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Online Review-Based Positioning Analysis Using Natural Language Processing Techniques

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Abstract. Online customer reviews represent a valuable source of information for businesses seeking to understand consumer perceptions and preferences. This paper introduces a framework for competitive positioning analysis by leveraging these online reviews and sentiment analysis. The framework employs Natural Language Processing (NLP) techniques in three phases: 1) identifying key themes and topics from reviews using Latent Dirichlet Allocation (LDA); 2) extracting product features through zero-shot text classification; and 3) visualizing competitive positioning via Net Promoter Score (NPS) and sentiment analysis plots. A case study on Amazon's laptop market revealed a moderate correlation (58.8%) between NPS and sentiment analysis, suggesting potential limitations in feature classification accuracy. While the study demonstrates the value of NLP for analyzing online reviews, it also emphasizes the need for improved feature recognition methods and more robust datasets to enhance the precision of competitive positioning analysis.

Keywords: Competitive Positioning Analysis · Online Customer Reviews · Natural Language Processing (NLP) · Sentiment Analysis · Competitive Intelligence (CI)

1 INTRODUCTION

Companies constantly seek ways to gain an edge over their rivals in demanding market conditions. Understanding customer perceptions and preferences is crucial for achieving this competitive advantage [18]. Online customer reviews have emerged as a valuable source of information, providing businesses with direct insights into consumer opinions about products and services. By analyzing these reviews, companies can identify areas of strength and weakness, adapt their offerings to better meet customer needs, and ultimately enhance their competitive positioning. This process of gathering and analyzing customer feedback aligns with the concept of competitive intelligence (CI), which involves systematically

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collecting and analyzing information about the competitive environment to support strategic decision-making [11]. Online reviews, therefore, represent a rich source of competitive intelligence, enabling businesses to make more informed decisions regarding product development, marketing strategies, and overall business practices. By effectively leveraging the information contained within online reviews, companies can gain a deeper understanding of customer needs and preferences, leading to improved competitiveness and success in the marketplace.

However, effectively leveraging competitive intelligence can be challenging. Some businesses may underestimate its value or struggle to implement it effectively [7]. While a top-down approach, where directives and strategies are formulated by upper management, can provide a clear direction, it may sometimes overlook valuable insights from frontline employees who interact directly with customers. Incorporating a bottom-up approach, which encourages feedback and ideas from all levels of the organization, can create a more comprehensive and nuanced understanding of the competitive landscape. For instance, a sales representative might notice a recurring customer complaint that was not captured in online reviews, or a customer service agent might identify a competitor's unique selling proposition that was previously unknown. By combining both approaches, companies can gather a richer set of data and make more informed decisions.

Competitive intelligence involves a comprehensive understanding of various factors, including the market dynamics, competitive landscape, and internal organizational factors. By analyzing readily available unstructured data such as customer reviews, businesses can extract valuable insights to inform their competitive strategies. Several studies have explored different approaches to analyze and leverage competitive intelligence [23], [6], [2]. For example, [23] utilized a sparse term-based Dirichlet process model and a bipartite graph model with a random walk algorithm to analyze asymmetric competition and identify emerging market trends. In another study, [2] employed unsupervised gradient-based deep learning with competitive learning to replicate the input distribution topology and gain insights into the competitive landscape's structure. These diverse approaches highlight the growing interest in leveraging advanced analytical techniques to gain a competitive edge.

Building upon these concepts, this study proposes a novel framework for analyzing a company's competitive position using online customer reviews and sentiment analysis. This framework uses Natural Language Processing (NLP) techniques to understand what customers are saying about products and services.

The framework has three main steps:

1) **Identify** key themes: It finds the main topics and issues that customers talk about in their reviews.

2) **Extract** product features: It automatically identifies and categorizes specific product features that customers mention.

3) **Visualize** competitive positioning: It creates visual maps that show how a product compares to its competitors based on customer sentiment and the Net Promoter Score (NPS).

A case study of laptops on Amazon revealed a moderate link between customer sentiment and NPS, suggesting that there's room for improvement in how the framework identifies and classifies product features. This study highlights how NLP can be used to analyze online reviews and improve competitive analysis, but it also shows the need for better methods to recognize product features and the importance of using large and diverse datasets.

2 RELATED WORKS

Competitive intelligence is a relatively novel discipline generating a growing interest in strategic management. It is a discipline that helps organizations adapt to environmental change and gain a competitive advantage in a volatile and competitive business environment [15, 19]. Competitive intelligence involves gathering and transforming data into applicable knowledge to understand the market, technology, customers, competitors, and other factors influencing a business [17]. It is a consensus-driven intelligence process that can be used at every activity level, including tactical and strategic decision-making [1]. The main objective of competitive intelligence is to master and know all the information with strategic value, allowing businesses to improve their competitive advantages and achieve success with new products [10].

It includes various types of intelligence, such as market intelligence, competitor intelligence, and internal intelligence [5]. Market intelligence refers to gathering and analyzing information about markets and supply chains to support strategic decision-making in organizations. It involves acquiring knowledge about market trends, customer preferences, competitor activities, and other relevant factors that impact business performance [21]. Competitor intelligence refers to gathering and analyzing information about a firm's competitors to gain strategic insights and identify opportunities and threats in the market [10]. Internal intelligence collects and analyzes information about an organization's internal operations, resources, and capabilities. It focuses on understanding the internal factors that impact the organization's Performance and competitive advantage [5].

Machine learning approaches for competitive intelligence include induction-based data mining software that uses machine-learning algorithms to analyze records in a firm's internal and customer databases, discovering patterns, transactional relationships, and rules that can predict future trends and indicate competitive opportunities. Another approach is using machine learning techniques in marketing management, such as consumer behavior analysis, optimization of product-market structure, and strategic marketing. Additionally, adaptive resonance models, which combine competitive learning with mechanisms for learning top-down expectancies and matching input patterns, are used for self-stabilizing learning in real-world applications [9].

Approaches to competitive intelligence vary in their methods and focus. One approach involves using non-hierarchical cluster analysis to identify optimum clusters based on the DaviesBouldin index and then extracting association rules from each cluster using support, confidence, and lift indices [3]. Another approach involves sentiment analysis to analyze consumers' opinions and statistical analysis to compare competitors using user-generated content from online media platforms. Syntactic-level text mining is another approach that improves competitive intelligence performance by leveraging web information and selecting different online data sources [14]. Text mining tools can also analyze social media sites and extract sentiments, passion, and reach, providing insights into financial Performance [22]. Finally, a text-mining-based decision-support model called MOETA integrates natural language processing technologies for event detection and opinion mining, aiming to distill unstructured textual data into helpful knowledge for decision-makers [8].

Current research primarily focuses on sentiment analysis to gauge customer sentiment and attitudes towards products and services. However, there are also some disadvantages to consider. CI can be time-consuming and resource-intensive, requiring continuous monitoring and analysis of information [16]. The research gap lies in applying topic modeling and zero-shot learning techniques to customer reviews to classify them into a pricing quality framework. This gap indicates the need for innovative methodologies that can provide a more comprehensive understanding of customer feedback related to pricing, ultimately assisting businesses in refining their pricing strategies and enhancing their competitive advantage. Addressing this research gap would contribute significantly to competitive intelligence by introducing advanced techniques that enable a deeper analysis of customer sentiments and perceptions in the context of pricing quality.

3 The Proposed Research framework

The framework of the methodology is shown in Fig. 1, in which there are three phases: mining useful information from online reviews, product Feature Extraction, and constructing positioning plots.

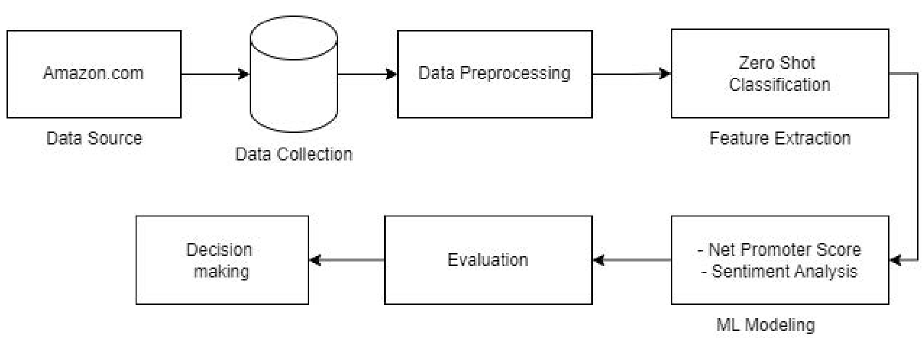

Fig. 1. Research Framework

According to Fig. 1, firstly, valuable insights are from online reviews through ethical data mining, encompassing data extraction from *Amazon*[3] in *phase-I*. In this phase, the gathered data collects pertinent information such as user sentiments, ratings, and detailed product attributes. Afterward, product feature extraction is focused on in *phase-II* in which key features influencing customer satisfaction, including performance, design, and pricing, are identified and categorized based on sentiment analysis of user reviews. Lastly, in *phase-III*, the customer's feeling can be evaluated by considering the net promoter and sentiment scores.

