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Aspect-Based Sentiment Analysis of Fashion and Apparel Related Reviews using Transformer Model

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ABSTRACT

The increasing reliance on e-commerce has led to a surge in customer-generated content, making sentiment analysis a crucial tool for understanding consumer preferences. This study presents a novel aspect-based sentiment analysis (ABSA) approach to extract fine-grained insights from customer reviews across multiple product categories, including lingerie, women's clothing, men's clothing, kids' apparel, home & furniture, and flowers & plants. We employ exploratory data analysis (EDA) to uncover key patterns in customer sentiment and utilize a transformer-based model with contrastive learning to enhance sentiment classification accuracy. Our approach effectively captures sentiment variations across nine different aspects, including quality, value for money, style, fit, material, warmth, comfort, support, and how well the product fits. The results demonstrate that our model outperforms traditional sentiment analysis methods, offering a more structured understanding of customer feedback. By analyzing customer sentiments from reviews, businesses can identify dissatisfaction patterns that may contribute to customer churn. Addressing these issues proactively can help improve customer retention and loyalty. These insights can help businesses refine their product offerings and improve customer satisfaction across diverse e-commerce categories.

Keywords: Natural language processing, Aspect-based sentiment analysis, Fashion and Apparel, E-commerce, Customer reviews, Consumer insights.

Introduction

The rapid expansion of electronic commerce has fundamentally transformed the structure of modern retail markets and consumer purchasing behavior. Digital platforms now provide consumers with immediate access to extensive product information, peer evaluations, and personalized recommendations, creating a highly data-driven commercial environment. In this evolving ecosystem, customer-generated content, particularly online reviews, has become one of the most influential sources of market intelligence for businesses seeking to understand consumer preferences, evaluate product performance, and strengthen customer loyalty (1, 2). The growing reliance on online shopping platforms has intensified competition among e-commerce firms, especially in the fashion and apparel industry, where consumer expectations regarding quality, fit, style, and comfort are highly subjective and continuously changing. Consequently, organizations increasingly depend on artificial intelligence-driven analytical techniques to extract actionable insights from massive volumes of unstructured textual data (3, 4).

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The fashion and apparel sector represents one of the most dynamic and consumer-sensitive domains within e-commerce. Unlike many other retail industries, fashion purchasing decisions are strongly influenced by emotional perceptions, aesthetic preferences, and experiential evaluations. Consumers not only assess objective attributes such as price and durability but also evaluate intangible dimensions including style compatibility, comfort, warmth, and product fit. Because these dimensions are highly individualized, online reviews play a central role in reducing uncertainty during purchase decisions (5, 6). Digital fashion commerce has further evolved through the integration of artificial intelligence technologies such as recommendation systems, virtual try-on tools, personalized styling algorithms, and predictive analytics, all of which aim to improve customer experience and retention (7, 8). In such an environment, understanding customer sentiment at a granular level becomes essential for strategic decision-making and sustainable competitive advantage.

Sentiment analysis has emerged as one of the most important applications of natural language processing and machine learning in business analytics. This analytical approach enables organizations to identify emotions, opinions, and attitudes embedded in textual content such as reviews, social media posts, and customer feedback (9). Traditional sentiment analysis techniques generally classify reviews into broad categories such as positive, negative, or neutral sentiments. Although such approaches provide useful high-level information, they often fail to capture the multidimensional nature of consumer opinions, especially in complex industries like fashion e-commerce where a single review may simultaneously contain both positive and negative evaluations regarding different product attributes (10, 11). For example, a customer may praise the style of a garment while criticizing its material quality or fit. Conventional document-level sentiment classification methods are incapable of adequately representing such nuanced evaluations.

To overcome these limitations, Aspect-Based Sentiment Analysis (ABSA) has gained significant scholarly and practical attention in recent years. ABSA extends traditional sentiment analysis by identifying specific product aspects or attributes and associating sentiment polarity with each individual aspect rather than with the overall review (11, 12). This fine-grained analytical approach provides a more accurate understanding of customer experiences and enables businesses to pinpoint precise strengths and weaknesses within their products or services. In the context of fashion retail, ABSA can reveal detailed customer perceptions regarding quality, fit, comfort, warmth, style, support, and value for money, thereby facilitating targeted product improvement and personalized marketing strategies (13, 14).

Recent advances in machine learning and deep learning have substantially improved the performance of sentiment analysis systems. Early approaches relied heavily on lexicon-based methods and classical machine learning algorithms such as Naïve Bayes, support vector machines, and random forests. While these methods demonstrated acceptable performance for basic sentiment classification tasks, they struggled to capture contextual semantics and long-range dependencies within textual data (15). The emergence of deep learning architectures, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory (LSTM) networks, marked a significant improvement in sentiment analysis capabilities by enabling models to learn hierarchical textual representations (16, 17). Nevertheless, these architectures still faced limitations when dealing with contextual ambiguity and complex linguistic structures.

Transformer-based models have revolutionized the field of natural language processing by introducing self-attention mechanisms capable of capturing contextual relationships across entire sequences of text. Models such as BERT, DistilBERT, and DeBERTa have demonstrated exceptional performance across various sentiment

analysis tasks due to their ability to generate context-aware embeddings and model semantic dependencies more effectively than traditional deep learning architectures (12, 18). In fashion e-commerce environments, transformer-based architectures are particularly valuable because customer reviews frequently contain nuanced expressions, implicit sentiments, and mixed evaluations that require sophisticated contextual interpretation. These advanced models therefore provide businesses with deeper insights into consumer behavior and purchasing motivations.

The increasing sophistication of ABSA methods has resulted in broad adoption across multiple industries. In finance, aspect-based models have been used to analyze investor sentiment and explain market behavior through fine-grained opinion mining (19, 20). In telecommunications, researchers have applied ABSA techniques to evaluate customer satisfaction and service quality in telecom reviews (21-23). Healthcare researchers have utilized transformer-based ABSA approaches to analyze patient opinions and improve healthcare service delivery (24, 25). Similarly, studies in hospitality and tourism have demonstrated the effectiveness of ABSA for evaluating customer experiences in hotels and restaurants (26-28). These diverse applications illustrate the flexibility and practical value of aspect-level sentiment analysis in extracting domain-specific customer insights.

Within the e-commerce domain, several researchers have focused specifically on sentiment analysis for fashion and apparel reviews. Bellar et al. evaluated multiple deep learning architectures, including CNNs, RNNs, and Bi-LSTM networks, for predicting customer sentiment in women's clothing reviews and demonstrated the effectiveness of transformer-based embeddings such as BERT and FastText (13). Similarly, Taneja et al. proposed a transformer-based unsupervised learning approach for imbalanced fashion review datasets and reported strong performance in both sentiment classification and product recommendation tasks (18). Shetty et al. employed machine learning classifiers including logistic regression, support vector machines, and random forests to analyze Amazon women's clothing reviews and achieved high classification accuracy using CountVectorizer and TF-IDF representations (17). Prince et al. also investigated sentiment analysis in online clothing reviews using advanced machine learning techniques and found strong predictive performance among ensemble and neural network models (14).

Despite these advancements, several limitations remain within existing research. First, many studies focus on overall sentiment classification rather than fine-grained aspect-level analysis, limiting the practical interpretability of their findings. Second, existing approaches often analyze aspects independently and fail to account for the interdependencies among related product attributes (10). In reality, aspects such as quality, comfort, fit, and material are frequently correlated, especially in fashion products. Ignoring these relationships may reduce model effectiveness and result in incomplete representations of customer evaluations. Third, many sentiment analysis datasets suffer from missing or sparsely annotated aspect ratings, creating challenges for reliable sentiment prediction and model generalization (11). Moreover, class imbalance remains a persistent problem in ABSA research because positive reviews often outnumber negative ones, particularly in commercial review datasets (18).

Another important challenge concerns multilingual and multicultural sentiment analysis. Savci and Das emphasized that sentiment analysis performance varies significantly across languages due to linguistic structures, spelling inconsistencies, and contextual differences (29). Similarly, studies involving Arabic, Amharic, and multilingual datasets have demonstrated the need for adaptable transformer architectures capable of handling diverse linguistic environments (22, 24). These findings indicate that future ABSA systems should incorporate more flexible and context-sensitive learning mechanisms to ensure robust cross-domain and cross-language performance.

The relationship between sentiment analysis and customer retention has also become increasingly important in e-commerce research. Customer churn prediction models indicate that dissatisfaction expressed in online reviews often serves as an early indicator of future customer loss (30, 31). Since retaining existing customers is generally more cost-effective than acquiring new ones, businesses must identify dissatisfaction patterns quickly and accurately (32). Aspect-based sentiment analysis offers substantial advantages in this regard because it enables firms to detect the precise aspects driving negative experiences. For instance, customers dissatisfied with warmth, fit, or material quality may exhibit different churn behaviors than customers dissatisfied with pricing or delivery. Consequently, integrating ABSA into customer relationship management systems can significantly improve personalization strategies and customer retention initiatives (3).

