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Dalian City New Energy Vehicle Online Reviews and Sales Data Analysis

Mowei Wu[1,*], Zhenqi Han[2]
[1]Shenyang Yingling International High School, Shenyang, Liaoning, China
[2]Bohai University, Jinzhou, Liaoning, China
**Corresponding Author*

Abstract: Against the backdrop of China's dual-carbon strategy, Dalian is actively promoting the development of its new energy vehicle (NEV) industry as a strategic initiative to drive regional industrial upgrading and sustainable growth. This study investigates key challenges impeding the NEV transition, including the slow adaptation of traditional automakers, technical limitations in low-temperature environments, and uneven distribution of charging infrastructure across urban and rural areas. To address these issues, a multi-source data analysis framework was employed, combining time-series forecasting with Latent Dirichlet Allocation topic modeling to capture evolving market trends, consumer preferences, and regional demand patterns. The results highlight a critical need for technological solutions tailored to cold climates, more efficient and accessible charging networks, and enhanced support for emerging NEV brands. Based on these findings, the study proposes targeted strategies for technological innovation, brand development, and infrastructure optimization, offering actionable, data-driven guidance for policymakers and enterprises seeking to accelerate NEV adoption and facilitate sustainable industrial transformation in Northeast China's traditional automotive hubs.

Keywords: New Energy Vehicles; Online Comments; Sales Data; Dalian

1. Data Collection and Preprocessing for Online Reviews of New Energy Vehicles in Dalian City

1.1 Data Sources

Given the rapid development of the automotive market, access to precise data can be highly beneficial to businesses [1-3]. With this objective in mind, this study conducted data collection on sales data from the Dalian region of Yiche.com and designed and implemented data analysis work. Manual data collection often suffers from slow speeds and high error rates. However, using Python web scraping can automate the entire data collection, cleaning, and storage process, significantly improving the speed and accuracy of data acquisition [4].

The system is designed using a layered approach. consisting of four main components: the network request layer, the data parsing layer, the pagination control layer, and the data storage layer. These four components collaborate through standardized interfaces to form a complete data processing pipeline. The network request layer simulates normal browser requests, the data parsing layer accurately retrieves and extracts webpage content, the pagination control layer implements the data collection process logic, and the data storage layer saves the collected data in a fixed structure. Part of the code is shown in Figure 1.

```
headers = {
    'User-Agent': 'Mozilla/5.0 (Windows NT 10.0; Win64; x64) AppleWebKit/537.36 (KHTML, like Gecko) Chrome
    'Referer': 'https://car.yiche.com/'
}

def parse_page(url):
    try:
        response = requests.get(url, headers=headers, timeout=10)
        response.raise_for_status()
    except Exception as e:
```

Figure 1. Partial Code of the Network Request Module

Each module uses code to achieve its respective objectives: requesting and obtaining data through legitimate means [5]; extracting data from the obtained data into structured information; saving the information obtained after accessing all page data locally according to user needs [6]; and providing the data to users through the same interface after data collection is complete. The above modules are based on standardized data interface URL input and DF output [7], and there are no dependencies between them. They form a request-parsing-storage data processing system.

1.2 Comment Data Sources

By scraping user reviews of cars, we developed a structured data crawler specifically designed for car review websites [3]. The crawler primarily uses the requests library to send network requests, BeautifulSoup to parse HTML pages, and pandas for data cleaning and storage. The program first retrieves user car review data through paginated scraping. Using CSS selectors, it precisely extracts nine core fields (including username, vehicle model, energy efficiency rating, and image links). After cleaning invalid filenames using regular expressions, it downloads user review images to the local "Review Images" directory (with subfolders created by username) using multithreading. Numeric data is then subjected to type conversion and null value cleaning, and the cleaned structured data is finally saved as an Excel file [6]. The entire process displays a progress bar using the tqdm library and sets a 1.5-second request interval to prevent anti-crawling measures. The data includes multi-dimensional information related to user vehicle purchases, covering username, vehicle model, rating, base vehicle price, fuel efficiency (L/100km), purchase date, comment time, detailed text evaluation, and image data.

1.3 Data Cleaning and Preprocessing

During the actual crawling process, some data values may be empty, so it is necessary to discard the data using [7], drop to delete the corresponding rows. After the data has been crawled from the web and pre nprocessed, the entire dataset is organized and presented in Tables 1-2 below.

