Education and Social Work
ISSN Print: 3079-515X
ISSN Online: 3079-5168
https://doi.org/10.63313/ESW.9004

The impact of social media comments on the sales of domestic new energy vehicles – a case study of byd

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How to cite this paper: Yang, W., Li, H., Yu, W., Yin, W., Lin, Y., & Chen, Q. (2025). The impact of social media comments on the sales of domestic new energy vehicles – a case study of byd. Education and Social Work, 1(1), 60-73. ISSN Print: 3079-515X; ISSN Online: 3079-5168.
https://doi.org/10.63313/ESW.9004
Published: 2025-03-18

Abstract

With the rapid development of information technology, social media has become an important platform for people to obtain information and exchange views. In the new energy vehicle (NEV) market, consumers' decision-making process is in-creasingly influenced by social media comments. This study aims to explore how user comments on social media affect the sales of BYD, China's domestic new en-ergy vehicle brand. By collecting and analyzing the comment data of BYD cars on relevant social media platforms, combined with sales data, text mining technology is used to reveal the rela-tionship between social media comments and sales. The research shows that by using the Latent Dirichlet Allocation (LDA) model to ex-tract the main topics in reviews and comparing them with the sales data of BYD's new energy vehicles, it is found that there is a positive correlation between spe-cific review topics and sales. For example, keywords such as "to work", "power" and "space" have a strong positive correlation with sales in the comment theme, indicating that the theme of these comments is more in line with the consumer demand of the new energy vehicle market, reflecting the concerns and interest points of consumers, and can help car companies develop more accurate market-ing strategies.

Keywords

Social Media Comments, New Energy Vehicles, Sales Impact, Text Mining, BYD

1. Introduction

In this study, we first employed the LDA model to extract the sales data of BYD at different time nodes. Concurrently, we collected user comments on social media during the same period and extracted the main topics from these comments. Subsequently, we compared these topics with the corresponding average sales volume to elucidate the specific impact of different comment topics on sales volume. Through this approach, we were able to gain a deeper understanding of how social media comments influence the market performance of BYD new energy vehicles.

1.1.Research background and significance

With the rapid progress of modern science and technology, the automobile industry has experienced significant growth. Traditional fuel vehicles, while convenient, consume limited resources and negatively impact the environment. Consumers increasingly prefer NEVs, especially pure electric vehicles, due to their economic and environmental benefits. This trend presents both opportunities and challenges for NEV manufacturers. [1] China's auto industry faces energy, environmental, and safety challenges. NEVs reduce emissions but require heavy investment and entail costs and uncertainties for manufacturers. However, their benefits are shared by society. [2] China leads in global automobile electrification. The NEV industry has moved from policy-driven to a combined policy-market phase, integrating with information, energy, and intelligent transportation to drive high-quality development. This makes NEV research a key focus for industry and academia.

Global NEV market share is rising, with support from US and European policies. China, facing energy and environmental issues, is promoting NEVs, focusing on industrializing pure electric, hybrid, and fuel cell vehicles.

The NEV industry involves complex interests. Uncontrolled public opinion can cause emergencies and regulatory burdens. Thus, monitoring online public opinion is crucial to identify needs, reduce discrepancies, and ensure industry health.

NEV research lacks links between user evaluations and sales. Reduced subsidies and tech progress quicken NEV upgrades. Online reviews, reflecting consumer satisfaction, affect car-buying decisions. Potential buyers rely on word-of-mouth to avoid costly errors. Thus, extracting useful review information aids informed choices.

The paper assesses how user comments on new energy vehicles impact sales and BYD’s brand perception. It shows that objective information helps consumer decisions. Social media comments identify product strengths and weaknesses, which can optimize design, service, and brand image. Comparative analysis offers insights for targeted strategies. The findings guide other NEV brands in addressing consumer concerns and enhancing competitiveness.

1.2.Research status at home and abroad

Since 2001, China's NEV industry has grown rapidly with government support, including the 863 Program, subsidies, tax exemptions, and relaxed foreign investment rules. The State Council's 2021–2035 plan aims for high-quality growth and global leadership. Hainan plans to ban traditional fuel vehicles by 2030. Wang Keqin and Liu Chaoming[5] proposed an IPCA method based on online reviews to identify target vehicle attributes needing improvement and suggest enhancement strategies. Cai et al.[6] developed a hybrid sentiment analysis method by annotating text data, calculating distances, and determining sentiment orientation. Shi et al.[7] divided comments into two parts and developed a method to calculate sentiment scores from sentences to articles, achieving promising results. Shen et al.[8] proposed a model based on ERNIE 7 and dual-attention mechanism to overcome polysemy limitations, achieving 95% accuracy on the training set.

