Sustainability of Second-Hand Fast Fashion: Sentiment and Content Analysis on Consumer Attitudes on Social Media

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Abstract

Major fast fashion companies have recently launched resale platforms for second-hand shopping. Although many experts consider these initiatives as a greenwashing strategy, it is unclear whether consumers agree with that or rather find such initiatives sustainable. Thus, the purpose of this paper is to examine consumer attitudes towards the sustainability of second-hand fast fashion. Accordingly, Instagram reels and posts related to second-hand fast fashion are identified and all comments under those contents are extracted. Next, these comments are analysed with a sentiment analysis and a content analysis. Results show that consumers express more positive sentiments towards resale companies that ban fast fashion items than towards resale companies that specialize in fast fashion. Comments referring to companies banning fast fashion resale show consumers’ predominant support of the ban, while companies doing fast fashion resale receive strong criticism on social media. Consumers are specifically concerned about the quality of second-hand fast fashion items as well as express social and ethical concerns towards fast-fashion resale. The resulting practical implication is that companies should consider discontinuing second-hand fast fashion.

Keywords
circular economy, pre-owned, sustainable consumer behavior, environmental sustainability, social media analytics

1. Introduction

There was a time when second-hand shopping might only be related to the economic factors of consumers. In recent times, second-hand shopping has received a makeover and has been associated with other factors such as sustainability, circular economy, and vintage (Daukantiene, 2023). According to a recent study from the online resale platform thredUP, (2023), the resale marketplace reached $177 billion in 2022 sales, up 28% over 2021. The report also states that Gen Z and Millennials are more interested in sustainability while second-hand shopping.

Researchers have studied the second-hand fashion trend and its relationship to sustainability as well as to other factors like quality, price, trend, etc. (Borusiak et al., 2020; Mohr et al., 2022). Although fast fashion giants like Zara, Shein, and Pretty Little Things have introduced their resale platforms to get a piece of this rising resale market share, many experts perceive these as a greenwashing strategy of the fast fashion companies to compensate for their negative environmental impact (Amatulli et al., 2016; Webb, 2022).

Fast Fashion refers to ‘inexpensive clothing produced rapidly by mass-market retailers in response to the latest trends’ (Oxford English Dictionary, 2023) and researchers have studied fast fashion widely (Amatulli et al., 2016; Yoon et al., 2020). However, the fast fashion resale field has not been thoroughly studied yet. Specifically, it remains uncertain what the consumers’ perspective on fast fashion resale is regarding sustainability. Investigating consumers’ attitudes towards the sustainability of second-hand fast fashion will fill the research gap by analyzing customers’ preferences in second-hand shopping and sustainable fashion. Such a study could provide insights into how fast fashion resale can be made more sustainable and eco-friendlier to consumers. Thus, it contributes to the literature on sustainable fashion,
circular fashion, and second-hand fashion. Moreover, such a study has the potential to influence marketing plans, consumer education programmes, and policy changes that collectively push for a more sustainable fashion industry.

1.1 Objectives
The purpose of this paper is to examine consumer attitudes towards the sustainability of second-hand fast fashion. Accordingly, Instagram reels and posts related to second-hand fast fashion are identified and all comments under those contents are extracted. Subsequently, these comments are analyzed with sentiment analysis using the language model SiEBERT (Hartmann et al., 2023) in combination with a chi-square test as well as a content analysis. The paper is organized as follows. A brief literature review is covered in section 2. Section 3 presents the hypotheses development. The research design is described in section 4. Section 5 presents the findings followed by a discussion in section 6. Finally, section 7 concludes the paper.