Table 1. 2023–2024 Vehicles Data Table

Year	Total number of vehicles (units)	Invalid value (vehicles)	Effective value (units)
2023	124302	333	123969
2024	135484	236	135248

Table 2. Data Table for the Past Six Months

Year	Total number of vehicles (units)	Invalid value (vehicles)	Effective value (units)
2024.11	12932	30	12902
2024.12	15299	7	15292
2025.01	6904	3	6901
2025.02	7127	5	7122
2025.03	12113	14	12099
2025.04	10895	5	10890

Table 3. Numerical Table for the Whole Year of 2024

Serial number	brand	Cumulative sales of brand vehicles
1	BYD	6033
2	Tesla	3756
3	AITO	3059
4	Toyota	790
5	Honda	2080

After data cleansing and integration, the quality of the data has significantly improved, becoming more accurate, complete, and standardized. With a large amount of high-quality data sources, a solid foundation has been laid for subsequent data analysis, topic mining, and correlation analysis combined with sales data. This enables more accurate understanding of consumers' views and needs regarding new energy vehicles, insights into market trends and patterns, and provides valuable reference information for relevant enterprises and decision-makers in the new energy vehicle industry.

2. Dalian City New Energy Vehicle Network Evaluation and Sales Data Analysis

2.1 Analysis of New Energy Vehicle Sales Data

2.1.1 Brand analysis of sales

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Table 3 shows the cumulative sales figures for selected automotive brands for the full year of 2024.The data indicates that BYD leads the pack with 6,033 units sold, significantly outpacing other brands; Tesla and Aito follow closely behind with 3,756 and 3,059 units sold respectively, demonstrating strong market competitiveness. Among traditional brands, Honda ranks fifth with 2,080 units sold, while Toyota ranks fourth with 790 units sold. Both brands' performance is relatively lackluster, reflecting the ongoing impact of new energy vehicle brands on the traditional gasoline vehicle market. Overall, BYD, Tesla, and Aion dominate the market, highlighting the strong position of new energy vehicles in the industry's transformation.

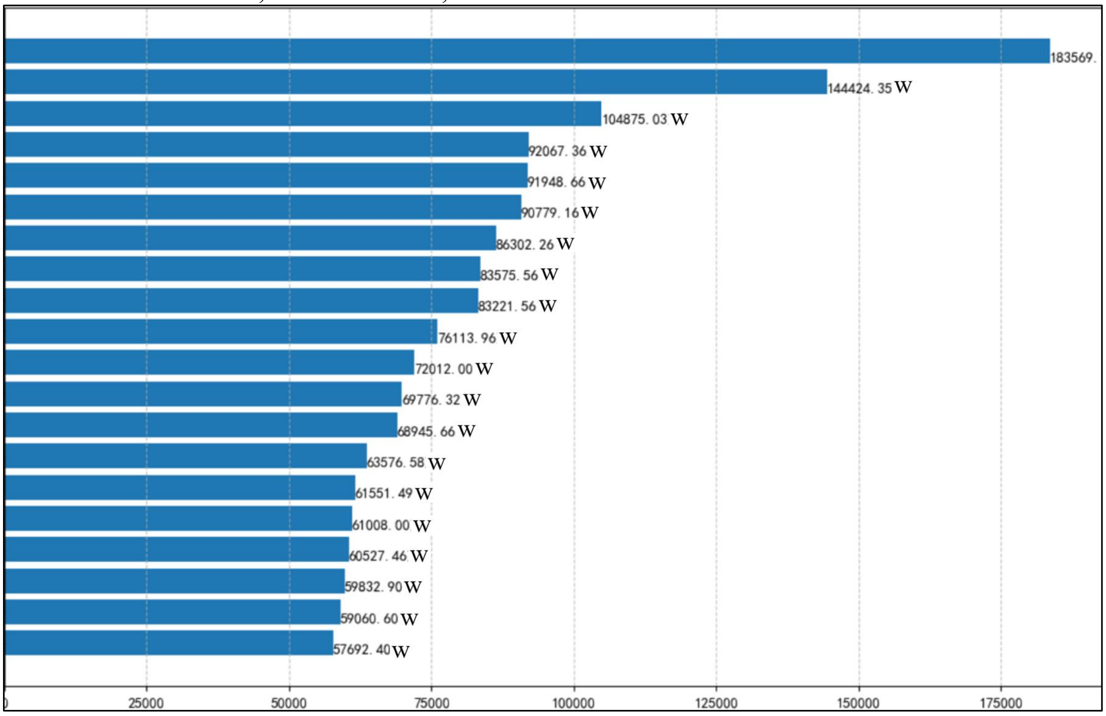

Figure 2. Top 20 total automobile sales in 2023-2024

Figure 2 shows the top 20 models in terms of total vehicle sales for 2023-2024 and their sales figures (in millions of yuan). The data shows that the Audi A6L leads the pack with 183,569.10 million yuan in sales, followed closely by the Tesla Model Y, Toyota Camry, Lexus ES, and other models. Other popular models include the Toyota Sienna, RAV4, BYD Song PLUS New Energy, and BMW X5, with new energy vehicles performing exceptionally well and occupying a significant market share.