Japan was an early pioneer in NEV research and development, designating it a national key project in the 1960s. In 1997, subsidies and tax incentives for NEV buyers further boosted the sector's growth.

In the US, NEVs are supported by policies like the Clean Air Act (2008), emissions trading, and tax credits (since 2010), which continued after the 2017 tax reform.

Germany's 2009 NEV plan aimed for one million registered NEVs by 2020, supported by €600 million in subsidies, boosting sales. The UK promoted NEVs through clean energy taxis and infrastructure. These efforts reduce pollution and advance NEV technology and market maturity. Scholars Johannes Lauer and Ingo Liefner[6] have noted that local governments in China, endowed with substantial financial resources, can stimulate vehicle purchases, particularly those of NEVs, through the formulation of local policies[7]. They argue that such policy measures can effectively foster local economic development while advancing environmental protection goals. In a comparative study of the NEV markets in China and South Korea, Hoch et al.[9] identified charging convenience and driving range as two critical factors influencing consumer satisfaction. This suggests that enhancing consumer acceptance of NEVs necessitates targeted improvements in these areas. From an alternative perspective, Jabbari et al.[10] compared the objective differences between traditional fuel vehicles and NEVs. They noted that while fuel vehicles benefit from easier energy access and lower costs, NEVs face challenges such as limited driving range and insufficient charging infrastructure. To address these challenges, they proposed an optimization strategy aimed at maximizing consumer satisfaction within the existing constraints. Finally, Safae Sossi Alaoui et al.[11] shifted their focus to the field of computer science. By comparing data mining and machine learning—two closely related technologies—they explored methods to extract valuable insights from large datasets. This research is particularly significant for the NEV industry, as data analysis and machine learning can help manufacturers better understand consumer demand, predict market trends, and formulate more effective product strategies and marketing plans[8].

Sentiment classification research started in the 1990s globally and later in China. Driven by Internet growth, Chinese researchers now use multiple methods to analyze sentiment in NEV reviews, identifying consumer preferences efficiently.

1.3.Research content and contributions

This study investigates how user engagement (likes and comments) on social media correlates with specific topics and impacts the sales performance of new energy vehicles (NEVs). The research involves:

1.Collecting and preprocessing user reviews, likes, and comments for BYD's NEVs to ensure data quality.

2.Using sentiment analysis to classify user comments and identify which sentiments drive higher engagement.

3.Applying the LDA model to extract key topics from user comments and analyze their correlation with sales performance.

The findings reveal the relationship between social media discussions and sales, offering strategic insights for BYD and the broader NEV industry.This study reveals the key topics of consumer discussions on social media and establishes the relationship between these topics and sales performance. These findings provide valuable market insights and strategic guidance for BYD and other NEV manufacturers.

1.4.Paper structure arrangement

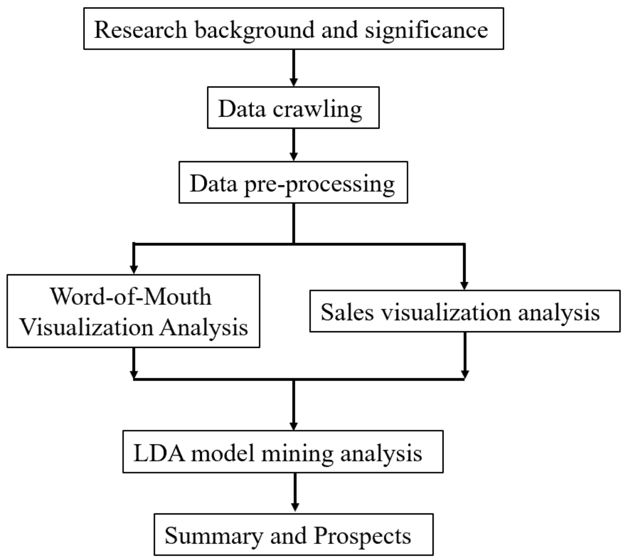

Figure1. Research Framework

This study examines the impact of social media comments on the sales of domestic new energy vehicles using BYD as a case study. It reviews existing literature to develop a research framework covering data collection, preprocessing, analysis, and visualization. Data were collected, cleaned, and analyzed using sentiment analysis, the LDA model, and pyLDAvis tool to identify key topics and sentiments related to BYD's vehicles. The study constructs a predictive sales framework based on thematic areas and aims to provide insights for manufacturers to improve product design and marketing strategies. It concludes by identifying limitations and suggesting improvements for future work to enhance reliability and offer evidence-based recommendations for industry and policymakers.