2. Literature Review
Due to consumers’ growing demand, more garments are being produced which need a constant supply of natural resources (Leal Filho et al., 2022). The fashion industry is anticipated to contribute nearly 25% of the global carbon budget by 2050 (Ellen Macarthur Foundation, 2017). Moreover, the fashion business contributes to 20% of the total global water waste and can potentially release about 22 million metric tonnes of microplastics into the ocean from 2015 to 2050 (Domenitz & Meiffren-Swango, 2023; UNECE, 2018). “The True Cost” documentary shows the reality of garment workers in developing nations working in factories placed in fragile buildings with bare minimum salaries and long shifts with overtime and being exposed to toxic chemicals (Morgan, 2015). The working conditions inside Chinese fast fashion giant Shein reported by a recent documentary include weary workers working up to 18 hours a day, frequently 7 days a week, being paid 2-3p per piece sewed, and paying hefty fines for mistakes (Seale, 2022). Moreover, over 160 million children are engaged in child labor and hazardous work, and most of these children are employed in the fashion industry (ILO, 2020). Thus, the promises of fast fashion companies about being sustainable and ethically producing eco-friendly items seem to be a greenwashing policy.

Although eco-friendly fashion is trending nowadays (Park & Lin, 2020), sustainability in fashion is an elaborated topic covering three essential aspects: environmental, social, and economic. Daukantiene (2023) analysed these three aspects based on different criteria such as (1) sustainable materials, design tools, and the impact of clothing technologies on sustainability for environmental aspects, (2) consumer awareness, eco-friendly clothes, renting, recycling, upcycling, and (3) buying second-hand clothing for the social aspect, circular vs. linear business model, strong brand value, slow fashion vs. fast fashion, and fair wages for the employees for economic aspects. Slow fashion focuses on slowing down the production and consumption processes, fostering sustainability in the fashion sector (Castro-López et al., 2021).

Several surveys show a positive shift in consumer behavior and attitudes toward sustainable fashion choices in recent times (KPMG, 2019; McKinsey & Company, 2020; Yonder, 2023). According to KPMG (2019), a few consumers even want to pay more for ethically produced sustainable garments. Consumers consider second-hand shopping as a good sustainable fashion alternative. According to Hristova (2019), the motivational factors behind consumers’ second-hand shopping can be described as (1) Financial or economic drivers, (2) Emotional or psychological drivers, (3) Social drivers, and (4) Ecological and distributional drivers. Further, a new report on second-hand resale showed that affordability is the key motivation followed by product variety, sustainability, and environmental awareness (Ettinger, 2022). In another survey conducted in the US, price, quality, selection, convenience, and transparency were the top five attributes motivating the fashion resale (thredUP, 2023).

Based on the literature reviewed, the main factors motivating second-hand fashion buys are: (1) Affordability, (2) Quality, (3) Environmental Sustainability, (4) Brand reputation, (5) Unique items, (6) Fashion and style, and (7) Social and ethical consideration. These factors will be used in the subsequent analysis.

3. Hypotheses Development
Since November 2022, a French online resale platform for pre-owned luxury items, Vestiaire Collective, has imposed a ban on all fast fashion items from its platform (OSF, 2022). Their mission is to eliminate all fast fashion by Better Friday 2024 (Vestiaire Collective, 2022). On the other hand, fast fashion companies like Zara and Shein are launching their own peer-to-peer resale platforms. Zara joined the resale business introducing rental, resale, and repair after being criticized for its high carbon footprint and because of consumers’ demand for more eco-friendly options.
Shein has also introduced a new peer-to-peer resale platform, “Shein Exchange” in the US. Though very low prices have increased Shein’s sales, experts doubt whether consumers will choose a poor quality $2 T-shirt from Shein Exchange over a brand-new $5 T-shirt from the retail site (Faithfull, 2022).

However, a shift has begun in fashion consumption patterns and nowadays consumers are becoming more interested in sustainable fashion for the sake of the environment and society (Castro-López et al., 2021). A study conducted in Spain shows that environmentally conscious consumers purchase fewer brand-new items, preferring preowned and rented options (Riesgo et al., 2022). Although consumers’ sentiments toward fast fashion resale have not been studied enough, several studies can be found on consumers’ sentiments toward fast fashion in general. For example, Xydia (2019) conducted interviews with customers of the fast-fashion retailer Primark and the results indicate (1) an increase in consistency between sustainability-conscious consumers' values and actions, (2) an increased consumer awareness of unethical greenwashing policies of fast fashion companies, and (3) consumers’ persistent guilt after purchasing from Primark. Moreover, consumers tend to avoid fast fashion due to poor quality, ethical concerns, and negative judgments of fast fashion's ideology (Yoon et al., 2020). Based on the discussion above, we can assume consumers might have a similar negative attitude toward fast fashion resale. Thus, the following hypothesis can be derived:

**Hypothesis (H1): Consumers express more positive sentiments towards resale companies that ban fast fashion items than towards resale companies that specialize in fast fashion.**

Darley & Lim (1999) show that consumers prioritising quality were more likely to purchase at a thrift store. However, nowadays thrift stores no longer solely offer high-quality garments. The rise of local thrift stores as sources of diverse fashion with both fast fashion and non-fast fashion items stimulated studies into how consumers perceive these combined offerings. Paz (2022) in an article for The New York Times discussed the end of The Golden Age of Thrifting because of thoughtless donations of low-quality fast fashion brands into local thrift stores, raising operational costs, encouraging overconsumption, and preventing consumers from finding the same durable, high-quality items as before. Author Adam Minter said in an interview, “If you donate trash to a thrift store, it doesn’t just disappear” (Iglesias, 2019; Paz, 2022). He also noted that smaller stores were particularly overburdened by incoming garments.

Further, Jiang (2015) found that most consumers prioritise an item's quality and price over the type of store selling the item. Thus, consumers are likely to prefer resale platforms that sell high-quality durable clothing over thrift stores that offer a mixture of fast and non-fast fashion. Accordingly, Hypothesis H2(a) can be developed:

**Hypothesis (H2a): Consumers express more positive sentiments towards resale companies that ban fast fashion items than towards local thrift stores containing both fast fashion and non-fast fashion items.**

Many individuals shop at local thrift stores because of the social and ethical issues that thrift stores promote (Lopez & Ouattara, 2021). Terrible working conditions and human rights violations at the factories of fast fashion companies like Shein (ILO, 2020; Morgan, 2015; Seale, 2022) are likely to put off consumers from fast fashion resale platforms like Shein Exchange. Hence, we can assume consumers would prefer local thrift stores over fast fashion resale platforms, which leads us to the following hypothesis H2(b):

**Hypothesis (H2b): Consumers express more positive sentiments towards local thrift stores containing both fast fashion and non-fast fashion items than towards resale companies that specialize in fast fashion.**

Nowadays, social media is not only for photo-sharing but also for knowledge-sharing between influencers and consumers. Social media platforms can play an important role in influencing consumer behavior (Jamil et al., 2022). Consumers usually rely on the contents depending on the trustworthiness of the influencers and the emotional bond between them and the influencer (Sokolova & Kefi, 2020). Study shows that consumers are indeed influenced by the actions of fashion influencers because individuals are more trustworthy than brands (Namitha R, 2020). Similarly, endorsements from influencers can potentially enhance consumers’ inclination to buy (Leenders, 2019).

So, social media can be used to spread environmental awareness. Hamid et al. (2017) showed that sharing content in online green communities can shift consumers toward sustainable fashion, while de Lenne and Vandenbosch (2017) showed that observing influencers sharing sustainable brands can also achieve that shift, and Palin and Sköld (2022) showed that Swedish Gen Z responds positively to sustainable Instagram influencers. Likewise, consumers can be
expected to be influenced by sustainable fashion influencers promoting second-hand shopping. However, online content that promotes consumption can also influence consumers by making them consume more (Frick et al., 2020).

Thus, we can stipulate that when it comes to fast fashion resale, consumers will form their opinions based on the social media content they follow. On the one hand, some influencers believe fast fashion resale is sustainable and hence create contents that support it. On the other, some influencers believe fast fashion resale promotes overconsumption and create contents that criticize it. Accordingly, it can be assumed that consumers are likely to be influenced by the social media content that they observe and form their attitude (for or against) depending on the views of the influencer that they follow. Hence, the following hypothesis H3 is derived:

**Hypothesis (H3): Consumers express similar sentiments towards social media posts supporting or criticizing fast fashion resale.**