Theoretical developments in ABSA have increasingly emphasized explainability and interpretability. Explainable transformer-based sentiment models allow organizations not only to classify customer opinions but also to understand the reasoning behind sentiment predictions (12). This interpretability is particularly important in managerial settings because business decision-makers require transparent and actionable analytical outputs rather than black-box predictions. Furthermore, recent studies have explored graph-based neural networks and contrastive learning techniques to improve aspect relationship modeling and semantic representation learning (33). These approaches have shown considerable promise in enhancing contextual understanding and discriminative learning capabilities within sentiment classification systems.

Exploratory data analysis also plays a critical role in developing effective sentiment analysis frameworks. Through statistical analysis and visualization techniques, EDA helps researchers identify patterns, outliers, correlations, and missing values within datasets (11). EDA techniques provide essential insights into customer behavior trends, review distributions, and aspect importance, thereby guiding feature engineering and model optimization strategies. The integration of EDA with transformer-based ABSA systems creates a more comprehensive analytical framework capable of generating both predictive and descriptive insights (10).

In recent years, the growing integration of artificial intelligence into fashion e-commerce has intensified the demand for advanced customer analytics systems. AI-enhanced recommendation engines, personalized styling platforms, and virtual fitting technologies increasingly rely on customer feedback data to optimize user experiences and improve conversion rates (6, 7). Social media marketing and digital branding strategies in fashion retail are similarly influenced by consumer sentiment expressed through online reviews and electronic word-of-mouth communication (5, 8). Consequently, the development of accurate and scalable ABSA systems is becoming a strategic necessity for modern e-commerce platforms seeking to maintain customer engagement and market competitiveness.

Although prior studies have substantially contributed to the advancement of sentiment analysis methodologies, there remains a need for more comprehensive transformer-based frameworks capable of simultaneously addressing aspect interdependencies, missing data challenges, class imbalance, and fine-grained sentiment representation in fashion and apparel reviews. In particular, there is limited research combining exploratory data analysis, multi-label aspect classification, transformer architectures, and contrastive learning mechanisms within a unified framework for fashion e-commerce applications (10, 13, 18). Furthermore, existing literature has rarely explored large-scale multi-category datasets encompassing diverse fashion and apparel product segments alongside detailed aspect-level evaluations.

Therefore, the aim of this study is to develop and evaluate a transformer-based aspect-based sentiment analysis framework for fashion and apparel e-commerce reviews by integrating exploratory data analysis, multi-label sentiment classification, and contrastive learning to generate fine-grained insights into customer perceptions across multiple product aspects and categories.

Methods and Materials

Dataset curation and preprocessing

Creating a comprehensive dataset for product analysis requires meticulous attention to several factors, including category diversity, review availability, and sentiment analysis. In our effort to build a robust dataset, we identified 615 distinct product categories from *Marks And Spencer*[1] website. However, certain challenges arose, particularly with categories that had sparse review counts, especially in earlier years such as 2013, when relevant information, such as aspect-level sentiments was limited. Additionally, older reviews, particularly from 2014 and 2015, were often inactive, highlighting the need for updated product lines to align with evolving consumer preferences.

To address these challenges and ensure the dataset's relevance, we adopted a strategic approach. By identifying the five most prominent products within each category—amounting to approximately 3,090 products—we aimed to capture a comprehensive snapshot of consumer sentiment and product performance. This careful curation process provided a rich resource for analyzing and gaining insights into diverse product categories.

To further enhance the dataset's quality and reliability, we excluded reviews lacking sentiment indicators by filtering based on essential fields such as "star ratings" or "recommended" attributes. This ensured the dataset's utility for subsequent analysis. These efforts enable meaningful exploration of consumer behavior and product dynamics in the digital marketplace. Additionally, we accounted for products that belonged to multiple categories or had variations, such as different colors, but shared the same reviews. For example, the "Supersoft Colour Block Crew Neck Jumper" appeared in both "Ivory Mix" and "Natural Mix" categories, sharing identical reviews. Including such variations ensured the dataset's inclusivity and accuracy.

Therefore, from the 615 product subcategories, we found 269 subcategories without any reviews. For the remaining 346 subcategories, we included 1,606 products (out of 25,784 visited products), selecting the five most-reviewed products in each subcategory. In cases where fewer than five products were available for a subcategory, we included as many products as possible with the highest review counts. For initial experiments, we focused on reviews for the top product in each category. However, due to crawling challenges, we ultimately collected data from 296 categories, covering approximately 300 products with a total of 106,000 reviews.

The final dataset, referred to as "Beauty," comprises 85,350 reviews and 20 features. It includes 9 distinct aspects: "Quality," "Value for Money," "Fit," "Style," "Material," "Warmth," "How did it fit?," "Comfort," and "Support." The main category of the dataset encompasses 6 primary product categories. Additionally, the dataset includes columns for sub-category and product title, which have 132 and 226 unique values, respectively.

During the data preprocessing stage, all text was first converted to lowercase to ensure consistency. Punctuation marks were then removed, as they typically do not contribute significant semantic information. Next, tokenization was performed, breaking the text into smaller units such as words. Finally, stopwords—common words that do not

[1] https://www.marksandspencer.com/

carry meaningful information, such as "the," "is," and "are"—were removed to enhance the model's efficiency and focus on more informative terms.

Proposed Transformer-Based Aspect-Based Sentiment Analysis

In our approach to ABSA, we leverage the inherent correlations between certain aspects, which we identified through detailed EDA. Recognizing these interdependencies, we frame the problem as a multi-label classification task. To enhance the model's ability to differentiate between correlated and uncorrelated aspects, we integrate a contrastive learning mechanism alongside a traditional binary cross-entropy (BCE) loss function. This novel combination significantly improves feature representation and classification performance, making our approach highly effective for fine-grained sentiment analysis.

Our methodology comprises four main steps. First, the data is structured as a multi-label classification problem, ensuring that multiple aspect labels can be assigned to each review. Next, we employ a state-of-the-art transformer-based model (DeBERTa-v3-large[1]), enhanced with a MLP layer at the top, serving as the final classifier. In the third step, the BCE loss is computed to optimize classification performance. Finally, we introduce a Contrastive Loss (CL) term, which is linearly combined with BCE loss to enforce aspect correlation constraints (Equation 1):

$$\text{Loss} = \text{BCE} + \text{CW} * \text{CL} \qquad (1)$$

where BCE represents binary cross-entropy loss, CW is the contrastive loss weight, and CL is the contrastive loss component.

The CL is designed with two key objectives. First, it identifies samples containing similar aspects based on a similarity loss metric. Second, it filters out samples that exhibit weak correlation, ensuring that the model learns more discriminative features. The calculation of CL follows these steps:

1. Generating high-dimensional embeddings for each review sample.
2. Computing an inner cosine similarity matrix to quantify relationships between samples.
3. Feeding the similarity matrix into a cross-entropy loss (CEL) function to compute the final contrastive loss.

This innovative loss formulation allows the model to embed correlation constraints directly into the learning process, refining the representation space in a way that standard BCE loss alone cannot achieve. By integrating cosine similarity into the loss function, our approach enhances the model's ability to capture subtle dependencies across aspects, leading to a notable performance boost in sentiment classification tasks.

Filling missing data with AI-driven completion

A crucial challenge in our study was addressing missing aspect ratings, particularly for "Material" and "Warmth," which lacked sufficient user-provided ratings compared to "Quality," "Value for Money," "Style," and "Fit." Given the importance of these aspects in understanding customer sentiment and optimizing platform decision-making, we devised an intelligent AI-driven method to impute missing values.

To achieve this, we leveraged the inherent correlations among aspects, as observed in our EDA. Our proposed solution employs a multi-label sentiment classification model that not only predicts sentiments for available aspects but also intelligently infers missing aspect ratings based on contextual information from user reviews. This method

[1] https://huggingface.co/microsoft/deberta-v3-large

ensures that platform owners gain a comprehensive understanding of product sentiment, even in cases where users omit explicit ratings.

Our dataset consisted of 85,350 reviews, yet only 7,656 reviews contained ratings for all six key aspects. This significant disparity further underscores the necessity of an AI-driven solution. By constructing a transformer-based multi-aspect model, we ensured that the model could simultaneously predict sentiment for multiple aspects with high accuracy. This approach allows e-commerce platforms to automatically fill in missing values, enriching their datasets and enabling more informed business decisions.

Findings and Results

Implementation

To ensure a well-balanced and statistically sound dataset for model training, we verified that both the training and test splits followed a normal distribution, making them suitable for learning generalizable patterns. Aspect ratings were categorized into sentiment labels: ratings of 4 and 5 were considered positive, while ratings of 1, 2, and 3 were treated as negative.

For evaluation, we allocated 20% of the dataset as the test set, while the remaining 80% was used for training. This split resulted in 6,124 samples in the training set and 1,532 samples in the test set. Detailed statistics for both sets are presented in Table 1, where a key observation is that, across all aspects, negative samples are generally fewer than positive ones. However, for the “Warmth” aspect, the negative ratings outnumber the positives, indicating that this aspect presents a greater challenge for sentiment analysis. This imbalance highlights the need for a robust model capable of accurately distinguishing subtle sentiment patterns, especially in more complex and nuanced aspects such as "Warmth."