2.Basic theories and methods of research work

2.1.Related research work

The LDA model in the study "The Impact of Social Media Comments on the Sales of

Domestic New Energy Vehicles: A Case Study of BYD" effectively extracts thematic structures from social media data, revealing consumer interests and mapping topic distributions across reviews. It allows for comparative analysis across different time periods, platforms, and vehicle types, and reduces data dimensionality for efficient analysis and prediction. However, the model has limitations: its interpretability is weak, making it hard to explain term groupings, and its performance is highly sensitive to parameter choices, such as the number of topics.

2.2.The Latent Dirichlet Allocation (LDA) model

The LDA model, also known as latent Dirichlet allocation, is a widely used topic modeling technique in the analysis of textual data. It identifies word categories by maximizing the co-occurrence probability of words, thereby inferring the topic distribution within a given text[12]. The core computation of the LDA topic model is based on two fundamental assumptions: first, that each document is a mixture of topics; and second, that each topic is characterized by a distribution over a set of words. In accordance with these assumptions, the LDA topic model constructs a sophisticated three-tier Bayesian probability model by integrating documents, topics, and words. This is illustrated in Figure 2.

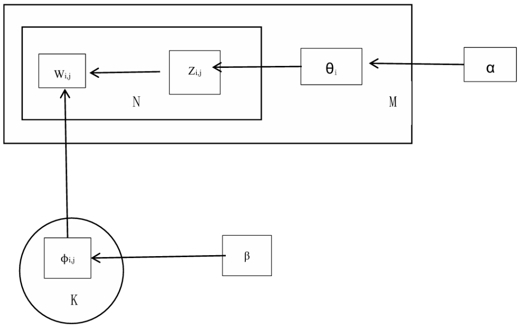

Figure 2. Model Structure

In this model, the LDA topic model conducts its analysis on individual documents, rather than treating the dataset as a single entity. M denotes the total number of documents under analysis; N signifies the cumulative word count across all documents; the value within Box K represents the number of topics; β denotes the prior Dirichlet parameter for the word distribution associated with each topic; $\emptyset_{i,j}$ represents the word distribution for topic $Z_{i,j}$. α is a K-dimensional vector, indicating the prior Dirichlet parameters for the topic distribution within each document; θ_i represents the topic distribution for document i; $Z_{i,j}$ denotes the topic assignment for the j-th word in document i and follows a multinomial distribution; $W_{i,j}$ indicates a specific word and also follows a multinomial distribution. This paper generates the probability of each word's occurrence within a document based on the assumed probability graph model, with the formula presented in Equation (1).

$$\prod_{k=1}^{K}\frac{\Delta(\overrightarrow{\emptyset_K}+\vec{\alpha})}{\Delta(\vec{\beta})}\prod_{m=1}^{M}\frac{\Delta(\overrightarrow{\theta_m}+\vec{\alpha})}{\vec{\alpha}} \tag{1}$$

3.Data acquisition and preprocessing

3.1.Data acquisition and data preprocessing

The word-of-mouth information used in this research is derived from the Autohome website, which is the leading online automotive platform in China, boasting over 72.9 million daily active users. Autohome is renowned for its comprehensive automotive content, including user-generated reviews, professional evaluations, and detailed vehicle specifications. This study conducts an in-depth analysis of user evaluations regarding the latest new energy vehicles, focusing on eight key attributes such as handling, power, space, and exterior design. These attributes are crucial for potential buyers, as they provide valuable insights into vehicle performance and influence purchasing decisions. Autohome's stringent data management ensures the accuracy, relevance, and high quality of user reviews and ratings, making it a reliable source for consumer perspectives.