4. Methodology
4.1 Data collection
The data collection process includes retrieving relevant Instagram posts and video reels, as well as the comments underneath with a specific focus on fast fashion resale. As stated above, Vestiaire has banned any fast fashion on its platform, and Shein has launched its resale platform. Local thrift stores, containing both fast fashion and non-fast fashion items like vintage or luxury items, are also popular among consumers. Several posts and reels are available related to these issues on Instagram. These contents are posted by the resale platforms, influencers, and conscious consumers where anyone can comment to share their perspectives. By employing web scraping techniques, like the Instagram API Token, relevant posts, comments, and discussions linked to the practice of fast fashion resale from relevant hashtags, user accounts of (1) thrifting influencers, (2) conscious consumers, (3) resale companies, and (4) fashion magazine have been extracted. Some of the hashtags used in this case are, #VESTIAIRECOLLECTIVE, #resale, #thrifting, #preloved, #FastResale?, #antifastfashion, #Secondhand, #Sustainablefashion, #Greenwashing, #Circularfashion, #Sheinexchange, #Saynotofastfashion. Some posts are also traced through Google search by using key phrases like “Instagram posts related to fast fashion resale”. Finally, 13 posts and 10 reels have been manually screened out as they share the most relevance to our research topic. The posts and reels are extracted using a Python library called “instaloader”. Using a valid Instagram ID and password the comments are extracted from the shortcode of a specific post or reel. In total, 1500 comments were extracted. All the posts were collected in June 2023.

4.2 Data Analysis
Step 1: Using Python all comments are extracted and saved as individual lists for each post or reel. All data are pre-processed by removing any irrelevant or duplicate comments and tokenized to break into individual words and emojis. Next, five groups are formed from those lists, categorized based on the themes of the Instagram posts/reels (Table 1).

<table>
<thead>
<tr>
<th>Group 1</th>
<th>Online resale platform banning fast fashion.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Group 2</td>
<td>Fast fashion brands getting into resale.</td>
</tr>
<tr>
<td>Group 3</td>
<td>Influencers criticizing fast fashion resale.</td>
</tr>
<tr>
<td>Group 4</td>
<td>Thrifting Influencers supporting fast fashion resale.</td>
</tr>
<tr>
<td>Group 5</td>
<td>Local thrift stores containing fast fashion and non-fast fashion items.</td>
</tr>
</tbody>
</table>

Step 2: For each group an individual dataframe is created with the pre-processed comments. On each dataframe the SiEBERT model is then applied to analyze the sentiment of each comment from each group. Using the existing “emoji” library in Python, emojis are converted to meaningful labels that indicate sentiment (e.g., happy, sad, neutral) to improve the overall sentiment analysis. A new dataframe is created for each group containing two new columns named “Score” and “Sentiment” (see Table 2). The “Score” column is for storing the sentiment scores for each comment and the “Sentiment” column is to show if the sentiment behind a comment is Positive or Negative.
Table 2. Sample dataframe after Sentiment Analysis using SiEBERT

<table>
<thead>
<tr>
<th>No.</th>
<th>Comments</th>
<th>Score</th>
<th>Sentiment</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>😊😊😊😊 yessss!!!!</td>
<td>0.99843</td>
<td>Positive</td>
</tr>
<tr>
<td>2</td>
<td>So why am I still able to upload fast fashion ...</td>
<td>0.991265</td>
<td>Negative</td>
</tr>
<tr>
<td>3</td>
<td>Fantastic 😊</td>
<td>0.998684</td>
<td>Positive</td>
</tr>
</tbody>
</table>

Table 3 shows the total sentiment counts for each group. Those counts are used to generate 2x2 contingency tables that are used to test the derived hypotheses with chi-square test with Yates correction. Results are shown in section 5.

