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TRANSFORMING PRODUCT INNOVATION TO MEET CUSTOMER NEEDS THROUGH AI MARKETING, A CUSTOMER FEEDBACK ANALYSIS WITH GPT-4O MINI

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Abstract

This research uses GPT to conduct sentiment analysis on customer reviews for biodegradable products. Sentiment analysis uses 4 categories, namely positive, negative, neutral and mixed, then for product improvement this study focuses on negative sentiment by adding negative sentiments from the mixed sentiments. Data collected from Amazon reviews regarding one brand of biodegradable trash bag in several stores. The GPT-4o Mini model was then used to categorize sentiment.The results of sentiment analysis show that most reviews are positive, but there are also many negative sentiments regarding product durability, leakage and price. The model used is able to accurately identify and extract negative sentiment even from a mixed sentiment, thereby providing a more complete understanding of customer dissatisfaction. This research emphasizes the importance of integrating AI-driver sentiment analysis into the marketing process.

Keywords: customer feedback; sentiment analysis; product development; customer need; ai marketing.

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INTRODUCTION

Market demand for environmentally friendly products is currently starting to increase. In line with environmental issues which are now an important part of consumer purchasing decisions. Increasing public awareness of the negative consequences of plastic waste has encouraged companies to innovate and support environmentally friendly products, including biodegradable plastic (Moshood et al., 2022; Yulianti et al., 2023). Demand for sustainable products in the export market has surged, with 88% of respondents in a 2021 Statista survey supporting sustainable practices as a company standard. Similarly, an Accenture survey in 2019 found that most consumers now buy more eco-friendly products than five years ago, favoring items made from recycled materials, sustainable processes, and fair labor standards. This shift has led companies worldwide to seek partners focused on sustainable production, prompting many manufacturing countries to adapt accordingly (kemenkopukm, 2024). A study by (Snapcart, 2024) identifies key factors influencing Indonesian consumers to choose sustainable products. Environmental concern is the leading motivator, with 38% of consumers selecting eco-friendly options to contribute to environmental protection. Health benefits also play a significant role, with 28% of consumers associating sustainable products with better health. Product quality is another consideration, with 16% of consumers viewing eco-friendly items as high-quality purchases. Additionally, 6% of consumers are influenced by the trend of eco-friendly products promoted by social networks and media. Notably, 8% of consumers feel that using sustainable products elevates their social status, enhancing their perceived classiness (Snapcart, 2024).

Therefore, it is important for companies to understand consumer needs for environmentally friendly products, especially biodegradable plastics so that they can be adopted by consumers (Hidayat, 2021). Related to this, marketing using AI, in this case sentiment analysis, is very important to be able to understand what consumers feel and think.

Because of their long-lasting character and affordability, plastics have met a variety of consumer needs over history (Saygin & Baysal, 2020). But the great environmental impact of these products, especially their long-lasting presence in ecosystems has led to major ecological problems. Plastics have been found to harm groundwater, soil quality, and aquatic life as well as to cause negative effects. An experiment in Bangladesh assessed how soil pollution from plastic affects plant growth, specifically using Amaranthus viridis. Mixed plastics (polyethylene and disposable plastic glass) were applied in varying amounts to observe growth impacts on plant height and girth. The study found that higher plastic concentrations, especially at 20g per 3kg soil, significantly slowed growth compared to the control, highlighting the adverse effects of plastic on plant development (Chae & An, 2018). Marine litter poses a serious environmental threat, particularly as global plastic production continues to rise. The most common litter types, including fishing gear, balloons, and plastic bags, present high risks to marine animals through entanglement and ingestion, especially affecting seabirds, sea turtles, and marine mammals. Entanglement poses a lethal risk, while ingestion is also significant but varies in impact. Chemical contamination was considered less severe, with mostly non-lethal effects (Wilcox et al., 2016). Microplastic pollution, affecting ocean surfaces, water columns, and sediments, has reached even the deep sea. Factors like urban proximity and ocean currents influence debris accumulation, especially in ocean convergence zones. Standardized global estimates are needed for effective management and reduction strategies(Galgani et al., 2015).