3.1 Phase I: Exploratory Data Analysis

In this phase, the primary objective is to mine valuable information from online reviews, specifically those from *Amazon*, i.e., online reviews of Amazon's users. Fig.2 shows an example of Amazon's product reviews, which are gathered by web data extraction, known as *Web Scraper*[4] such as *Product's name*, *Review's title*, *Review's content*, *Reviewer's country*, *Review's date*, *Actual Price*, *Brand*, *Model*, *Screen size*, *HDD size*, *CPU Model*, *RAM*, *Graphic Card*, and *Rating*. A total number of 10,225 valid online reviews were collected by October 2023.

product	title	review	country	date	actualprice	totalrating	brand	Model Name	Screen Size
lenovo legion 5' gaming laptop, 17.3" fhd (1920...	a gaming laptop that wont break the bank	my laptop came well protected and packaged. at...	the united states	19-08-23	836.94	15	lenovo	lenovo legion	17.3
lenovo legion 5 gaming laptop, 17.3" fhd (1920...	it would be best to avoid this device and perh...	i opened the machine and was initially excited...	the united states	28-02-22	836.94	15	lenovo	lenovo legion	17.3

Fig. 2. An example of Amazon's product reviews which are gathered by web data extraction

Data with missing fields were excluded from the analysis to guarantee its integrity. Initial exploration suggested the presence of outliers and skewed distributions within certain numerical features, such as null and duplicate values. Missing values can introduce complexities in calculations or create ambiguities

[3] https://www.amazon.com/
[4] https://webscraper.io/

in how they should be handled. Some data will also be filtered, such as values containing *RAM* lower than 2 GB, which is inconsistent with the gaming laptop minimum requirement.

3.2 Phase II: Product Feature Extraction

This phase focuses on feature extraction using zero-shot text classification, where key features influencing customer satisfaction are identified and categorized based on user reviews in Section 3.1. According to feature categorization, there are four clusters, i.e., the category of *Performance*, the category of *Price*, the category of *Design*, and the category of *Battery Life*. This categorization helps organize and understand the diverse aspects of gaming laptops that impact user satisfaction. By employing a zero-shot classification pipeline using the Facebook/bart-large-male model. The transformer architecture includes an attention mechanism that allows the model to selectively focus on relevant parts of the input sequence. This enables the model to extract important relationships between words and better capture the meaning of the input text. Perform the model with customer reviews in the dataset without finetuning the model. Obtained data on confidence scores or probabilities associated with each label. Fig.3 shows scores that indicate the model's confidence in its predictions for each label. Higher scores suggest greater confidence.

brand	review	performance	price	Design	Battery Life
lenovo	my laptop came well protected and packaged. at...	0.948494	0.907713	0.814273	0.575647
lenovo	i opened the machine and was initially excited...	0.875574	0.361003	0.458609	0.385738
lenovo	bought this laptop a little over a year ago an...	0.993486	0.292151	0.537078	0.931718
msi	i love this laptop. i'm disappointed i can't h...	0.748404	0.437733	0.531509	0.424489
dell	not the best and may have heating issues but i...	0.474426	0.982228	0.093020	0.012050
...	...	...	...	...	...
asus	great gaming laptop with some minor bluetooth ...	0.252324	0.006448	0.024046	0.095763
asus	laptop was great when i first got it but withi...	0.840510	0.058931	0.322200	0.001383
asus	bought this computer for dual purpose for my s...	0.793563	0.561768	0.022796	0.070455
asus	it is the perfect gaming laptop, also it's por...	0.861903	0.302620	0.595678	0.197675
asus	best gaming laptop i have owned. i like the ke...	0.091538	0.020062	0.002909	0.016788

Fig. 3. An example of confidence scores in each label.

To translate confidence scores into actionable insights, a threshold of 0.8 was applied, classifying scores above the threshold as positive, which means 1, and those below as negative. An overall sentiment score for each gaming laptop product, considering the sentiments associated with all identified features. This provides a holistic view of customer satisfaction with each product.

3.3 Phase III: The Customer's Satisfaction Evaluation

Net promoter and sentiment scores can evaluate the customer's satisfaction in this phase. Net promoter score is a market research metric based on a single survey question asking respondents to rate the likelihood that they would recommend a product or a service to friends. Otherwise, it measures customer loyalty and willingness to recommend a product, service, or enterprise to others. Managers widely adopted the net promoter score to measure customer mindset and predict sales growth [8]. They used it to measure customer satisfaction in various industries, including higher education [12]. The net promoter score separates the customer's satisfaction into three categories: *Promoter* (customers answering with the highest), *Passive* (responses of average), and *Detractor* (responses below average). It is formulated as follows: Equation 1 that takes the difference between "Promoters" and "Detractors" and divides it by the overall sample size—hence the name "Net Promoter" [4].

$$NetPromoterScore = (\sum Promoters - \sum Detractors)/SampleSize \tag{1}$$

However, customer reviews are a quantitative indicator of customer loyalty and satisfaction. This paper computes the net promoter score for each aspect of the laptop based on customer reviews. According to their reviews, it classifies clients into three classes, i.e., promoters, passives, and detractors.

On the other hand, this paper also indicates customer satisfaction based on sentiment analysis, which analyzes online reviews to determine if the emotional tone of the text message is positive, negative, or neutral. This paper computes the sentiment score for each aspect of the laptop based on customer reviews, similar to the net promoter score. The emotional tone of online reviews classifies clients into three classes, i.e., positive, negative, and neutral. All of them are determined to be similar in customer loyalty and satisfaction of the net promoter score. Positive is similar to promoters, negative is similar to detractors, and neutral is similar to passives.

For sentiment analysis, the sentiment score is considered Using VADER, which is a lexicon and rule-based feeling analysis model attuned explicitly to social media sentiments, after classifying each review into relevant attributes (e.g., price, battery life, design, and performance) using zero-shot classification with a transformer-based model (3.2). VADER is particularly effective for analyzing online customer reviews with emotive elements, and its results obtain sentiment scores for different attributes in gaming laptop reviews. The compound score is a normalized, weighted composite score that ranges from -1 (most negative) to +1 (most positive). Obtain and analyze sentiment scores for various attributes of gaming laptops using VADER.

Based on this phase, there are two valuable insights into customer perceptions, i.e., comprehensively understanding the key features that significantly influence customer satisfaction regarding true customer feeling from the net promoter score and predictive customer feeling from the sentiment score. This information lays the groundwork for constructing a detailed competitive positioning analysis in the subsequent stages and helping brands identify strengths and areas of improvement.

4 Experiment Evaluation

Visualizations were employed to illustrate the relationships between variables and customer sentiment. Scatter plots were used to examine correlations such as price vs. performance, potentially incorporating sentiment as an additional dimension through color coding. The position of a brand/product on the plot reflects how consumers perceive it concerning those key dimensions. For example, a product in the upper-right quadrant of a Price vs Performance plot is perceived as high-price and high-performance. The proximity of data points suggests a similarity in how consumers perceive those brands. Clustered together, brands are seen as direct competitors. White spaces (areas without data points) highlight potential market opportunities where no product fulfills a specific consumer need (e.g., low-price, high-performance).

4.1 Setup

The data in this experiment was gathered from online reviews of Amazon's users, such as *Product's name*, *Review's title*, *Review's content*, *Reviewer's country*, *Review's date*, *Actual Price*, *Brand*, *Model*, *Screen size*, *HDD size*, *CPU Model*, *RAM*, *Graphic Card*, and *Rating*. A total number of 10,225 valid online reviews were collected by October 2023. The key features are extracted using zero-shot text classification, where key features influencing customer satisfaction are identified and categorized based on user reviews that there are four clusters, i.e., the category of *Performance*, the category of *Price*, the category of *Design*, and the category of *Battery Life*. Customer satisfaction is based on the customer's true feelings, the Net Promoter Score, and predictive customer feelings based on the sentiment score. Both scores are used to create a perceptual map to compare the performance of the predictive customer's satisfaction to that of the real customer based on the online text reviews.

4.2 Perceptual Maps Regrading from the Net Promoter Score

The experimental result shows a competitive positioning plot to give a quick snapshot of how major brands or products are perceived relative to each other. It highlights who your direct competitors are and helps identify potential market gaps. Fig 4 Show the competitive positioning plot of price and performance.

Several brands cluster in the upper left quadrant as Value for Money cluster, including Lenovo, Asus, Acer, and Dell. These brands might be attractive to those seeking a balance between affordability and good performance—a cluster that needs improvement in the Price and Performance plot. Lower right and lower left quadrants, e.g., Alienware, Razer, and Gigabyte, are positioned here, indicating a potential need for improvement in either perceived price or performance.

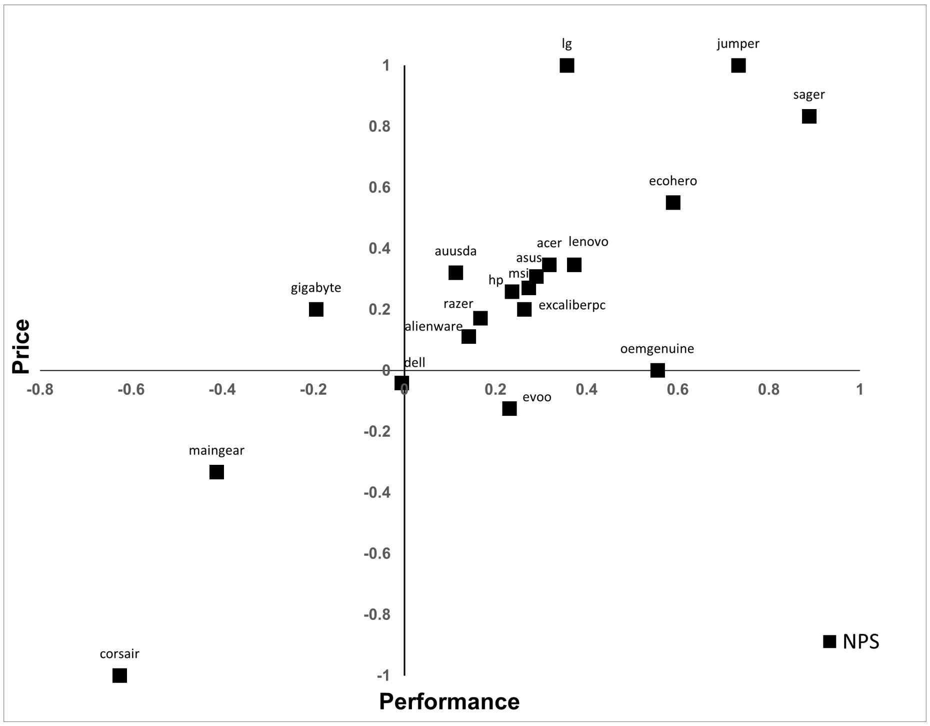

Fig. 4. Price and performance positioning plot on NPS result

Fig 21 Show Competitive Positioning plot of design and performance. Brands in the upper right quadrant, e.g., sager and jumper, are perceived as excelling in design and performance. These are likely premium brands targeting customers who prioritize top-of-the-line aesthetics and specs. Brands in the lower right quadrant, e.g., gigabytes, are perceived as having a more favorable design NPS than performance NPS. This suggests a potential focus on design for these brands. They might appeal to users who value looks alongside decent performance. Brands in the upper left quadrant have a higher performance NPS than design NPS. These brands might be known for their powerful specs but might not prioritize design as much. They may target gamers who prioritize performance over aesthetics. Brands positioned closer to the center, e.g., Dell, Alienware, razer, and Asus, might be seen as offering a more balanced experience in both design and performance. Brands positioned in the lower left quadrant, e.g., corsair and Main Gear, negatively perceive both design and performance based on NPS. This suggests a need for improvement in both areas to improve customer sentiment.