Table 1: Data splitting

	Quality	Value for Money	Fit	Style	Material	Warmth
Train (positive/negative)	4285/ 614	4253/ 464	4231/ 668	4508/ 391	4277/ 622	1824/ 3075
Valid (positive/negative)	1090/ 135	1077/ 148	1077/ 148	1137/ 88	1084/ 141	455/ 770
Test (positive/negative)	1341/ 191	1316/ 216	1337/ 195	1402/ 130	1331/ 201	560/ 972

To ensure optimal performance of our proposed model, we carefully fine-tuned the hyper-parameters based on empirical analysis (Table 2). The training process was conducted using a batch size of 2, with a total of 3 epochs to balance computational efficiency and generalization. The CW was set to 0.1, ensuring that the model effectively captured aspect correlations without overpowering the BCE loss. We utilized the DeBERTa-v3-large transformer model, a state-of-the-art architecture known for its enhanced contextual representations, with a tokenizer maximum length of 300 tokens to accommodate comprehensive review content.

The training was executed on a high-performance computing environment equipped with an NVIDIA RTX A3090 GPU (24GB memory), 4 CPU cores, and 80GB RAM. This setup ensured efficient handling of the computational demands associated with transformer-based training, particularly when integrating contrastive learning into the multi-label classification framework.

Table 2: Model hyper-parameters.

Parameter	Value
Batch size	2
Epochs	3
CW	0.1
Tokenizer max length	300

EDA and data visualization

EDA is a crucial phase in the data analysis process, serving as an essential step in understanding and interpreting datasets. The primary objective of EDA is to uncover underlying patterns, identify anomalies, and assess data quality through a variety of statistical and graphical methods (Data et al., 2016). By visualizing the data and examining its distribution, outliers, and correlations, EDA enables researchers to generate hypotheses and refine their analytical approach without making prior assumptions. This process plays a key role in guiding feature selection, informing model development, and ensuring the robustness of subsequent statistical testing (Mukhiya & Ahmed, 2020).

The reviews were collected from January 2011 to February 2024, and Figure 1 illustrates the number of reviews for each year. As shown, the number of reviews before 2018 is relatively low; therefore, we excluded data prior to 2018 and focused on the period from January 2018 to February 2024 for analysis. Notably, 2023 has the highest number of reviews, while 2018 has the fewest. This distribution is reasonable for data analysis, as reviews for older products may be scarce due to the fast-paced nature of the fashion industry, where new products are released each season, leading to a decline in the use of previous year's items. The number of reviews saw a significant increase from 2022 to 2023 and from 2020 to 2021, while the increase between 2018 and 2019 was minimal. This trend reflects the growing popularity of online shopping, as consumers find it more convenient and relaxing to explore a wide range of products from the comfort of their homes.

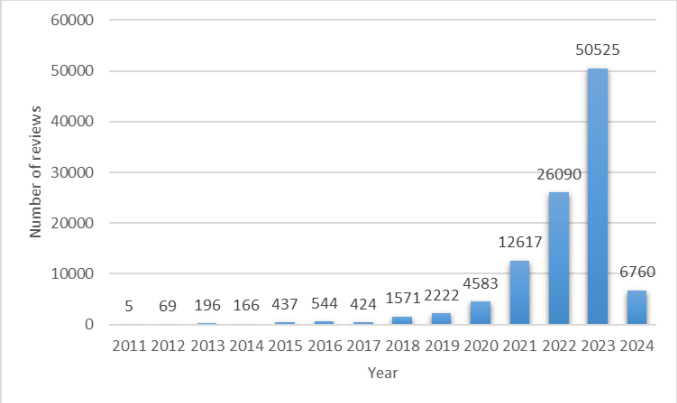


Figure 1: Number of reviews per year

Table 3 presents the statistics regarding the number of reviews per main category. The first three main categories of products receive a significantly higher number of reviews, while the remaining three categories have a comparatively lower number of reviews. Moreover, Table 3 presents the number of sub-categories within each main category, highlighting the significance of conducting both main-category and sub-category specific analyses to

identify top-selling and trending categories over time. It is evident that the Men category, with 33 sub-categories, contains a higher number of sub-categories compared to the Women category, which has 18 sub-categories. However, the number of products differs: there are 51 products for Women and 44 for Men, which does not align with the sub-category distribution. Additionally, the Flowers & Plants category does not include any sub-categories, as only one product from this category is featured in the study.

Table 3: Review distribution across main categories, as well as number of sub-categories and products

Main category	Number of reviews	Numbers of sub-category	Numbers of product title
Lingerie	30594	13	44
Women	24813	18	51
Men	16552	33	44
Kids	7373	46	58
Home & Furniture	5047	20	25
Flowers & Plants	971	1	1

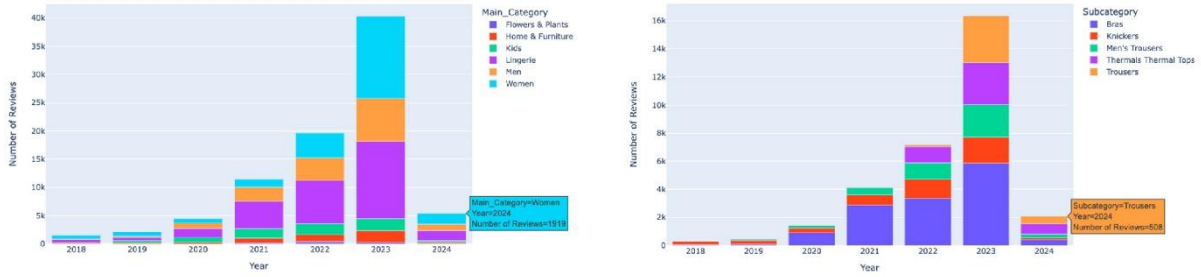
Among the 6 main categories and 131 sub-categories, Table 4 provides a summary of the statistics for the top 15 sub-categories. The majority of the top sub-category products belong to the Women and Lingerie categories, reflecting trends over the past seven years. As observed, most of the average ratings for the top 15 products exceed 4, with the exception of the "Footwear Slippers" sub-category under the Women's main category, which has an average rating of 3.8. This sub-category, which has been included in the dataset from 2022 to 2024, is a newly introduced category for women.

Table 4: Top 15 sub-categories statistics

Main category	Sub-category	Number of reviews	Average review rating	Year
Lingerie	Bras	13630	4.263036	[2018, 2019, 2020, 2021, 2022, 2023, 2024]
Lingerie	Thermals Thermal Tops	4894	4.755703	[2021, 2022, 2023, 2024]
Lingerie	Knickers	4870	4.324992	[2021, 2022, 2023, 2024, 2020, 2018, 2019]
Men	Trousers	4571	4.436176	[2021, 2022, 2023, 2024, 2019, 2020]
Women	Trousers	3962	4.279754	[2022, 2023, 2024]
Women	Knitwear Jumpers	3849	4.248406	[2023, 2024, 2022, 2019, 2020, 2021]
Women	Jeans	3622	4.314854	[2023, 2024, 2018, 2019, 2020, 2021, 2022]
Women	Coats & Jackets	3460	4.545917	[2022, 2023, 2024, 2021, 2020]
Women	Knitwear Cardigans	2548	4.183085	[2018, 2019, 2020, 2021, 2022, 2023, 2024]
Men	Shoes Slippers	2523	4.587518	[2023, 2024, 2018, 2019, 2020, 2021, 2022]
Kids	Boys Joggers	2372	4.360378	[2023, 2024, 2019, 2020, 2021, 2022]
Women	Footwear Slippers	1612	3.831761	[2022, 2023, 2024]
Lingerie	Shapewear	1482	4.265376	[2022, 2023, 2024, 2019, 2020, 2021]
Men	Tops T-shirts	1234	4.219923	[2022, 2023, 2024]
Lingerie	Slips Full Slips	1223	4.522344	[2018, 2019, 2020, 2021, 2022, 2023, 2024]

We analyze the frequency distribution of product categories over time by examining the number of reviews allocated to each main and sub-category per year. Figure 2(a) presents a bar plot illustrating the sales trends across main categories over the past seven years. The results indicate that *Lingerie*, *Women*, and *Men* categories have consistently dominated sales, whereas categories like *Flowers & Plants* have received significantly fewer reviews.

To gain deeper insights, we further examine sub-category trends. Among 131 unique sub-categories, we select the top five based on review frequency to ensure clear visualization. As shown in Figure 2(b), *Bras*, *Knickers*, *Men's Trousers*, *Thermals Thermal Tops*, and *Trousers* emerge as the most reviewed sub-categories, aligning with the top-performing main categories. These findings highlight consumer preferences, emphasizing the strong demand for apparel-related products in recent years.

