Analysing the Modest Fashion Market: An Empirical Study of E-commerce Best-Selling Products

Abstract

Purpose

This study examines the dynamics of the modesty-conscious market within the global fashion industry. Specifically, the research aims to understand and analyse the preferences of consumers in this market segment and provide guidance for fashion companies seeking to engage with this sizable audience.

Study Design/Methodology

Utilising a mono-method quantitative research approach, this study analyses fashion datasets obtained from e-commerce websites, employing a comprehensive big data analytics framework.

Findings

The findings highlight a persistent and growing demand for modest fashion, displaying resilience in the face of challenges presented by the COVID-19 pandemic. Modest shoppers demonstrate price sensitivity, and their preference for premium brands over affordable ones varies considerably. Crucial factors contributing to the success of modest clothing as best-sellers include price, retailer, colour, and fabric, while the discount feature holds less significant importance.

Originality

This research contributes to the academic literature on modest fashion by employing a unique combination of exploratory data analysis and machine learning techniques with fashion e-commerce datasets. The study addresses a gap in use of big data within this field, providing novel insights into consumer demand for modest garments.

Value

This study challenges the prevailing assumption that modest fashion consumers prioritize premium pricing, offering fresh insights into their price sensitivity across both mass-market and luxury segments. It contributes to the literature on consumer behavior in niche fashion markets and introduces a theoretical framework for understanding the intersection of fashion, culture, and consumer economics within the context of modest fashion.

Research Limitation

While this research provides significant insights, it is important to acknowledge its limitations. The study relies on data gathered from certain e-commerce websites, and specific nuances of consumer behaviour may not be fully captured. Additionally, the scope is limited to a specific timeframe and may not account for long-term market shifts.

Practical Implications

Fashion companies could use the results of this study to customise their strategy for engaging the modesty-conscious demographic. Comprehending the significance of elements such as price, retailer, colour, and fabric can allow firms to enhance their product offerings and marketing strategies.

Social Implications

The study highlights the social ramifications of the modesty-focused industry, stressing the changing tastes and requirements of customers within this sector. By aligning their strategies with these societal shifts, fashion companies can contribute to a more inclusive and diverse industry landscape.

Keywords: Modest Fashion Marketing, Machine Learning in Fashion, Data-Driven Fashion Strategies, Consumer Behavior Analytics, Modesty-Conscious Apparel

1. Introduction

The fashion industry experienced significant disruptions and challenges over the past five years partly due to the COVID-19 pandemic. According to a report by The Business of Fashion and McKinsey & Company (2021), the industry's profit plummeted during COVID-19. However, one of the sectors that experienced significant growth was e-commerce retail sales, with an increase of USD 0.897 to USD 4.248, accounting for a 26.7% increase in the year 2020 compared to a 12.37% increase in the year before (Chevalier, 2024). Edge by Ascential (2022) forecasts that e-commerce will account for approximately 40% of chain retail sales by 2026. As a result, brick-and-mortar retail sales are expected to decline gradually. This shift towards online retail has been accelerated by lockdown measures and changes in consumer behaviour during the pandemic.

In addition to the overall growth in e-commerce, there is a specific market segment within the fashion industry that has been thriving which is the modest fashion industry. Modest fashion refers to clothing that adheres to certain modesty standards, such as loose-fitting garments and headscarves for women (Esposito 2020). The global modest fashion industry was valued at $283 billion in 2018 and is expected to reach $402 billion by the end of 2024 (The Economist, 2020). A major catalyst behind this growth is the substantial expenditure within the Muslim consumer market, commonly known as "Generation M," contributing a noteworthy $44 billion to the overall $1.9 tr global Muslim market (Usher, 2018). The internet has played a crucial role in enabling these consumers to express their preferences and demands for modest fashion options.

In response to the impact of the pandemic, brands increasingly turn to e-commerce and social media platforms like Facebook and WhatsApp to showcase products (Sumarliah et al., 2021). Numerous fashion brands rely on e-retailer platforms such as Amazon, JD.com, or Alibaba to generate online revenue due to the absence of their proprietary e-commerce platforms (Ingram, 2020). These companies focus on the most selling products to maximise their profit, but they lack a comprehensive understanding of product success factors that can help long-term growth.

Consequently, there is a need for diverse measurement tools to optimize revenue generation from e-commerce.

Internet and social media platforms provide fashion retailers with information about consumer behaviour and preferences. The changing landscape of internet usage has allowed billions of users to not only browse and shop online but also access fashion brands' information and services and communicate with them on social media (Ren et al., 2018). The rise of online activity has generated a wealth of data, offering businesses invaluable insights into customer behavior and strategies for improvement. However, the data collected from the internet is often vast, incomplete, noisy, obscure, and random, which presents challenges in effectively utilizing it for business purposes (Russom, 2011).

While online shopping and the modest fashion industry continue to grow, there's still a need for a deeper look into the factors driving this sector. Although research has focused on the expansion of e-commerce and broader fashion trends, the specific dynamics of modest fashion have largely been overlooked. With so much available information on the rise of e-commerce and changing customer habits (Fisher and Raman, 2018; Chevalier, 2024), it's surprising that we still lack comprehensive data on how modest fashion performs in this booming online market.

Research is needed to have a deeper understanding of the modest fashion business, which is defined by its conformance to certain modesty standards and its significant growth driven by Muslim customers (Randeree, 2020; Kamarulzaman and Shaari, 2023). Online modest clothing shopping is on the rise, but very little is known about this demographic or what makes them special (Asmawi et al., 2024). Neither the relative success of mass-market nor luxury brands nor the sensitivity of consumers to price nor their preferences for certain product qualities have been thoroughly investigated in the context of modest fashion (Zainudin et al., 2020; Benissan, 2021).By showing how this demographic's tastes and requirements are changing, the study elucidates the societal implications of the modesty-conscious sector. This abundance of online activity produces massive volumes of data, also called big data, which can be utilised to understand customer behaviour and direct company plans. However, the unpredictability, breadth, incompleteness, noise, and obscurity of internet data pose hurdles to its efficient use for commercial purposes (Russom, 2011).

Despite the growth of e-commerce and interest in modest design, there is a significant lack of study about the precise variables driving this business. Although research has been undertaken about the expansion of e-commerce and general fashion trends, the complex factors influencing modest fashion have mostly been overlooked. Consider the plethora of evidence about e-commerce evolution and alterations in customer behaviour (Fisher and Raman, 2018; Chevalier, 2024). Nonetheless, regarding the popularity of modest fashion within this burgeoning internet sector, there is a conspicuous absence of specific information.

The modest fashion business, mostly propelled by Muslim customers and characterised by particular modesty norms, has experienced considerable expansion; nonetheless, it remains inadequately studied (Randeree, 2020; Kamarulzaman and Shaari, 2023). Despite the increasing popularity of purchasing modest apparel online, there remains a paucity of knowledge on this group and its distinct features (Asmawi et al., 2024). Comprehending the changing choices and requirements of this demographic helps illuminate the wider societal implications of the modest fashion trend. Furthermore, further investigation is required to assess the performance of mass-market and luxury brands in this domain, particularly in relation to price sensitivity and consumer preferences for certain product qualities (Zainudin et al., 2020; Benissan, 2021).

This research objectives to fill these gaps by focusing on the following key areas:

- To analyze the sustainability and growth prospects of modest fashion within the broader fashion industry, considering post-pandemic shifts and evolving consumer preferences,
- To determine which sector—mass-market or luxury—holds a higher market share and demand in the e-commerce space for modest fashion,
- To investigate how price changes affect consumer demand for modest fashion, focusing on the response to price reductions for both mass-produced and luxury items,
- To which product features, including colour, material, and style, most significantly impact consumer demand for modest fashion.

Based on the above objectives, the research questions below were set:

RQ1: Is the longevity of modest fashion foreseeable within the fashion industry's landscape?

This research question aligns intending to understand whether modest fashion will continue to thrive and remain relevant in the fashion industry post-pandemic.

RQ2: Which sector of e-commerce retailers has greater demand: high street/mass-market brands or premium/luxury brands?

This question addresses the need to compare the market share and consumer preference between mass-market and luxury modest fashion brands in e-commerce.

RQ3: Is consumer demand significantly influenced by price sensitivity, particularly when popular products undergo price reductions, resulting in increased demand?

This question aims to understand how pricing strategies affect consumer behaviour in the modest fashion sector, particularly in relation to price changes for different product categories.

RQ4: What key product attributes—such as colours, materials, and styles—significantly influence consumer demand within the market?

This question seeks to determine which specific attributes of modest fashion products drive consumer demand, providing insights into how to tailor offerings to meet market needs.

2. Literature Review

2.1.Modest Fashion

The concept of modesty in academic literature traces back to Thomas (1899), asserting the direct link between modesty and clothing, particularly in women's intention to cover themselves after puberty to avoid displeasing men. Harms (1938) expanded on this, highlighting clothing's multifaceted role in serving modesty, adornment, and protection, yet also potentially acting against modesty by emphasising sexual attraction. Esposito (2020) defined modern modest clothing as garments featuring loose-fitting shapes, less revealing fabrics, and covering most body parts, often associated with self-representation of specific faiths. However, Mumin (2010) argued that the fashion industry, predominantly controlled by men, shapes the concept of modesty, potentially influenced by men's perceptions of what constitutes attractiveness for women.

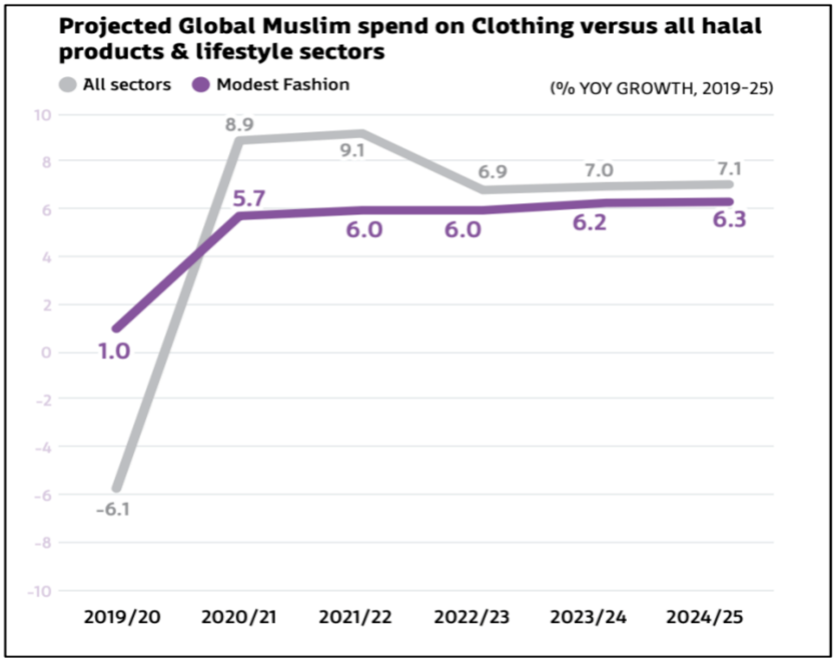
Recent research has added nuance to these foundational ideas. Babakhani (2024) examined the cultural and theological importance of modest attire in Muslim communities, emphasising the intricate interplay between piety, identity, and global fashion trends. The study demonstrated that modest attire is not just a response to masculine expectations but also a manifestation of autonomy, spirituality, and identity. Asmawi et al. (2024) investigated the emergence of "modest fashion" as a worldwide phenomenon, highlighting the substantial growth of the modest apparel sector and the increasing demand from women of many religious and cultural backgrounds. This expansion suggests a transformation in women's self-representation and the rising impact of women in influencing fashion sectors hitherto controlled by males.