Although switching to biodegradable plastics could offer a potential solution to plastic waste issues, consumer acceptance depends on more than just environmental benefits; it is also shaped by how these products meet expectations regarding durability, usability, and cost. (Folino et al., 2020) emphasize that the biodegradation of bioplastics is influenced by environmental conditions, material composition, and microbial action, with significant variations in degradation rates across compost, soil, and some aquatic environments. This suggests that product performance in real-world conditions is crucial for consumer satisfaction. Similarly, Hottle et al. (2017) highlight that the environmental trade-offs associated with biodegradable plastics, such as methane emissions in landfills versus the benefits of recycling make it essential to present these materials as both effective and environmentally sound alternatives. Thus it is importance to manage consumer expectations and clearly communicating the benefits and limitations of biodegradable plastics. Notwithstanding these developments, consumer opinions about biodegradable plastics, especially for everyday objects like garbage bags are still not fully understood. In order to forward the Bio-based Economy (BBE), Sleenhoff and Osseweijer (2015) underline the need of including and guiding consumers.

Many customers have a good view of bioplastics' ability to replace conventional plastics (Filho et al., 2022). However, marketing biodegradable plastic has many challenges, some of which include misunderstanding on the part of consumers regarding the benefits of the product. Then excessive expectations from consumers as well as regarding price. Apart from that, limited access for consumers to own the product. These challenges hinder the adoption of this biodegradable plastic for consumers (Aureli et al., 2023; Filho et al., 2022). Company marketing must overcome these challenges by stressing their environmental advantages and raising the perceived value of their biodegradable products if they are to effectively sell them. Green marketing strategies and green supply chain management have been shown to significantly improve business performance, with green innovation playing a crucial role in enhancing these outcomes (Rahmatullah et al., 2024).

Research by Bojanowska and Sulimierska (2023) and Jin et al. (2022) found that Consumer demographics such as age and education have a greater influence than gender, health or location or product awareness and understanding of biodegradable products, therefore companies must create targeted communications to increase the target group's specific knowledge regarding the benefits of biodegradable products. Therefore, sentiment analysis This is very useful for businesses because it can improve their marketing plans by matching products with consumer expectations.

Natural language processing or NLP is a tool commonly used to carry out sentiment analysis, sometimes this approach is also called opinion mining. This approach carries out identification, extraction and evaluation of subjective information from many sources including consumer reviews and social media. (Subramanian et al., 2024). By paying attention to consumer reviews, companies can gain important insights into consumer opinions, emotions, and preferences. Businesses can use this information to design better products and create smarter marketing campaigns. Sentiment analysis helps them figure out what's making customers unhappy and which product features they love most. By addressing these points, companies can highlight what people like and solve any issues that might hold them back from buying.

Take Coca-Cola and Nike, for example. Coca-Cola checks social media to see how people feel about their brand. They tweak their ads and campaigns to match what customers want. Nike does something similar. They read reviews and feedback to improve their products. It's a great way to show customers they're listening, which builds loyalty and keeps people coming back. (Widewail, 2023).

Sentiment analysis can help spot trends in what people want and why they buy. It also shows what types of messages work best for different groups. At Mohan Automobile Service Station in West Bengal, they used Google Forms to gather customer feedback. Then, they analyzed it with Python Monkey Learn tools. By sorting feedback into positive, negative, or neutral, they found gaps in their service. This helped them improve and meet customer expectations better.(Biswas & Rakshit, 2022). Likewise, sentiment analysis can help businesses who market biodegradable garbage bags understand consumer dissatisfaction, more particularly in relation to product performance, durability, and quality.

Analyzing customer reviews has its own challenges, this is because sometimes a review can contain more than one sentiment, positive and negative (Fernando & Cuandra, 2023; Regi & Leelipushpam, 2024; Zhao et al., 2024). This research addresses the challenges of analyzing feedback that contains both positive and negative sentiments by using the GPT-4o Mini model. The model excels in this task due to its sophisticated understanding of natural language, which allows it to accurately identify and analyze various expressions, slang, and context-specific references within a single review. The ability to assess consumer feedback is crucial for improving marketing strategies and product development in the rapidly evolving e-commerce landscape (Adak et al., 2022).

