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Social Media Data Analytics in the Automotive Industry: A Study of the Interactive Impact of Marketing Strategies and User Ratings

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Abstract: In the era of ubiquitous social media, car companies are navigating the challenges of user feedback on these platforms. This study investigates the influence of social media interactions on the market competitiveness and brand image of automotive firms. Using Python for web scraping, this study collected and analyzed user comments from Sina Weibo, focusing on both traditional fuel and new energy car companies. The comments were subjected to sentiment analysis using a sentiment dictionary, revealing users' emotional tendencies towards various car brands. The findings indicate notable differences in social media sentiment and brand positioning among different car companies. These insights are crucial for automotive companies to leverage social media feedback to enhance their products, services, and brand strategies.

Keywords: Social Media, Data Analytics, Marketing Strategy, Automotive Industry, User Reviews

1. Introduction

With the rapid development of social media, users are not only the recipients of information, but also the creators and sharers of information [1]. For this reason, automotive companies are scrambling to engage in social media interactions to understand customer feedback and needs for their products and services. In the era of widespread popularization of "buyers show", although customer reviews can indicate the quality of their products, car companies are more concerned about the brand image, after-sales service and market competitiveness reflected behind them. Therefore, how to utilize social media data to interpret user reviews has become the focus of the automotive industry.

The purpose of this paper is to investigate whether social media data can be a powerful indicator for car companies to improve their competitiveness in the market. To this end, the paper will analyze the emotional tendencies embedded in customer review data to determine whether car companies can better adjust their products and services, or even change their brand strategies. In addition, it is hoped that by actively engaging in the interaction, car companies can develop a closer relationship with their customers, cultivate their brand loyalty, and be more responsive to market changes. Social media has had a profound impact on the automotive industry, and customer interactions on social media have made product and service reviews crucial. The main objective of this study is to delve into the application of social media data analytics in the automotive industry, especially the impact of user reviews on marketing strategies.

Yajie Ding et al. emphasized the significant impact of salespeople's activity and flexibility on social media on sales performance in the field of complex products [2]. Shen Tiantian took Tesla Motors as the research object and concluded that the rise of the new energy vehicle market has pushed automobile companies to adopt novel marketing strategies to meet market demand [3]. Zhou Yanfeng and colleagues pointed out the importance of social media communication and consumer emotional tendency analysis in the "Micro-influencers' era", and their data analysis revealed the emotional tendency of consumers and the characteristics of consumer groups, which provided guidance for the marketing of internet celebrity brands [4]. In the field of fintech and product planning, Oh S et al. explored how fintech companies can develop marketing strategies by analyzing text data [5]. Not only that, Fuciu M's research demonstrated that social media analysis can also help enterprises better understand and meet the needs of the target audience, so as to achieve higher financial benefits [6], while Jeong B et al. used topic modeling and sentiment analysis to identify potential opportunities in product planning [7]. These studies highlight the high value of social media data analytics in different fields, both in theoretical and practical perspectives with new perspectives and guidance.

Therefore, while current social media data analytics have shown positive and innovative applications in different industries, it is not yet sufficient in the automotive industry whether users' interactions on social media have an impact on their market trends. In particular, there is a lack of sentiment analysis of comments on social media interactions of different car companies.

2. Theoretical Foundations

2.1. Role of Social Media in the Automotive Industry

Currently, car companies are widely embarking on different social media, and the evolution of their social media is the focus of attention in the automotive industry. On social media platforms, the official account of a car company is not only a marketing communication center, but also a center for user interaction and content sharing. Therefore, users can not only get information about models and brands but also share their car-buying experiences and reviews. This kind of interaction not only promotes the exchange of information between users but also makes it easier for car companies to reach the real needs and feedback of first-tier users. Social media has become a key way for the automotive industry to understand consumer perceptions and market trends.

2.2. Data Analysis and Marketing Strategy

When developing marketing strategies, data analytics can provide decision-makers with information about market trends, user needs and competitors. In the social media environment, analysis of user comments can help car companies better understand users' emotional tendencies, primary concerns and motivations for purchasing cars. This information provides the basis for developing targeted marketing strategies, which are expected to improve market competitiveness.

2.3. Dictionary-based Sentiment Analysis

Sentiment analysis is a technology that can automatically identify and analyze the sentiment information in text, and it plays an important role in the fields of public opinion monitoring, user sentiment analysis and brand management. Sentiment analysis methods can be studied from two perspectives: unsupervised learning and supervised learning [8], and this paper adopts a dictionary-based unsupervised learning method.