Karakavak and Ozboluk (2024) assert that the progression of modest fashion has been profoundly impacted by digital platforms and social media, which have been instrumental in enhancing the exposure and acceptability of modest attire. Social media, especially Instagram and blogs, has played a crucial role in advancing modest fashion trends and linking designers, bloggers, and customers (Kamarulzaman and Shaari, 2023; Abbas, 2023). Barron (2020) elucidates how these channels have facilitated the rise of new modest fashion influencers who influence customer tastes and dictate trends. Moreover, research by Ashraf et al. (2023) highlights that enhanced visibility on these platforms has resulted in heightened acceptability and mainstream incorporation of modest fashion, mirroring wider transformations in cultural perspectives and fashion industry norms.

The fashion business is undergoing a notable transition from Western to South and East Asian markets, offering both possibilities and problems (Bai et al., 2022). The increasing desire for modest fashion in areas such as the Middle East and Southeast Asia offers substantial market potential for businesses, although it also prompts worries around cultural appropriation and authenticity (Cheang et al., 2021). Western fashion firms frequently penetrate these markets with designs that may seemingly address modesty yet lack a profound comprehension of local customs and beliefs. This may lead to goods that prioritise exploiting a trend above authentically honouring traditional customs (Karakavak and Ozboluk, 2024). The commercialisation of modest fashion may result in a weakening of its cultural value, as manufacturers prioritise marketability above authentic portrayal. This tendency exacerbates the risk of perpetuating stereotypes, since Western perceptions of modest fashion may oversimplify or distort the variety inherent in modest wearing practices (Abbas, 2023). Consequently, although the proliferation of modest fashion in these burgeoning areas presents economic advantages, it also requires a more nuanced and knowledgeable strategy to preserve cultural authenticity and respect.

The transition of fashion markets from the West to the South and East, driven by the considerable purchasing power of Muslim consumers, has prompted luxury labels like as Dolce & Gabbana to focus on affluent Middle Eastern clientele with products like the abaya (Lodi, 2020). This trend extended to other renowned clothing giants like H&M, Macy's, and Marks and Spencer, who launched dedicated modest clothing lines (Thomson Reuters, 2018) by signalling the mainstream acceptance of modest fashion. The internet's evolution played a crucial role in this transformation, with online retailers and platforms like Instagram propelling the rise of millennial Muslim influencers and it contributes significantly to the legitimacy and popularity of modest fashion (Lewis, 2015).

Vogue business highlighted Muslim consumers' growing interest in luxury modest fashion (Benissan, 2021). It indicates that despite a temporary slowdown after initial growth in 2018, luxury brands witnessed heightened interest in modest clothing, especially during Ramadan (DinarStandard (2022).



Source: DinarStandard, 2022

Figure 1*: Projected Global Muslim Spend on Clothing versus All Halal Products & Lifestyle Sector*

It appears in Figure 1 that there is a definite demand among modest consumers for luxury fashion. However, a significant quandary arose when the luxury online retailer designed for this demographic, known as "The Modist," encountered closure due to pandemic-related challenges. This occurrence has prompted the formulation of research inquiries, which will be elaborated upon below.

2.1.1. The Factors Influencing Dressing Modestly

Individuals' dress choices are heavily influenced by social norms and peer pressure. According to Lipson et al. (2020), social conformity commonly impacts fashion choices, leading people to change their apparel to fit the standards of their social groupings. This phenomenon is especially visible in communities with strong cultural or religious identities, when modesty transcends personal desire and becomes a community obligation. Social networks commonly favour the wearing of hijab or other modest clothing in numerous Muslim communities, as people want acceptance and a sense of belonging (Rumaney and Sriram, 2023).

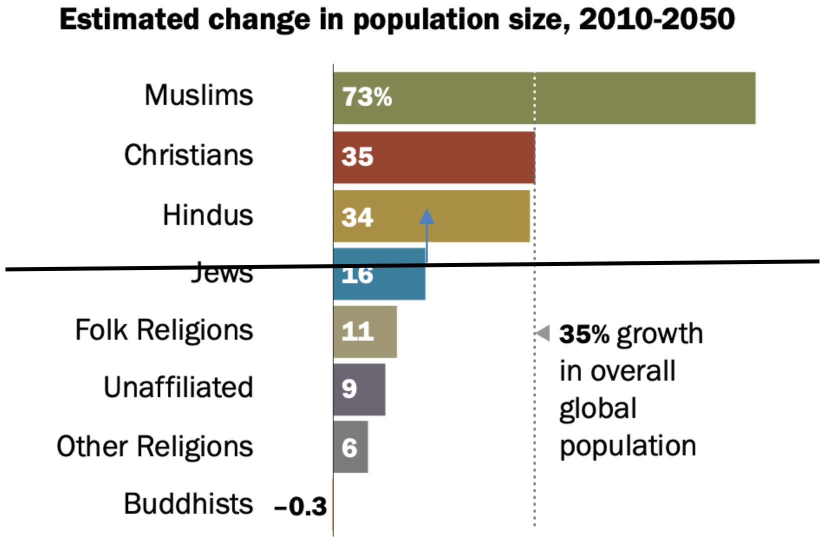
Furthermore, the importance of media and popular culture cannot be underestimated. Research conducted by Karakavak and Ozboluk (2024) demonstrates that media portrayals of modesty may profoundly affect public attitudes and personal decisions. The representation of modest fashion in mainstream and social media has sparked renewed interest in modest attire, especially among younger generations aiming to harmonise personal expression with cultural norms (Ashraf et al., 2023; Lewis and Aune, 2023). Thus, sociocultural factors derived from community dynamics and dominant media narratives define the area of modest clothes.

People's attitudes about modest attire are heavily influenced by their cultural and religious beliefs. According to Slater and Demangeot (2021), the cultural environment frequently determines modesty norms, which can vary greatly among nations. In many cultures, modesty is connected with virtue and morality, prompting people to adopt dress traditions that reflect these principles. In Orthodox Jewish communities, women frequently follow severe dress rules that promote modesty as a display of their religious dedication (Taylor-Guthartz, 2021).

The psychological components of self-esteem, body image, and identity development profoundly impact decisions regarding modest attire. Studies by Hwang and Kim (2020) and Slater and Demangeot (2021) demonstrate that persons with a good body image are more inclined to articulate their unique style, which may or may not conform to modesty standards. In contrast, individuals experiencing body image concerns may adopt modest attire as a kind of self-defence or to evade scrutiny (Dhillon and Gammage, 2023). Moreover, modest attire can function as a means of identity expression, especially for individuals aiming to affirm their ethnic or religious identity within a heterogeneous community (Ashraf et al., 2023). A research conducted by Lewis and Aune (2023) revealed that numerous women perceive modest attire as a means to assert control over their bodies and contest dominant beauty norms. This agency is especially important in situations when modest attire is perceived as a means of resisting hypersexualization and objectification.

Mumin's (2010) research divided views about human clothing and ornamentation into four categories: protection, modesty, display, and communication. The study concluded that, while ideas of protection and modesty had certain limitations in explaining current clothing behaviours, conceptions of display and communication were more believable and widely accepted. Nevertheless, it was observed that none of these ideas thoroughly examined the impact of faith and beliefs on clothing selections, especially regarding the rationale for women's inclination towards modest attire. Hashem (2018) examined these four theories but favoured modesty and ornamentation as better appropriate for the study and discourse of modest fashion.

The primary motivation identified for women dressing modestly was religious beliefs, as highlighted by studies (Wani, 2013; Shriver, 2017; Hassan et al., 2019; Radwan et al., 2019). Lewis (2013) pointed out that the origin and initial focus of modest fashion were among women belonging to the three major Abrahamic faiths: Islam, Judaism, and Christianity. She also mentioned various motivations driving modest dressing, including practicality, body image considerations, and life changes. Despite modest fashion being broader than one religion, academic research predominantly revolves around the Muslim community in discussions on modest fashion. This focus is due to Islam's status as the second-largest religion, as reported by the Pew Research Center (2015), and the projected global rise in the Muslim population, expected to reach 73% in the foreseeable future (Figure 2). Hence, academic papers often use the Muslim community as a representative group for discussions on modest shoppers due to their prominence and a sizeable presence in the modest fashion landscape.



Source: Pew Research Center, 2015

Figure 2*: Estimated Change in Population Size, 2010-2050*

The term "hijab" is frequently used interchangeably with modest fashion within the context of Muslim modest wearers defined by Sumarliah et al. (2021) as an embodiment of religious faith, the hijab is worn as an act of obedience to God. According to El Guindi (1999), its literal meaning is "barrier or partition and implies a complete covering comprising ankle-length, loose-fitted attire. Investigating this phenomenon anthropologically, Shriver (2017) highlighted that women wearing hijabs as fashionistas aim to assert their agency, beauty, and religious values. Shriver (2017) delineated how hijabi women actively choose to wear hijabs, showcasing their agency, self-expression, and adherence to religious beliefs.

2.1.2. The Modest Fashion Shopping Behaviour

Modest fashion, often characterized by clothing that provides more coverage than mainstream fashion, is embraced by individuals from diverse backgrounds, including religious communities, cultural groups, and those who simply prefer a more conservative style (Zainudin et al., 2020). One of the key motivators for modest fashion purchasing behaviour is the alignment of clothing selections with personal values and beliefs. AbdelAziz et al. (2023) found that customers frequently want attire that expresses their ethnic and religious identities. Muslim women, for example, who may follow strict dress standards, frequently prefer labels that provide attractive yet modest alternatives. The association between fashion and personal views affects shopping decisions, brand loyalty, and community engagement (Asmawi et al., 2024). Key factors in modest fashion purchasing are price sensitivity and accessibility (Randeree, 2020).

Ajaib and Altunisik's (2022) study reveals that customers frequently have difficulties in locating affordably priced modest fashion options, perhaps dissuading them from making purchases. Retailers who effectively traverse this problem by providing a wide variety of price points and accessible designs are more likely to attract a varied consumer base. Furthermore, the inclusion of modest fashion in mainstream retail environments has been connected to enhanced exposure and acceptability of this style, allowing customers to purchase more easily (Pemberton and Takhar, 2021).