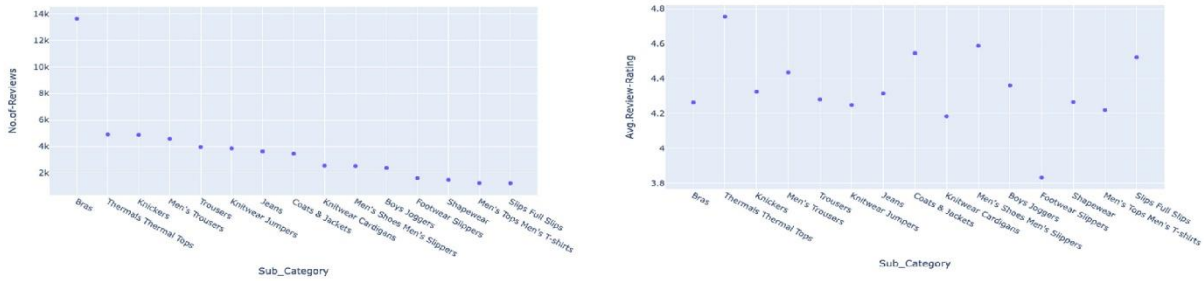


(a) (b)

Figure 2: Number of reviews per year in the (a) main category per year, (b) top 5 sub-categories

Figure 3(a) highlights that certain sub-categories, such as *Bras*, *Thermals Thermal Tops*, *Knickers*, and *Men's Trousers*, have consistently remained in demand over the years. Both the number of reviews and high average ratings indicate their sustained popularity. Additionally, items like *Trousers*, *Tops*, and *T-shirts* have gained traction in recent years, reflecting emerging fashion trends.

However, as shown in Figure 3(b), the only sub-category with notably lower customer satisfaction is *Footwear Slippers*, which has an average rating of 3.8, indicating relatively lower approval compared to other top-selling products.



(a) (b)

Figure 3: (a) number of reviews, (b) average review rating, in top 15 sub-categories

Figure 4 illustrates the top 8 most frequently reviewed products over time, revealing shifts in consumer interest. The absence of reviews for some products in earlier years reflects the evolving nature of fashion, where new designs gradually replace older trends. While essential items like *slippers* have been reviewed consistently over the years,

newer products such as *Tops* have gained popularity more recently, becoming trendy since 2023. This pattern highlights the continuous transformation of the fashion industry and changing consumer preferences.

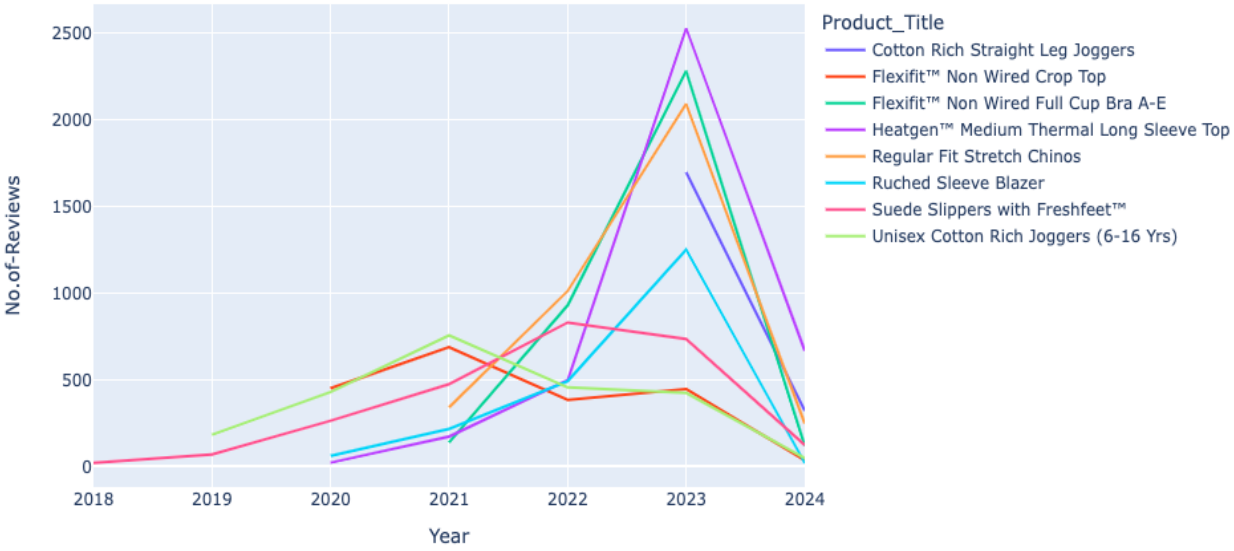


Figure 4: Top 8 products with a high number of reviews

To assess customer satisfaction across main categories, we analyze the overall rating distribution by summing review ratings per category each year. Based on Figure 5(a), the results indicate that *Lingerie*, *Women*, *Kids*, and *Men* categories have the highest customer satisfaction. Interestingly, while the *Kids* category has relatively low sales (as shown in Figure 2(a)), it maintains high satisfaction. This could suggest that kids' products are either high-priced and well-received or that customers prefer purchasing such items in person rather than online, leading to fewer reviews. Further, Figure 5(b) highlights the top-performing sub-categories. *Bras*, *Knickers*, and *Jeans* have consistently high sales and strong review ratings, making them some of the most popular products. Additionally, *Coats & Jackets* and *Dresses* have emerged as best-selling categories since 2021, indicating their recent introduction and growing consumer interest.

Figure 5: Sum of review rating per year in the (a) main category, (b) top 5 sub-categories

To analyze customer feedback, we generate three types of word clouds. Figure 6(a) highlights frequently mentioned terms in customer reviews from 2018 to 2024, with phrases like good quality, good fit, happy, and value

for money indicating overall positive sentiment. In Figure 6(b), positive reviews emphasize aspects such as quality, fit, and price, while also mentioning popular products like trousers, jumpers, and shirts, suggesting high sales and customer satisfaction. However, Figure 6(c) reveals common complaints related to size, color, and material, with many customers mentioning product returns due to these issues, reflecting key challenges in online shopping.

Figure 6: Word cloud on review content (a) all reviews, (b) recommend products, (c) not recommend products

To analyze customer recommendations, we examine the “recommended” column of dataset, where “Yes, I recommend this” indicates a positive recommendation and “No, I don’t recommend this” indicates a negative one. A small portion of reviews (1.5%, totaling 1,282) lack a recommendation. As illustrated in Figure 7, the majority of reviewers express satisfaction and recommend their purchases, while 12.4% do not recommend the products.

Figure 8(a) highlights the distribution of positive and negative recommendations across six main categories. Notably, the Lingerie and Women’s categories, which receive the highest number of reviews, also exhibit high rates of both positive and negative recommendations. The largest share of negative feedback comes from three major categories: Lingerie, Men, and Women. Meanwhile, Flowers & Plants, despite receiving fewer reviews overall, show a relatively high proportion of negative recommendations, suggesting lower customer satisfaction.

A more detailed breakdown at the sub-category level, presented in Figure 8(b), reveals that Bars products receive a significant number of both positive and negative recommendations. Other sub-categories generally maintain a strong positive reception with fewer negative reviews.

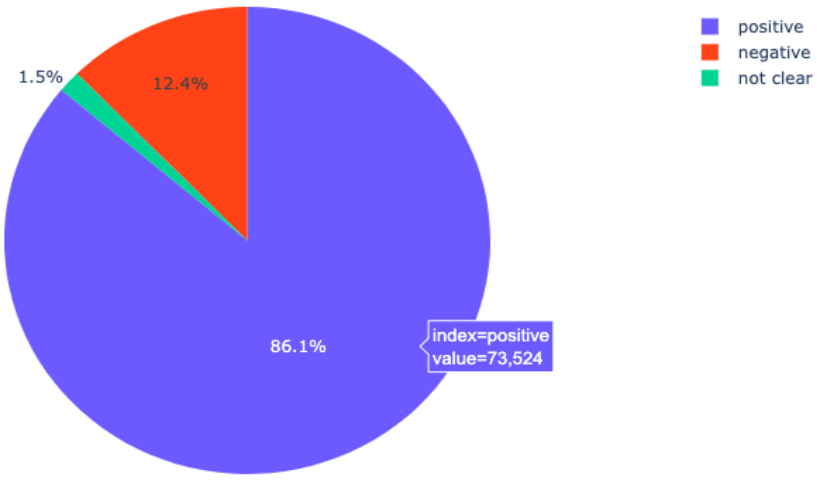
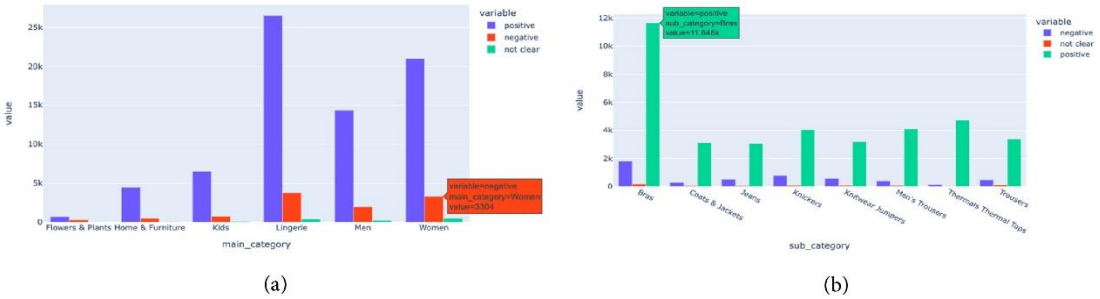