In addition to the title, the word-of-mouth data includes detailed user reviews and ratings. Autohome, as the largest automotive website in China, exercises stringent control over the management of this data to ensure its accuracy, relevance, and high quality. The dataset used in this study contains 65,209 entries related to BYD new energy vehicles. These entries cover various aspects such as handling, power, space, and exterior design, providing comprehensive insights into consumer evaluations. The extracted text data are detailed in Table 1

Table 1. Crawled Text

User_nick	Title	Content	Content_bu	Date
Sanhe Little Slob	The luxury of this car is beyond imagination	The best part is its appearance. The car looks really stunning, with a stylish and bold design and sharp headlights.	The only thing that bothers me is the new car smell when I first brought it home.	2024-03-25
Be a decisive middle-aged girl	2024 Han DM-i Glory Edition: Lower electric cost than fuel, endless driving possibilities!	I love its appearance the most. The long body and sleek, flowing lines give it a very upscale look. Driving it makes me feel proud.	The car is quiet during test drives, but the noise level increases on highways, and the sound insulation isn't as good as I expected.	2024-03-19
Xiaogan Car Friends 2039809	Driving the Han enriches my life.	I'm most satisfied with the appearance. The car looks quite imposing from the front, and the overall design has a strong, muscular feel.	The ride is a bit bumpy over speed bumps, which affects the driving comfort.	2024-03-19

3.2. Text data preprocessing

Text data requires preprocessing to remove noise and ensure quality. This study involves multiple preprocessing stages: data segmentation, cleaning, tokenization, and stop-word removal.

3.2.1. Data cleaning

The central focus of this investigation is on the word-of-mouth assessments of new energy vehicle users, the concerns they articulate, and the public's perspectives regarding the developmental trajectory of new energy vehicles. Given the variable quality of data harvested from the Internet, the process of data cleaning assumes particular significance to ensure the precision and validity of subsequent analytical procedures.

Data cleaning involves removing duplicates, simplifying vocabulary, and eliminating short sentences. In this research, pandas in Python was used to remove duplicate text, condense repetitive expressions, and filter out strings with fewer than eight characters. These steps enhance analysis reliability.

3.2.2.Word Segmentation and Stop Word Removal

Chinese word segmentation is crucial for text mining, enabling computers to break down sentences into lexical units. There are three main methods: statistical segmentation, dictionary-based segmentation, and grammar/rule-based segmentation. Statistical segmentation identifies words based on co-occurrence frequency in a corpus, effectively recognizing unregistered words without a predefined dictionary. However, it requires a high-quality training corpus and significant computational power.

Dictionary-based segmentation matches strings against a pre-compiled dictionary, which is simple but heavily dependent on dictionary comprehensiveness and unable to handle ambiguities or unregistered words.

Grammar/rule-based segmentation uses syntactic and semantic analysis to resolve ambiguities and identify unregistered words. However, it faces technical challenges due to the complexity and ambiguity of grammatical rules. Currently, the majority of word segmentation tools integrate or combine the aforementioned three predominant word segmentation techniques. Within the Python programming language, users have access to a range of word segmentation tools, including jieba, THULAC developed by Tsinghua University, and Pangu segmentation, among others. For the purposes of this research, the jieba word segmentation tool was employed. This tool amalgamates statistical-based approaches with dictionary-based mechanical methods and permits the incorporation of custom dictionaries, thereby augmenting the precision and naturalness of the segmentation process.

Stop words are functional terms that lack practical significance for data analysis and occur frequently after word segmentation[13]. Not removing them can significantly impair subsequent analytical procedures. This group of words primarily includes particles expressing modality, conjunctions, prepositions, adverbs, and similar terms, such as "le," "ba," "ah," "oh," "jiu," and "de." Stop words are frequent but insignificant terms in data analysis. Subsequently, a word cloud is generated.

The word cloud visualizes word frequency by adjusting word size, making high-frequency words stand out. It helps identify key concerns of new energy vehicle users, including emotional inclinations, performance focus, and practical preferences.

In the realm of emotional inclination, terms such as “commuting,” “shopping,” and “transporting children” are prominently positioned within the word cloud. This suggests that new energy passenger vehicles excel in accommodating the demands of daily family transportation. Furthermore, the significant presence of these terms indicates a substantial demand for vehicles that cater to everyday family needs.