Customer feedback can be a very important insight for companies because customer feedback can be an indication of customer preferences, their behavior and also their experiences when using the company's products or services. Customer feedback can help companies to develop marketing strategies and also help in decision making. Increase online reviews. Currently, especially on platforms such as Amazon and eBay, the availability of customer feedback can also be increased in the form of customer reviews so that this feedback can be used by companies to better increase consumer satisfaction (Juju & Supriadi, 2024; Nurjanah & Juanim, 2020). Apart from that, feedback from consumers can also be used to improve products (Lin & Kim, 2023). Sentiment analysis plays a key role in this process by providing businesses with a comprehensive understanding of consumer opinions and experiences.

Analysis of customer reviews carried out systematically can encourage companies to be able to identify consumer sentiment, whether the sentiment is positive, negative or neutral, so that the company can further understand consumer needs, meet these needs and also know what is needed to correct deficiencies in the products offered and maintain the advantages of the products offered (Kumar & Reddy, 2022; Reddy et al., 2024). The accuracy and efficiency of sentiment analysis is currently increasing so that sentiment analysis can provide more reliable insight (Yadav et al., 2023). By using sentiment analysis in a product rating system, consumers can provide a more comprehensive understanding, not just numbers in the form of rankings, but with sentiment analysis, products are evaluated in different ways, thereby encouraging product improvements that are more in line with consumer needs.

In the field of natural language processing or NLP, sentiment analysis specializes in understanding human opinion through analysis in text form. Initially, sentiment analysis used methods such as support vector machines or SVM and naïve bayes, where at that time sentiment analysis relied only on simple and precise algorithms system so that it is often difficult to understand the complexity of human language, especially in understanding context and nuance (Dilshodjon, 2023; Pritam, 2024).

Then there is aspect base sentiment analysis or ABSA where this model is a more advanced model in NLP. This model method focuses on the identification and extraction of sentiments where specifications relate to certain aspects of a product or service discussed in a text. This approach is very useful when dealing with mixed sentiments where different parts of a sentence may express varying emotions, compare to previous method. Aspect-based sentiment analysis methods often use machine learning algorithms such as logistic regression and support vector machine algorithms. These algorithms work well for separating sentiments but often have difficulty dealing with mixed emotions. These methods rely heavily on clearly worded opinions and often fail to capture hidden context (Siddiqua et al., 2024).

Sentiment analysis helps businesses to understand customer feedback especially on platforms like Play Store. It is a useful way to understand what people feel and think about their products. (Sakhdiah et al., 2024). This analysis is crucial for businesses as it can guide decision making, strengthen consumer relationships and improve products and services. Advanced language models such as OpenAI GPT-4 significantly improve sentiment analysis capabilities. With its efficient design and ability to understand complex languages, GPT 4 excels in providing good accuracy and being able to interpret language findings (Belal et al., 2023; Sakhdiah et al., 2024). For example, JPT 4's ability to understand Slank idioms and specific content references is very useful for analyzing various customer feedback so that it can provide detailed and accurate analysis and sentiment can be interpreted better (Harel-Canada et al., 2024; Sakhdiah et al., 2024; Shahriar et al., 2024). Na (2024) analyzes online reviews of energy saving grade 1 refrigerators using the LBBA model to extract consumer sentiment and highlight important measures such as performance level, noise level and effectiveness, providing insights to support green consumption. Xuan et al. (2024) used sentiment analysis on 20,000 online reviews of a washing machine to understand consumer demand for environmentally friendly products in relation to its design. Similarly, Chuang et al. (2023) analyze 85,306 online reviews of green products, showing high overall consumer satisfaction. They identify nine positive sentiment topics, such as quality and fast delivery, and three negative ones, including poor service and noise.

This study focuses on identifying and analyzing negative sentiments in consumer reviews for a brand of bio degradable trash bags, with particular attention to mixed sentiments in individual reviews. By isolating and combining negative aspects of consumer reviews along with general negative feedback, this study aims to build a comprehensive analysis of negative sentiment. Text mining and machine learning to such as python's NLTK will be used to ensure a structured and reliable sentiment analysis process.