Figure 7: Recommendation distributions



(a) (b)

Figure 8: Recommendation distributions in (a) main categories, (b) top 8 sub-categories

To conduct a comprehensive analysis, it is essential to examine how many values are left unreported by reviewers across various aspects. We analyzed missing values for nine aspects in Figure 9, where the red colors represent missing data. As shown, aspects such as Material, Warmth, Comfort, and Support are frequently left blank by users. This may be because customers tend to prioritize Quality over these features when leaving reviews. Additionally, the Value for Money aspect is the most commonly commented on, with most reviews including this information. This suggests that one effective approach for studying customer satisfaction is to focus on the Value for Money aspect, as it reflects the logical expectation that people seek good-quality products at a reasonable price. It also shows that customers frequently consider Style and Fit when making their purchasing decisions.

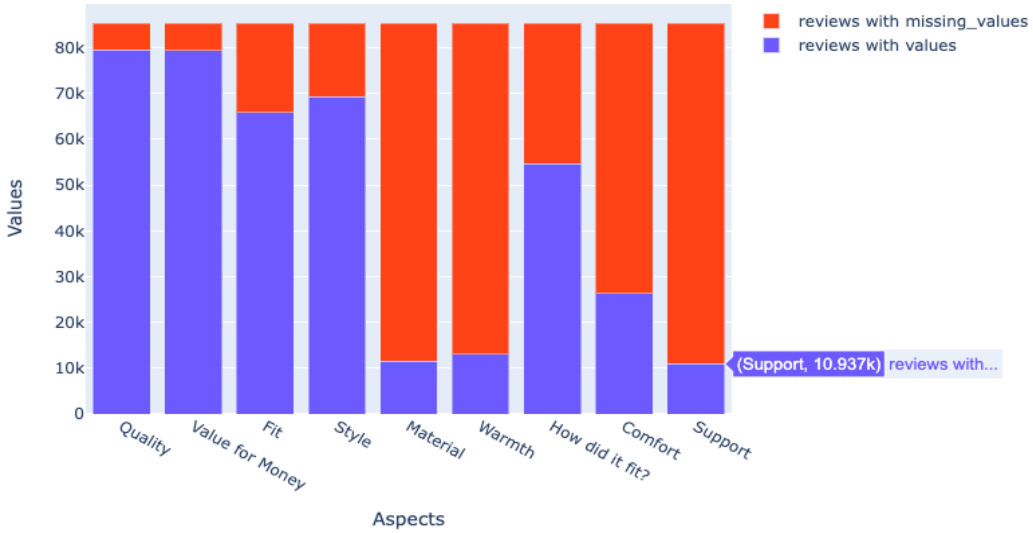


Figure 9: The number of missing values for each aspect

Figure 10 illustrates the distributions of all aspects, revealing several key patterns. Aspects such as Quality, Value for Money, Fit, Style, and Material exhibit similar distributions, with the majority of ratings falling between 3 and 5, and a few outliers below 3. In contrast, aspects like Comfort and How did it fit? show more distinct distributions. The Warmth aspect has a rating range from 2 to 5, with its median lower than the other aspects mentioned. Additionally, referring to Figure 9, we observe that a significant number of values for aspects such as Warmth and Support are missing, which aligns with the observed distribution. However, for aspects like How did it fit? and Comfort, despite having more reviews than Warmth and Support, the ratings are not well-distributed.

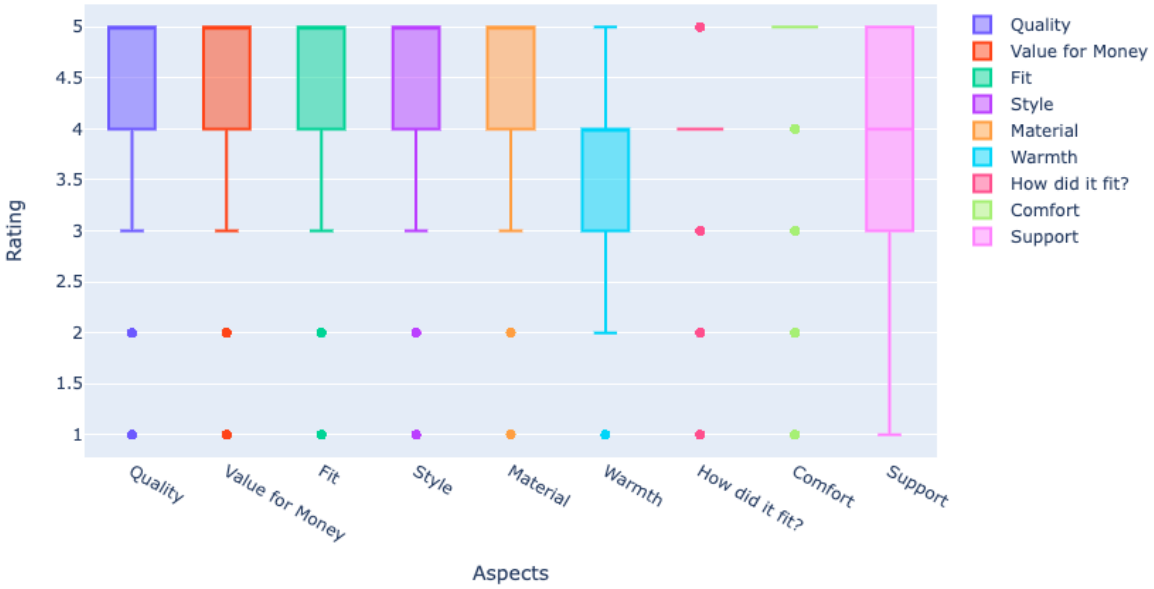


Figure 10: Aspects distributions

By examining the behavior of nine key aspects across six main product categories, as illustrated in Figure 11, we can identify trends, strengths, and areas that require improvement.

For *Flowers & Plants*, customers primarily provide feedback on *Quality* and *Value for Money*, while other aspects do not seem relevant to this category. Over the past seven years, products in this category have generally been well received, maintaining a relatively high average rating of approximately 3.8 out of 5. This indicates that customers find these products satisfactory in terms of both quality and affordability.

In the *Home & Furniture* category, *Value for Money* plays a crucial role, with customers expressing satisfaction with pricing in recent years. Additionally, the *Style* aspect is highly appreciated, particularly before and after 2020, except during the COVID-19 pandemic when ratings dropped. The high ratings for *Style* (averaging around 4.5 out of 5) suggest that aesthetic appeal is a major factor in purchasing decisions. However, aspects like *How did it fit?* are not applicable to this category. Interestingly, in the early years (2018–2020), customers found these products expensive, as indicated by lower *Value for Money* ratings.

The *Kids* category exhibits significant variation across aspects such as *Quality*, *Value for Money*, *Style*, and *How did it fit?*. While these products have historically been well received, 2024 marks a decline in ratings for *Quality* and *Value for Money*, suggesting a perceived decrease in quality and an increase in prices. This shift implies that children's products are becoming less appealing to online shoppers due to their higher costs and potentially lower durability.

For *Lingerie*, customer reviews are predominantly from women, making this one of the most frequently reviewed categories. Products in this category score highly in *Quality*, *Value for Money*, *Style*, *Material*, and *Fit*, indicating strong customer satisfaction. Additionally, customers frequently highlight the *Comfort* of lingerie, reinforcing its appeal. However, the *Support* aspect consistently receives lower ratings, suggesting a potential area for improvement in product design.

In the *Men's* category, customers express satisfaction with *Quality* and *Value for Money*, but concerns arise regarding *How did it fit?*, leading to frequent product returns. Between 2019 and 2020, discussions around *Comfort* were common, but this aspect has received less attention in recent years. This decline may be attributed to changes

in fashion trends, where newer styles focus less on comfort, or the increased availability of free-size options, reducing fit-related concerns.

The *Women's* category is among the most frequently reviewed, with notable dissatisfaction regarding the *Warmth* aspect. Over time, fashion trends appear to have influenced perceptions of warmth, with ratings consistently lower in this aspect. The year 2020 stands out as a particularly poor year for this category in terms of warmth ratings, possibly due to shifts in consumer expectations or seasonal product offerings.