Figure 3 shows the top 20 models in terms of total sales from November 2024 to March 2025. The best-selling model is the Wuling M9, followed by the Audi A6L and Model Y. As can be seen, the list includes models from many different brands, so sales performance after discounts during this period is diverse. Overall, competition among models is intense.

2024 to March 2025 in an intuitive pie chart format.

Figure 4-7 Grouped line charts provide an intuitive overview of the trends and changes in the automobile sales market from November 2024 to April 2025. To facilitate understanding, the Top 20 vehicles are grouped into four categories based on sales volume, with four corresponding charts: the first tier is plotted by sales volume, the second tier is plotted by sales volume, the third tier is plotted by sales volume, and the fourth tier is plotted by sales volume. The charts are divided into two sections from top to bottom: the upper section displays the order of vehicle models and sales volume in ascending sequence from top to bottom; The lower part uses different column colors to represent different vehicle models. The staircase-style graphical chart combination form illustrates the sales performance of vehicles in each tier, clearly showing the sales trends and highlighting the prominent effect of leading models. The sales curves of the top five vehicles show minimal changes, reflecting the high stability of leading models; however, the rankings of vehicles between 10th and 15th show significant fluctuations.

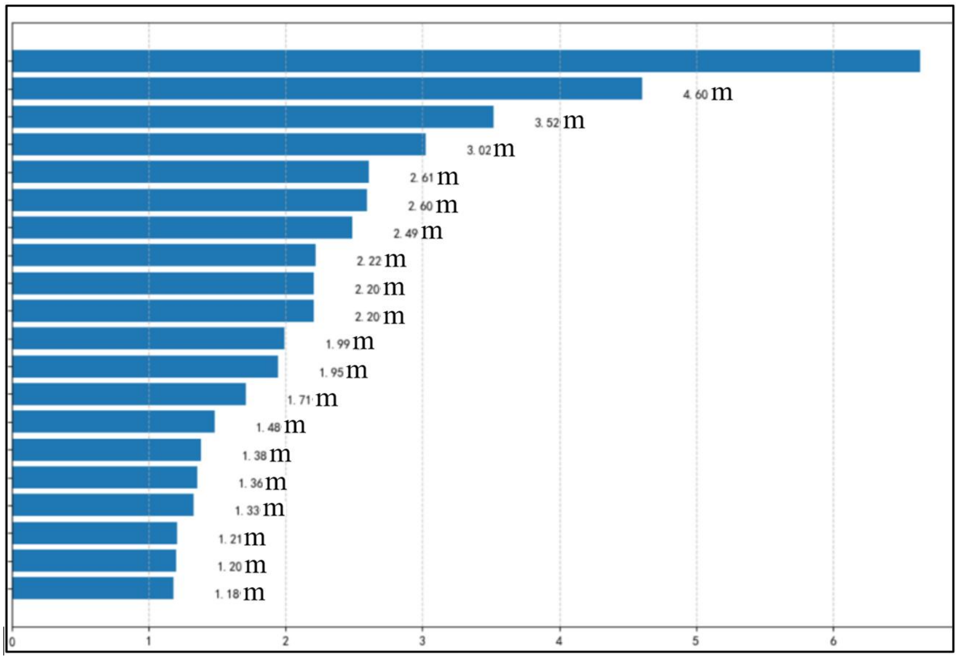

Figure 3. Top 20 Models by Total Car Sales Volume

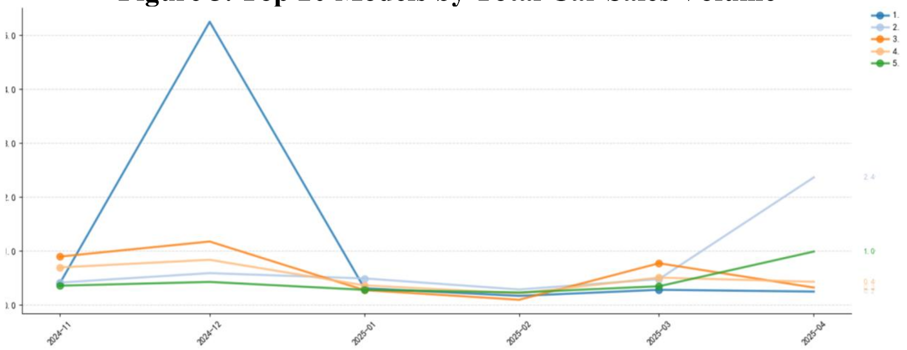

Figure 4. Sales Rankings

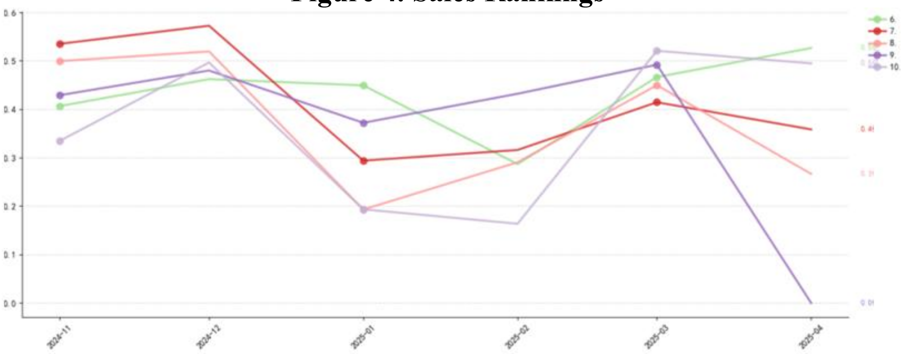

Figure 5. Sales Rankings for Models 6-10 (Unit: 100 million yuan)

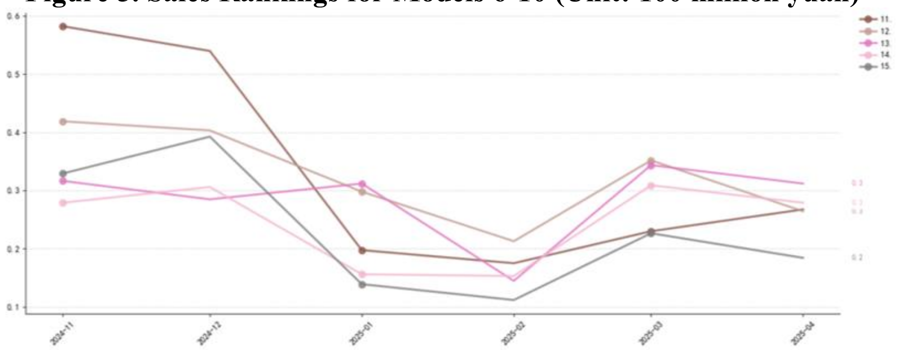

Figure 6. Sales Ranking 11th - 15th Model Trends