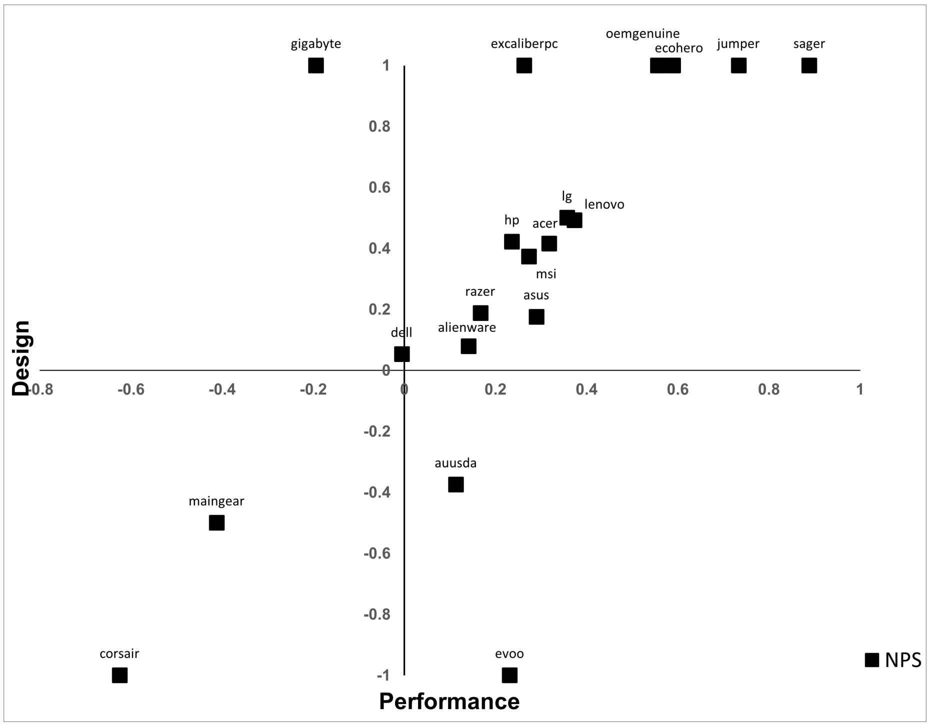

Fig. 5. Design and performance positioning plot on NPS result

Fig 6 shows the competitive positioning plot of performance and battery life. A cluster of brands in the center area, e.g., Dell, Lenovo, HP, and Acer. This suggests that these brands are perceived as offering a mid-range experience in both performance and battery life. sager, eco-hero, OEM genuine, and jumper are positioned in the upper right quadrant. This indicates a positive perception of their performance, but their battery life NPS might be lower. These brands likely target gamers who prioritize performance over unplugged use. main gear is positioned in the upper left quadrant. This suggests a potentially more robust perception of battery life, but performance NPS might be lower. These brands might appeal to gamers who value extended battery life for tasks beyond gaming.

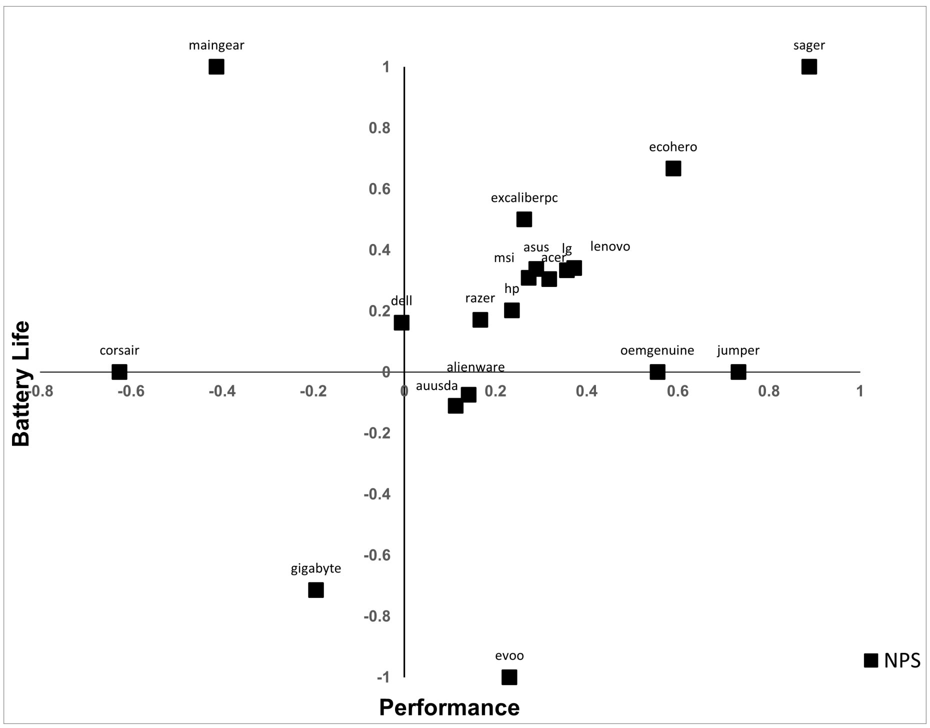

Fig. 6. Performance and battery life positioning plot on NPS result

Fig 7 Show the competitive positioning plot of price and design. Several brands cluster in the upper right quadrant, including Lenovo, Asus, Acer, and Dell. This indicates a positive perception of their design relative to price. These brands might be attractive to those seeking a balance between affordability and good design. Gigabytes are positioned in the upper mid-quadrant. This suggests a perception of premium design, but their price NPS might be lower. These brands might target those who prioritize design and are willing to pay more. Corsair and Evoo are on the lower left quadrant, suggesting a perception of lower price and design scores.

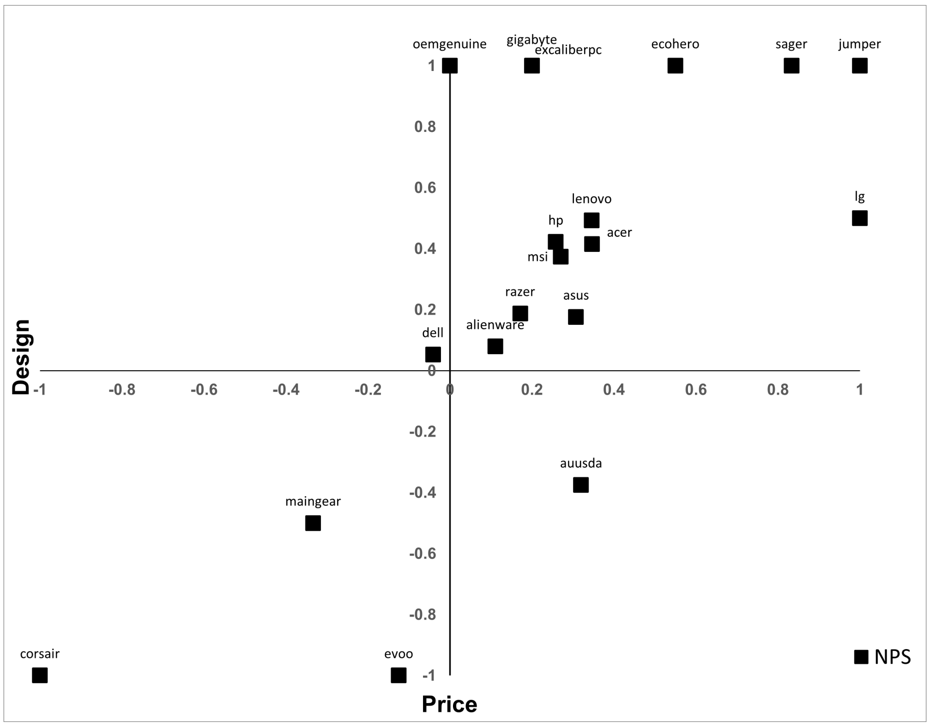

Fig. 7. Price and design positioning plot on NPS result

Fig 8 shows the competitive positioning plot of price and battery life. Brands in the upper right quadrant are perceived as excelling in performance and battery life. These are likely top-of-the-line gaming laptops ideal for gamers who demand powerful specs and long battery life, but they might also come at a premium price. Brands in the lower right quadrant have a higher performance NPS than battery life NPS. These brands are known for their powerful specs but may have shorter battery life. They target gamers who prioritize performance over unplugged use. Brands in the upper left quadrant are perceived as having a more positive battery life NPS compared to performance NPS. This suggests these brands prioritize long battery life, but performance might not be their strongest selling point. They might appeal to gamers who value extended unplugged use, perhaps for productivity tasks alongside gaming. Brands positioned closer to the center might be seen as offering a more balanced experience in both performance and battery life. Based on NPS, brands in the lower left quadrant negatively perceive performance and battery life. This suggests a need for improvement in both areas to improve customer sentiment.