Table 3. Total positive and negative sentiment counts for each group

<table>
<thead>
<tr>
<th>Group</th>
<th>Group 1</th>
<th>Group 2</th>
<th>Group 3</th>
<th>Group 4</th>
<th>Group 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Positive sentiment counts</td>
<td>296</td>
<td>58</td>
<td>193</td>
<td>34</td>
<td>116</td>
</tr>
<tr>
<td>Negative sentiment counts</td>
<td>196</td>
<td>269</td>
<td>105</td>
<td>13</td>
<td>220</td>
</tr>
</tbody>
</table>

Step 3: In this step, individual word clouds are generated for each group. To do so required libraries like pandas, nltk, stopwords, word cloud, and matplotlib are imported first. Then the data are loaded into pandas dataframe, ensuring it contains columns for 'comments', 'score', and 'sentiment'. Next, all comments are tokenized, converted to lowercase, and all stopwords, and non-alphanumeric characters are removed. Two separate sets of strings are created, one for positive, and another for negative comments. Then those comments are extracted to generate two different word clouds for each group. After that, a content analysis is performed to analyze and extract meaningful information from the comments systematically. To do so, a coding scheme is generated (see Table 4) with categories and subcategories to capture relevant themes and patterns from the buzzwords presented by the word clouds and motivational factors previously discussed relating to second-hand shopping. Then the comments are manually annotated and relevant codes from the coding scheme are allocated based on the presence of buzzwords and the corresponding motivational factors. After that, a frequency table is created by tallying the frequency of each code (motivating factor) in the comments. The frequency table shows the frequency count for the appearances of each motivational factor in the comments. The result is discussed in the next section with the frequency table for each group altogether.

Table 4. Coding Scheme Generation for the Content Analysis

<table>
<thead>
<tr>
<th>Coding Scheme</th>
<th>Positive buzzwords criteria</th>
<th>Negative buzzwords criteria</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price / Affordability</td>
<td>Affordable deals</td>
<td>Overpriced</td>
</tr>
<tr>
<td></td>
<td>Discounts and sales</td>
<td>Expensive</td>
</tr>
<tr>
<td></td>
<td>Bargains and good value</td>
<td>Not worth the cost</td>
</tr>
<tr>
<td>Quality</td>
<td>Good condition</td>
<td>Poor quality</td>
</tr>
<tr>
<td></td>
<td>Well-maintained items</td>
<td>Damaged items or not as described</td>
</tr>
<tr>
<td></td>
<td>Like-new products</td>
<td></td>
</tr>
<tr>
<td>Environmental Sustainability</td>
<td>Environmentally friendly</td>
<td>Not eco-friendly</td>
</tr>
<tr>
<td></td>
<td>Reduce, Reuse, Recycle</td>
<td>Environmental impact issues</td>
</tr>
<tr>
<td></td>
<td>Eco-conscious shopping</td>
<td></td>
</tr>
<tr>
<td>Brand Reputation</td>
<td>Trustworthy sellers</td>
<td>Bad experiences with brands</td>
</tr>
<tr>
<td></td>
<td>Authenticity of designer items</td>
<td>Counterfeit or fake items</td>
</tr>
<tr>
<td></td>
<td>Positive experiences with brands</td>
<td>Trust issues with sellers</td>
</tr>
<tr>
<td>Unique Items</td>
<td>Vintage and one-of-a-kind products</td>
<td>Lack of unique products</td>
</tr>
<tr>
<td></td>
<td>Rare and hard-to-find items</td>
<td>Limited selection</td>
</tr>
<tr>
<td></td>
<td>Uncommon fashion pieces</td>
<td></td>
</tr>
</tbody>
</table>
5. Results

5.1 Results from the Sentiment Analysis (SA)

To test the derived hypotheses, the sentiments associated with the comments of the different groups are compared in a pairwise manner using a chi-square test with Yates correction (results are shown in Table 5).

First, groups 1 and 2 are compared to test H1 (see Table 5A). For group 1 (online resale platform banning fast fashion), the positive sentiment counts are more than the negative ones. Whereas, for group 2 (fast fashion brands getting into resale), the negative sentiment counts are more than the positive ones. Comparing groups 1 and 2, the chi-square test indicated a significant relationship between two categorical variables, namely the type of resale company (banning fast fashion items and specializing in fast fashion) and the binary perception of it (POSITIVE or NEGATIVE), thus H1 is supported. Consumers appear to have a more favourable opinion of resale businesses that prioritise sustainability by banning fast fashion indicating that they are responsive to sustainability-focused actions.