The findings will help improve products by focusing on things like making them tougher and less likely to leak. For instance, if reviews often mention that the bags rip easily, the company can work on making them stronger. Then, they can use that in marketing—showing customers they've listened and fixed the problem. It builds trust and gets more people to try the biodegradable option.

Sentiment analysis can also help with smarter marketing, like creating loyalty programs that encourage eco-friendly habits or sending personalized messages to keep customers interested. This not only makes the product more appealing but also inspires people to make greener choices.

METHOD

This study focuses on identifying key areas of consumer dissatisfaction with biodegradable garbage bags and offering targeted recommendations for product and marketing improvements. A structured, multi-step approach, incorporating artificial intelligence and data analysis, was used to thoroughly examine user reviews.

Information Gathering. Data was collected from Amazon reviews across nine stores selling the same brand of biodegradable garbage bags, resulting in a dataset of 949 reviews. Web scraping was conducted using Selenium, adhering to Amazon's scraping limitations, to extract review texts, ratings, and timestamps for comprehensive analysis.

Data Preprocessing. The raw data underwent thorough cleaning to improve quality for sentiment analysis: (1) Text Cleaning: Removed HTML tags, special characters, and irrelevant numerical data to reduce noise. (2) Tokenization & Stopword Removal: Split reviews into individual words and removed common stopwords (e.g., "and," "the," "is") to focus on meaningful content. (3) Lemmatization: Reduced words to their root forms (e.g., "running" to "run") to ensure consistent sentiment interpretation.

Sentiment Interpretation. The GPT-4o Mini model was chosen for its advanced ability to interpret mixed sentiments. Unlike simpler models like Support Vector Machines or Naive Bayes, GPT-4o Mini effectively handles complex language structures, including idioms, slang, and contextual nuances. Reviews were categorized as positive, negative, mixed, or neutral, enabling a detailed analysis of specific consumer sentiments.

To tackle reviews with mixed feedback, GPT-4o Mini was used to focus on the negative parts. First, the reviews were broken into individual sentences to make it easier to analyze them piece by piece. Then, sentences with negative feedback were identified and pulled out, ensuring no critical details were overlooked. These isolated negative sentences were combined with fully negative reviews into one dataset. To keep it clean, duplicates were removed, resulting in a solid collection of data ready for further analysis.

TF-IDF was used to pull out key terms from the dataset of negative feedback. It worked by looking at how often a term showed up (TF) and how unique it was across the dataset (IDF). This helped spot the most important issues, like durability and leakage, that needed attention.

Once the key terms were identified, similar complaints were grouped using topic modeling and clustering. This made it easier to find patterns in the feedback. The recurring issues, like leaks and weak durability, pointed to areas that needed fixing. The insights were used to recommend ways to improve the product and focus marketing efforts. For example, the company could highlight these fixes in campaigns to win back trust and boost satisfaction.

This step-by-step methodology offers a solid framework for analyzing consumer feedback, with each step strategically designed to improve product relevance and boost customer satisfaction. As shown in Table 1, the raw dataset included many columns, with one key column being "REVIEWS 2," which contained the textual reviews. Other Colomns is just another colomn that got extracted but have no significant use in this research such as name, date, etc.

Table 1. Dataset Before Preprocessing

No	Other Columns	Reviews 2
1	...	Durable, biodegradable and well made. Would recommend.
2	...	I moved to this brand from another whips quality tanked late. Even the tank lasted longer.
3	...	These are great bags with handles....and they are strong. I'm happy with the compostable.
4	...	Plastic is plastic, right? Biodegradable means plastic is still plastic.
5	...	These bags are really great. They are a bit thinner than a normal bag but completely...