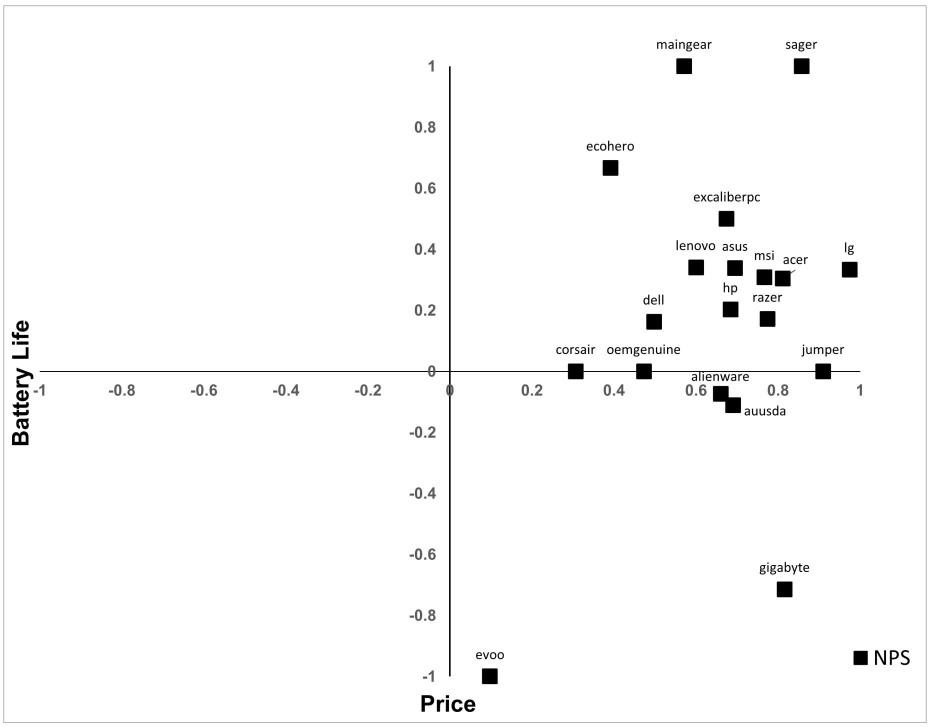

Fig. 8. Price and battery life positioning plot on NPS result

Fig 9 Show Competitive Positioning plot of design and battery life. Cluster of brands in the center area, e.g., Dell, Acer, Lenovo, and HP. These brands are perceived as offering a mid-range experience in design and battery life and holding significant market share. Ecohero, excaliber, and sager are positioned in the upper right quadrant. This indicates a positive perception of their design, and they also have a decent market share. These brands might appeal to users who value aesthetics alongside decent battery life. Maingear stands out in the upper left quadrant, suggesting a stronger perception of battery life. However, its design score and market share are lower than some centrally located brands. Based on NPS, Corsair's lower left quadrant needs design and battery life improvement. Gigabyte is positioned on the lower right quadrant, indicating a need for improvement in perceived battery life, while the design might be viewed more favorably. It also has a smaller market share.

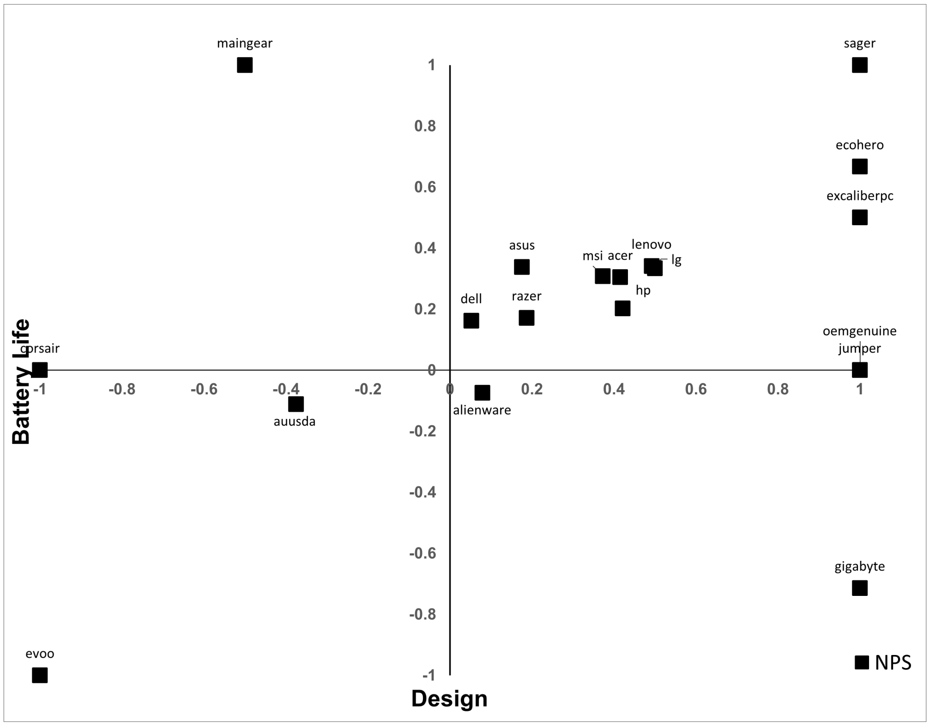

Fig. 9. Design and battery life positioning plot on NPS result

4.3 Perceptual Maps Regrading from the Sentiment Analysis

The sentiment analysis positioning plot further elaborates on the customer perceptions by categorizing the sentiment expressed in reviews for different attributes like price and performance. While the NPS plot quantitatively captures customer loyalty and satisfaction, the sentiment analysis plot provides a qualitative perspective, revealing the emotional tone behind the scores. The competitive positioning plot based on sentiment analysis of price and performance in fig10 provides valuable insights into brand performance and customer perceptions.

Top Right Quadrant: Brands like LG, Sager, Jumper, Razer, Gigabyte, and MSI show positive sentiment for both price and performance, indicating high overall customer satisfaction. These brands should continue leveraging their strengths to maintain their competitive edge by promoting balanced performance in both areas.

Top Left Quadrant: Corsair stands out with very high-performance sentiment but lower price sentiment. Corsair should enhance its price perception to complement its strong performance, ensuring a more balanced overall satisfaction.

Bottom Right Quadrant: Aausda, found in this quadrant, is praised for its price but faces negative sentiment regarding performance. This brand should prioritize improving performance features to align with its positive price perception.

Bottom Left Quadrant: Evoo faces challenges in both price and performance, indicating significant customer dissatisfaction. Comprehensive improvements are necessary for Evoo to improve its market positioning.

Center Cluster: Brands like Oemgenuine, Asus, HP, Lenovo, Alienware, Maingear, Excaliberpc, Dell, and Ecohero receive mixed to positive sentiment in both price and performance. These brands are competitive but have opportunities to enhance their performance and pricing perceptions further to stand out more in the market.

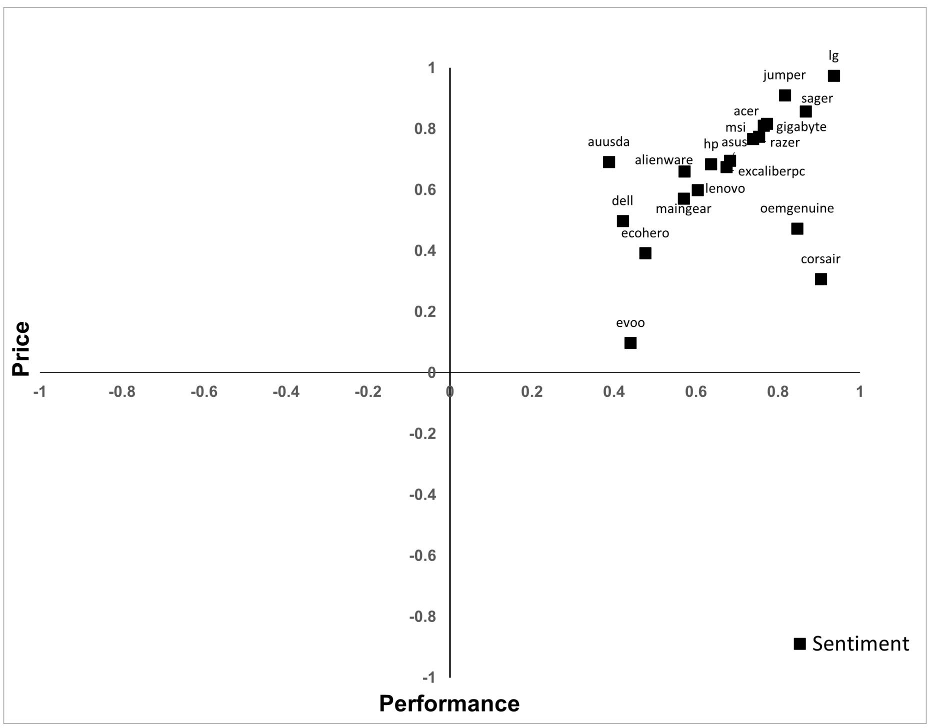

Fig. 10. Price and performance positioning plot on sentiment analysis result

The competitive positioning plot based on sentiment analysis of design and performance in gaming laptops provides valuable insights into brand performance and customer perceptions in Fig 11.

Top Right Quadrant: Brands like LG, Sager, Jumper, Razer, Gigabyte, MSI, and Excaliberpc show positive sentiment for both design and performance, indicating high overall customer satisfaction. These brands should continue leveraging their strengths to maintain their competitive edge by highlighting their balanced performance in both areas.