Furthermore, recent research has focused on the influence of ethical considerations on modest fashion buying behaviour (Mehta et al., 2023). Consumers are becoming more conscious of the ethical consequences of their purchase decisions, resulting in a preference for firms that prioritise sustainability and ethical manufacturing processes. According to a research by Biancone et al. (2023), modest fashion buyers are more inclined to support firms that demonstrate a commitment to ethical principles such as fair working conditions and eco-friendly materials. This trend underscores the necessity of openness in the fashion business, as well as the need for firms to properly convey their ideals.

In a qualitative study of Muslim women in their twenties, Hashem (2018) identified four phases based on interview data: awareness, contemplation, decision, and retention. Although this study was conducted in 2018, the findings are still applicable and form the conceptual basis. Additional research (Wani, 2013; Hassan et al., 2019; Radwan et al., 2019; Kusumawati et al., 2019) supports this.

As a result, this study emphasises the need of taking into account religious beliefs, cultural influences, self-awareness, fashion consciousness, buying habits, and preferred shopping venues while investigating the purchasing behaviour of modest fashion customers (Hashem, 2018). Research indicates that the initial phase in the purchasing behaviour of modest fashion consumers is "awareness" (Hashem, 2018). Consumers possessing purchasing power in this industry are frequently digitally adept, compelling companies to advertise on social media platforms like Instagram, Twitter, and YouTube. In the contemplation stage, Muslim modest consumers emphasise their Islamic principles while selecting design items (Wani, 2013; Hassan et al., 2019; Kusumawati et al., 2019), deriving inspiration from many sources that extend beyond traditional modest fashion parameters. Brands should offer varied options to avoid imposing rigid concepts of modest fashion, as noted by Radwan et al. (2019). They highlight that Italian brands often fail to understand the preferences of Muslim women seeking fashion items labelled as "Muslim dresses."

Hashem (2018) finds Millennial Muslim women in European countries tend to favour mainstream brands over specific modest fashion brands and prefer online shopping due to limited free time. Hashem (2018) suggested that mainstream brands have a significant opportunity to cater to Muslim and modest fashion consumers. This aligns with the trend observed in the industry, with major retailers like Nike, DKNY, and Tommy Hilfiger integrating hijab and Ramadan collections into their offerings. While this challenges retailers specializing in Islamic styles, it signifies the evolution of modest fashion into a "mainstream fashion subculture". Additionally, religious consumers tend to prioritize quality over price, preferring products that demonstrate value for money (Kusumawati et al., 2019; Islam and Chandrasekaran, 2020). However, fashion-conscious consumers show more loyalty toward and advocacy for premium modest fashion brands (Kusumawati et al., 2022).

The reviewed studies shed light on factors influencing the purchasing journey of millennial Muslim consumers, emphasizing the role of online platforms, religious values, fashion knowledge, variety of choices, and product quality. Nevertheless, these studies were conducted before the pandemic, overlooking the significant changes in the shopping landscape, especially the shift to fully online shopping experiences. Moreover, the research primarily gathered consumer insights and lacked perspectives from the company side. Hence, this study aims to bridge this gap by leveraging fashion e-commerce datasets to understand modest fashion customers' preferences, providing guidance for fashion companies.

2.2. Theoretical Concepts and Analytical Framework

The study incorporates a framework based on the marketing research process by Big Data Analytics (BDA) framework for organizational leverage proposed by Mathrani and Lai (2021). It seeks to get a better knowledge of modest fashion customers' decision-making processes while also looking at the role of big data analytics in defining marketing tactics in this industry. Using the BDA paradigm established by Mathrani and Lai (2021), the study aims to show how exploiting large data sources, particularly from e-commerce platforms, may give important insights regarding modest fashion purchasing behaviour.

The study uses a variety of theoretical frameworks to completely explore the intricacies of modest fashion consumption behaviour. The research attempts to provide light on the multidimensional nature of modest fashion consumption by building on Hashem's (2018) thesis about the numerous motivations that drive faith-based customers' fashion purchases. By combining these theoretical underpinnings and applying them to the context of the marketing research process and the BDA framework, the study hopes to make a significant contribution to understanding consumer behaviour in the modest fashion market and assist businesses in more effectively navigating this complex terrain.

2.3.Conceptual Framework

According to Russom (2011), big data was previously considered as a technological barrier because to the massive volume of internet-collected data, but it has now emerged as a huge potential. Thomassey and Zeng (2018) discuss the potential advantages of big data in the fashion sector, emphasising the need of firms implementing business intelligence (BI) or data analytics technologies to harness unused data for better understanding customers and the business landscape. This involves using predictive analytics, statistics, natural language processing (NLP), data mining, and artificial intelligence (AI), which are very useful in the fashion industry.

However, Mathrani and Lai (2021) indicated that managing big data analytics (BDA) necessitates robust computational capabilities and substantial maintenance costs. Yet, in the e-commerce realm, BDA offers valuable insights into users' purchasing behaviour, enhancing engagement and user retention (Akter and Wamba, 2016). Additionally, Fisher and Raman (2018) suggest that BDA in retail can significantly improve performance, minimize lost sales and overstock, reduce labour costs, and enhance profits. Akter and Wamba (2016) compiled BDA applications in e-commerce, categorizing data into transaction, click-stream, video, and voice data, highlighting the immense benefits, especially from transaction data alone, for e-tailers. Therefore, this study aims to focus on analyzing customer demands and preferences using transaction data obtained from e-commerce websites.

The big data analytics (BDA) framework proposed by Mathrani and Lai (2021) established the groundwork for the conceptual framework validating the application of big data analytics in fashion businesses (Mathrani and Lai, 2021) for predicting demand and enhancing effective product decision-making.

3. Methodology

3.1. Data collection and source

This study utilized secondary data obtained from Stylumia (https://cit.stylumia.com/insights), a fashion intelligence company offering AI-driven analytics for apparel brands. Stylumia compiles data from various e-commerce sites to provide trend insights. We used Stylumia's Consumer Intelligence Technology (CIT) which allows us to filter preferences based on various criteria like retailers, geography, and price point. The dataset from Stylumia was deemed suitable for this research due to its supervised and structured nature achieved through machine learning processes and primarily computer vision applied to the gathered information in real time on chosen fashion brands. Three nominal valued datasets were used in this research: the fashion e-commerce dataset, the trend demand dataset, and the trend price dataset.

The study focused on specific parameters which are shown in Table 1 below:

Table 1*: Criteria Applied in the Research*

Parameters	***Criteria***
Categories	The emphasis was on modest fashion, featuring loose-fitting, concealing attire. This led to the selection of product categories such as dresses, Arab clothing, and abayas, in line with modesty standards.
Retailers	A total of 51 retailers, including Amazon, ASOS, H&M, and others, were chosen after filtering for their adherence to modest fashion requirements, ensuring a diverse representation in the market.
Geography	Retailers from various countries, such as Australia, Denmark, France, Germany, India, Italy, Japan, Spain, UAE, UK, and the US, were selected based on their offerings meeting the study's criteria.
Department	The study centred on the women's department, excluding categories like girls and baby girls as they fell outside the scope of modest fashion.
Date range	Data spanning from March 21, 2021, to August 14, 2022, was utilized to capture trends during this trading period.
Price	Both original (list price) and selling prices were considered, ranging from £2.4 to £8,600. Products with discounts of up to 80% were included in the analysis.
Attributes	Specific attributes such as non-fitted silhouette, long sleeves, and maxi dress length were chosen to comply with the modesty requirements.
Brands	A broad dataset encompassing over 100 brands, ranging from high-street to luxury, was gathered to ensure diversity without targeting specific brands.

Demand	The study took into account various product demand rankings, including best seller, good seller, average, and poor seller, to investigate the factors influencing the performance of modest fashion categories.

These parameters were defined and used in the data generation process. We generated three different datasets which are explained below.

3.1.1. Fashion E-commerce Dataset

The dataset used for this fashion e-commerce study was obtained from Stylumia around June 2022, comprising 22 columns and 670 observations. It encompassed various variables such as product code, retailer information, image links, product URLs, names, launch dates, pricing details, discount information, and categorical attributes like brand, category, and department.

The product code and retailer columns included unique identifiers and retailer-specific details, while the image and URL columns provided visual and web links. Product names described the items, and launch dates indicated their initial appearance online. Pricing details were also present, including list price, selling price, and markdown information.

Certain categorical data, like retailer and discount information, were transformed into numeric variables to facilitate machine learning model development. Brand data, containing numerous options, was challenging to process. Discount details were converted into binary variables for discounted (1) and non-discounted (0) items.

Unique variables from Stylumia, such as rank labels and rank percentile groups, determined product demand based on a machine learning model. These categorical values were converted into numeric representations: rank labels were assigned numeric values indicating different seller categories, and binary values were allocated to classify items as best/good sellers or average/poor sellers.

The dataset included colour information, converted into 65 numerical options corresponding to colour names. Initially, categorized by demand and market segment, product positioning was redefined in this study based on pricing into value or luxury goods. Information like size availability, product descriptions, feature lists, and style attributes were available but needed to be translated into numerical values. Consequently, for numerical representation, only fabric or material details were extracted and categorized into six types, like cotton, polyester, silk, viscose, Tencel, and others.

Table 2 presents the fashion e-commerce dataset variables.

Table 2*: Fashion E-Commerce Dataset Variables*

Variable name	***Description***
Launch date	The date the products were first launched on the retailer/marketplace website
Retailer	The retailer name

List price/GBP	The price listed on the website when the product first showcased on the e-commerce
Rank label	Rank label based on the product’s performance: “Best seller”, “Good seller”, “Average seller” and “Poor seller”
Rank percentile Group	Product was put in the percentile group before decided the rank label: “1-10”,”20-30”,“30-40”,“40-50”,“50-60”,“60-70”,“70-80”,”80-90”, and ”90-100”
Retailer colour name	The product’s colour as described by the retailers
Fabric	New variable created to describe the fabric derived from product description, feature list and style attributes variables
retailcode	Numerical value for “Retailer” variable
fabriccode	Numerical value for “Fabric” variable
colorcode	Numerical value for “Retailer color name” variable
rankcode	Numerical value for “Rank label” variable
rankbinary	Binary value for “Rank label” variable: (1) for best and good seller, (2) for Average and Poor seller
Discountlabel	Whether the product had a markdown or not before it was sold out or taken down from the retailer/marketplace website, the code instruction (1) for yes (0) for no

The fashion e-commerce dataset was split into two segments according to price points: mass market and premium luxury categories. In the mass market segment, focusing on best-selling items and retailers, products ranged from £2 to £200. The standout retailers in this price range were Amazon United States (US) and Amazon United Arab Emirates (AE), contributing a total of 22 best-selling products.