Unprocessed data undergoes several text cleaning steps in the preprocessing stage. Python libraries like NLTK and Pandas are essential to this process. Pandas structures the data in a DataFrame, enabling efficient organization, filtering, and manipulation. NLTK handles key text preprocessing tasks, including: (1) Tokenization: Splitting reviews into individual words. (2) Stopword Removal: Using NLTK's predefined lists to exclude common, non-informative words (e.g., "and," "the," "is"). (3) Lemmatization: Reducing words to their base forms (e.g., "running" to "run") for consistency.

Table 2. Dataset After Preprocessing

No	Other Columns	Cleaned_Reviews
1	...	durable biodegradable well made would recommend
2	...	moved brand another whip quality tanked late even tank lasted longer
3	...	great bag handlesand strong im happy compostable
4	...	plastic plastic right biodegradable mean plastic still plastic
5	...	bag really great bit thinner normal bag completely

In this data preprocessing stage, we get a clean and more structured dataset as seen in table 2 above. This change can increase the reliability of data for analysis by reducing noise thereby ensuring consistency in the data.

RESULTS

To understand customer opinions on biodegradable garbage bags, we analyzed Amazon reviews to sort feedback into positive, negative, mixed, or neutral categories. This helped highlight customer satisfaction levels and pinpoint areas that need improvement. The reviews, cleaned and loaded from an Excel file into a Pandas DataFrame, were processed using the OpenAI GPT-4o Mini model. A custom function labeled the sentiments for each review, and the results were saved in a new column called "GPT_Sentiment." This approach gave a clear picture of what customers think, making it easier to suggest product improvements and create focused marketing strategies.

Table 3. Sentiment Added

Cleaned_Reviews	GPT_Sentiment
durable biodegradable well made would recommend	positive
moved brand another whip quality tanked late excellent stronger easier use love handle	positive
great bag handlesand strong im happy compostable	positive
plastic plastic right biodegradable mean plastic break landfill biodegrables break benzene xylene toxic material compostable plastic break soil food grown premise compostable plasticssuperbio fit neatly gallon trash bin bit thin side tear put sharp item like flower stem shrubbery clipping however work well regular kitchen trash coffee grind food waste paper towel etc trash taken least week work fineif allow bag sit lot moisture long period time imagine bag start breakdown however encountered yet	mixed
bag really great bit thinner normal bag completely job fill easy tie issue dont compost thus sure purchasing bag go landfill making difference	mixed
little thin work great purpose feel good use something doesnt destroy planet	positive

Upon observing the sample dataset, it was noted that the GPT-4o Mini model demonstrated a notable ability to accurately recognize mixed sentiments within the reviews. Table 3 shows the sentiment analysis function, which classifies reviews as positive, negative, mixed, or neutral, effectively identified instances where reviews contained both positive and negative elements. The sentiment distribution of the reviews, as classified by the GPT-4o Mini model, is summarized in the table 4 below.

Table 4. Sentiment Distribution

Sentiment	Count
Positive	550
Mixed	201
Negative	184
Neutral	14

This section aims to present the findings from the sentiment analysis, focusing on the distribution of sentiments in customer reviews and an in-depth examination of mixed sentiments to uncover key areas of consumer concern. According to the analysis, 57.96% of the reviews were positive; followed by mixed opinions (21.18%); and negative sentiments (19.39%). Only 1.48% of reviews were neutral, quite a small fraction. The GPT-4o Mini model showed a remarkable ability in precisely spotting mixed emotions, so offering a whole knowledge of the several points of view found in the reviews. The high proportion of positive reviews (57.96%) suggests that the product is generally well-received by consumers, which may indicate a strong brand perception and customer satisfaction. This positive sentiment dominance implies that while the product meets or exceeds expectations for many customers, there is still room for improvement, especially considering the 21.18% mixed and 19.39% negative reviews.

Negative words from reviews categorized as having mixed sentiment then were extracted using the GPT-4o Mini API. The sentiment analysis results first were loaded into a Pandas DataFrame then filtered to separate mixed sentiment reviews. Then a function was developed to send every review to the GPT-4o Mini model, which would identify and extract negative sentences. A new column in the DataFrame included the taken sentences. After the results were confirmed and stored in a fresh Excel file, they allowed a targeted analysis of negative feedback in mixed sentiment reviews for more thorough understanding of consumer issues.