Next, groups 1 and 5 are compared to test H2a (see Table 5B). For group 5 (local thrift stores containing fast fashion and non-fast fashion items), the negative sentiment counts are more than the positive ones. Comparing groups 1 and 5, the chi-square test indicated a significant relationship between two categorical variables, namely the type of resale platform (banning fast fashion items and containing fast fashion and non-fast fashion items) and the binary perception of it (POSITIVE or NEGATIVE), thus H2a is supported. So, consumers have a more favorable opinion of resale companies that take a clear stance against fast fashion than they have of local thrift stores that contain both fast fashion and non-fast fashion items. This indicates that unique sustainability measures are preferred by consumers.

Similarly, when groups 2 and 5 were compared to test H2b (see Table 5C), the chi-square test indicated a significant relationship between two categorical variables, namely the type of resale platform (specializing in fast fashion and containing fast fashion and non-fast fashion items) and the binary perception of it (POSITIVE or NEGATIVE), thus H2b is supported. So, consumers appear to react more positively towards local thrift stores with a diverse inventory than towards resale businesses that sell primarily fast fashion items.

Finally, to test H3 groups 3 and 4 are compared (see Table 5D). The positive sentiment counts are more than the negative ones for both group 3 (thrifting influencers criticizing fast fashion resale) and group 4 (thrifting influencers supporting fast fashion resale). Comparing groups 3 and 4, the chi-square test indicated no significant relationship between two categorical variables, namely the content type (supporting fast fashion resale and criticizing fast fashion resale) and the binary perception of it (POSITIVE or NEGATIVE), thus H3 is supported. So, consumers appear to respond similarly whether they encounter social media posts supporting or criticizing fast fashion resale.

To sum up, consumers’ positive attitudes toward resale companies prioritising sustainability and negative responses to fast fashion resale companies indicate a general interest in sustainable fashion. In addition, similar sentiments toward social media content about fast fashion resale suggest that consumers comparably view the concept regardless of the perspective presented (for or against). Table 6 provides a summary of evidence supporting the hypotheses.
Table 5. Contingency tables for Chi-square test on the Counts from Sentiment Analysis

<table>
<thead>
<tr>
<th></th>
<th>Positive</th>
<th>Negative</th>
<th>Total</th>
<th>( \chi^2 )</th>
<th></th>
<th>Positive</th>
<th>Negative</th>
<th>Total</th>
<th>( \chi^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Group 1</td>
<td>296</td>
<td>196</td>
<td>492</td>
<td>B</td>
<td>Group 1</td>
<td>296</td>
<td>196</td>
<td>492</td>
</tr>
<tr>
<td></td>
<td>Group 2</td>
<td>58</td>
<td>269</td>
<td>327</td>
<td></td>
<td>Group 5</td>
<td>116</td>
<td>220</td>
<td>336</td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td>354</td>
<td>465</td>
<td>819</td>
<td>Total</td>
<td>412</td>
<td>416</td>
<td>828</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>C</th>
<th>Positive</th>
<th>Negative</th>
<th>Total</th>
<th>( \chi^2 )</th>
<th>D</th>
<th>Positive</th>
<th>Negative</th>
<th>Total</th>
<th>( \chi^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Group 2</td>
<td>58</td>
<td>269</td>
<td>327</td>
<td>Group 4</td>
<td>34</td>
<td>13</td>
<td>47</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Group 5</td>
<td>116</td>
<td>220</td>
<td>336</td>
<td>Group 3</td>
<td>193</td>
<td>105</td>
<td>298</td>
<td>0.73</td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td>174</td>
<td>489</td>
<td>663</td>
<td>Total</td>
<td>227</td>
<td>118</td>
<td>345</td>
<td></td>
</tr>
</tbody>
</table>

* p < 0.05, ** p < 0.01, *** p < 0.001

Table 6. Hypotheses support overview

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Support</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1: Consumers express more positive sentiments towards resale companies that ban fast fashion items than towards resale companies that specialize in fast fashion.</td>
<td>Yes</td>
</tr>
<tr>
<td>H2a: Consumers express more positive sentiments towards resale companies that ban fast fashion items than towards local thrift stores containing both fast fashion and non-fast fashion items.</td>
<td>Yes</td>
</tr>
<tr>
<td>H2b: Consumers express more positive sentiments towards local thrift stores containing both fast fashion and non-fast fashion items than towards resale companies that specialize in fast fashion.</td>
<td>Yes</td>
</tr>
<tr>
<td>H3: Consumers express similar sentiments towards social media posts supporting or criticizing fast fashion resale.</td>
<td>Yes</td>
</tr>
</tbody>
</table>