Top Left Quadrant: Corsair stands out with very high-performance sentiment but lower design sentiment. Corsair should enhance design features to complement its strong performance perception, ensuring a more balanced overall satisfaction.

Bottom Right Quadrant: Ecohero, found in this quadrant, is praised for its design but faces negative sentiment regarding performance. This brand should prioritize improving performance features to align with its positive design perception.

Bottom Left Quadrant: Evoo faces challenges in both design and performance, indicating significant customer dissatisfaction. Comprehensive improvements in both areas are necessary for Evoo to improve its market positioning.

Center Cluster: Brands like Oemgenuine, Asus, HP, Lenovo, Alienware, Maingear, Dell, and Aausda receive mixed positive sentiments in design and performance. These brands are competitive but have opportunities to enhance their design and performance perceptions further to stand out more in the market.

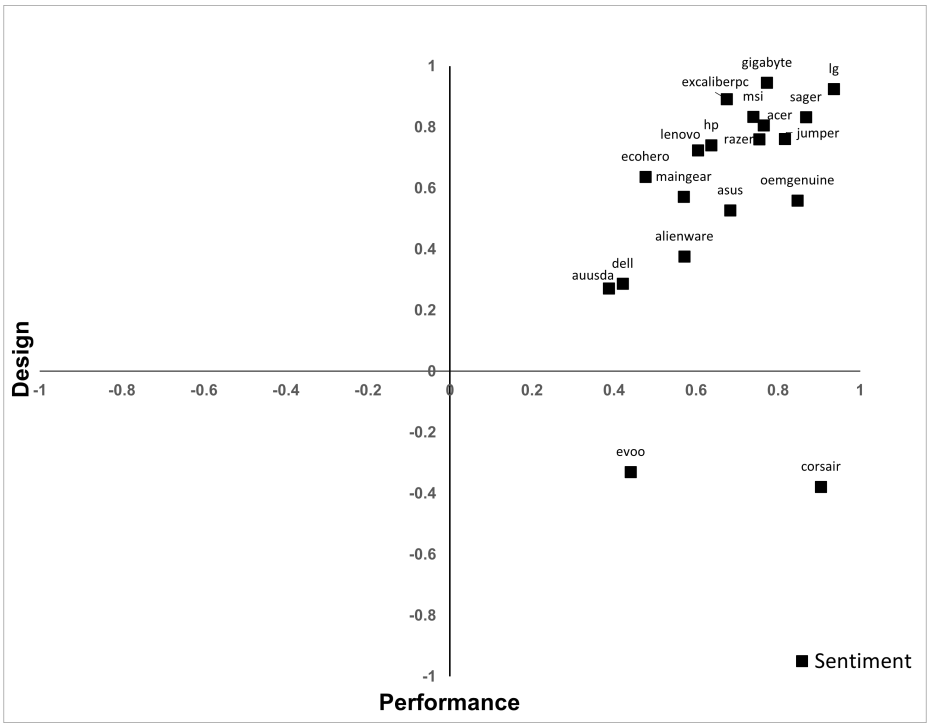

Fig. 11. Design and performance positioning plot on sentiment analysis result

The competitive positioning plot based on sentiment analysis of performance and battery life in fig 12 reveals key insights into brand performance and customer perceptions.

Top Right Quadrant Brands like LG, Corsair, Oemgenuine, Sager, Razer, Jumper, Gigabyte, and MSI get positive sentiment for both performance and battery life, indicating high overall customer satisfaction. These brands should continue leveraging their strengths and maintain their competitive edge by highlighting their balanced performance in both areas.

Bottom Right Quadrant Alienware and Ecohero, found in this quadrant, are praised for their performance but face low positive sentiment regarding battery life. These brands should prioritize improving battery performance to align with their upbeat performance perception.

Bottom Left Quadrant Evoo faces performance and battery life challenges, indicating significant customer dissatisfaction. Comprehensive improvements in both areas are necessary for Evoo to improve its market positioning.

Center Cluster Brands like Dell, Aausda, Lenovo, HP, Asus, and Excaliberpc receive mixed positive performance and battery life sentiments. These brands are competitive but have opportunities to enhance their performance and battery life perceptions further to stand out more in the market.

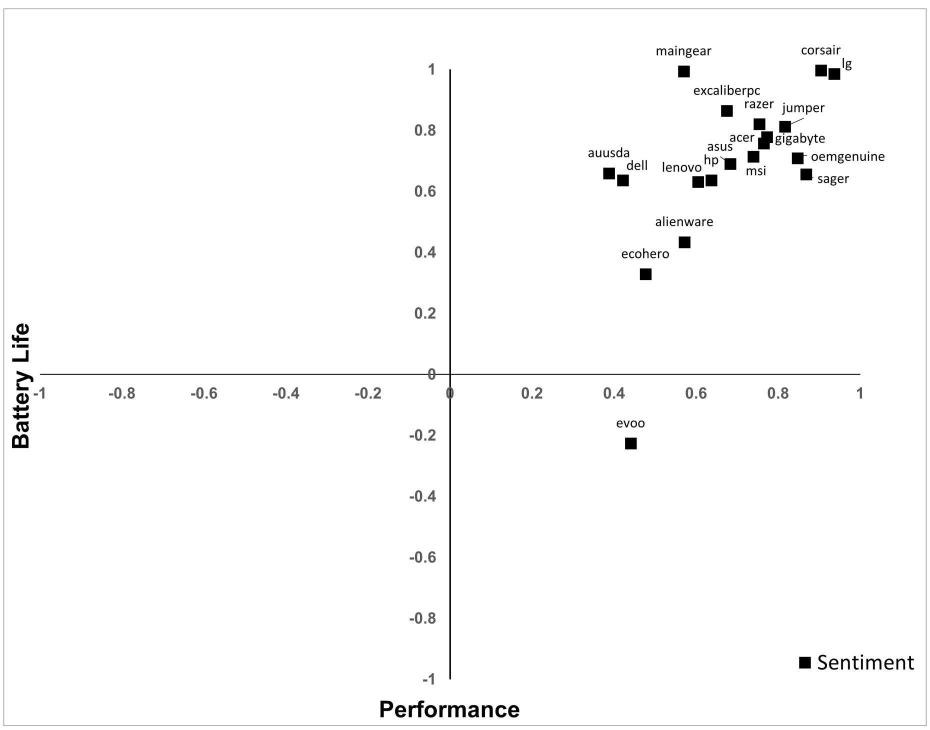

Fig. 12. Performance and battery positioning plot on sentiment analysis result

Fig 13 shows a competitive positioning plot based on sentiment analysis of price and design in gaming laptops, highlighting distinct clusters of brand performance and customer perceptions. In the top right quadrant, brands like LG, Excaliberpc, Jumper, Razer, Gigabyte, MSI, and Sager are perceived positively for both price and design, indicating high overall customer satisfaction. These brands should continue leveraging their strengths to maintain their competitive edge and market leadership.

In the top left quadrant, brands such as Ecohero and Oemgenuine enjoy positive sentiment for design but less favorable sentiment regarding price. These brands might consider revising their pricing strategies or enhancing the perceived value of their products to better align with customer expectations.

The bottom right quadrant includes brands like Alienware and Asus, which are praised for their price but face negative sentiment in design. These brands should prioritize improving design features to match their positive price perception, ensuring a more balanced overall satisfaction.

Brands in the bottom left quadrant, such as Evoo and Corsair, face challenges in both price and design sentiment, indicating significant customer dissatisfaction. Comprehensive improvements in both areas are needed for these brands to enhance customer satisfaction and competitive positioning.

Brands clustered around the center, including Maingear, Lenovo, HP, and Dell, generally receive mixed to positive sentiment in price and design. These brands are competitive but have opportunities to improve their design and pricing perceptions to stand out in the market.

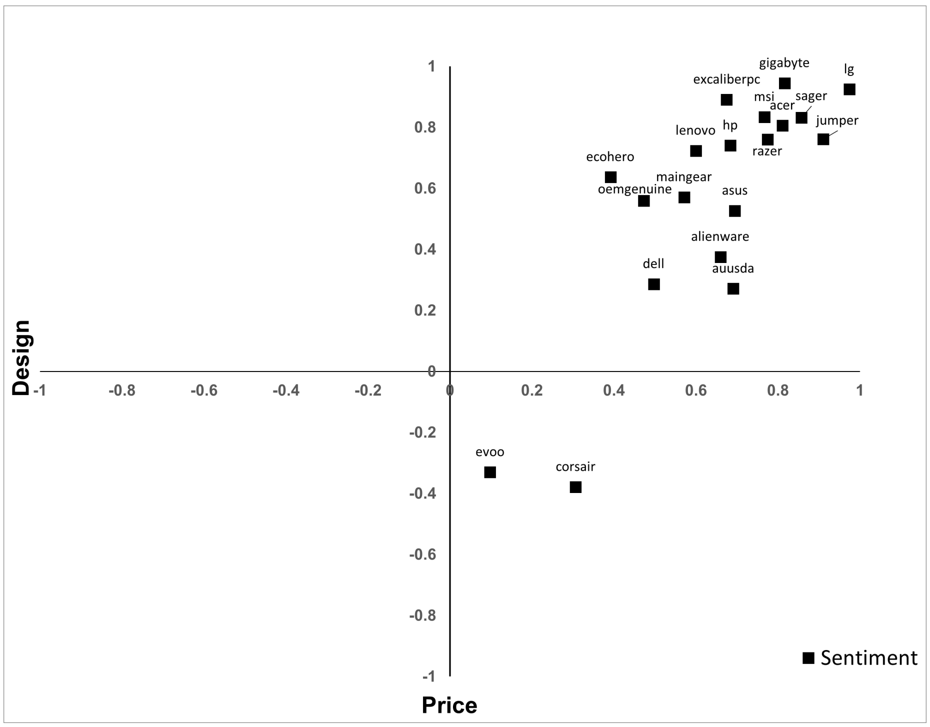

Fig. 13. Price and design positioning plot on sentiment analysis result

The competitive positioning plot based on sentiment analysis of price and battery life in gaming laptops in fig14 reveals distinct clusters of brand performance. In the top right quadrant, brands like LG, Excaliberpc, Jumper, Razer, Gigabyte, MSI, and Sager show positive sentiment for both price and battery life, indicating solid customer satisfaction. These brands should continue leveraging their strengths to maintain their competitive edge.