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A sentiment lexicon is a vocabulary of emotionally relevant words and phrases, where each word or phrase is assigned a sentiment polarity such as positive, negative or neutral. By matching user reviews with the sentiment dictionary, the sentiment score for each review can be calculated to determine the user's emotional tendency [9]. Data visualization, on the other hand, helps transform complex data into easy-to-understand graphs and charts, helping decision-makers better understand user feedback and trends.

3. Data Processing and User Evaluation Analysis

3.1. Data Collection and Sampling

To obtain typical social media data related to the automotive industry, this paper selects the official microblogs of five automotive companies in different countries on the Sina Weibo platform, including three new energy automotive companies and two traditional fuel automotive companies, and collects their microblog comment data by using Python to perform web crawling.

In this paper, posts related to the latest information released by car companies, such as the release of new cars and technologies, were selected. The posts are also screened according to the popularity of the posts and the completeness of the data to ensure that the selected samples can represent the users' real views and evaluations of the car companies and products; the activity level and the number of followers of the users as well as the hotness of their comments are also taken into account to ensure that the samples have a certain degree of representativeness.

To realize the collection and processing of microblog comment data, Python programming language and related libraries are used in this phase. The data collection process includes the following steps:

Send an HTTP request to simulate a browser to get data and generate random User-Agent information with a fake user agent;

Parses JSON data to extract comment information and converts GMT to standard format;

Store data to CSV file, create DataFrame using Panda’s library, and ensure UTF-8 encoding and compatibility;

Uniqueness processing: de-duplicate comment data.

3.2. Data Processing Operations

Remove duplicate data: Use the Pandas library's UNIQUE function to remove duplicate comment data to ensure the uniqueness and accuracy of the data.

Noise Filtering: Identifies and removes noise from posts, such as special characters and irrelevant content.

Handling of missing values: Missing values were handled to ensure data integrity and analyzability.

Text standardization: the text data were standardized, including the use of the Jieba library for word splitting, removal of stop words, etc., to carry out the next analysis of the sentiment analysis.

3.3. Sentiment Analysis Operations

Feature extraction: This paper uses the Sklearn library in Python to perform TF-IDF feature extraction on comments to identify key sentiment words and improve their weights.TF-IDF consists of word frequency (TF) and inverse document frequency (IDF), TF indicates the frequency of the occurrence of the sentiment words in the comments, and IDF indicates the differentiation of the words.

Calculate the affective tendency score: match the comments to Xu Linhong's Dalian University of Technology Chinese Affective Vocabulary Ontology [10] and calculate the affective polarity value to derive the affective tendency of the comments.

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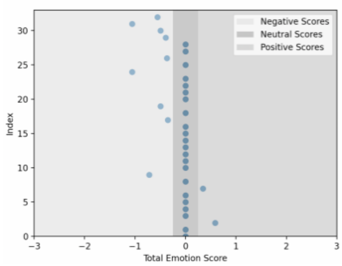
Sentiment score calculation: the formula is as follows: E(C) = Σ (V(TF×IDF) * V(polarity))

Here, E(C) is the sentiment propensity score of comment C, V(TF×IDF) represents the importance weight of the sentiment word, V(polarity) denotes the sentiment polarity value of the sentiment word, and n denotes the number of sentiment words in the comment.

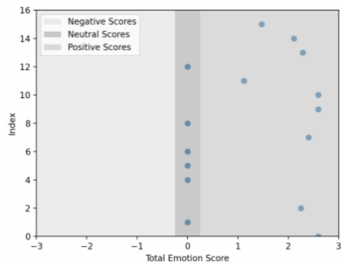
Visualizing the sentiment distribution: a scatterplot was created using the matplotlib library to show the distribution of sentiment scores, divided into negative, neutral, and positive intervals, marked with different colors. Negative intervals have a score less than -0, neutral intervals i.e. 0, and positive intervals are greater than 0.

3.4. User Evaluation Content Analysis

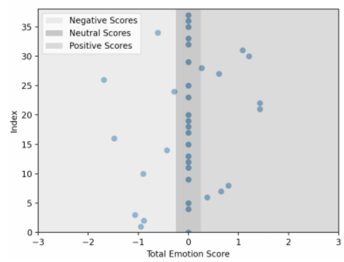
This paper, after carrying out the above operations on the hot posts of new product releases under the official microblogs of five different automobile companies, analyzes in depth the content of the users' comments on the five automobile companies and discusses the results with the results of the sentiment analysis.