Table 5. Negative Sentiment Extracted

Negative_Sentences
Here are the sentences with negative sentiment extracted from the mixed review: 1. "plastic break landfill biodegrables break benzene xylene toxic material" 2. "bit thin side tear put sharp item like flower stem shrubbery clipping" 3. "if allow bag sit lot moisture long period time imagine bag start breakdown"
The sentences with negative sentiment from the review are: - "bit thinner normal bag" - "issue dont compost thus sure purchasing bag go landfill"
The review you provided, "strong light elastic," does not contain any negative sentiment. It appears to express positive or neutral characteristics about an item. If you have a longer review or specific sentences you would like me to analyze for negative sentiment, please provide that content, and I will help identify and extract the relevant sentences.
The sentences with negative sentiment extracted from the review are: - "need throw bag" - "bag disintegrating"

GPT-4o Mini was able to identify negative sentiment within reviews that had been classified as mixed sentiment as shown in Table 5, along with GPT-4o Mini comment such as “The review you provided”. It demonstrated an impressive ability to isolate specific negative sentences from the broader context of these mixed reviews. Furthermore, the GPT-4o Mini also showed a remarkable capacity for correcting misclassified reviews. It successfully identified and extracted negative sentiments even from reviews that were initially mislabelled, thereby improving the overall accuracy of sentiment analysis.

From here, we then conducted a manual observation, removing rows of reviews that did not show negative sentiment. we extracted the negative sentiment sentences identified by GPT-4o Mini and combined them with the initial negative sentiments identified at the beginning. This process allowed me to compile a more comprehensive dataset of negative sentiments.

Table 6. Unigram and Bigram Analysis

Rank	Unigram	Unigram Frequency	Bigram	Bigram Frequency
1	bag	465	plastic bag	30
2	trash	119	trash bag	28
3	plastic	88	garbage bag	23
4	use	86	compostable bag	10
5	garbage	68	using bag	9

The analysis of the unigram and bigram frequencies in the table 6 above reveals several key themes. Unigrams refer to single words, while bigrams are pairs of consecutive words, both providing insights into commonly discussed topics or concerns in reviews. For instance, unigrams such as "bag," "trash," and "plastic" indicate frequent mentions of fundamental bag functions, while bigrams like "plastic bag" and "trash bag" reveal comparisons with traditional plastic bags, highlighting usage and performance discussions. Reviewers frequently mention the basic functionalities of the bags, such as holding trash and garbage, and often compare them to traditional plastic bags. There are significant discussions about the usability and performance of the bags, as well as their compostable nature. These insights can guide improvements in product design, marketing strategies, and customer education about the benefits and proper use of biodegradable trash bags.

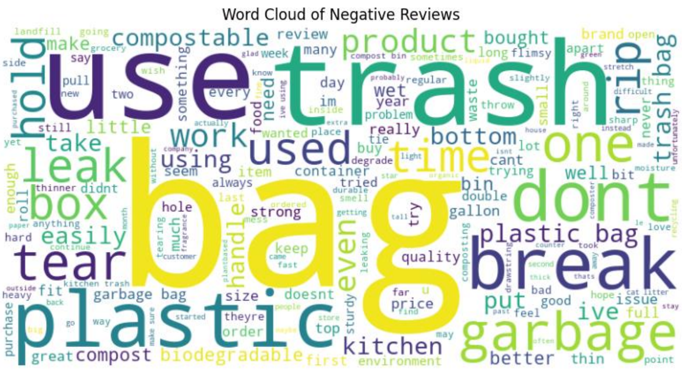

Figure 1. Wordcloud Result

The word cloud from figure 1 highlights key areas of concern for users, particularly around the durability (breaking and tearing), usability (leakage and capacity to hold trash), and the material (plastic vs. compostable attributes). The frequent mention of usage contexts like the kitchen and terms related to quality suggest that while the bags are designed to be environmentally friendly, there may be significant gaps in meeting user expectations for everyday functionality and reliability.