Conversely, the premium luxury category encompassed products priced from £200 to £5000. In this segment, Farfetch US and Farfetch United Kingdom (UK) emerged as the top-performing retailers, accounting for 19 best-seller products. This division based on market segmentation aimed to compare the demand between these two distinct market segments using smaller, more concentrated datasets. Additionally, both datasets provided insights into each product's demand trends and performance analysis concerning pricing over a one-year duration.

3.1.2. Trend Demand Dataset

The trend demand dataset was generated through Stylumia's analysis of product ranks, tracking demand from a product's initial launch to the present time. This rank was determined based on the product's availability on retailers' websites. Approximately 41 best-selling products were individually tracked to compile the demand reports. These reports were segregated based on market segmentation (mass market or luxury), combining around 20 different reports for each segment into an Excel sheet. This aggregation resulted in 76 observations for the mass market and 145 observations for the luxury segment.

Table 3 shows the trend demand variables including an explanation of the variables.

***Table 3**: Trend Demand Dataset Variables*

Variable name	*Description*
Rank date	The date when the product's demand experienced change
Trend demand	The product rank (based on demand) scale in percentile from 0^{th} to 100^{th}

3.1.3. Trend Price Dataset

The trend price analysis involved monitoring e-commerce website activities. Stylumia gathered data on the initial price, discounted price, and selling prices of each individual product. However, it's important to note that Stylumia did not track prices on a daily basis but rather recorded changes only when e-tailers modified the prices. Consequently, this specific report had fewer observations. Upon aggregation, a notable difference emerged between the mass and luxury markets. The mass market segment had only 14 observations, while the luxury market had a significantly higher count of 150 observations.

The price analysis variable is shown in Table 4.

Table 4*: Price Analysis Dataset Variables*

Variable name	*Description*
Price date	The date when the product's prices experienced some adjustment
Selling Price GBP	The selling price indicated what the prices customers paid for the product on those dates

3.2. Exploratory Data Analysis

Data analysts commonly employ exploratory data analysis (EDA) to investigate and comprehend datasets. EDA relies on data visualization techniques like bar charts, line charts, histograms, scatter plots, and box plots to discern anomalies, patterns, and hypotheses that might not be evident in text-based inputs (Liu, 2014). Yu (2010) suggests that data mining extends the principles of EDA, as it does not start from preconceived notions or specific hypotheses but aims to uncover patterns within data. Additionally, many data mining methods are non-parametric and often resilient to multicollinearity. Newer EDA techniques, like clustering processes, are adept at handling outliers (Yu, 2010).

3.2.1. Clustering

The clustering method, previously discussed as a part of the new EDA within data mining, has been employed for various purposes. In marketing, cluster analysis is commonly used for customer segmentation, product grouping, and identifying companies with similar strategies (Saunders, 1994). Its applications span across diverse fields like psychiatry, astronomy, weather classification, bioinformatics, and genetics (Landau et al., 2011). In this study, clustering was used to classify products and uncover latent structures within the dataset that were not immediately discernible through visual exploration.

Clustering encompasses several techniques, including the hierarchical method, partitioning method, grid-based method, and density-based method. Arora et al. (2016) suggested that k-medoids presented a more robust algorithm compared to k-means. While k-means employed the sum of Euclidean metrics, k-medoids replaced non-representative objects with representative ones, resulting in fewer overlapping clusters. This research focused on the partitioning method, specifically utilizing k-medoids. The novelty of this study lies in its implementation of clustering on a mixed dataset containing categorical, nominal, and numeric variables commonly found in actual marketing data. Consequently, this research utilized the Gower distance for k-medoid clustering, departing from the typical use of Euclidean distance.

4. Findings and Analysis

4.1.Descriptive Statistics

The fashion e-commerce dataset consisted of 670 observations. Based on the descriptive statistics (Table 5), the price range for modest fashion varied, with the lowest price recorded at £2.29 and the highest at £8303.52. The most frequently occurring price point was £100.

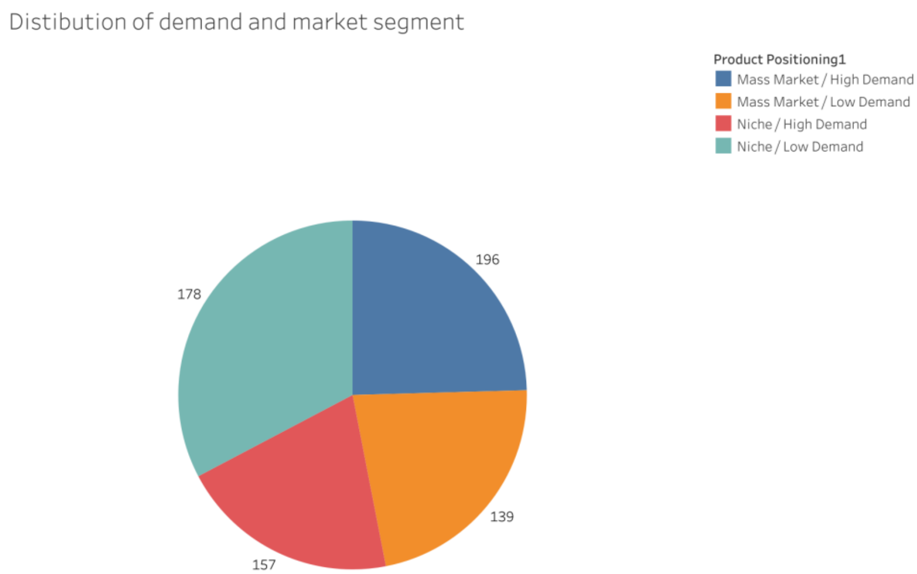
Table 5: *Descriptive Statistics*

Variable	N	Minimum	Maximum	Mean	Median	Mode	S.D
List price / GBP	670	2.29	8308.52	505.365	100.0	100.00	1024.4

The dataset pertaining to list prices exhibits a notable skewness, as evidenced by a reported mean of 505.3 and a median of 100. Within our sample, a diverse array of retailers is represented, encompassing entities such as Amazon and Myntra, characterised by comparatively modest price points. Conversely, the sample also includes luxury retailers like Farfetch, renowned for their markedly elevated price points. This spectrum of retail entities contributes to the observed variability in the list price dataset, reflecting the wide range of pricing strategies and market segments embraced within the retail landscape of modest fashion.

4.2. Exploratory Data Analysis

Exploratory data analysis was conducted using Tableau software to visually represent findings. In the fashion e-commerce dataset focusing on modest attire, there were 670 observations. According to the pie chart in Figure 3, over half of these observations, specifically 353 products, fell into the high-demand category, while 317 products were classified as low-demand. The mass market exhibited slightly higher demand compared to the niche market. Specifically, there were 196 high-demand products and 139 low-demand products within the mass market. On the other hand, the niche market comprised 178 low-demand products and 157 high-demand products. This suggests that products scatter uniformly between types of demand and market segments.



Source: Authors, 2023

Figure 3: *The Summary of the Dataset Based on Demand and Market Positioning*

Figure 4 indicates the most popular e-tailers categorised by price points. The figure below presents only the best-selling and good-selling retailers falling within the 70th to 80th percentile and 90th to 100th rank percentile groups. These are the most popular products on e-commerce. The legend shows the price range categories for products/retailers, where blue represents affordable products, red indicates high-priced goods, and purple to yellow hues denote mid-priced retailers. Farfetch and Amazon are market leaders in high priced and low priced products within modest fashion along with H&M UK. All these brands are within the top 10 percent based on popularity in e-commerce sites. Some boxes have missing names as the corresponding text does not fit into the box. A detailed summary of the related dataset is presented in Appendix

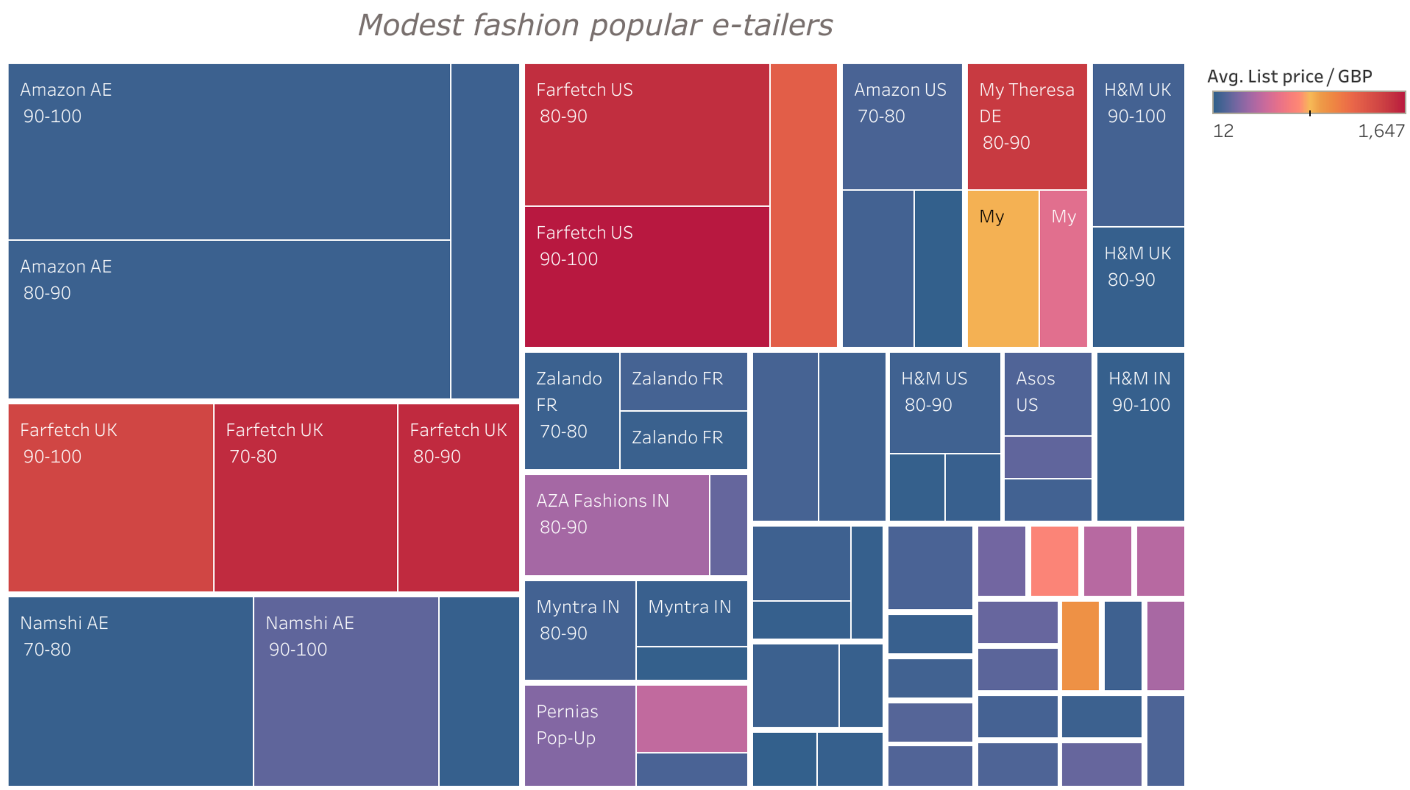


Figure 4*: The visualisation to shows which retailers were popular in different price ranges*

The data corresponding to the above visualisation

As reflective by the blue colour, retailers like Amazon, H&M, ASOS, and Myntra cater to affordable selections for modest fashion. Conversely, Farfetch and My Theresa are known for offering more upscale and luxurious clothing options as shown in the red colour. Figure 4's visualization highlights the popularity of both affordable and expensive retailers in the modest fashion category. However, the mass market segment held the most significant share of products across all e-retailers.