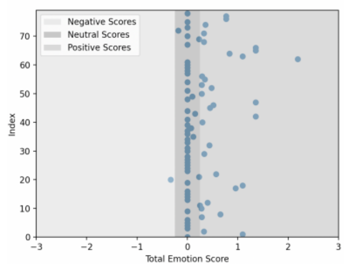
(a)Tesla



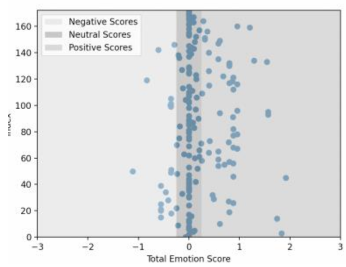
(b)Mercedes-Benz



(c)Porsche



(d)Leading Ideal



(e)Xiaopeng

Figure 1: Sentiment analysis results of five car companies

The results of the sentiment analysis visualization for the five car companies are shown in Figure 1, i.e., Tesla and Porsche have a neutral to negative sentiment tendency, Mercedes-Benz and Leading Ideal have a positive sentiment tendency, while Xiaopeng has a more neutral to positive sentiment tendency. The following is the analysis of the processing results:

Tesla: Most of its negative sentiment stems from dissatisfaction with the car company's long delivery lead time and large price fluctuations. Although users hold high expectations for Tesla, they express little acceptance of its price fluctuations.

Mercedes-Benz: Its positive sentiment stems from the high sense of expectation users have for the luxury automotive brand Mercedes-Benz Cars and praises the new product's usual sense of solidity.

Porsche: Porsche Cars, which is also a luxury first-tier brand with Mercedes-Benz, has significantly more negative sentiment, stemming from the concerns brought about by this type of traditional car company's move towards new energy sources, as well as complaints generated by the cutbacks in new products.

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Leading Ideal: As a young Chinese brand, Ideal, most users expressed their exclamations and praises for China's technological development in their positive reviews.

Xiaopeng: Also from China, Xiaopeng Auto's positive sentiment stems from its customers' pride in the rise of China's new energy automotive industry, with several users mentioning Xiaopeng's specialized safety technology and acknowledging the industry's progress.

3.5. Brand Image and Market Competitiveness

The results of sentiment analysis can be compared horizontally with the brand image and market competitiveness of each car company, as shown in Table 1:

Table 1: Brand image and market competitiveness of five automobile companies

Vehicle Manufacturer	Emotional Disposition of Users	Brand Image	Market Competitiveness
Tesla	Neutral-negative	Prices fluctuate widely Long delivery lead time	Need to upgrade
Mercedes-Benz	Positive	Calm and steady luxury brand	Strong competitive
Porsche	Neutral-negative	Complaints of reduction configuration	Strive to improve
Leading Ideal	Positive	New force	Relatively competitive
Xiaopeng	Neutral-positive	Industry benchmark	Relatively competitive

By deeply analyzing the content of user reviews and the results of sentiment analysis to better understand the brand image and market competitiveness of each automotive company, it provides useful insights for brand management and marketing. Companies can take appropriate measures based on these analytics to improve their products and services and increase customer satisfaction while strengthening their brand image and market competitiveness.

4. Conclusion

The study reveals that different car companies are impacted by varying customer sentiment tendencies. Customer sentiment significantly influences brand image; positive reviews enhance brand image and consumer trust, whereas negative feedback can damage it. User reviews accurately reflect perceptions of product quality and service experience, indicating that car companies can leverage social media feedback to improve these aspects. Additionally, customer sentiment not only affects brand image but also impacts market competitiveness, with positive reviews potentially attracting new customers and increasing market share, while negative feedback can lead to a decline in market share and customer loss.

The study acknowledges limitations, including data source restrictions and sentiment analysis accuracy. Future research could incorporate time-series analysis to assess long-term effects and expand the sample size for more comprehensive insights. It could also consider conducting similar studies on different social media platforms for broader market feedback.This research offers valuable insights for car companies regarding user feedback and emotional tendencies, guiding them to enhance product and service quality, customer satisfaction, brand image, and market competitiveness. The study also highlights the importance of understanding how social media comments influence the

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brand image and market competitiveness of automobile companies, providing direction for future research and practice.

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