In the top left quadrant, Corsair is appreciated for its battery life but faces negative sentiment regarding price. Corsair should consider revising its pricing strategy or enhancing perceived value to align with customer expectations.

In the bottom right quadrant, Alienware is praised for its price but faces negative sentiments about battery life, suggesting a need for performance improvements.

Evoo faces price and battery life challenges in the bottom left quadrant, indicating significant customer dissatisfaction. Comprehensive improvements in both areas are needed for Evoo to improve its market positioning.

Brands like Maingear, Oemgenuine, Dell, Lenovo, Asus, HP, and Aausda, clustered around the center, received mixed to positive sentiment in price and battery life. These brands have opportunities to enhance their perceptions further to improve customer satisfaction.

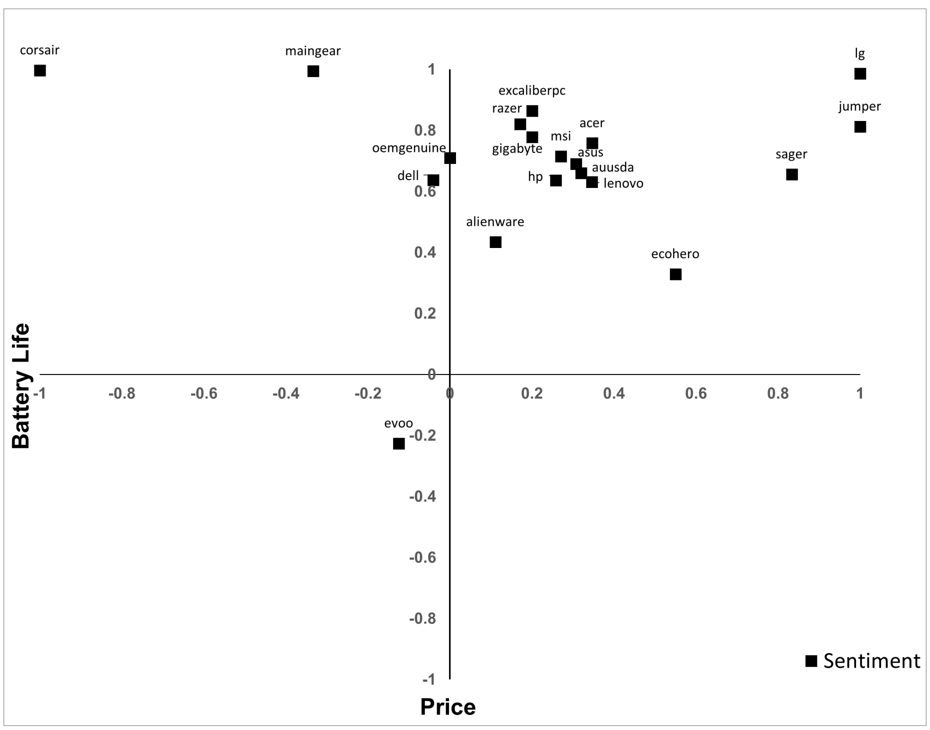

Fig. 14. Price and battery positioning plot on sentiment analysis result

The competitive positioning plot based on sentiment analysis of design and battery life in gaming laptops in Fig 15 reveals distinct brand performance and customer perceptions clusters. Brands like LG, MSI, and Sager are positioned in the top right quadrant and have cheerful design and battery life sentiments, indicating high overall customer satisfaction. These brands should continue leveraging their strengths in both areas to maintain their competitive edge.

In the top left quadrant, Corsair stands out with positive sentiment towards battery life but negative sentiment regarding design. This suggests that while customers appreciate the battery performance, the design is lacking. Corsair should improve its design to complement its strong battery life perception, and marketing efforts should highlight upcoming design enhancements.

The bottom right quadrant includes brands like Alienware and Ecohero, which are praised for their design but face negative sentiment regarding battery life. These brands should prioritize enhancing battery performance to balance customer satisfaction and match their positive design perception.

Finally, brands in the bottom left quadrant, such as Evoo, face design and battery life challenges, indicating significant customer dissatisfaction. These brands need comprehensive improvements in both areas to improve overall customer satisfaction and market positioning.

Brands clustered around the center-right, including Maingear, Asus, HP, Dell, Lenovo, Oemgenuine, and Aausda, generally receive positive sentiment in design but mixed to positive sentiment in battery life. These brands are competitive but have opportunities to enhance their battery life perceptions further.

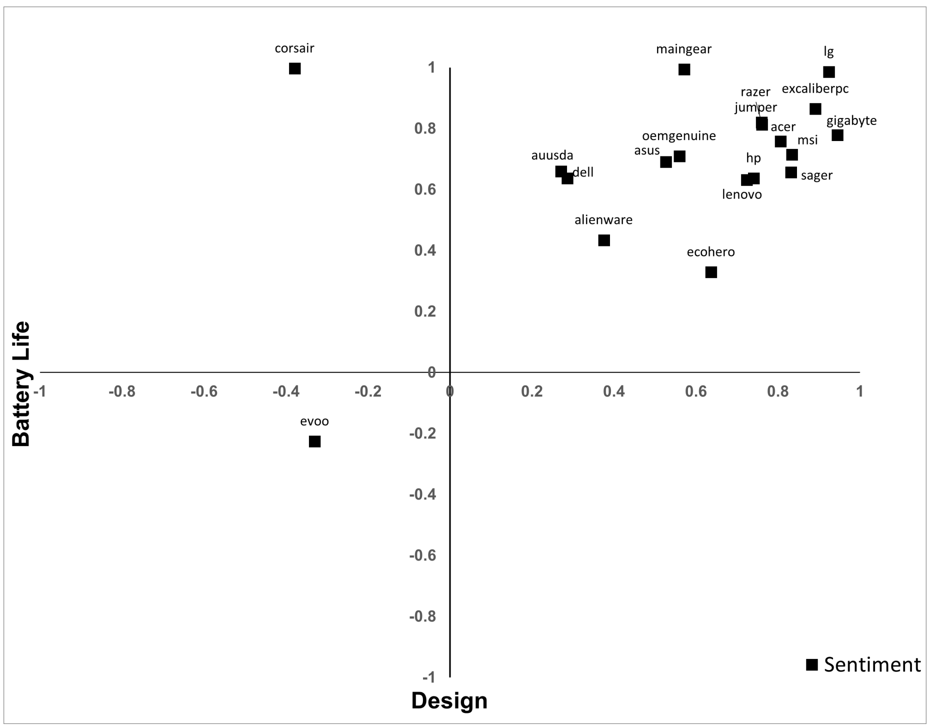

Fig. 15. Design and battery positioning plot on sentiment analysis result

By integrating both NPS and sentiment analysis, a comprehensive view emerges, allowing brands to pinpoint specific attributes that drive customer loyalty and satisfaction and areas requiring enhancement. This dual approach provides a robust framework for developing targeted strategies that address customer feedback's quantitative and qualitative dimensions.

4.4 Comparison between NPS and Sentiment Analysis

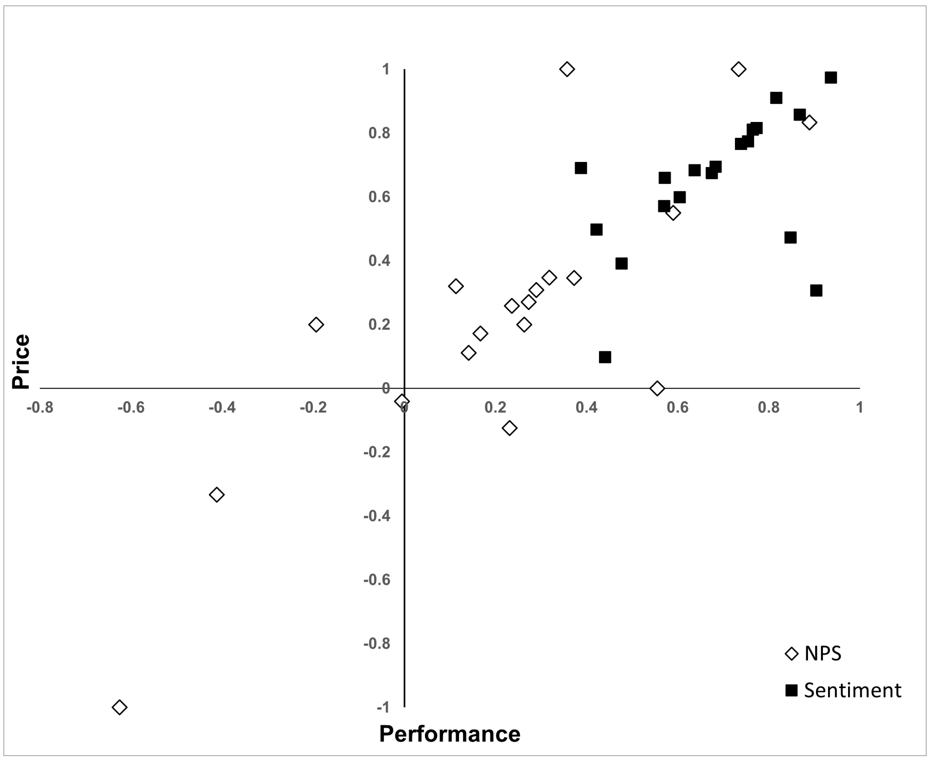

Fig. 16. Comparison between NPS and Sentiment on Price and Performance positioning plot