The best and good-selling retailers of mass-market offered products with a price average between £12 to £140. Some retailers in the mid-range, such as Namshi AE and Pernias pop-up, provided a mix of mid to high-priced items with average prices ranging from £25 to £413. In contrast, the best and good-selling retailers in the upper-class segment offered products on average starting from £500 and above.

In summary, 114 best and good-selling products in the mass-market segment, 39 in the middle or mixed market, and 62 in the premium or luxury market (See Table in the Appendix). Regarding the most demanded modest attire providers, Amazon significantly offered mass-produced clothing online, while Farfetch dominated in designer-made options in e-commerce.

Based on these findings, Amazon and Farfetch emerged as the most significant retailers in the modest apparel sector. Consequently, these two retailers could serve as benchmarks to gauge demand trends as well as the average price for modest clothing items in both mass-market and designer brand categories. Over a one year period from 2021 to 2022, Stylumia tracked the demand progression for each product. This analysis specifically focused on investigating the demand trend for best-selling products (90-100th rank percentile group) from both Amazon and Farfetch, aiming to understand the demand pattern from the previous year until the present.

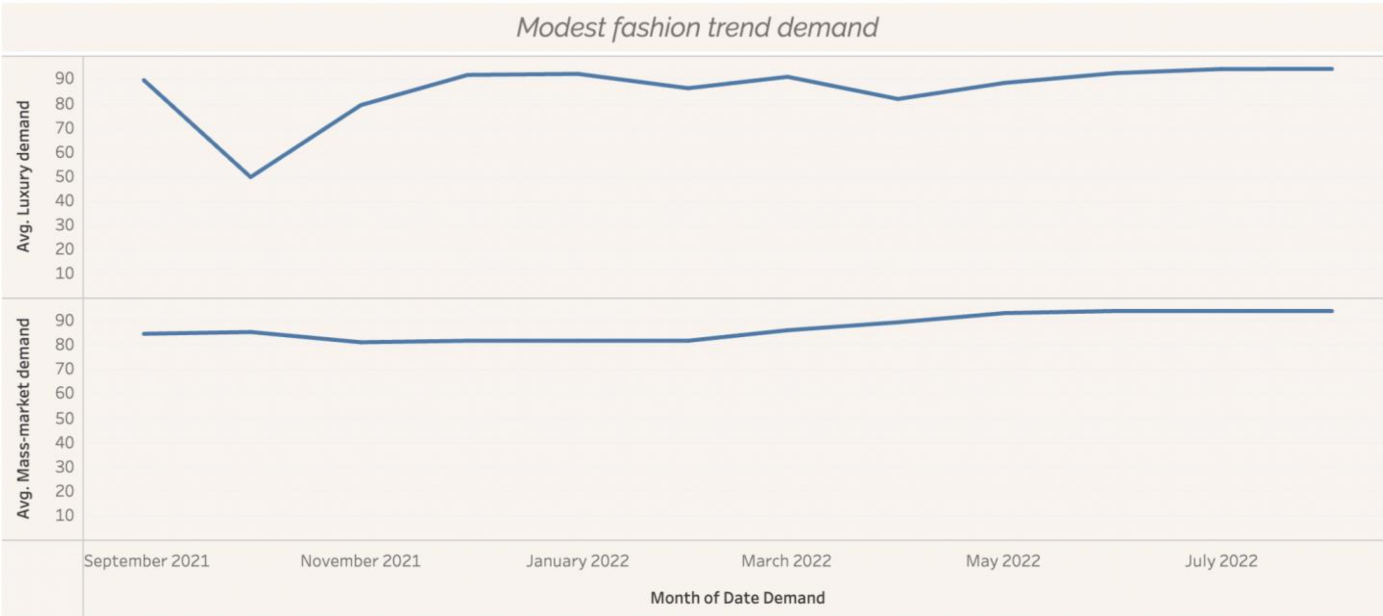


Figure 5*: The Demand Progression for Best-Seller Products from Luxury and Accessible Retailers*

In Figure 5, based on the rank percentile described on the y-axis, both luxury (Farfetch) and mass market (Amazon) displayed an upward trend. In September 2021, the demand rank for best-selling products from both mass-produced and luxury fashion retailers hovered around the 80th percentile. However, Farfetch was slightly higher by 5 percentile points compared to Amazon. Initially, luxury demand outperformed low-cost items but declined below the 50th percentile around October 2021, whereas the mass-market products' demand remained stable.

Despite the dip in October, the high-end retailers maintained demand rank at around 80th to 91st percentile since late 2021. Moreover, since December 2021, the demand for modest luxury products showed an increased trend with the highest being in the 94th percentile. Nevertheless, overall demand for both the categories remained stable over a one year period with absence of seasonality and fluctuations.

Furthermore, Figure 6 below explores the optimal price range for a modest garment to become a best-selling product. However, this visualization is based on the fashion e-commerce dataset without distinguishing between market segments. Hence, the median selling price was utilized to assess central tendency, considering a diverse selling price range from £2 to £8,000.

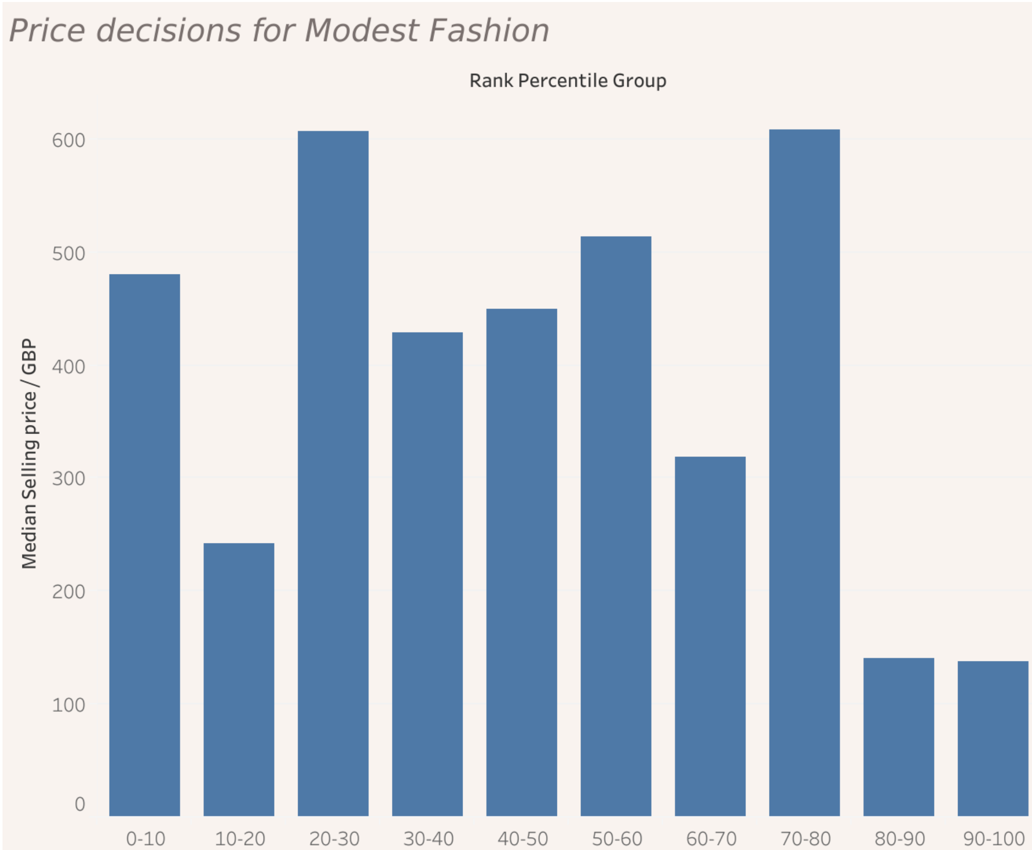


Figure 6: *The Summary of Prices in each Demand Rank Percentile Group*

Figure 6 illustrates the relationship between product rank percentile groups and their respective median selling price ranges. The X-axis denotes the rank percentile group, while the y-axis displays the median selling price range for each rank percentile group. For instance, products in the 90-100th rank percentile group exhibit the lowest median selling price, approximately £137.3. Similarly, the 80-90th percentile group includes products priced around £140. Conversely, products in the least demanded percentile groups, such as 0-10th, feature a median selling price of £480. The 10-20th percentile group comprises products priced at £242, while the 20-30th percentile group features the highest median selling price at £607. Generally, there exists an inverse relationship between price and demand, where higher-priced products tend to attract lower demand. However, the 70-80th percentile group, with a median selling price of around £600, presents an intriguing observation, potentially falling into various seller categories. Dresses priced below £200 are identified as the most demanded and best-selling modest apparel items, indicating a uniform distribution across different price points, with greater availability of items in lower price ranges.

Moreover, exploring other factors influencing garment preferences among modest shoppers is crucial besides affordability. For instance, analysing colours and fabrics helped determine their significance.