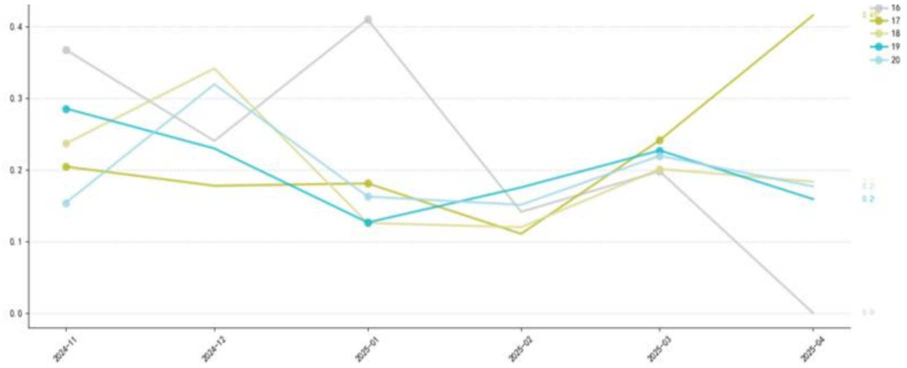

Figure 7. Sales Ranking 16-20 Model Trend

From the sales figures for new energy vehicles in November and December 2024, this period represents one of the peak periods. The reason for this small peak is due to the strong sales of the Aito M9, which led to increased inquiries during this period. As shown in the appendix figure of the literature review method from Baidu Baike, during the period from November 26, 2024, to December 25, 2024, there was only one month in which the number of large orders reached 20,000 units within a single month. This indirectly indicates that this high-end new energy vehicle is highly popular among people. This data also demonstrates the current level of acceptance for new energy vehicles and highlights the high level of acceptance for high-tech vehicle models.

However, within 1–2 months of the sharp increase in sales of the Asking M9, the overall sales of new energy vehicles experienced a temporary decline. This is a typical "demand pull-forward effect," where some consumers with the intention to purchase a vehicle completed their purchase plans before the end of the year, leading to a short-term saturation of the new energy vehicle market; Additionally, the arrival of the Spring Festival consumption season boosts consumer spending, further expanding the sales peak originally seen in November and December, resulting in a more pronounced decline in subsequent sales. This is a normal consumption pattern, as consumer goods often experience shifts in consumption timing due to objective factors such as holidays and seasons, leading to significant fluctuations in sales volumes at different time points.

2.1.2 Cluster analysis

The data collected by this study from 2023 to 2025 to the present is shown in the Table 4 [4]. The table shows the year, the average lowest price for that year, total sales, and total sales price, as shown in Table 4.