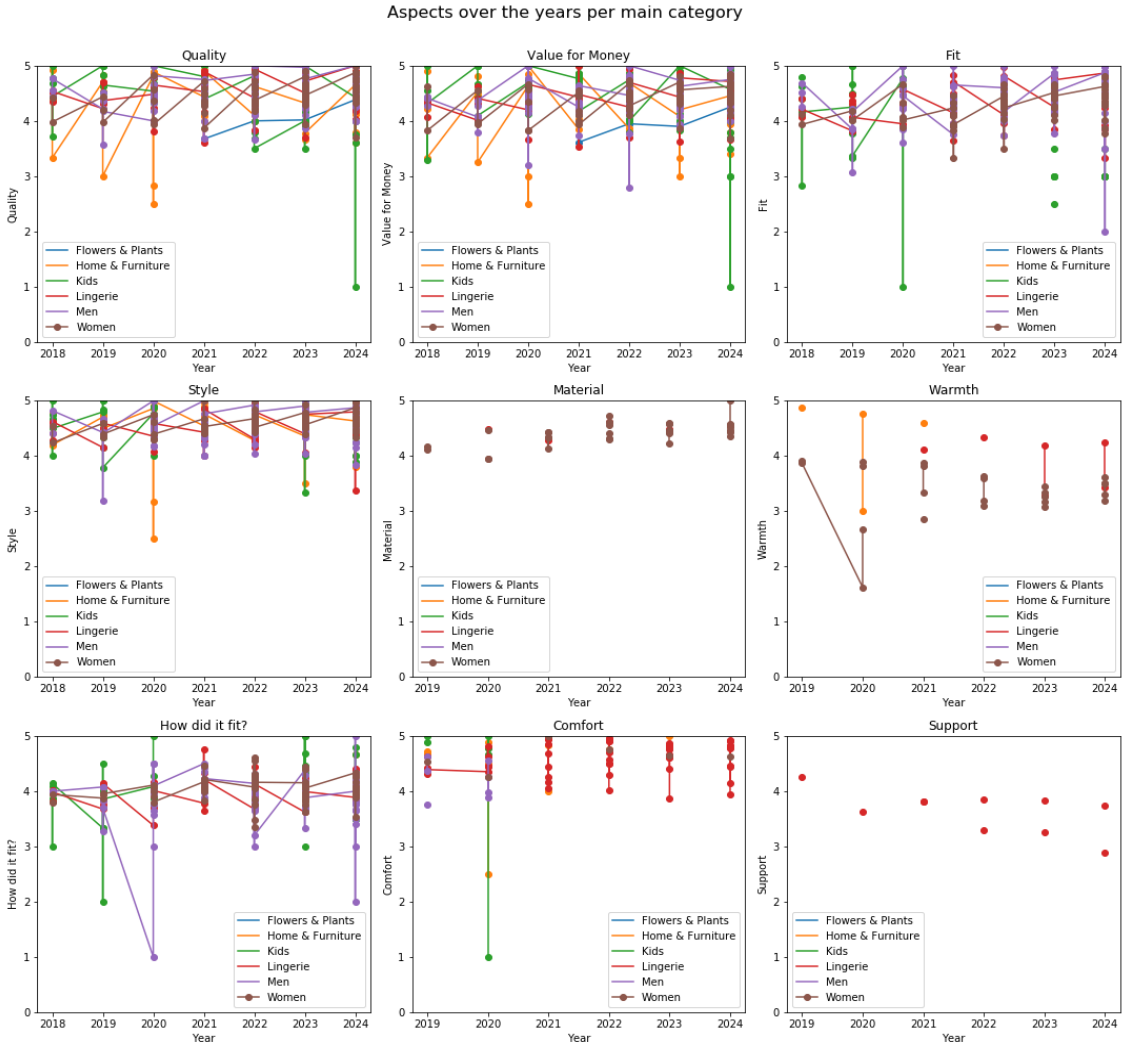


Figure 11: Aspect analysis of main categories

The aspect ratings for the top-15 sub-categories, as shown in Figure 12, provide a deeper understanding of customer feedback on various product features. By analyzing these aspects, we can gain valuable insights into which product qualities influence customer satisfaction the most and identify areas that need improvement. A closer look at the correlation between individual aspects and overall ratings reveals important patterns that contribute to a more understanding of consumer preferences.

For the *Quality* aspect, there is a clear correlation with overall ratings. Products such as *Footwear Slippers* show a significant gap in quality ratings, indicating that customers are not satisfied with the quality of these products.

Similarly, *Thermals Thermal Tops* exhibit a noticeable gap between quality and overall ratings, suggesting that while customers may rate these products positively, there is still room for improvement in terms of perceived quality.

The *Value for Money* aspect, on the other hand, does not show a strong correlation with overall ratings. Products like *Footwear Slippers* also struggle in this area, with customers perceiving a mismatch between the value they get and the price they pay. *Thermals Thermal Tops* again show a gap between the value for money rating and the overall rating, suggesting that customers feel these products may not offer the best value despite their positive overall reviews.

When it comes to *Style*, there is a clear correlation with overall ratings, and the distribution follows a normal pattern. However, certain products such as *Boys Joggers* face a style-related issue. Despite being of good quality, these products receive lower ratings for style, likely due to a lack of design updates over time. Similarly, the *Fit* aspect follows a similar pattern to *Style*, showing a high correlation with overall ratings. However, like *Style*, *Boys Joggers* also receive lower ratings for fit, further highlighting dissatisfaction with this particular product category.

The *Material* aspect presents a different challenge. While many products lack sufficient ratings for material quality, a few categories, such as *Knitwear Jumpers*, *Coats & Jackets*, and *Knitwear Cardigans*, receive ratings that correlate well with overall satisfaction. This suggests that customers pay particular attention to material quality in these categories, likely due to seasonal factors and regional preferences. For instance, in colder climates, the material of coats and jackets becomes a crucial factor in customer satisfaction. However, a high number of missing values for this aspect indicates that many customers do not prioritize it in their reviews.

The *Warmth* aspect, like *Material*, suffers from a low number of reviews. Products such as *Knitwear Jumpers* and *Coats & Jackets* receive more attention in terms of warmth, which is logical given the seasonal nature of these products. Interestingly, *Thermals Thermal Tops* also receive some attention for warmth, even though their material quality may not be highly rated. This suggests that customers may prioritize warmth over material quality when purchasing such items.

The *How did it fit?* aspect shows no significant correlation with overall ratings and follows a non-normal distribution. Similar to the *Style* and *Fit* aspects, *Boys Joggers* again emerge as a product category with a large gap between overall ratings and fit, indicating customer dissatisfaction. Despite a relatively large number of reviews, the poor reception of this category signals a need for further improvement in fit.

The *Comfort* aspect suffers from a lack of reviews, which explains the low ratings observed for some categories. However, products such as *Bars*, *Thermals*, *Knickers*, and *Shapewear* perform well in terms of comfort, suggesting that customers are generally satisfied with the comfort provided by these products.

The *Support* aspect, like *Comfort*, has a low number of reviews, resulting in a lack of data to make definitive conclusions. However, products in the *Bars* and *Shapewear* categories do receive positive feedback regarding support, highlighting customer satisfaction in these areas despite the low overall attention given to this aspect.