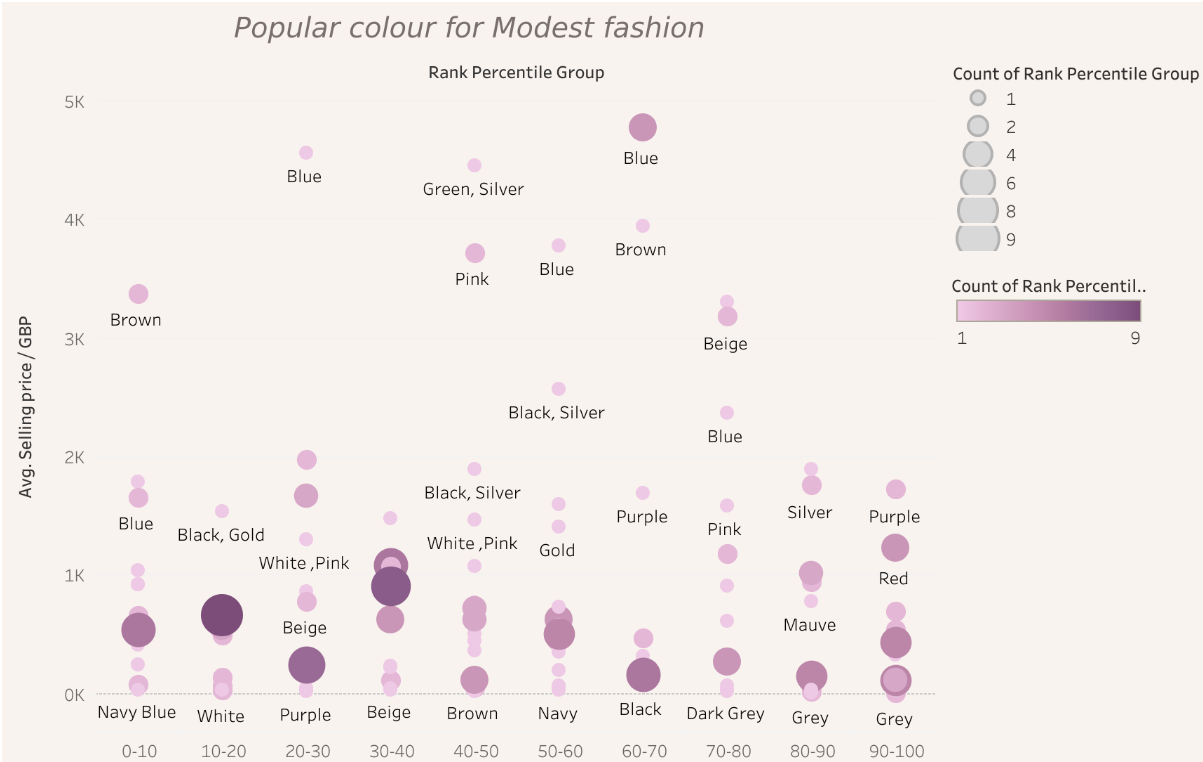


Figure 7: *The Most Frequent Colour Apparent in each Demand Rank Percentile Group*

Figure 7 consolidates the most frequent colours in each demand rank to delve deeper into which colours are more favourable for modest apparel. The legend indicates the "count" of products with sizes and shades of purple, where larger sizes and darker purple signify higher frequency in those ranks. Y-axis explains the average selling prices for each colour in modest garments and X-axis depicts the rank percentile group.

In the top-ranking group (90-100th percentile), featuring best-seller products, various colours like black, beige, blue, cream, green, grey, navy blue, orange, pink, purple, red, and white were observed. Prices ranged from £16 to £1,722, with purple being the most expensive. Black, blue, and red were the most frequent colours. Moving to good seller group (70-90th percentile), brown, dusty pink, khaki, mauve, dark grey, dark blue, and pink with silver were noted alongside these colours. Pink, silver, brown, beige, and blue had high average selling prices, starting from over £1,000. In the average seller segment (30-70th percentile), colours included beige, black, light grey, blue, brown, burgundy, gold, pink, purple, and more, with prices ranging from £30 to £4,770. In the poor seller category (0-30th percentile), prominent colours included beige, black, brown, green, blue, grey, orange, pink, and red. Blue and brown were the most expensive, with average selling prices of £4,559 and £3,372, respectively. The cheapest colour was white, with an average selling price of £14.

In summary, best-selling products generally had a maximum price range under £2000, with higher prices correlating to lower sales potential. Blue and brown colours tended to have excessively high prices compared to others, hindering sales. Mixed colours performed moderately compared to solid colours. Additionally, black, followed by beige and pink, emerged as the most frequent colours in the modest fashion category, yet their prevalence across rank percentile groups doesn't guarantee popularity. Retailers should consider factors beyond colour, such as pricing and seasonal relevance, as reliance solely on colours doesn't ensure product success.

Moreover, another significant aspect worth examining was the fabrics or materials used. The scatter and box plots in Figures 8 and 9 delve into the fabrics employed for modest fashion garments.

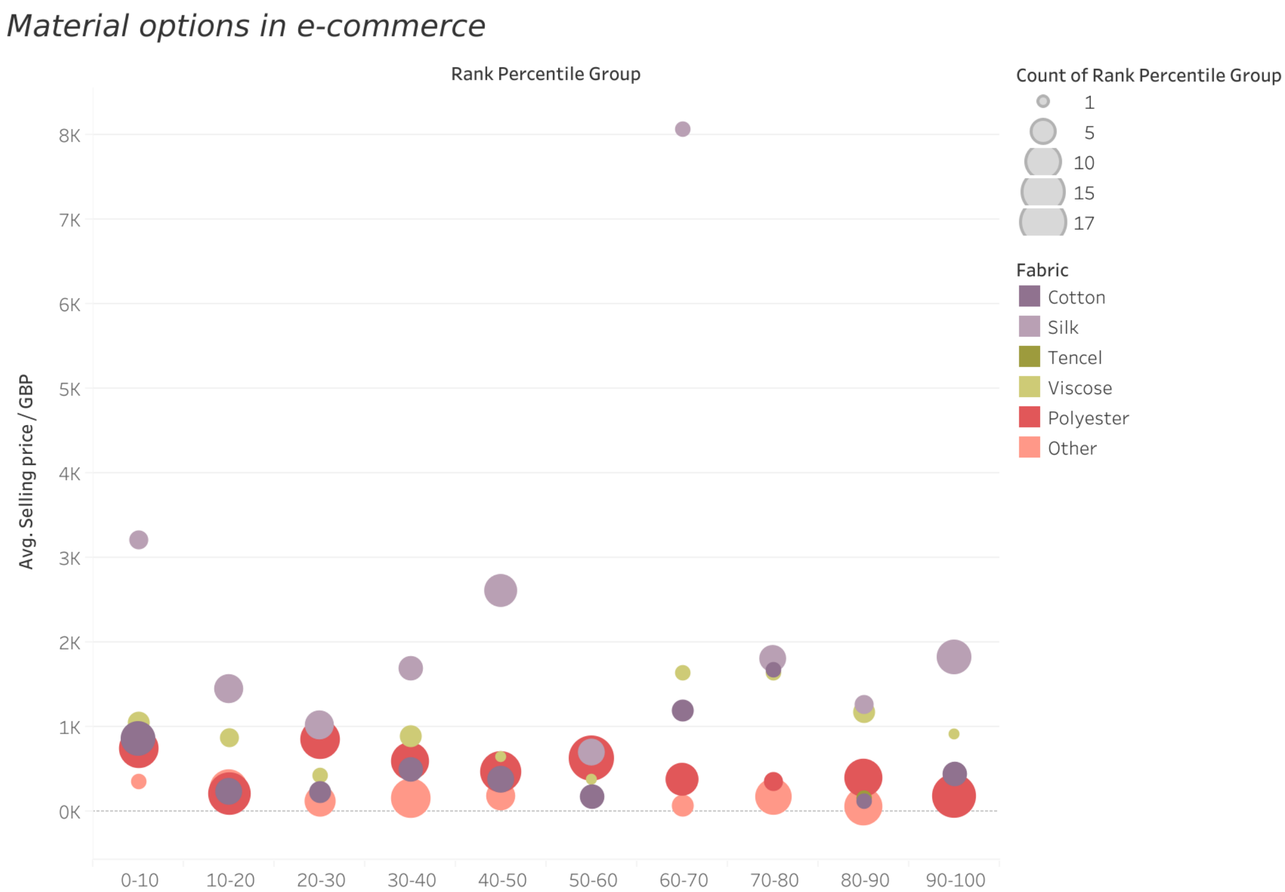


***Figure 8**: The Summary of the Material Availability based on Demand Rank and Price*

Initially, fabrics identified within the fashion e-commerce dataset were categorised into six types: cotton, silk, Tencel, viscose, polyester, and other materials (e.g., chiffon, georgette, or linen). According to Figure 8, Y-axis explains the average selling price of each fabrics and X-axis describes the rank percentile group with 90-100th percentile as "best seller", 70-80th to 80-90th percentile as "good seller", 30-40th to 60-70th percentile as "average seller" and 0-10th to 20-30th percentile as "poor seller". As shown from the figure, polyester was the most prevalent fabric across rank groups and tended to be associated with lower prices compared to other fabrics. The second most frequently available fabric was categorised under 'other', followed by silk and cotton. Each fabric type was distributed across various rank percentile groups, suggesting that no single fabric stood out as distinctly superior as the motivation for effective sales, as all categories experienced instances as both best sellers and poor sellers.

However, it is worth noting that 41 polyester products were in the "poor seller" percentile and only 31 were in the "best seller" percentile. In contrast, silk was higher in price and accounted for 19 best-selling products, with only 17 performing poorly. Ultimately, polyester is still a favourable fabric for retailers to manufacture compared to organic materials such as cotton and silk.

Interestingly, despite polyester products being more numerous (41) among poor sellers compared to best sellers (31), silk, which typically commanded higher prices, had 19 best-seller products and only 17 performing poorly. Nevertheless, in the realm of modest attire, retailers offered larger quantities of polyester than natural or organic materials.

The box plot illustrated in Figure 9 shows the performance of each fabric concerning price points. Given that no specific fabric was favoured by customers, this visualization could serve as a guide for retailers in setting prices for various materials to align with consumer expectations.