Table 4. All Data Statistics Table

year	Average lowest price for the year (10,000)	Total sales (units)	Total sales (10,000)
2023	31.53	123969	2858945.5
2024	30.44	135248	2928005.3
2025 (As of April 1)	28.39	37012	762985.1

In this case, the algorithm constructs a multidimensional space using three features: "lowest price," "sales volume," and "total sales price," all of which have been standardized. First, three cluster centers are randomly initialized. Then, each sample is assigned to the nearest cluster center by calculating the Euclidean distance. The mean of each cluster is recalculated as the new center point, and the "assignment-update" process is repeated until the center points stabilize. This process ensures that samples within a cluster have high similarity while maximizing differences between clusters, ultimately revealing potential segmentation patterns in market performance across different price segments: Cluster 0 may represent high-priced, low-sales models, Cluster 1 corresponds to mid-range, high-volume models, and Cluster 2 may represent product categories that achieve scale sales through low-price strategies. This quantitative grouping provides data support for developing differentiated pricing and marketing strategies.

Figure 8 shows the price gradient analysis of the automotive market, which exhibits a three-tiered segmentation structure: the low-price segment (0–100 million yuan) dominates sales revenue due to its dense model lineup and economies of scale, reflecting the mainstream preference for economical consumption; The high-price segment (2 million to 7 million yuan) suffers from sales revenue contraction due to sparse data and low demand elasticity, highlighting the limitations of a niche market; the mid-price transition zone (1 million to 2 million yuan) exhibits significant differentiation, with some models achieving sales breakthroughs by balancing configuration, brand, and service, while others perform poorly due to misaligned pricing strategies, reflecting the complexity of consumers' multi-dimensional considerations. The chart on the right further reveals the logic driving sales: the low-price segment relies on sales volume, the high-price segment is constrained by scarce demand, and the mid-price segment requires cluster analysis to optimize product positioning and price matching. Strategically, companies should consolidate their scale advantages in the low-price segment, precisely target high-potential positioning in the mid-price segment, and cautiously assess the effectiveness of investments in the high-price segment.

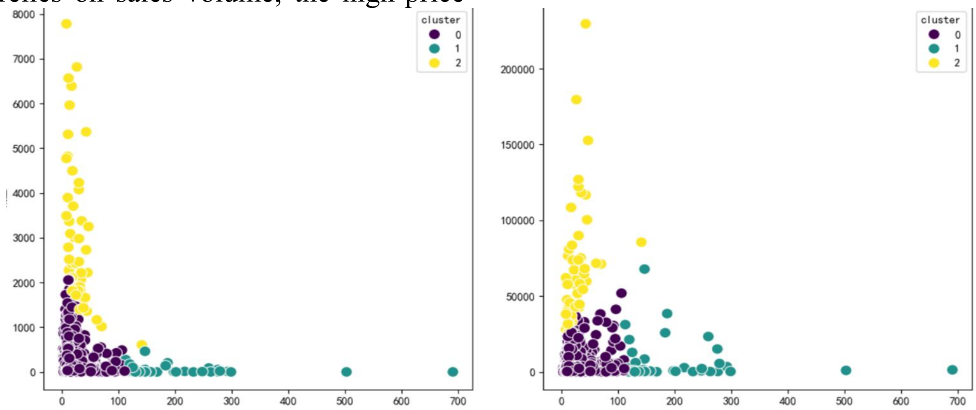

Figure 8. Cluster Analysis

2.1.3 Data reliability analysis

The results of Figure 9 the data analysis show that the vast majority of vehicle models are concentrated at the lower end of the price range, while a small number of high-end models form a significant long-tail effect. The kurtosis coefficient of 68.18 reveals that the distribution curve has an unusually sharp peak and a heavy tail, suggesting the existence of a dispersed distribution of extremely high-priced models. Combined with the fact that 79.8% of sales are concentrated in price ranges below the average, this empirically validates the “pyramid-shaped” structural characteristics of the automotive consumer market, where entry-level models dominate sales volume, while luxury models, though scarce in number, significantly elevate the overall price level through ultra-high pricing. This aligns closely with the “anchor effect” pricing strategy commonly observed in the luxury goods market.

Figure 10, the nuclear density concentration area has density contour lines extending upward along the vertical axis (sales dimension), revealing a trend of increasing sales for low-priced models. At the same time, the contour lines extend to the right along the horizontal axis (price dimension), forming a long-tail distribution and creating a discrete “high-price island” (300-700 million yuan range). Notably, a significant data gap emerges in the mainstream price range (1 million to 3 million yuan), where the nuclear density contour lines form a ring-shaped blank zone, suggesting a gap in the mid-to-high-end market. This aligns closely with the market segmentation phenomenon caused by luxury brands' price anchoring strategies.