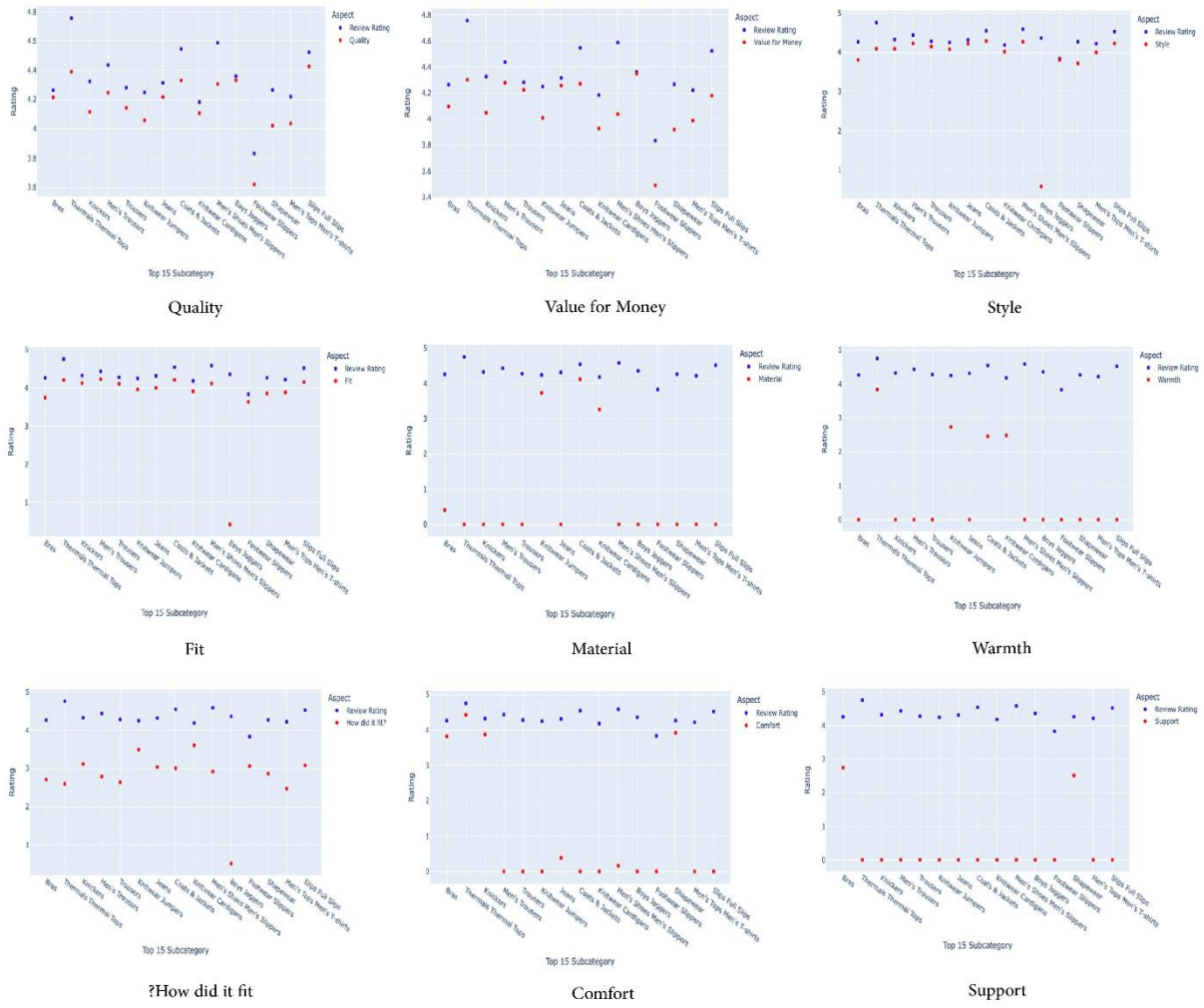


Figure 12: Aspect ratings for top-15 sub-categories.

Evaluation

To assess the performance of our proposed model, we utilized two key evaluation metrics: accuracy and F1-score. Accuracy measures the proportion of correctly classified instances over the total samples, providing an overall measure of correctness. However, since our dataset exhibits class imbalances in certain aspects (e.g., "Warmth"), F1-score is particularly important as it represents the harmonic mean of precision and recall, ensuring a balanced evaluation of the model's effectiveness across both majority and minority classes.

To provide a robust comparative analysis, we implemented a traditional TF-IDF with random forest (RF) model as a baseline. TF-IDF is a widely used text representation technique that transforms textual data into numerical features based on word frequency and importance. We then employed a random forest classifier, an ensemble-based decision tree model, to predict aspect sentiments. While this approach has been effective in many text classification tasks, it does not leverage contextual information and aspect correlations, which are crucial in multi-aspect sentiment analysis.

Table 5 presents a detailed comparison between the TF-IDF with random forest model and our proposed transformer-based model. Our model consistently outperforms the traditional base model in both accuracy and F1-score, demonstrating the advantages of deep contextual embeddings over simple term-frequency-based features. The average accuracy increased from 88.30% to 89.76%, and the average F1-score improved from 88.39 to 89.34. One notable observation is that both models struggled with the "Warmth" aspect, where the accuracy slightly dropped from 73.36% (TF-IDF + RF) to 72.25% (Transformer), while the F1-score saw a marginal improvement. This could be attributed to data sparsity and subjectivity in how users perceive warmth in different products. The model might require additional fine-tuning or larger datasets to capture this aspect more effectively.

Table 5: Summary of Findings

	TF-IDF with random forest		Proposed transformer model	
	Accuracy	*F1-Score*	*Accuracy*	*F1-Score*
Quality	91.97	95.60	94.90	97.09
Value for Money	90.07	94.53	93.60	96.32
Fit	90.40	94.78	91.44	95.05
Style	93.40	96.52	92.62	95.99
Material	90.60	94.86	93.73	96.41
Warmth	73.36	54.05	72.25	55.21
Averaged-Scores	88.30	88.39	89.76	89.34

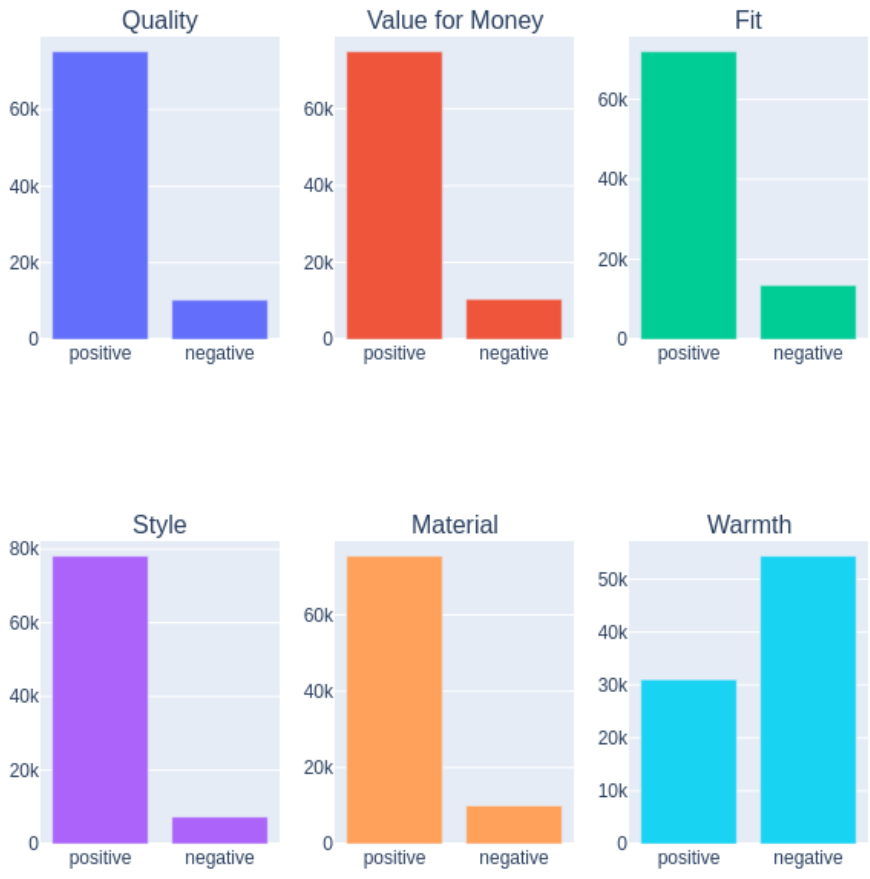


Figure 13: Sentiment analysis per aspect.

Figure 13 illustrates the sentiment distribution across six key aspects. The analysis reveals that the majority of reviews for "Quality," "Value for Money," "Fit," and "Style" are overwhelmingly positive, aligning with our earlier EDA, where a significant portion of customers recommended the products. Interestingly, while our model confirms that

customers are generally satisfied with the "Material" aspect, it highlights a contrasting trend for "Warmth," where the proportion of negative reviews surpasses the positive ones. This observation suggests that customers frequently express dissatisfaction with the warmth-related features of the products, making it the most challenging aspect to analyze.

Discussion and Conclusion

The findings of this study demonstrate the effectiveness of transformer-based aspect-based sentiment analysis (ABSA) for extracting fine-grained customer insights from fashion and apparel e-commerce reviews. The proposed model achieved superior performance compared with the traditional TF-IDF with random forest baseline across most evaluated aspects, confirming the capability of transformer architectures to capture contextual semantics and nuanced customer opinions more effectively. The average accuracy and F1-score improvements indicate that incorporating contextual embeddings and contrastive learning mechanisms enhances sentiment prediction performance in multi-aspect review environments. These findings align with prior research emphasizing the superiority of transformer-based approaches over conventional machine learning techniques in sentiment analysis tasks (12, 13, 18). The results also reinforce the argument that deep contextual models are particularly valuable in domains such as fashion e-commerce where customer opinions are multidimensional and highly subjective.

One of the most important findings of this study concerns the strong performance of the model across aspects such as quality, value for money, fit, style, and material. The high classification scores for these aspects indicate that customer reviews contain highly distinguishable linguistic patterns associated with these product characteristics. This result is consistent with previous studies showing that fashion consumers frequently focus on visible and experiential attributes when evaluating apparel products online (14, 17). The dominance of positive sentiments across these aspects further suggests that most consumers perceive online fashion products favorably when expectations related to quality, aesthetics, and fit are fulfilled. Similar findings were reported in hospitality and restaurant sentiment analysis studies, where quality and service-related attributes demonstrated strong predictive relevance for overall customer satisfaction (26, 27). In the current study, the positive distribution of sentiments across key aspects highlights the importance of maintaining consistent product quality and pricing strategies in order to sustain customer loyalty and favorable electronic word-of-mouth communication.