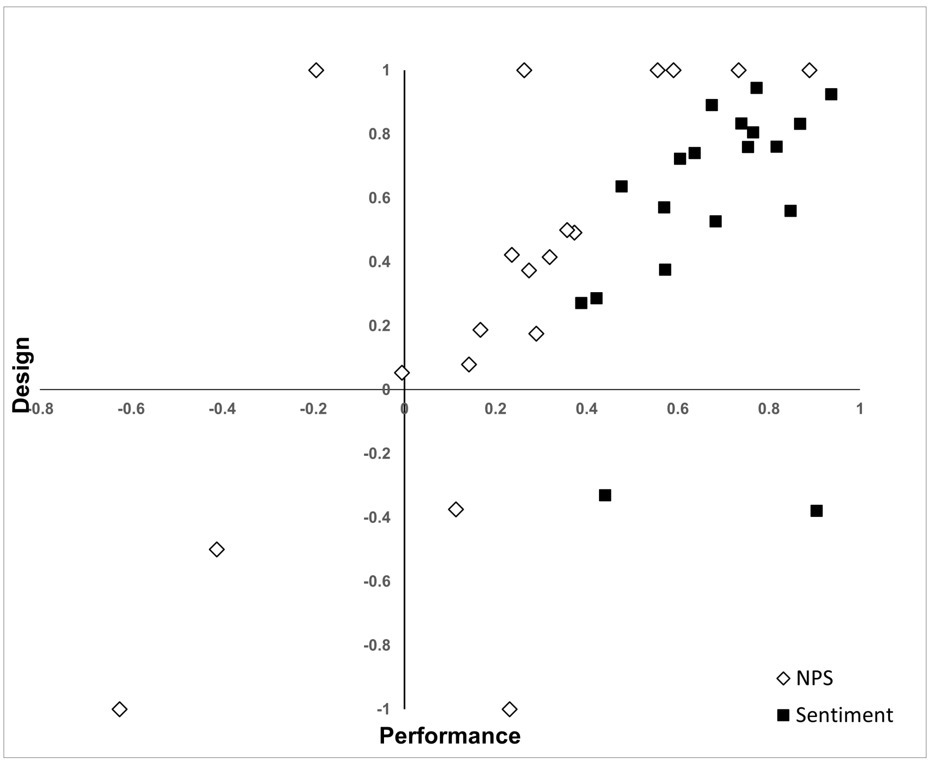

Fig. 17. Comparison between NPS and Sentiment on Performance and Design positioning plot

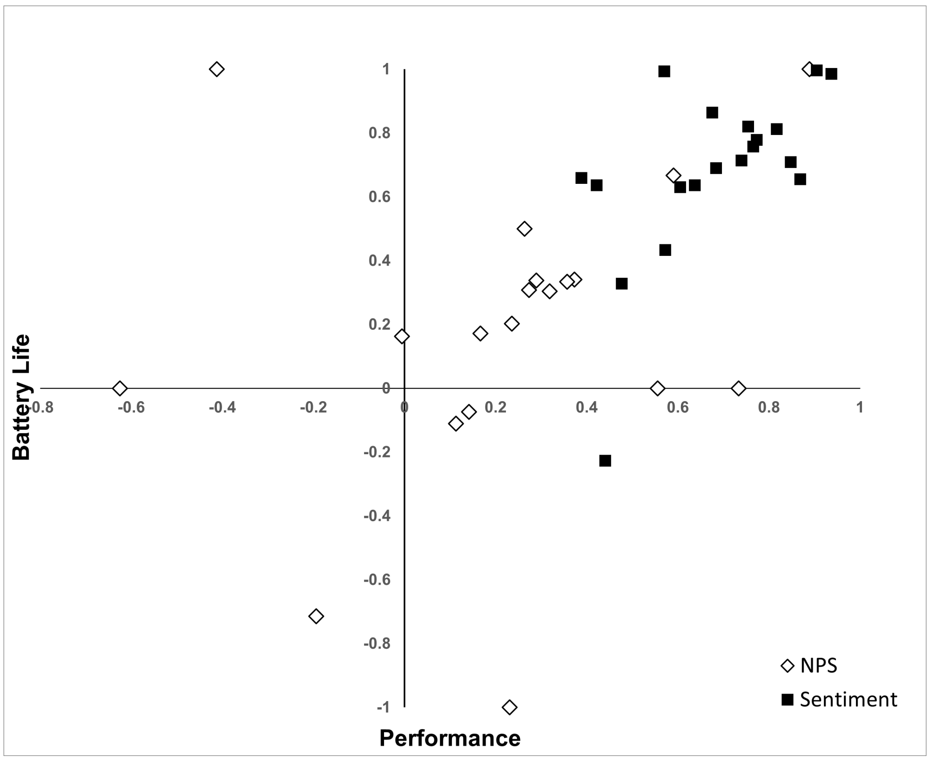

Fig. 18. Comparison between NPS and Sentiment on Performance and Battery life positioning plot

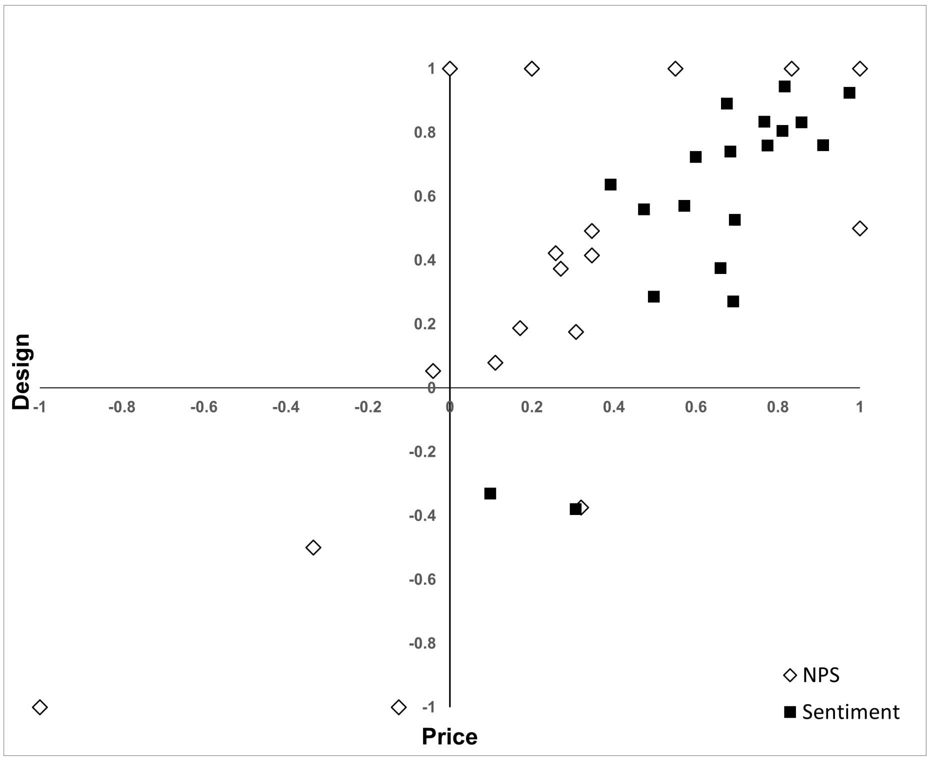

Fig. 19. Comparison between NPS and Sentiment on Price and Design positioning plot

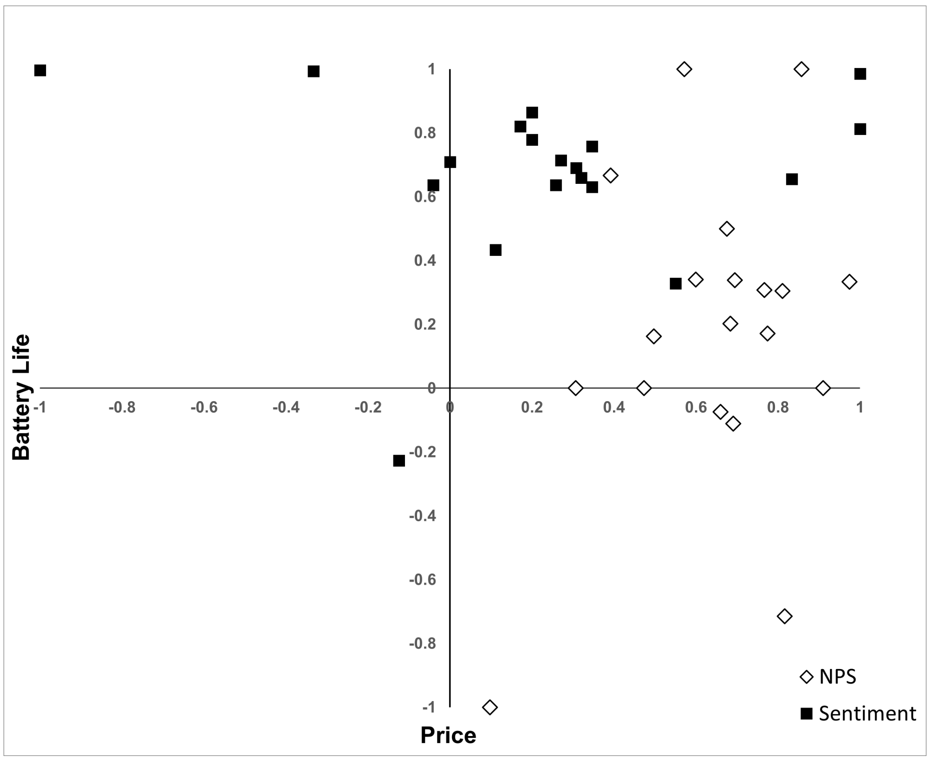

Fig. 20. Comparison between NPS and Sentiment on Price and Battery life positioning plot