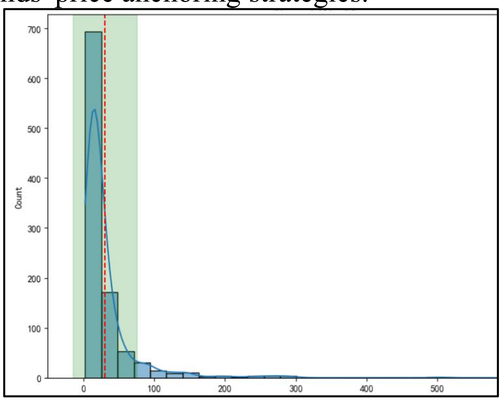

Figure 9. Visualization of Price Distribution Characteristics

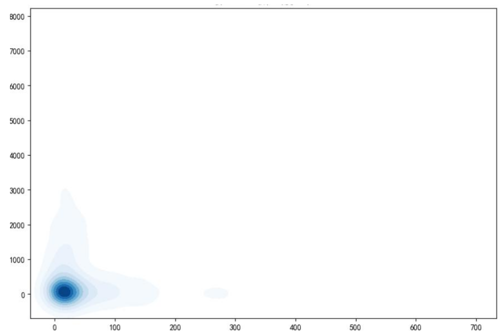

Figure 10. Sales Clustering Chart

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2.2 Analysis of New Energy Vehicle Market Growth Trends and Model Distribution

2.2.1 Sales time trend analysis

A time-series analysis of new energy vehicle sales data in Dalian City indicates that sales fluctuations are driven by four key factors: seasonal patterns, policy interventions, economic conditions, and technological advancements. Seasonal characteristics are evident in the following patterns: a small peak in March, a peak in July, and an annual peak in December; Policy factors include the exemption of purchase tax and vehicle purchase subsidies, which significantly lower the barriers to consumption and stimulate the conversion of potential buyers; economically, increases in disposable income and positive consumer confidence indices positively impact purchasing power, while economic downturns lead to delayed consumption; technological advancements drive demand through product innovation, with a notable example being the sales boom triggered by the introduction of extended-range technology in the Aito M9. The interplay of these four factors collectively shapes the dynamics of the regional market.

2.2.2 Analysis of the relationship between price and sales volume

Based on an empirical analysis of the new energy vehicle market in Dalian City, there is a significant negative correlation between price and sales volume, with a clear price-sensitive range in the market. Data shows that the core price range is between 150,000 and 200,000 yuan, accounting for 19.23% (26,052 units) of the total sales volume of 135,484 units, indicating that this price range offers the best value for money and is most recognized by consumers; The market for vehicles priced above 300,000 yuan shows a sharp decline in demand: the 300,000–500,000 yuan price range accounts for 15.86% of total sales (21,490 units), while the segment above 500,000 yuan accounts for only 2.86% (3,874 units), indicating a limited audience for high-end models. Notably, price elasticity varies significantly across models: Highly elastic models (e.g., BYD Qin PLUS DM-i, with annual sales of 6,033 units): These models are highly price-sensitive, with even minor price changes causing significant fluctuations in sales volume, necessitating competitive pricing through cost optimization; Low-elasticity models (such as the Tesla Model Y and the Aito M9): Brand premium and technological barriers (such as the Model Y's intelligent driving features and the Aito M9's extended-range technology) reduce price sensitivity. The Model Y sold 3,756 units annually, while the Aito M9 reached 3,059 units, validating that the high-end market can achieve premium returns through quality improvements.

Corporate pricing strategies must dynamically balance the price-volume-revenue triangle. A typical case study shows that a 10% price increase for a certain vehicle model led to an 8% decline in sales volume, but since the price increase exceeded the sales loss, revenue still achieved net growth. This highlights the importance of managing the critical point—when the price elasticity coefficient $|E_p| < 1$ (i.e., the rate of change in demand is lower than the rate of change in price), a price increase can boost total revenue. Therefore: Mass market strategy: For the core price range of 150,000–200,000 yuan (accounting for nearly 1/5 of the market), using the BYD Qin PLUS DM-i as a model, reduce costs through scaled production to maintain price competitiveness; High-end market strategy: For low-elasticity models priced above 300,000 yuan, emphasize technological differentiation and brand value to support profit margins through premium pricing; Elasticity-driven pricing mechanism: Establish a demand curve model to monitor the price elasticity of each model in real time and develop differentiated promotional and pricing strategies.

In summary, pricing in the Dalian market requires three-dimensional coordination: anchoring the core price range of 150,000-200,000 yuan to expand the base, utilizing elastic differences to lay out the product matrix, and optimizing sales through critical point optimization to maximize sales. Regional consumption characteristics and competitor dynamics need to be incorporated into the elasticity calculation framework to improve strategy adaptability.

2.3 Analysis of Online Comments on New Energy Vehicles

Step 1: Read the data

In the Excel file “Commentdata. Xlsx,” use the read_excel function in the pandas library to read the data, and then use the drop_duplicates method to remove duplicate rows.

Step 2: Text Cleaning

A function called clear_character is defined to clean up the text data. This function removes Chinese characters, special symbols, and numbers from the regular expression, leaving only Chinese characters and spaces. The cleaned text will be used for subsequent cutting and stopping.