In the realm of performance considerations, the frequent occurrence of terms such as “power,” “range,” “self-driving tours,” “long-distance travel,” and “cost-effectiveness” indicates that consumers harbor elevated expectations for the performance of new energy passenger vehicles. These points show consumers want better driving experiences and see new energy vehicles as equivalent to traditional ones, guiding industry product development and service improvement.

In the realm of practicality requirements, terms such as “trunk,” “seating comfort,” “interior appointments,” and “interior space” emerge with significant frequency. This indicates that the spaciousness of the interior and the comfort of the seating experience are key considerations for proprietors of new energy passenger vehicles. These proprietors have explicit expectations regarding the household functionality of the vehicle.

Users focus on convenience, experience, and functions in new energy vehicles, aiding manufacturers in refining products and boosting satisfaction.

4.Experimental results

This study assesses how social media interactions impact BYD’s new energy vehicle sales by analyzing sales data alongside user comments and likes over multiple time intervals using a scatter plot.

In the scatter plot, the X-axis represents the range of product sales, whereas the Y-axis indicates the average number of likes per user review within the corresponding sales range, as shown in Figure 4. More likes in higher sales suggest positive feedback boosts sales, while fewer likes in lower sales highlight areas needing improvement. This analysis helps firms like BYD understand consumers, adapt strategies, and enhance competitiveness.

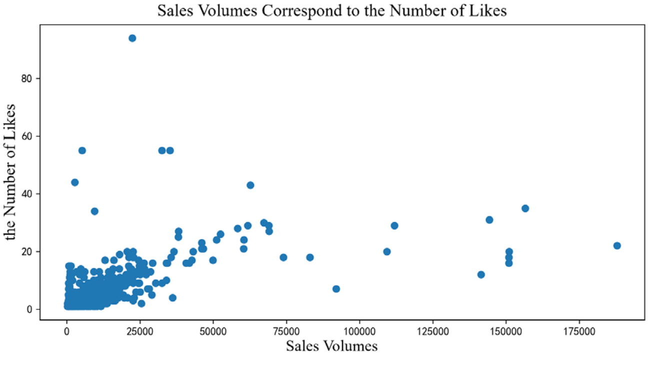

Figure 4. Sales Volumes Correspond to the Number of Likes

The relationship between likes and comments is examined by analyzing social media data to see their correlation. We collect BYD's sales data and the corresponding number of likes and comments at specific time points.

This paper presents a scatter plot where the X-axis represents the frequency of likes, and the Y-axis corresponds to the frequency of comments. Each point on the graph represents a distinct time point or user, with the coordinates indicating the number of likes and comments associated with that time point or user. Take Figure 5 for ref-erence.

The scatter plot indicates a positive correlation between likes and comments, with outliers showing high likes but few comments. More likes and comments correlate with higher sales, while a negative correlation needs further investigation. Analyzing likes and comments with sales data reveals how social media impacts sales. This helps firms understand consumers, improve offerings, and boost competitiveness.

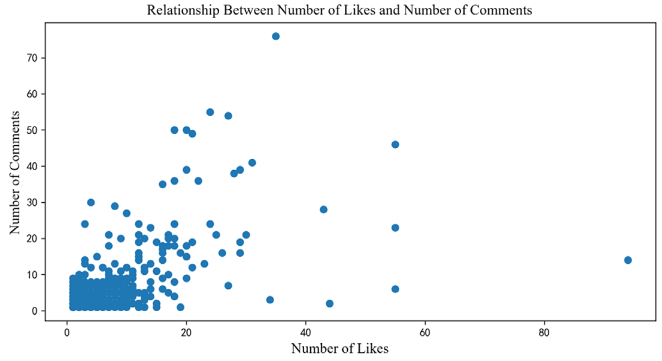

Figure 5. Relationship Between Number of Likes and Number of Comments

This analysis examines the link between social media reviews and BYD's new energy vehicle sales using sales data and user comments across fiscal years. A Python-generated line chart shows sales trends over years, months, and days, revealing market dynamics and consumer behavior changes. Yearly data indicates sales growth or decline, while monthly data highlights high-sales months and low-sales periods. Daily data shows peak sales on weekends. This analysis supports market strategies, refines product offerings, and enhances brand positioning. The study also finds that positive social media feedback correlates with higher sales.