The findings additionally revealed that the “Warmth” aspect represented the most challenging sentiment category for both the baseline and transformer-based models. Unlike other aspects, warmth-related reviews demonstrated lower classification accuracy and more negative sentiment distributions. This outcome may be explained by the subjective and context-dependent nature of warmth perceptions in apparel products. Customers evaluate warmth differently depending on climate, personal preferences, seasonal expectations, and intended product usage. The high rate of missing values associated with this aspect further contributed to modeling complexity. These results support previous studies emphasizing that sparse annotations and aspect imbalance significantly reduce ABSA performance (10, 11). Similar challenges were observed in multilingual and healthcare-related sentiment analysis research where certain aspects lacked sufficient contextual consistency for accurate prediction (24, 25). Therefore, the findings indicate that aspects characterized by subjective interpretation and sparse data require more advanced representation learning and larger annotated datasets.

Another significant result concerns the effectiveness of contrastive learning integration within the transformer framework. The proposed methodology successfully captured interdependencies among aspects rather than

treating each aspect independently. This contributed to improved contextual understanding and enhanced sentiment discrimination across correlated product attributes such as fit, comfort, quality, and material. These findings are theoretically important because many prior studies relied primarily on isolated aspect classification approaches without explicitly modeling aspect relationships (10, 33). By incorporating contrastive loss into the learning process, the current model generated more discriminative embeddings capable of distinguishing subtle sentiment differences. This supports the growing body of literature advocating the integration of self-supervised and representation learning strategies into ABSA systems to improve semantic modeling and contextual robustness (12, 20).

The exploratory data analysis also generated several important managerial and behavioral insights. The review distribution analysis revealed that categories such as lingerie, women's apparel, and men's clothing consistently dominated customer engagement over time. This finding reflects the high purchasing frequency and emotional involvement associated with these product categories within online retail environments. The prominence of lingerie and women's fashion reviews aligns with earlier studies emphasizing the strong influence of social identity, aesthetics, and self-expression in fashion consumption behavior (5, 6). Furthermore, the increasing number of reviews between 2020 and 2023 highlights the accelerating adoption of online shopping and digital commerce following broader technological and behavioral shifts in consumer markets. This trend supports previous findings suggesting that consumers increasingly rely on online reviews and AI-driven recommendation systems to reduce uncertainty and improve purchasing confidence (7, 8).

The findings related to customer recommendations and review polarity provide additional evidence regarding the strategic importance of online review analysis. Most reviewers expressed positive recommendations, indicating generally high satisfaction across product categories. However, categories such as Flowers & Plants exhibited proportionally higher negative feedback despite lower review volume. This suggests that low-frequency categories may still contain substantial dissatisfaction patterns that can negatively influence customer trust and retention if ignored. Prior research in customer churn prediction demonstrated that unresolved dissatisfaction signals often contribute to long-term customer loss and declining brand loyalty (30, 31). Therefore, the current findings reinforce the importance of continuously monitoring customer sentiment at both macro and micro levels to identify hidden dissatisfaction trends before they escalate into churn behavior.

The analysis of sub-category trends also produced noteworthy findings. Products such as bras, trousers, knitwear, and thermals consistently received high ratings and large review volumes, indicating stable consumer demand and favorable customer experiences. Conversely, categories such as footwear slippers and boys' joggers exhibited lower evaluations for style, fit, and quality. These findings demonstrate that consumers are highly sensitive to functional and aesthetic inconsistencies in fashion products. Similar conclusions were reached in prior e-commerce sentiment studies where product-specific weaknesses strongly influenced overall customer satisfaction and repurchase intentions (15, 34). The ability of ABSA systems to identify these product-level deficiencies provides retailers with actionable insights for improving design quality, product descriptions, and inventory decisions.

An important contribution of this study lies in its AI-driven approach for handling missing aspect ratings. Many online reviews contain incomplete evaluations because customers selectively comment on aspects they consider most relevant. In the present dataset, aspects such as material, warmth, comfort, and support showed substantial missing rates. By leveraging contextual relationships among aspects, the transformer-based model successfully inferred missing sentiment information and generated more complete sentiment representations. This finding

extends previous literature that primarily relied on fully annotated datasets without addressing the practical reality of incomplete customer feedback (10, 11). The successful implementation of AI-driven completion mechanisms demonstrates the potential of advanced machine learning systems to overcome sparsity limitations in real-world e-commerce data environments.

The multilingual and domain-adaptive implications of the findings are also significant. Although the present study focused primarily on English-language fashion reviews, the strong performance of transformer architectures suggests broader applicability across multilingual and cross-domain contexts. Previous studies involving Arabic, Turkish, Amharic, telecom, and healthcare datasets similarly demonstrated the flexibility of transformer-based ABSA approaches across linguistic and industrial domains (22, 29, 35). The current results therefore support the growing consensus that contextual language models provide scalable and adaptable solutions for large-scale sentiment analysis tasks.

The findings additionally highlight the growing importance of explainable and data-driven business intelligence systems in e-commerce environments. Organizations increasingly depend on AI-powered analytics to optimize digital marketing, recommendation systems, and customer engagement strategies (2, 4). The ability of ABSA models to identify aspect-level strengths and weaknesses enables firms to develop more targeted interventions, improve product development processes, and enhance customer experience management. In fashion retail specifically, fine-grained sentiment insights may improve personalization systems, virtual try-on technologies, and AI-assisted recommendation engines (6, 7). Consequently, the practical implications of the current findings extend beyond sentiment classification and contribute to broader digital transformation initiatives within e-commerce ecosystems.

From a theoretical perspective, this study contributes to the evolving literature on sentiment analysis by demonstrating the effectiveness of combining exploratory data analysis, transformer-based contextual modeling, contrastive learning, and multi-label classification within a unified ABSA framework. Unlike many previous studies that focused on isolated sentiment tasks or narrow product categories, the present research examined multiple apparel-related categories and aspects simultaneously, thereby providing a more comprehensive representation of customer behavior. This integrated approach advances existing research by illustrating how contextual dependency modeling and AI-driven feature learning can improve both predictive accuracy and interpretability in complex sentiment analysis environments (10, 12, 33).

The findings further reinforce the strategic relationship between customer sentiment analysis and long-term customer retention. Positive evaluations regarding quality, fit, and value for money are likely to strengthen customer trust and encourage repeat purchases, while negative sentiments related to warmth, support, and fit may contribute to dissatisfaction and future churn. Previous customer retention studies emphasized that retaining satisfied customers is substantially more cost-effective than attracting new consumers (3, 32). The current results therefore demonstrate that ABSA systems can function not only as analytical tools but also as predictive mechanisms for customer relationship management and loyalty optimization.

One particularly noteworthy implication concerns the role of electronic word-of-mouth in shaping brand perception. The word cloud analysis revealed that terms such as “good quality,” “good fit,” and “value for money” appeared frequently in positive reviews, whereas complaints centered primarily around size, material, and color mismatches. These findings confirm that customer-generated content strongly influences consumer trust and purchasing decisions within online retail environments. Prior studies similarly reported that eWOM and sentiment-

driven recommendation systems significantly affect customer engagement and brand loyalty in fashion e-commerce (3, 5). Thus, organizations capable of effectively analyzing and responding to online reviews may strengthen their competitive positioning and improve long-term consumer relationships.

This study has several limitations that should be acknowledged. First, the dataset was collected primarily from a single e-commerce platform, which may limit the generalizability of the findings across other online retail ecosystems and cultural contexts. Second, some aspects such as warmth, comfort, and support contained substantial missing values and class imbalance, which may have affected predictive consistency despite the implementation of AI-driven completion techniques. Third, the study relied exclusively on textual review data and did not incorporate multimodal information such as product images, videos, clickstream behavior, or purchase histories that could enrich sentiment interpretation. Finally, although the transformer-based framework demonstrated strong performance, the computational complexity and resource requirements associated with large language models may limit practical implementation for smaller organizations with restricted technological infrastructure.

Future research should extend the current framework by integrating multimodal sentiment analysis approaches that combine textual, visual, and behavioral customer data. Researchers may also investigate advanced self-supervised learning and graph-based representation techniques to further improve aspect dependency modeling and sentiment explainability. Cross-cultural and multilingual analyses involving diverse fashion markets would provide additional insights into the generalizability of transformer-based ABSA systems. Moreover, future studies could explore real-time sentiment monitoring systems integrated with recommender systems and churn prediction models to support adaptive and dynamic e-commerce decision-making environments.

From a practical perspective, e-commerce businesses should implement aspect-level sentiment monitoring systems to continuously evaluate customer perceptions regarding product quality, fit, style, comfort, and value for money. Fashion retailers should prioritize the identification of recurring dissatisfaction patterns, particularly in aspects associated with product returns and negative recommendations. Companies may also leverage transformer-based sentiment analytics to optimize recommendation systems, personalize marketing campaigns, improve product descriptions, and refine inventory management strategies. Additionally, organizations should invest in AI-driven customer feedback systems capable of transforming unstructured review data into actionable business intelligence for enhancing customer satisfaction, retention, and long-term brand loyalty.

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Authors' Contributions

All authors equally contributed to this study.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

All ethical principles were adheried in conducting and writing this article.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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