5.2 Results from the Content Analysis (CA)

To obtain a more detailed understanding of consumer attitudes toward second-hand fashion, we conduct a content analysis of the comments for each of the five groups using the eight main categories from the coding scheme presented in Table 4. In addition, we also generate word clouds for both the positive and negative comments of each group. Table 7 shows the main results from the content analysis, while Figures 1-5 show the word clouds.

Group 1 comments (online resale platform banning fast fashion) have mostly positive sentiments from the SA. The highest frequency counts for positive comments belong to the “General agreement” code. However, most people are opinionated in the negative comments where the second and third highest frequency counts belong to the “Social and ethical consideration” and the “Environmental sustainability” code. Consumers expressing negative sentiments in the social and ethical consideration category want online resale companies to define fast fashion brands before banning them on their platforms. Some used the term greenwash to define the ban as a business strategy of the company. The most frequently used words are, define, fast fashion, and brands. Some comments are, “Pls define ‘Fast Fashion’” or “How u gonna define fast fashion? A lot of brands are still fast fashion in disguise”. Consumers expressing negative sentiments from an environmental concern find fast fashion resale more sustainable than contributing to landfills. The most frequently used words in this case are landfill, sustainable, resale, and planet. An example is, “Better to resale than end up in the landfill”. Specific mentions of fast fashion brands in some comments provide insight into how consumers perceive certain brands. For example, some consumers mentioned Zara as being affordable and serving good quality in the past. Some believe so-called luxury brands should also be banned for greenwashing consumers, some dislike the concept of certain brands. The rest are negative because brands like Zara are still being sold on other resale platforms. However, some consumers expressing positive sentiments perceive fast fashion as delivering poor quality without any resale value and not eco-friendly or unethical. More negative comments in the “Quality” code showed that some consumers prefer fast fashion resale over throwing into landfills.
For group 2 (fast fashion brands getting into resale), the highest and third highest frequency counts for negative comments belong to the “Social and ethical consideration” and “Quality” codes, and most comments are related to fast fashion brand Shein launching their new online resale platform. Many consumers are not happy about it. Some frequent buzzwords related to the “Social and ethical consideration” code are greenwashing, production, people, workers, and slavery. It demonstrates how consumers view Shein's new resale platform as a form of greenwashing and are aware of the company's unethical business practices, such as underpaying and mistreating their employees and overproducing cheap garments. A few positive comments are also in this category. After manual annotation, they are found to be biased with false positive sentiments, which is discussed in the conclusion section. In negative comments for the "Quality" code, words like cheap, clothes, quality, garments, last, and waste are frequently used. It indicates consumers view Shein’s apparel as low-quality and not durable. For example: “Their clothes are such low quality that they wouldn’t last past one or two wears. There’s no possible way they could be resold”. The negative comments in the “Environmental Sustainability” code show that consumers find Shein unsustainable and polluting the environment whereas some frequently used buzzwords are sustainable, resale, environment, and planet.

For Group 3 (influencers criticising fast fashion resale), the top three frequency counts for positive sentiment belong to "General agreement", "Social and ethical consideration" and "Environmental sustainability". Frequently used buzzwords under these codes are consumerism, overconsumption, influencer, charity shop for "Social and ethical consideration" and sustainable, environment, second hand, resale, and landfills for "Environmental sustainability". For negative comments, the top three frequency counts belong to "Social and ethical consideration", "Environmental sustainability" and "General agreement". After manual annotation, the underlying reasons behind both positive and negative comments could be found similar to previous groups as per the coding scheme. However, the fast fashion brand Shein has been criticized in this group of comments as well.
For group 4, the theme is thrifting influencers supporting fast fashion resale. Although the influencer promotes fast fashion resale in her videos, she supports only specific resale platforms such as Depop, vinted, and eBay, not initiated by any fast fashion companies. Consumers also support this logic as one states, “But I like your point that if we don’t buy direct from the retailers they’ll be pushed to rethink their process, and it looks like they are if some are launching reselling platforms.” Some followers find fast fashion resale ethical as it contributes to a circular economy. However, a few biases in the SA have been noticed while performing the manual annotation.