Step 3: Stop word processing

To ensure the quality of stopwords, methods such as Chinese stopword lists, Harbin Institute of Technology stopword lists, and Baidu stopword lists are used to classify stopwords. The stopword set in “stopwords_hit.txt” is read and added to the list. During this process, additional stopwords are defined and added to the stopword set.

Step 4: Word segmentation and stop word removal

During Chinese word segmentation, the jieba library is used to automatically segment inactive words. It has two functions: comment_cut and rm_stop_word. These two functions are applied to each annotation data in df3, and the processing results are saved in the “comment_processed” column.

Step 5: Remove Low-Frequency Words

First, the annotated data is searched, and the frequency of each annotated word in the annotation is calculated. Second, a minimum threshold is set, and only words above this threshold are retained. Based on this, a new method—rm_low_frequence_word—is proposed.

Step 6: Construct Latent Dirichlet Allocation Topic Modeling

This paper constructs a line chart of the relationship between the number of themes and confusion and consistency. Confusion refers to the accuracy of the model's prediction of the word distribution in a document. The lower the confusion, the higher the accuracy. Consistency refers to the strength of the semantic association between words within a theme. The higher the consistency value, the better the interpretability of the theme. The weight can be adjusted according to actual needs. Through comprehensive analysis, the number of themes was determined to be 6. An analysis of Figure 11 the number of selected topics is presented.

In this paper, Python is used to perform topic analysis and build an Latent Dirichlet Allocation topic model, generating a total of six topics. The topic vectors and the most frequently occurring words under each topic are printed.

The final extraction results are obtained. The results are shown below:

Theme 0: Keywords: if, range, feel, this model, car, design, aspects, appearance

Semantic focus: Focus on users' cognitive framework regarding the compatibility between vehicle design language and functionality. By using limiting words to establish product positioning analysis dimensions, the juxtaposition of exterior design elements and range parameters reflects consumers' balancing mechanism between aesthetic demands and technical indicators. The use of contrasting expressions suggests potential discrepancies between subjective experiences and official marketing claims.

Theme 1: Keywords: vehicle, feel, good, and, so, especially, really. Semantic focus: Building an emotional evaluation system for the overall vehicle experience. Progressive conjunctions link subjective feelings with objective facts, while degree adverbs reinforce the credibility of the evaluation, forming a multi-dimensional sensory cognitive network that includes handling feedback, functional adaptability, and more.

Theme 2: Keywords: fuel consumption, but, also, engine, driving, one, mode, range

Semantic Focus: Revealing the complex mechanisms of the power system's coordinated operation. Transitional words highlight the efficiency contradictions between traditional fuel units and new drive modes, while measure words refer to specific driving scenarios. Multi-mode switching strategies become the key variable in balancing fuel consumption and range.

Theme 3: Keywords: mode, configuration, and, absolutely, so, really, fuel consumption, not bad

Semantic Focus: Exploring the path of intelligent configuration reshaping driving behavior. Absolute expressions reflect users' trust in pre-set driving logic, while causal chains reveal how configuration upgrades achieve dual goals of fuel consumption control and performance enhancement through mode optimization.

Theme 4: Keywords: Range, Seats, High-Speed, Also, Experience, But, Really, Mode

Semantic Focus: Analyzing the composite

demand matrix of long-distance driving. Frequently occurring scenario-specific terms and sensory description terms intertwine, with ergonomic seat design and range strategy optimization becoming core elements in alleviating driving fatigue and range anxiety.

Theme 5: Keywords: But, Not Bad, Electric Vehicle, Appearance, Sufficient, Aspect, Acceleration, So

Semantic Focus: Demonstrating the evolution of consumer perception during the electrification transition. The contrast between traditional powertrains and electric acceleration highlights the experiential gap, while evaluations of sufficiency reflect users' recalibration of functional thresholds for electric vehicles. Appearance design emerges as a key moderating variable in technology acceptance.

The specific keyword distribution chart is shown in Figure 12.