To investigate the correlation between social media comments and BYD's new energy vehicle sales, this study introduces the "comment-to-sales ratio." It compiles BYD's sales data and user comments from social media at specific time intervals, using the LDA model to extract dominant topics from the comments.

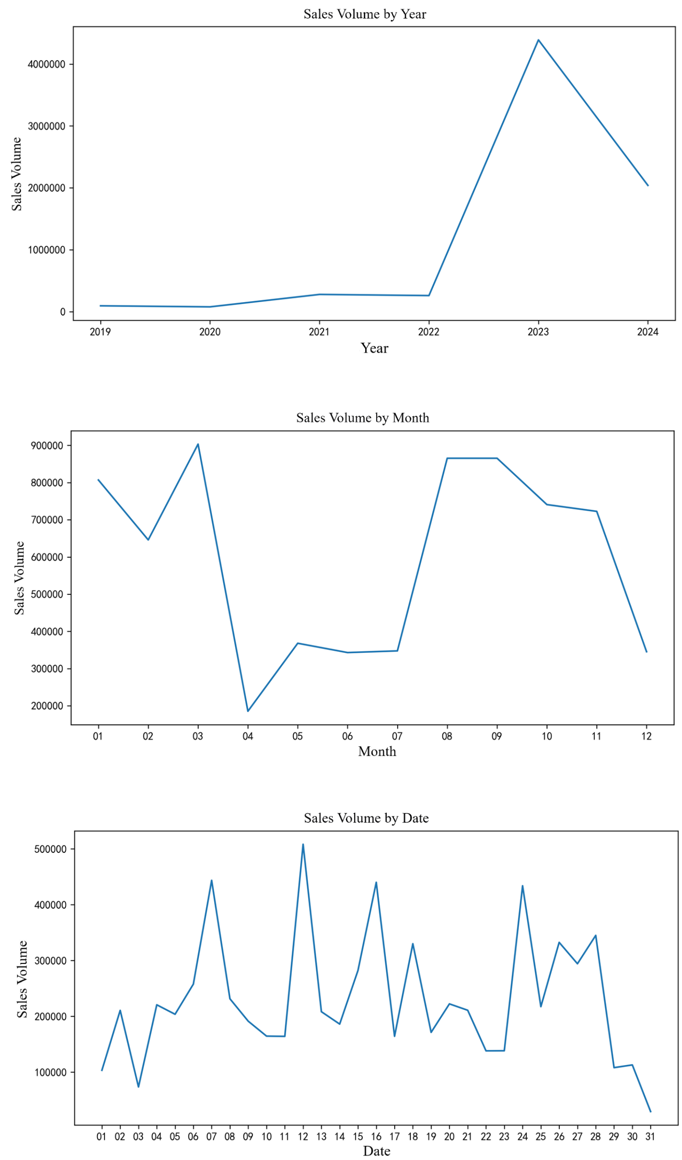

Figure 6. Sales Volume by Year, Month, and Day

In the LDA analysis process, each topic is modeled as a probability distribution over a specific set of vocabulary, with each document regarded as a mixture of multiple topics. Utilizing this method, the study identified the frequent themes within the comments and conducted a comparative analysis with the sales data of BYD new energy vehicles from January 2019 to January 2024, as presented in Table 2. Specifically, the research correlated the extracted comment topics with the corresponding average vehicle sales volumes to quantify the impact of various comment themes on sales performance. For instance, the analysis revealed that keywords within Topic 7, including “sports,” “atmosphere,” “appearance,” “power,” “temperament,” “safety,” “handsome,” “satisfaction,” “interior,” and “commuting,” exhibited a positive correlation with sales volumes. This finding suggests that these themes are more aligned with consumer preferences in the new energy vehicle market, indicating that they may exert a significant influence on product sales promotion. This study uses sentiment analysis and the LDA model to examine how social media comments relate to BYD's new energy vehicle sales, supporting marketing strategies and consumer behavior insights.