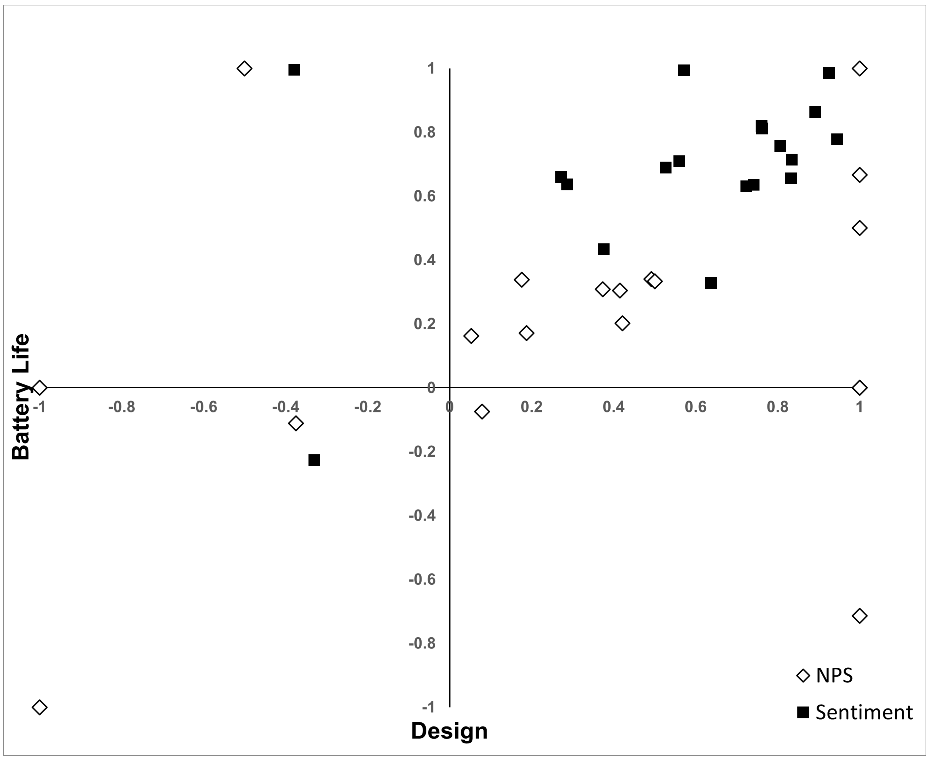

Fig. 21. Comparison between NPS and Sentiment on Design and Battery life positioning plot

4.5 Rank Correlation Analysis

Spearman's Rank Correlation Analysis assesses the rank correlation between two datasets, focusing on the relative rank of values rather than the actual value differences. This nonparametric method is advantageous when the exact values are less critical, making it suitable for models requiring less accuracy in absolute value estimates, such as loss prediction models or exposure models [13]. Unlike Pearson's correlation coefficient, which measures the linear relationship between variables based on covariance and standard deviations [20], Spearman's coefficient is based on ranked values, making it ideal for evaluating relationships involving ordinal variables.

categories	Spearman's Footrule Scores
Performance	82
Price	52
Design	58
Battery life	104

Table 1. Spearman's Footrule Scores

The Spearman footrule score gives you a straightforward numerical indication of how much two ranked lists agree or disagree. Lower scores indicate higher similarity, while higher scores indicate greater differences. The maximum possible Spearman footrule score for 19 items can be calculated using the formula for the worst-case scenario, which is when one list is the reverse of the other. The maximum footrule score can be given by

$$MaxFootruleScore = \sum_{i=1}^{n} |OriginalRank_i - ReversedRank_i|$$

The maximum possible Spearman footrule score for 19 items will be 180. To get a sense of how different the rankings are as a proportion, you could calculate the ratio Proportion of similarity:

$$ProportionOfSimilarity = \frac{MaxFootruleScore - FootruleScore}{MaxFootruleScore} \qquad (2)$$

categories	Proportion of similarity
Performance	54.4%
Price	71.1%
Design	67.8%
Battery life	42.2%

Table 2. Proportion of similarity

The similarity between Net Promoter Score (NPS) and sentiment rankings is a key indicator of the accuracy and robustness of this model. By comparing NPS, an established measure of customer advocacy, with sentiment scores derived from customer opinions, we can assess how well sentiment reflects customer behavior and whether this model accurately captures customer preferences across different product factors. The Performance factor shows moderate similarity between NPS and sentiment rankings. This indicates that while the general perception of performance aligns somewhat with the Net Promoter Score, there are still noticeable discrepancies. Price shows the highest similarity between NPS and sentiment scores, suggesting that the model accurately reflects how price perception influences customer loyalty. The alignment indicates that when customers perceive a brand as offering good value, they are more likely to recommend it, and sentiment analysis effectively captures this relationship. The design follows closely behind the price in terms of accuracy. The 67.8% similarity demonstrates that the model does a good job of linking positive design sentiment with customer advocacy. This suggests that aesthetic or usability factors captured in sentiment scores generally align with how likely customers are to promote the brand. Battery Life exhibits the lowest similarity, with over 57% dissimilarity between NPS and sentiment. This suggests that the model is less accurate in capturing the relationship between customers' satisfaction with battery performance and their likelihood to recommend the product.

Overall, the model's accuracy in predicting customer advocacy (NPS) based on sentiment is moderate to strong in some areas. However, further refinement may be needed for factors like Battery Life and Performance. Suggesting that the model may not fully capture the complexities influencing customer recommendations, such as brand loyalty or multi-dimensional product experiences.

5 DISCUSSION

The competitive positioning plots based on sentiment analysis of various attributes in gaming laptop's price, battery life, design, and performance offer detailed insights into each brand's strengths and areas for improvement.

LG demonstrates strong positive sentiment across all attributes, including price, battery life, design, and performance. LG should continue leveraging and promoting its balanced offerings to maintain its competitive edge.

Sager also shows positive sentiment in all key areas. By emphasizing its marketing and product development strengths, Sager can further reinforce its market leadership.

Jumper, Razer, Gigabyte, MSI, and ExcaliberPC enjoy high customer satisfaction, particularly in design and performance. These brands should continue to capitalize on their balanced performance and affordability to stay competitive.

Corsair stands out for its high-performance sentiment but faces price and design perception challenges. Corsair should focus on enhancing its design features and reassessing pricing strategies to create a more balanced overall customer satisfaction.

Oemgenuine is positively perceived for performance and price but has mixed sentiments regarding design. Oemgenuine should improve design features and highlight these enhancements in its marketing efforts to align with customer expectations.

Asus, HP, Lenovo, Alienware, Maingear, and Dell receive mixed positive sentiment across various attributes. These brands should fine-tune their strategies to improve perceptions in both dimensions. Enhancing value perception through strategic pricing marketing design and performance improvements can further differentiate these brands.

Aausda is appreciated for its price but faces negative sentiment regarding performance and battery life. Prioritizing improvements in these areas will help balance customer perceptions and enhance market positioning.

Ecohero is praised for its design but needs to improve performance, price, and battery life. By building on its design strengths and addressing other areas, Ecohero can create a more balanced offering.

Evoo faces significant customer dissatisfaction across all attributes. Comprehensive price, design, performance, and battery life improvements are necessary to effectively improve Evoo's market positioning and meet customer expectations.

By focusing on these strategic insights, each brand can develop targeted strategies to address specific customer concerns, enhance overall satisfaction, and improve competitive positioning in the gaming laptop market. This multi-faceted analysis provides valuable guidance for brands to better align their offerings with customer expectations and achieve more robust market performance.

The analysis results present insightful information about attribute scores and customer attitudes regarding gaming laptops. Nevertheless, the feature set and approach used now might not accurately reflect the details of user preferences. The paper critically evaluates the current approach's weak points and suggests ways to improve future work by implementing new features to increase the analysis's robustness. Furthermore, the relative importance of sentiment versus numerical ratings for various attributes may not accurately reflect the weighting mechanism used in the score calculation.

6 CONCLUSION

This paper focuses on the problem of predictive customer feelings and proposes a framework for online review-based positioning analysis using sentiment analysis. This framework effectively classifies customer opinions and visualizes the data in competitive positioning by machine learning. The insights from this paper can empower businesses to align their marketing efforts with customer sentiments and preferences, leading to improved competitiveness and better customer engagement in today's dynamic market landscape. For the experiment results, the data was gathered from online reviews of Amazon's users, consisting of 10,225 valid online reviews collected by October 2023. The key features are extracted using zero-shot text classification, where key features influencing customer satisfaction are identified and categorized based on user reviews that there are four clusters, i.e., the category of *Performance*, the category of *Price*, the category of *Design*, and the category of *Battery Life*. The customer's feelings are based on the true customer feelings from the net promoter score and predictive customer feelings from the sentiment score. Both scores are used to create a perceptual map to compare the performance of the predictive customer's feelings to that of the real customer based on the online text reviews. While the analysis provided some insights, the results with an average Proportion of Similarity between NPS and sentiment analysis around 58.88% did not meet the initial expectations, largely due to limitations in the data. The most significant limitation of this study was the lack of sufficient and diverse data, which likely impacted the model's ability to capture meaningful relationships between sentiment and NPS. In conclusion, while the current analysis yields valuable insights, acknowledging its limitations is crucial for refining future methodologies. With future improvements, we hope to develop a more adaptable and comprehensive analytical framework for evaluating consumer attitudes and attribute scores. These enhancements refine the accuracy of our analyses and ensure that our methodology remains responsive to the ever-changing landscape of consumer preferences in the gaming laptop market.

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