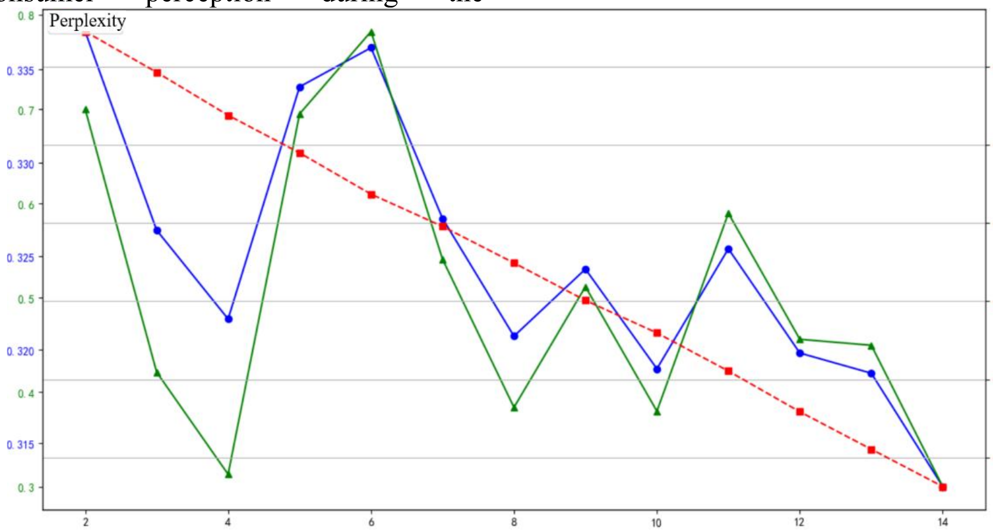

Figure 11. Analysis of the Number of Themes Selected

2.4 Correlation Analysis between Online Reviews and Sales Data

A Pearson correlation analysis based on new energy vehicle sales data and online reviews in Dalian City indicates that consumer sentiment significantly influences market performance: positive reviews (e.g., praise for range, charging efficiency, and interior design [8]) are positively correlated with sales volume and revenue ($r > 0$), promoting purchasing decisions through social proof mechanisms; negative reviews (focusing on range defects, insufficient charging infrastructure, or quality issues) lead to a decline in demand ($r < 0$), with a single negative incident potentially triggering a sales slump; neutral reviews, lacking emotional direction, show no statistically significant correlation with sales. Brand penetration strengthens this effect, with high-market-share brands achieving higher conversion rates from positive reviews.

Companies must establish dynamic reputation management strategies: real-time monitoring of public sentiment, targeted optimization of product pain points (such as range and charging experience), and incentivizing positive word-of-mouth to drive sales growth [9,10].

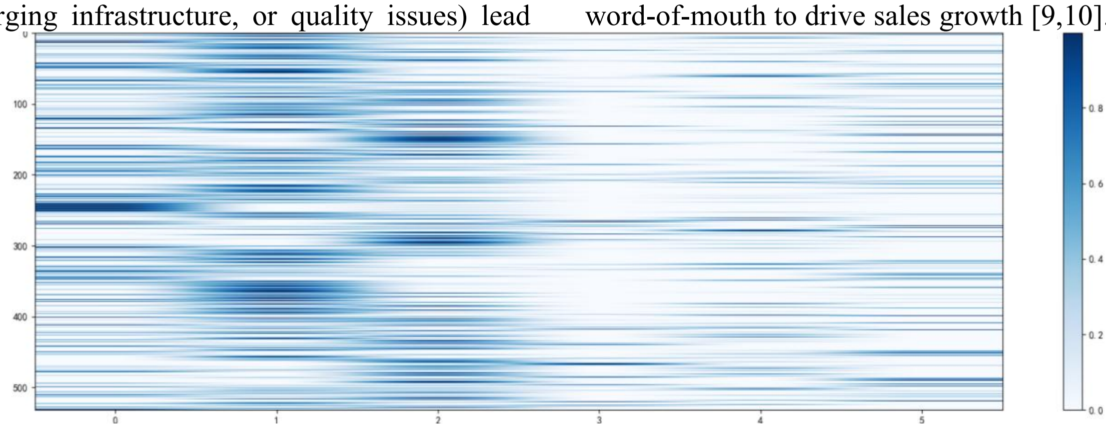

Figure 12. Heat Map Showing the Distribution of Topics Across all Documents

3. Conclusion

Based on an analysis of the new energy vehicle market data in Dalian City (2023-2024), the main conclusions are as follows: The market size continues to expand, with sales growth driven by four key factors: policy guidance, increased environmental awareness, technological advancements, and improved infrastructure. BYD holds a dominant position, while brands like Tesla and Aito cater to niche market segments through differentiated designs. Consumer sentiment is generally positive, with negative evaluations concentrated on range, charging infrastructure, price, and safety performance. Demand shows regional and demographic segmentation—urban consumers prefer mid-to-high-end models and technological features, while rural users prioritize cost-effectiveness. Sales exhibit seasonal fluctuations (peak at year-end, lows at the beginning of the year and during the tourist season), with policy interventions (purchase tax exemptions, license plate incentives) significantly influencing trends. Market performance shows: urban areas have higher sales than rural areas; SUVs are the best-selling models (BYD Qin PLUS is the top-selling sedan), while MPVs have the lowest demand; price sensitivity is prominent, with the 15–200,000 yuan price range becoming the core sales segment due to its optimal cost-effectiveness. Online sentiment is significantly positively correlated with sales, with comments focusing on range, charging infrastructure, price, features, and design directly reflecting market hotspots.

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