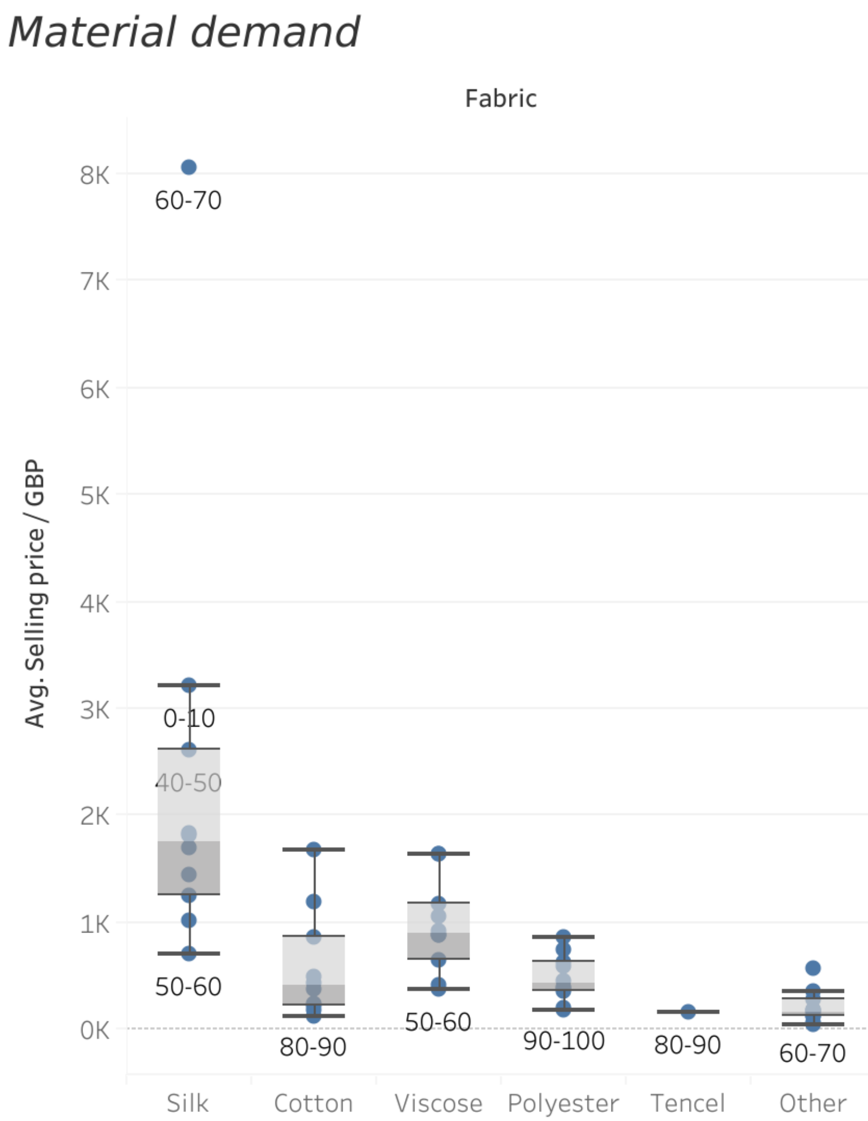


Figure 9: Price Demand for each Material

Silk performed well when priced between approximately £1,800 and £3,000 but showed a significant decline in performance when the price reached £3,000, with one outlier at £8,000, which was considered an average seller. For cotton, its optimal price range for better sales was observed between £120 and £450. Selling cotton at higher prices carried the risk of decreased performance, although it still showed acceptable performance between £1,100 and £1,600. Viscose fabrics performed better when priced around £900 to £1,600; prices lower than £1,000 negatively impacted sales. In contrast, polyester was favoured when priced below £400. Limited data was available for Tencel, but it seemed to perform well when sold at around £159, so it was considered a good seller. Regarding other fabric categories, including a mix of wool, chiffon, or linen, the optimal price range for better sales was generally under £200. In contrast, prices exceeding £300 tended to classify products as poor sellers.

In summary, silk fabrics are best suited for luxury garments, while viscose serves as a more affordable alternative. Polyester emerged as the most commonly used fabric in the mass-market sector, primarily due to its lower cost without much emphasis on quality. Therefore, rather than relying extensively on polyester, cotton fabrics should be incorporated substantially for modest attire to meet consumer demand.

4.2.K-medoid clustering for exploratory data analysis

We used k-medoid clustering which is a prominent unsupervised machine learning algorithm to identify sought-after products and the features influencing demand. This was operationalised using R, a popular programming language on IDE R-Studio.

K-medoid clustering is a partitioning method that aims to divide a dataset into clusters where each cluster is represented by a single data point known as a medoid (Kaufman & Rousseeuw, 1990). This algorithm is capable of handling categorical variables. Unlike k-means clustering, which uses centroids, k-medoid clustering selects actual data points as cluster representatives, making it more robust to outliers and noise in the dataset (Park &Jun, 2009). The technique allocates data points to the surrounding medoids periodically and changes the medoids to lower the total dissimilarity in every cluster. K-medoid clustering has been applied in various disciplines, including bioinformatics, image segmentation, and consumer segmentation in marketing research (Datta, et al. 2003), thanks in great part to its ability to identify natural groupings within data. Clustering was implemented to divide distinct groupings that represented a variety of attributes, including price, demand rank, colour, and fabric.

The partitioning around medoids (PAM) method was employed for clustering due to the dataset's diverse nature, which included both numerical and categorical values. In addition to the quantitative variable "list price/GBP," qualitative attributes such as "retailer," "discount label," "rank percentile group," "retailer colour name," and "fabric" were assessed. Gower's distance, a measure that can evaluate the similarity and dissimilarity of observations, was employed to facilitate the k-medoids algorithm. This measure is capable of addressing numerical, categorical, and dichotomous variables (Gower, 1971).

Gower's distance calculation for numerical variables typically entails calculating the dissimilarity between two data points (i and j) by accumulating the weighted absolute differences over each variable (k) and dividing by the sum of the weights.

$$d(i,j) = \frac{\sum_{k=1}^{p} W_k \left|Variable_k(i) - Variable_k(j)\right|}{\sum_{k=1}^{p} w_k}$$

For categorical variables, Gower's distance is computed based on the presence or absence of a particular category across observations.

$$d(i,j) = \frac{\sum_{k=1}^{p} W_k \delta_{ikj}}{\sum_{k=1}^{p} w_k}$$

Here, δ_{ikj} is 0 if the category of the variable is different between observations i and j, and 1 if they are the same.

Subsequently, a silhouette plot was generated to determine the optimal number of clusters post Gower's distance calculations. As shown in Figure 14, the silhouette plot indicated the highest value at 4, leading to the creation of 4 clusters. The summaries and details of these clusters are presented in Figure 10 and Table 6 and it presents the characteristics and distinctions between the identified clusters.

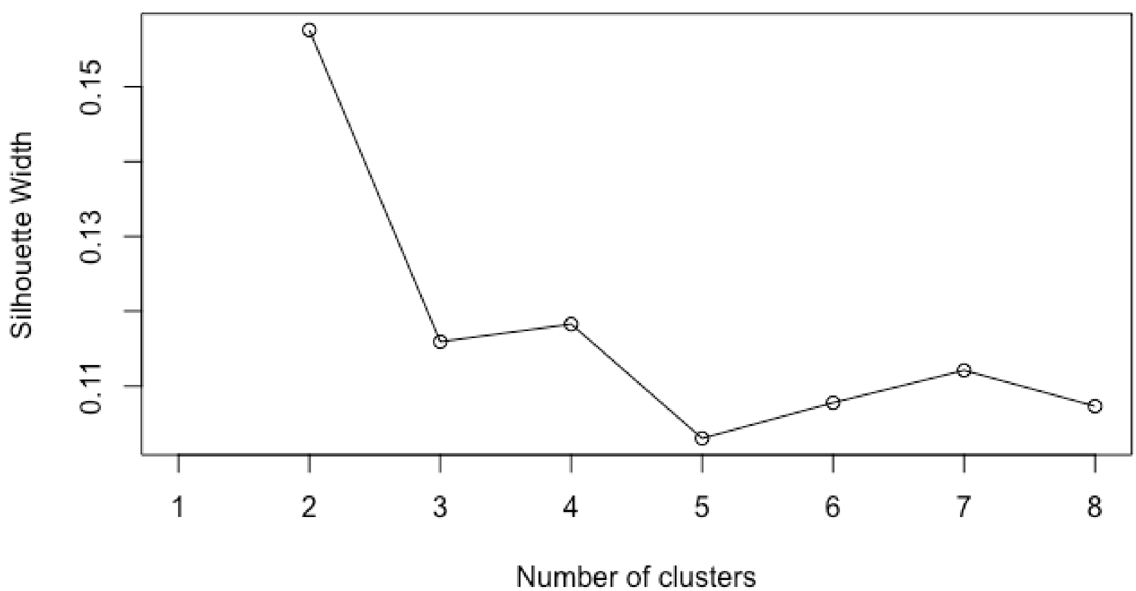


Figure 10: *Number of Clusters Decision with Silhouette Plot*

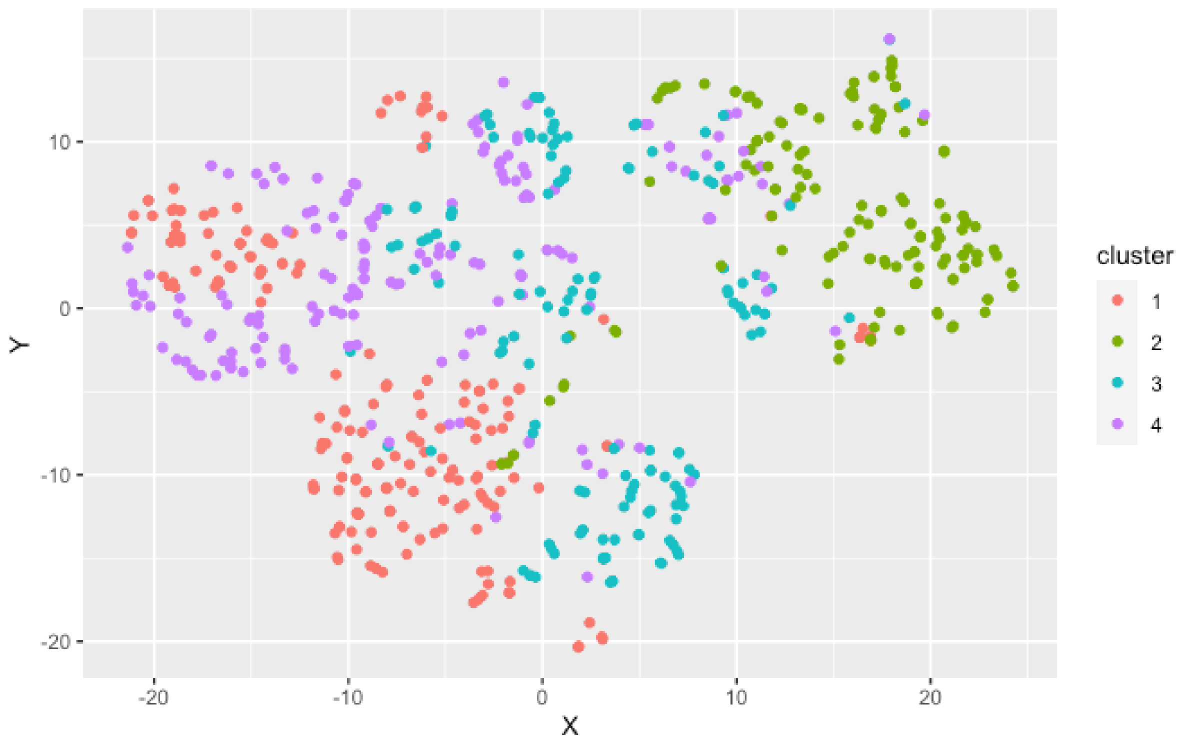


***Figure 11**: Four Clusters Plot*

Cluster	**Retailer**	**Average List price / GBP**	**Discount**	**Rank percentile group**	**Prominent Colour**	**Fabric**
1	Amazon AE	89.03	No	90-100	Black	Other
2	Namshi AE	237.53	Yes	60-70	Black	Other
3	Farfetch UK	1126.19	No	40-50	Pink	Cotton
4	Farfetch US	711.76	No	10-20	Black	Polyester

***Table 6**: Summary of results of k-medoid clustering*

The outcomes generated by the k-medoids clustering algorithm align with the earlier visualisations conducted during exploratory data analysis. Three primary retailers, namely Amazon, Farfetch, and Namshi, were identified in the modest fashion category. Namshi, although not previously included in the EDA due to its focus on contrasting markets, was found to offer mid-priced products and did not hold significant relevance for the analysis. The clusters derived from the data could be interpreted as follows: clusters 1 and 2 mainly represent affordable clothing, whereas clusters 3 and 4 comprise pricier items.