Tae 2. Sales Ratios Corresponding to Review Themes

Thematic Features	Sales Ratios
Topic 0: Economy, Cost-performance ratio, Charge, Exterior, Save, Power, Abundant, Convenience, Range, Dimension	Average sales for Topic 0: 11643.685714285713
Topic 1: Young, Dimension, Exterior, Half-Axle, Preference, Exterior, Comfort, Resonance, Safety, Advantage	Average sales for Topic 1: 6701.923076923076
Topic 2: Electricity Consumption, Exterior, satisfaction, Electricity Consumption, AC, Plagiarism, System, Simplicity, Aesthetics, New Energy	Average sales for Topic 2: 9955.634615384615
Topic 3: Power, Charge, Still, Just, Interior, kilometer, Exterior, Popular, SUV models	Average sales for Topic 3: 15672.127272727274
Topic 4: Hiding, Space, Taillight, HUD, Large Screen, Frameless, Spoiler, Range, Charge, Commute	Average sales for Topic 4: 16528.380952380954
Topic 5: Complain, Expensive, Maintenance, Electricity Consumption, Exterior, Configuration, Commute, Tire, Coupe, Fault	Average sales for Topic 5: 3907.136363636364
Topic 6: Electricity Consumption, Convenience , Fashion, Movement, Design, Young Exterior, Control, Interior, satisfaction	Average sales for Topic 6: 15909.05769230769
Topic 7: Space, Presence, Appearance, Power, Aura, Safety, Stylish, satisfaction, Interior, Commute	Average sales for Topic 7: 18273.5
Topic 8: Energy Consumption, satisfaction, Yuan Pro, Driving, Space, Handling, Performance, Direction, Flexible, Special	Average sales for Topic 8: 7426.20634920635
Topic 9: Body, Turning, Exterior, Fastback, Design, Smooth, Advanced, Charging, Acceleration, Interior	Average sales for Topic 9: 6867.96

To elucidate the correlation between these two variables, this study utilizes box plots to visually depict the relationship. Box plots are a graphical tool used to illustrate the distribution of data, clearly showing the minimum value, first quartile (Q1), median (Q2), third quartile (Q3), and maximum value of the dataset. In this research, time points are used as the categorical axis for the box plots (X-axis), with sales data employed to construct the distribution on the vertical axis of the box plots (Y-axis).

This study uses box plots to analyze sales fluctuations over time and links social media comment topics to sales dynamics. BYD can leverage this insight to adjust promotion strategies, target consumer needs, and refine manufacturing plans to lead in the competitive NEV market.As depicted in Figure 7.

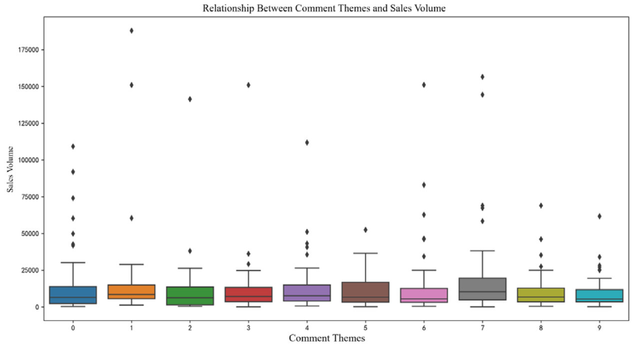

Figure 7. Relationship Between Comment Themes and Sales Volume

Through the process of extraction and comparative analysis of the thematic features identified by the LDA model, the highest and lowest sales ratios are presented in Table 3. This analysis reveals that the actual sales dynamics are reflected in the thematic patterns of social media comments. For instance, in Topic 5, negative phrases such as "complaints," "expensive," "maintenance," and "malfunctions" are frequently observed, which typically correspond to consumer dissatisfaction and a lower inclination to purchase. Consequently, the sales ratio associated with this theme is relatively low. These findings suggest that BYD should focus on the cost-performance ratio and quality management of its products to enhance consumer satisfaction and improve the brand image.

In Theme 7, the most salient and prominent terms within the word cloud are "commuting," "power," and "space," with the remaining terms also representing high-intention phrases. BYD should strengthen its favorable product features and enhance marketing efforts to boost sales. Social media feedback offers real-time market insights and consumer sentiment. Regular analysis of comment themes can help BYD adjust strategies and positioning promptly.

The study shows that social media comment themes align with factors influencing sales outcomes. These insights help identify changing consumer demands and areas for improvement. BYD can use this data to refine products and services, boost sales, and enhance brand value.

