4%	42.1%
None	13.8%	1.7%	10.4%	17.1%

Paid standard shipping

Label	Shares of Preference	Std Error	Lower 95% CI	Upper 95% CI
online purchase	11.9%	1.4%	9.2%	14.6%
in-store purchase	70.2%	2.5%	65.3%	75.1%
None	17.9%	1.6%	14.7%	21.1%

Paid express shipping

Label	Shares of Preference	Std Error	Lower 95% CI	Upper 95% CI
online purchase	5.7%	0.9%	4.0%	7.5%
in-store purchase	73.5%	2.4%	68.8%	78.1%
None	20.8%	1.8%	17.2%	24.3%

Luxury Fashion Scenario

Free standard shipping

Label	Shares of Preference	Std Error	Lower 95% CI	Upper 95% CI
online purchase	27.5%	1.9%	23.8%	31.1%
in-store purchase	62.1%	2.4%	57.4%	66.8%
None	10.4%	1.3%	7.8%	13.1%

Paid standard shipping

Label	Shares of Preference	Std Error	Lower 95% CI	Upper 95% CI
online purchase	14.3%	1.8%	10.8%	17.9%
in-store purchase	73.7%	2.5%	68.7%	78.7%
None	12.0%	1.4%	9.3%	14.6%

Paid express shipping

Label	Shares of Preference	Std Error	Lower 95% CI	Upper 95% CI
online purchase	5.7%	1.0%	3.8%	7.6%
in-store purchase	78.7%	2.2%	74.3%	83.0%
None	15.7%	1.6%	12.6%	18.8%

Note. Results obtained from Choice Simulator of Lighthouse Studio 9.16.0

Appendix D: Evaluating the Effect of Return Policies on Shares of Preference Using Confidence Intervals

Fast Fashion Scenario

Free postal drop-off

Label	Shares of Preference	Std Error	Lower 95% CI	Upper 95% CI
online purchase	47.5%	1.9%	43.7%	51.3%
in-store purchase	38.7%	1.7%	35.4%	42.1%
None	13.8%	1.7%	10.4%	17.1%

Paid postal drop-off

Label	Shares of Preference	Std Error	Lower 95% CI	Upper 95% CI
online purchase	39.8%	1.9%	36.0%	43.7%
in-store purchase	46.3%	2.0%	42.4%	50.2%
None	13.9%	1.7%	10.6%	17.1%

In-store return

Label	Shares of Preference	Std Error	Lower 95% CI	Upper 95% CI
online purchase	41.1%	2.1%	37.0%	45.3%
in-store purchase	44.5%	2.0%	40.6%	48.5%
None	14.3%	1.8%	10.8%	17.8%

Luxury Fashion Scenario

Free postal drop-off

Label	Shares of Preference	Std Error	Lower 95% CI	Upper 95% CI
online purchase	23.7%	1.5%	20.8%	26.7%
in-store purchase	60.3%	2.4%	55.7%	65.0%
None	15.9%	1.3%	13.3%	18.6%

Paid postal drop-off

Label	Shares of Preference	Std Error	Lower 95% CI	Upper 95% CI
online purchase	20.4%	1.3%	17.9%	23.0%
in-store purchase	62.4%	2.3%	57.8%	67.0%
None	17.2%	1.4%	14.5%	19.9%

In-store return

Label	Shares of Preference	Std Error	Lower 95% CI	Upper 95% CI
online purchase	21.7%	1.5%	18.6%	24.7%
in-store purchase	62.0%	2.4%	57.2%	66.8%
None	16.3%	1.3%	13.7%	19.0%

Note. Results obtained from Choice Simulator of Lighthouse Studio 9.16.0

Appendix E: Part-Worth Utilities of Demographic Segments

Average Utility Values (by Gender)

		Fast Fashion		*Luxury Fashion*	
Attribute	Label	Male	Female	male	Female
Price	€25 / €500	11.78	8.55	35.59	38.14
	€50 / €1,000	-17.88	-12.54	14.47	12.43
	€75 / €2,000	6.11	3.99	-50.06	-50.57
Promotion	social media	3.07	8.79	6.87	9.3
	Influencer	-11.89	-10.51	-3.44	-6.91
	e-mail newsletter	9.05	10.88	0.86	-4.36
	display advertising	-0.23	-9.15	-4.29	1.97
Selection	in-store	-20.2	-26.42	-22.87	-27.35
	online selection	20.2	26.42	22.87	27.35
Purchase	in-store	53.89	52.36	58.26	60.63
	online purchase	-53.89	-52.36	-58.26	-60.63
delivery policy	free standard	102.57	115.89	83.11	89.04
	paid standard	-25.15	-20.68	1.14	-2.15
	paid express	-77.43	-95.2	-84.25	-86.9
return policy	free postal drop-off	8.99	14.01	1.86	4.43
	paid postal drop-off	1.22	-9.77	-0.72	-3.89
	in-store	-10.21	-4.24	-1.14	-0.54
	None	-8.62	-14.76	20.78	14.54

Note. Results obtained from Analysis Manager of Lighthouse Studio 9.16.0

Average Importances (by Gender)

	Fast Fashion		*Luxury Fashion*	
Attribute	Male	female	male	female
price	9.26	8.24	18.04	18.01
promotion	10.51	11.48	6.64	8.22
selection	10.35	10.81	10.84	12.39
purchase	23.39	20.5	28.07	22.99
delivery policy	36.53	38.91	30.24	31.2
return policy	9.95	10.05	6.18	7.18