Firstly, cluster 1, characterised by economical prices, often lacked discounts, predominantly showcased black-coloured garments, and encompassed a variety of fabrics excluding polyester, silk, and cotton. Cluster 2, also offering affordable items but slightly pricier than Cluster 1, predominantly featured black clothing, experienced markdowns frequently, and demonstrated an average performance in demand rank. In contrast, clusters 3 and 4, representing expensive items with minimal discounting, showed poor demand performance. Cluster 3 was costlier than Cluster 4 and offered pink-coloured cotton fabric garments, while Cluster 4 primarily featured polyester.

Table 7: *Summary of the findings*

Analytical methods	**Tool/Technique**	**Result**
Exploratory data analysis	Data visualisation	EDA provides a better understanding of the modest dresses category, and the relationship between the clothing attributes through a set of visualisations
Clustering	Unsupervised machine learning	This method created an unsupervised classification from the fashion e-commerce dataset, resulting in 4 clusters featuring the list price, discount, retailer, colour, fabric and demand rank.

5. Discussion and Conclusion

This section provides a comprehensive summary of the findings obtained through this research project. The aim is to contribute valuable insights for fashion managers operating within the modest wear segment by leveraging data visualization and mining techniques to enhance decision-making and gain a competitive edge in niche markets. Additionally, we address the study's limitations and suggest potential directions for future research.

5.1.Research Findings

This paper delves into the intricacies of the modest fashion domain, noting that consumers in this sector predominantly come from religious backgrounds and possess a robust fashion sense. The surge in modest fashion is traced back to influential online discussions within the modest community, prompting fashion establishments to tailor their offerings to meet the specific needs of this market. Notably, some retailers faltered in understanding the market's preferences, providing only traditional or religiously inclined fashion choices.

Contrary to prior studies suggesting that fashion-conscious modest wearers are not price-sensitive and prefer high-quality premium brands, the research reveals that pricing significantly influences demand across both affordable and premium market segments. In the affordable segment, consumer purchase decisions were notably affected when prices exceeded £40, indicating a preference for more economical products. Conversely, in the premium segment, consumers exhibited less receptiveness to sudden price changes and favoured consistent pricing within a specific range.

Exploratory data analysis uncovered that mass-market products outperformed high-priced goods, suggesting a predilection for purchasing from mass retailers rather than premium ones. This implies that online modest fashion consumers are price-sensitive toward popular brands and products, irrespective of market segmentation.

The two biggest retailers in the modest apparel market emerged as Amazon and Farfetch. Concerning colours, when compared to other colours, blue and brown had a tendency to have higher prices. In contrast to solid colours, mixed colours did not perform as well. Furthermore, black, beige and pink, emerged as the most frequent colours in the modest fashion category,

Concerning material, polyester was the most common fabric across rank groups and tended to be associated with lower prices. Overall, concerning materials, no specific fabric stood out as “poor sellers” or “best sellers" or considered as favourites for customers. However, silk fabrics have a higher price and are suited for luxury garments. Whereas, ster was the most common fabric and associated with the mass market sector.

Moreover, the study delves into the impact of the COVID-19 pandemic on consumer shopping behaviour, observing a substantial increase in online shopping activities, generating extensive sales and transaction data. Consequently, the analysis predominantly focuses on post-pandemic online commerce trends, utilising big data analytics. Given the limited literature on fashion for modest wear, the study employs data analysis techniques to show the significance of price, retailer, colour, and fabric in determining the best-selling modest-wear products. These findings align with existing research, emphasising the importance of quality, material, style, and colour in consumer purchase decisions.

5.2. Managerial Implications

The research offers several managerial implications for fashion brands in the modest wear segment:

1. The conceptual framework developed in this study can guide fashion brands in employing BI and BDA for improved demand forecasting.
2. Leveraging established online marketplaces: Recognizable online platforms can serve as effective sales channels to reach a broader consumer base. Providing diverse options and high-quality products within an appropriate price range is crucial.
3. Focusing on price optimization: Price emerged as a significant factor influencing consumer behaviour. Instead of offering discounts, optimizing prices and products before production can be more effective.

Overall, these implications aim to assist fashion managers in making informed decisions to meet the demands of modest wear consumers effectively.

5.3.Attainment of Research Questions

RQ 1: Is the longevity of modest fashion foreseeable within the fashion industry's landscape?

The examination of top-selling retailers in both affordable and high-end price ranges post-pandemic in 2021 and 2022 revealed increased demand in both market segments. This sustained demand indicates that modest fashion will remain a sought-after category even after the crisis.

RQ 2: Which sector of e-commerce retailers have greater demand: high street/mass-market brands or premium/luxury brands, determining which retailers hold the highest market share in online sales?

Similarly, the findings from exploratory data analyses indicated that there was demand for both high-street and luxury brands. However, the more affordable options were preferred over the branded designs.

RQ 3: Is consumer demand significantly influenced by price sensitivity, particularly when popular products undergo price reductions, resulting in increased demand?

As per the exploratory data analysis and machine learning techniques, it was discovered that consumers of modest fashion were sensitive to prices, which contrasts with existing literature. Yet, the increase in demand occurred when retailers reduced prices for popular mass-produced dresses. However, markdowns on premium products seemed to negatively impact the attractiveness of luxury branding.

RQ 4: What key product attributes—such as colours, materials, and styles—significantly influence consumer demand within the market?

The outcomes of the machine learning models indicated that the most influential factors for highly demanded products were, in descending order, price, retailer, colour, and fabric/material. The analysis from exploratory data suggested that products priced approximately between £137 to £140 consistently achieved the best-selling status. Consumers frequently purchased modest fashion from top retailers, including Amazon, Farfetch, and Namshi. Regarding colour choices, retailers primarily offered neutral tones like black and beige, making it challenging to draw definitive conclusions. However, investigations highlighted the popularity of basic or neutral colours, often leading to swift sales. Furthermore, silk and viscose fabrics were deemed luxurious as they sold better when priced above £1,000, while polyester garments were considered a more affordable option and didn't perform well when priced over £400.

5.4.Originality and Contribution

The research refutes the widely held assumption that modest fashion consumers prioritise affordability over premium pricing, illustrating a high degree of price sensitivity in both the mass-market and luxury sectors. The research exposes this consumer behaviour, providing fashion companies with actionable data to improve their pricing strategies. Retailers should recognise that modest fashion consumers prioritise quality and brand recognition, but they are also significantly influenced by equitable pricing, particularly in the inexpensive category, where prices exceeding £40 discourage purchases. This discovery encourages merchants to prioritise price optimisation over aggressive discounting in order to maintain a balanced sense of value and increase sales.

The study emphasises the necessity of utilising existing online platforms such as Amazon and Farfetch, where modest fashion has experienced considerable growth. Brands may enhance their reach by emphasising various channels, therefore increasing the accessibility of their products to a worldwide audience. Furthermore, identifying product features, such as the preference for neutral colours (black, beige, and pink) and the prevalence of polyester in low-cost categories, provides merchants with precise guidelines for inventory management, product design, and material sourcing.

This study conceptually contributes to the literature on consumer behaviour in niche fashion markets by giving a thorough understanding of the particular interests and purchasing patterns of modest fashion clients. This study challenges previous research that highlights the premium-seeking behaviour of modest fashion buyers, demonstrating that cost is a crucial factor across all consumer priorities, including premium sectors. This change in comprehension offers a novel theoretical framework for examining the convergence of fashion, culture, and consumer economics in specialised marketplaces.

The use of big data analytics and machine learning algorithms to investigate the modest fashion sector constitutes a significant methodological contribution. The application of data-driven methodologies to examine post-pandemic consumer patterns, price dynamics, and product characteristics offers a strong framework for future study in fashion retail. This research illustrates how firms may utilise advanced data analytics to make educated, evidence-based decisions, therefore establishing a novel paradigm in fashion management theory that prioritises technology in comprehending customer demand and enhancing corporate operations.

5.5.Limitations and Further Research

Fashion Datasets: The research encountered constraints stemming from insufficient open-source fashion databases, impeding a thorough examination of sales transactions and daily demand. Future study should entail partnerships with established small fashion enterprises to get historical sales data.

Fashion Categories: The limited availability of data constrained the research to certain modest fashion categories, neglecting several fashion categories that failed to adhere to modesty norms. Future research should focus on choosing suitable modest fashion manufacturers to increase the availability.

Machine learning Models: The unquantifiable and categorical features of the dataset limited the study in machine learning. More thorough datasets with continuous variables, use several machine learning techniques, and evaluate their effectiveness should be the focus of further studies using these approaches.

Finally, we provide opinions on consumer behaviour, small fashion upkeep, and relevant suggestions for further research to expand knowledge.

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Appendix 1

Modest fashion popular e-tailers

Retailer	Rank Percentile Group	Avg. List price ..	Count of Rank ..
Amazon AE	90-100	38	20
	80-90	37	18
	70-80	42	6
Amazon IN	70-80	28	1
Amazon US	90-100	12	2
	80-90	59	3
	70-80	79	4
Asos AU	80-90	54	1
Asos FR	70-80	111	1
Asos UK	70-80	100	1
Asos US	90-100	97	2
	80-90	58	1
	70-80	140	1
AZA Fashions IN	90-100	154	1
	80-90	328	5
Carma Online Shop IN	70-80	188	1
End Clothing ES	80-90	707	1
End Clothing FR	70-80	380	1
End Clothing IT	90-100	380	1
End Clothing UK	70-80	159	1
Farfetch UK	90-100	1,423	10
	80-90	1,575	6
	70-80	1,571	9
Farfetch US	90-100	1,647	9
	80-90	1,557	9
	70-80	1,262	5
Free People US	90-100	128	1
H&M IN	90-100	22	4
H&M JP	90-100	66	1
H&M UK	90-100	63	4
	80-90	21	3
H&M US	90-100	29	1
	80-90	53	3
	70-80	18	1
Jolly Chic AE	90-100	22	1
	80-90	23	1
	70-80	45	2
Macys US	70-80	93	1
My Theresa DE	90-100	535	2
	80-90	1,496	4
	70-80	856	3
Myntra IN	90-100	30	2
	80-90	60	3
	70-80	15	1
Namshi AE	90-100	137	9
	80-90	22	4
	70-80	25	12
Netaporter UK	70-80	975	1
Next UK	80-90	46	1
Ogaan IN	80-90	335	1
Pernias Pop-Up Shop IN	90-100	233	3
	80-90	413	2
	70-80	82	1
Shein US	90-100	21	1
	80-90	12	1
Splash Fashion AE	90-100	40	1
The Iconic AU	80-90	156	1
Zalando DE	80-90	25	1
	70-80	40	2
Zalando ES	80-90	51	3
	70-80	68	3
Zalando FR	90-100	34	2
	80-90	67	2
	70-80	37	3
Zalando IT	80-90	81	2
Zalando UK	70-80	90	1