Table3. Comparison of the Highest and Lowest Sales Ratios Corresponding to Review Themes

Thematic Features	Sales Ratios
Topic 5: Complain, Expensive, Maintenance, Electricity Consumption, Exterior, Configura-	Average sales for Topic 5: 3907.136363636364

tion, Commute, Tire, Coupe, Fault	
Topic 7: Space, Presence, Appearance, Power, Aura, Safety, Stylish, satisfaction, Interior, Commute	Average sales for Topic 7: 18273.5

5.Summary and outlook

This study examines how user comments on social media impact BYD's NEV sales. Using text mining and LDA, it finds a positive correlation between comments on topics like "commuting," "power," and "space" and sales volumes. Positive social media interactions also boost sales performance. BYD should emphasize these strengths, improve after-sales service, and engage with consumers to enhance satisfaction and loyalty. Monitoring social media commentary helps firms align with market demands and refine strategies, fostering positive word-of-mouth.

In conclusion, prioritizing the influence of social media, enhancing interaction with consumers, and continuously improving products and services are essential for domestic new energy vehicle firms to excel in the highly competitive market and to ensure long-term sustainable development.

Acknowledgements

This work was partly supported by College Students' Innovative Entrepreneurial Training Plan Program of China (Grant No. 202412792041).

References

[1] Li, Yuhui. (2019). Text Mining Analysis of New Energy Vehicles in China. Un-published master's thesis, Guangxi Normal University.

[2] Chen, L. (2023). Research on Influencing Factors of New Energy Vehicle Sales Based on Multiple Linear Regression. Statistics and Application, 12(1), 17-24. DOI: 10.12677/SA.2023.121003

[3] Xu, L. Y. (2015). Economic evaluation of the investment in new energy vehicles in China: A case study of Beijing City. Master's thesis, Beijing Jiaotong University.

[4] Chen, Q., Deng, H. Y., & Zhang, R. S. (2019). New energy vehicle policy and situ-ation analysis based on LDA thematic model. Journal of Guangzhou University (Natural Science Edition), 18(5), 34.

[5] Wang, K. Q., & Liu, C. M. (2022). Product design improvement based on im-portance performance competitor analysis of online reviews. Journal of Computer Integrated Manufacturing Systems, 28(5), 1496-1506. DOI: 10.13196/j.cims.2022.05.020

[6] Tanțău, A., & Gavrilescu, I. (2019). Key anxiety factors for buying an electric ve-hicle. Management & Marketing. Challenges for the Knowledge Society, 14(2).

[7] Zhao, Z., & Cai, W. (2010). Localization Problem of Faulty Links Based on Sim-ple Network Tomography. Computer Science, 37(1), 108-110. DOI: 10.3969/j.issn.1002-137X.2010.01.025

[8] Shi, W., Wang, H. W., & He, S. Y. (2013). Sentiment analysis of Chinese online reviews based on semantics. Journal of the China Society for Scientific and Tech-nical Information, 32(8), 8. DOI: 10.3772/j.issn.1000-0135.2013.08.009

[9] Yang, B., Cao, Z., Guo, G., Liu, S., & Shen, B. (2022). Research on prediction method of

flank wear state of milling cutter based on convolutional neural network. Tool Technology, (056-005).

[10] Jabbari, P., Khaloei, M. and MacKenzie, D. (2019) Estimating Potential Demand for Long-Distance Electric Vehicle Travel in Washington State. 98th Annual Meet-ing of the Transportation Research Board, Washington DC, 13-17 January 2019, 1-7.

[11] Alaoui, S. S., Farhaoui, Y., & Aksasse, B. (2022). Hate Speech Detection Using Text Mining and Machine Learning. International Journal of Decision Support Sys-tem Technology, 14(1).

[12] Peng, G., & Yuefen, W. (2016). Identifying Optimal Topic Numbers from Sci-Tech Infor-mation with LDA Model. Journal of Modern Information Technology, 32(9), 42-50. DOI: 10.11925/infotech.1003-3513.2016.09.05

[13] Yu, M. Y., & Shen, B. (2023). Analysis of Sales of New Energy Vehicles in the Changing International Situation–Composite Forecasting Model Based on Unex-pected Factors. China Journal of Commerce, 12, 164-168. DOI: 10.19699/j.cnki.issn2096-0298.2023.12.164

[14] Chen, Y. P. (2023). Research on the relationship between social media com-ments and the sales volume of new energy passenger cars [D]. Northern National University.