![Figure 4](image.png)

**Figure 4.** Word cloud presenting buzzwords from group 4

For group 5 (local thrift stores containing fast fashion and non-fast fashion items), the top three negative sentiment frequency counts belong to “Brand reputation”, “Affordability” and “Quality” codes. Manual annotation shows that some consumers show negative sentiments toward specific fast fashion brands like Shein and Zara and do not want them at thrift stores. Others find it strange that low-quality second-hand fast fashion items are being sold at a higher price at thrift stores. Some think most fast fashion clothes are made of cheap materials and not durable. Several consumers express negativity due to their ethical and environmental sustainability concerns related to fast fashion resale and want a shift in the fashion industry. According to one comment, “Unfortunately, we are stuck in this loop of Fast Fashion consumers only wanting to consume fast fashion but now at even cheaper prices that is being available through thrifting. A shift in the mindset is necessary for this to change.”. Customers expressing positive sentiments can be categorised as (1) those who believe pre-owned fast fashion products are affordable, occasionally unique, and of okay quality, and (2) those who prefer buying second-hand fast fashion rather than contributing to landfills.

![Figure 5](image.png)

**Figure 5.** Word cloud presenting buzzwords from group 5
Table 7. Frequency count table for all groups

<table>
<thead>
<tr>
<th>Coding Scheme</th>
<th>Group 1</th>
<th>Group 2</th>
<th>Group 3</th>
<th>Group 4</th>
<th>Group 5</th>
</tr>
</thead>
</table>
sentiments toward social media content about fast fashion resale suggest that consumers comparably view the concept regardless of the perspective presented (for or against).

The findings from the CA showed that most consumers’ positive sentiments toward fast fashion resale were not due to affordability, but they prefer replacing new purchases with second-hand fast fashion items rather than contributing to landfills. Most consumers decide on the sustainability of fast fashion items based on their brands and feel the necessity of transparency and awareness in the fashion industry. On the other hand, most negative comments addressed fast fashion garments’ cheap quality without resale value, and unethical and non-eco-friendly production. To conclude, the main factors influencing consumers’ decisions regarding the sustainability of fast fashion resale were found to be: (1) Social and ethical consideration, (2) Environmental sustainability, (3) Quality, and (4) Brand reputation.

This paper has three main limitations. First, a limited number of contents are available related to fast fashion resale on Instagram compared to other topics such as sustainable fashion or fast fashion in general, which led to a relatively small sample of posts and reels being analysed. However, 1500 comments are a reasonable starting point for sentiment analysis on fast fashion resale as they represent a broader population on Instagram. Second, manual annotation detected two contexts where some consumers reacted to the content while others reacted to the content creator confusing the model, which resulted in some bias in the sentiment categorization. In addition, the model failed to determine the true sentiment of some comments due to the presence of negative words or emojis in positive comments or vice versa. However, the inaccuracy level was quite low to affect the overall result. Third, although the coding scheme generated in this study worked well to interpret most comments, for a few where keywords were absent, it performed poorly. In such instances, the underlying contexts were detected after manual annotation.

In the future, using our findings new research can be initiated to further investigate consumers’ second-hand shopping habits such as if a purchase of preowned fast fashion items replaces the purchase of a new fast fashion item or not. A large-scale survey with numerous participants from different regions can be conducted to validate our results. Furthermore, consumers’ actual shopping behavior and the attitudes shown on social media platforms can also be compared by comparing actual sales data for second-hand fast fashion to our findings from this study.

The main practical implication of this study is that the results can be used to stimulate a broader societal transition towards conscious consumerism by increasing awareness of the environmental impacts of fast fashion and the role of fast fashion resale in mitigating these effects. These insights could reform the marketing strategies of resale platforms and the resulting practical implication is that companies should consider discontinuing second-hand fast fashion.

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