Using the results above, we then employed text mining techniques to analyze negative sentiments in reviews of biodegradable trash bags. We began by loading the combined dataset of negative sentiments from an Excel file. The text data was transformed using the Term Frequency-Inverse Document Frequency (TF-IDF) method, excluding common words such as "bag," "plastic," and "trash" to focus on more meaningful terms. The optimal number of clusters was determined using the Silhouette Method, and K-Means clustering was then performed with the optimal number of clusters.

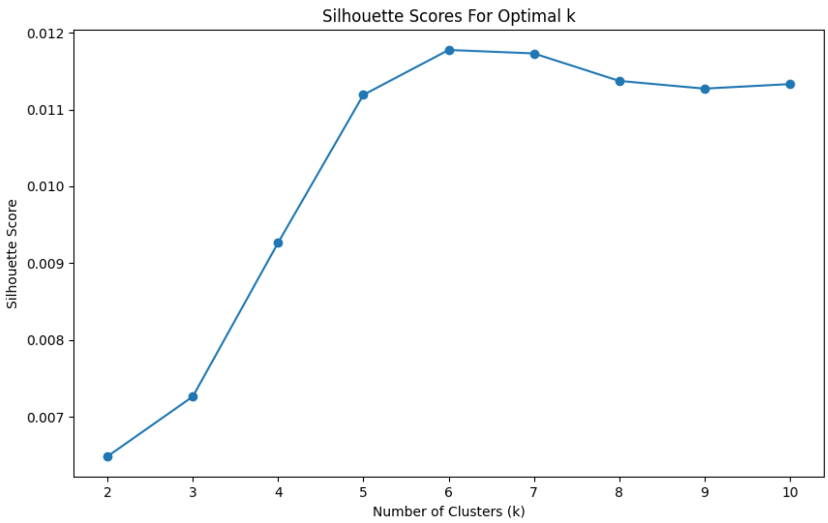

Figure 2. Silhouette Scores Result

Silhouette scores were calculated for a range of cluster numbers (from 2 to 10), with the highest score indicating the optimal clustering configuration. Silhouette scores are a measure of how well data points fit within their assigned clusters compared to other clusters. The score ranges from -1 to 1, where a higher value indicates better-defined clusters. A positive score suggests that data points are closer to their cluster's center than to other clusters, signifying strong cohesion within clusters and clear separation between clusters. This metric is crucial for evaluating clustering quality and determining the optimal number of clusters, as shown in Figure 2. Based on Figure 2, the optimal number of clusters was determined to be 6.

After the clustering process, six distinct clusters were formed, each highlighting specific aspects of consumer feedback:

Cluster 0: Keywords include "garbage," "use," "little," "work," "flimsy," "advertised," "used," "biodegradable," "bad," and "throw." This cluster focuses on issues related to product performance and durability. Words like "flimsy" and "bad" suggest unmet customer expectations, particularly regarding the advertised quality.

Cluster 1: Keywords include "easily," "tear," "handle," "rip," "strong," "easy," "tie," "open," "plant," and "time." This cluster highlights problems with ease of use and physical integrity. While terms like "easy" suggest handling convenience, words like "tear" and "rip" reflect concerns about fragility.

Cluster 2: Keywords include "compost," "need," "bin," "food," "use," "really," "leak," "compostable," "day," and "waste." This cluster centers on practical use and compostability. While consumers value the compostable nature of the bags, concerns about leakage persist. One review mentioned

Cluster 3: Keywords include "bit," "pricey," "quality," "little," "thinner," "tell," "big," "leak," "narrow," and "heavy." This cluster raises concerns about price and quality. Words like "pricey" and "leak" highlight dissatisfaction with the cost-to-quality ratio.

Cluster 4: Keywords include "break," "easily," "using," "heavy," "brand," "description," "time," "know," "old," and "faster." This cluster emphasizes reliability and long-term viability concerns. Customers expressed dissatisfaction with product consistency.

Cluster 5: Keywords include "box," "ive," "hold," "item," "kitchen," "apart," "review," "time," "using," and "used." This cluster focuses on usability and customer feedback, particularly in high-use contexts like kitchens.