Note. Results obtained from Analysis Manager of Lighthouse Studio 9.16.0

Average Utility Values (by Age)

		Fast Fashion			Luxury Fashion		
Attribute	Label	younger than 27	28-43	44-59	younger than 27	28-43	44-59
price	€25 / €500	7.94	9	9.07	27.18	41.21	34.91
	€50 / €1,000	-15.71	-16.39	-3.27	10.6	10.65	21.3
	€75 / €2,000	7.77	7.39	-5.8	-37.78	-51.86	-56.22
promotion	social media	2.33	10.77	5.26	5.28	10.51	5.47
	Influencer	-9.69	-14.38	-9.12	-0.24	-10.05	1.77
	e-mail newsletter	6.05	12.01	10.81	-4.55	-3.04	-1.91
	display advertising	1.31	-8.4	-6.94	-0.49	2.58	-5.33
selection	in-store	-22.79	-25.7	-26.06	-38.31	-20.53	-31.97
	online selection	22.79	25.7	26.06	38.31	20.53	31.97
purchase	in-store	54.91	48.54	66.53	59.06	52.49	78.28
	online purchase	-54.91	-48.54	-66.53	-59.06	-52.49	-78.28
delivery policy	free standard	112.63	109.84	128.79	85.38	83.1	98.46
	paid standard	-25.88	-21.5	-22.26	7.45	-1.1	-5.16
	paid express	-86.75	-88.34	-106.53	-92.83	-82	-93.3
return policy	free postal drop-off	10.17	13.47	11.82	1.57	4.02	7.56
	paid postal drop-off	-2.92	-4.46	-12.76	1.6	-5.69	0.76
	in-store	-7.24	-9.01	0.94	-3.17	1.68	-8.32
	None	-27.97	-7.04	-26.62	-6.57	28.49	-2.38

Note. Results obtained from Analysis Manager of Lighthouse Studio 9.16.0

Average Importances (by Segment)

	Fast Fashion			*Luxury Fashion*		
Attribute	younger than 27	28-43	44-59	younger than 27	28-43	44-59
price	8.79	8.77	6.83	15.34	19.18	16.93
promotion	9.92	12.17	9.03	7.38	8.86	4.92
selection	10.07	10.76	11.15	13.15	11.95	11.42
purchase	22.26	19.6	25.46	24.99	22.39	29.92
delivery policy	39.31	37.7	40.07	31.43	30.23	32.55
return policy	9.65	11	7.46	7.72	7.39	4.26

Average Utility Values (by Income)

		Fast Fashion			Luxury Fashion		
Attribute	Label	€20,000 - €39.000	€40,000 - €59.000	€60,000 - €79.000	€20,000 - €39.000	€40,000 - €59.000	€60,000 - €79.000
price	€25 / €500	6.7	16.47	14.43	34.58	33.35	44.82
	€50 / €1,000	-18.5	-31.77	-13.16	6.44	2.02	19.3
	€75 / €2,000	11.8	15.31	-1.28	-41.02	-35.37	-64.12
Promotion	social media	-8.17	13.45	-1.02	9.17	13.77	7.31
	influencer	-8.27	-9.77	-9.18	-8.04	-16.2	-6.61
	e-mail newsletter	9.72	10.89	12.36	-6.47	-8.35	4.51
	display advertising	6.73	-14.57	-2.15	5.33	10.79	-5.21
selection	in-store	-17.62	-13.33	-22.09	-33.14	-3.01	-28.72
	online selection	17.62	13.33	22.09	33.14	3.01	28.72
purchase	in-store	56.44	20.67	58.79	55.64	20.38	63.87
	online purchase	-56.44	-20.67	-58.79	-55.64	-20.38	-63.87
delivery policy	free standard	98.62	59.38	115.23	78.98	59.84	97.06
	paid standard	-29.37	-11.61	-26.12	9.03	1.99	-4.16
	paid express	-69.26	-47.77	-89.12	-88.01	-61.82	-92.9
return policy	free postal drop-off	14.92	16.94	11.73	6.49	-3.86	8.67
	paid postal drop-off	5.17	-4.12	-8.42	-0.44	-10.9	-2.98
	in-store	-20.09	-12.82	-3.3	-6.04	14.76	-5.7
	None	-22	29.08	-12.87	22.26	46.64	27.41

Note. Results obtained from Analysis Manager of Lighthouse Studio 9.16.0

Average Importances (by Income)

	Fast Fashion			*Luxury Fashion*		
Attribute	€20,000 - €39.000	€40,000 - €59.000	€60,000 - €79.000	€20,000 - €39.000	€40,000 - €59.000	€60,000 - €79.000
price	9.5	14.58	8.79	18.07	19.57	19.08
promotion	11.57	17.98	10.27	10.04	13.34	6.44
selection	8.77	9.44	10.72	11.72	11.46	11.38
purchase	20.79	14.12	22.07	22.28	16.59	24.93
delivery policy	37.96	27.25	39.42	29.98	26.51	32.47
return policy	11.42	16.63	8.73	7.9	12.53	5.7

Note. Results obtained from Analysis Manager of Lighthouse Studio 9.16.0