The analysis reveals key themes in customer feedback across the clusters. Including direct quotes strengthens the findings, providing tangible connections between identified issues and real user experiences, while also highlighting areas for potential product improvement.

DISSCUSSION

Following the identification of the created clusters and thorough study of the reviews inside each cluster, the following suggestions for enhancing biodegradable waste bags have been made: (1) Enhance Durability: Cluster 0, 1, 3, 4: Emphasize on raising the bags' durability and strength. The bags tearing, breaking, and leaking worries consumers. Using better design or stronger materials will help to address these problems. Think about strengthening important places that might leak and rip. (2) Improve Quality for Price: Cluster 3: Attend to the worries regarding the bags' "pricey" relative to their quality. Make sure the product justifies its price by either improving its qualities or reevaluating the pricing approach. (3) Leakage Prevention: Cluster 2 and 3: Improve the bags' sealing mechanisms or make them from stronger materials so they don't leak, particularly if people are going to use them for composting and other waste management purposes. (4) Consistency and Reliability: Cluster 4: Work on keeping constant quality over several batches. Consumers should be free to believe that every purchase will satisfy the same high standards. Apply more rigorous quality control policies to guarantee dependability of the products. (5) Customer Feedback Integration: Cluster 5: Review and evaluate customer comments constantly to find reoccurring problems. Talk to clients to find out their worries and show your will to solve them.

Consumer feedback has highlighted key areas for improving biodegradable trash bags. Addressing these issues can boost customer satisfaction, enhance product quality, and strengthen market positioning in Indonesia. Here’s what needs attention: (1) Durability. Strengthen biodegradable materials to reduce tearing, breaking, and leaking. In Indonesia’s humid, tropical climate, these problems are worse, so reinforcing areas like handles and seams is crucial. Labeling the improved bags as "Tropical-Climate Resistant" can appeal to eco-conscious customers looking for reliable options. This approach positions the product as practical and suitable for the local environment. (2) Price and Quality Balance. Many consumers feel the bags don’t match their price. To fix this, surveys or market research can find the right price range. Offering basic and premium options might work well. Budget-friendly packs with discounts can attract cost-conscious buyers, while premium versions focus on extra durability and eco-friendly features. Testing these ideas through pilot programs can ensure they meet customer expectations. (3) Leak-Proof Design. Leaks are a major concern, especially for households handling wet organic waste. Stronger materials, reinforced bottoms, or double-sealed designs can prevent leaks. Marketing can use videos and testimonials to show how the bags perform in real-life situations. This builds trust and highlights their reliability in daily use. (4) Consistency. Consumers need to trust the product to be reliable every time. Strict quality control ensures consistent performance across all batches. Branding can emphasize this with messages about dependability. A "Satisfaction Guarantee" could also encourage first-time buyers by reducing the risk of trying a new product. (5) Customer Feedback. Listening to customers is key. Use platforms like WhatsApp and local social media to gather feedback, making it easy for Indonesians to share their opinions. Reward programs for feedback can boost engagement. Analyze the input to spot trends and prioritize improvements. Partnering with local influencers can amplify these campaigns and build stronger connections with the audience.

By tackling these areas, biodegradable trash bags can become a more appealing, trusted choice for consumers in Indonesia.

CONCLUSION

Using GPT4o-Mini to analyze reviews for biodegradable trash bags worked well, especially for picking out complaints hidden in mixed feedback. It flagged issues like tearing and leaking, even in reviews that also mentioned positives. These insights helped businesses focus on fixing problems, like reinforcing seams and making the bags more leak-proof. Marketing could then highlight these upgrades to rebuild trust. This shows how useful AI tools can be for improving products and marketing. With GPT4o-Mini's ability to understand language, businesses can focus on what matters most—like fixing durability issues or tweaking prices to match what customers expect. Marketing campaigns can also emphasize long-term benefits, like saving money and helping the environment, which builds loyalty. That said, the study has its limits. It focused on just one brand of trash bags, so the findings might not apply to others or to different markets. Broader research could compare multiple brands or categories of biodegradable products to give a fuller picture. Adding more advanced techniques to understand subtle sentiments and context could also improve future analyses

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