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The Impact of Consumer Sentiment on Brand Reputation in the New Energy Vehicle Industry

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Abstract. With the development of science and technology, social media has become one of the sources that people give their opinions and exchange information. Currently, people's choice of car usage starts to transfer to new energy vehicles (NEV) due to many reasons. This study collects mix of data: Gain consumer sentiment data through over 7000 pieces of comments about three brands of NEV on two social media platforms; Collect brand reputation indexes through questionnaires from over 200 respondents. Correlation analysis, sentiment analysis derived from textual data and regression analysis will be used to investigate the relationship between consumer sentiment and brand reputation of NEV brands. The results shown that there is a weak positive relationship between consumers' sentiments and brand reputation index. However, the impacts on brand reputation by negative sentiments is not greater than positive sentiments, which point out the meaningfulness for future research on generalizability of negativity feedback and differentiation of industry-specific factors.

Keywords: New energy vehicles (NEV), social media, brand reputation, consumer sentiment.

1. Introduction

Consumer sentiment on social media has a strong influence on others' purchasing decisions as the sentiments would change people's perception of brand. Since consumers now have diverse channels to express their perspective and gain other people's opinions due to rapid iteration of technological advancement. Under the frequent occurrences of environmental pollution such as global warming which sourced from green gas emission from fossil fuel, introduction of new energy vehicles changed people's mind and consumers are willing to embrace this new model of car to reduce pollution. There are vast amount of research paper and literature review in past five years to examine the impact of consumer sentiments on brand reputation, for example, some researchers found that sentiment analysis provides actionable insights into consumer attitudes and opinions, which are crucial for shaping brand strategy, some researchers found that enterprises are able to better understand the unique attributes that consumers have for the brand [1,2]. However, only limited papers focus on NEV industry which is popular recently. Additionally, China is the country occupy the largest market share in global NEV market about 68%, studying on market sentiment in Chinese social media platform is an effective choice to generalize to the global NEV market [3].

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This industry-focused research on impact of sentiment on reputation of NEV brands offers new insights on how NEV brands can manage their brand reputations by emotional factors This study collects two-part data to support hypothesizes. First, the author utilizes Python web crawler to collect comments from two social media platforms: Weibo and Xiaohongshu (RED) in terms of three NEV brands, helping gather comprehensive consumers' feedback for generalization. For ethical and confidentiality causes, the actual company names are not disclosed. Instead, three representative brands are referred to as Brand A for the international high-technology one, Brand B for the domestic technology-oriented one, and Brand C for the domestic premium one throughout this study; Secondly, the author collect responses from respondents via questionnaires about brand trust, brand reputation, purchase willing and sentiment perception to get brand reputation indexes, for which increase validity of the findings. The author would use correlation, sentiment analysis and regression analysis to deal with data.

2. Methodology

2.1. Data collection

The author makes two hypothesizes:

H1. There is a positive relationship between consumer sentiment and brand reputation in NEV brands.

H2. The negative sentiment has greater intensity than positive sentiment on brand reputation in NEV brands.

The author collects two parts of data to test the relationship between consumer sentiment and brand reputation. Regarding to consumer sentiment, the author uses Python web scraping to access to totally 8375 pieces of comments, which is easy to gain a big sample size of over 5000 and captures the natural expression of consumers under different scenarios in order to avoid social desirability bias [4] when using subjective collection methods. And the data is collected from brand A, B, C sourced from Weibo and RED. The allocation of data points is listed in Table 1:

Table 1. Allocation of data points by NEV brand and platform

Platform/NEV Brand	Brand A	Brand B	Brand C	Total
RED	856	988	444	2288
Weibo	2765	933	2389	6087
Total	3621	1921	2833	8375

Choices of these three brands are because they each reflect characteristics that are international high technology, domestic technology-oriented and domestic premium, which together shape the overview of current Chinese NEV market, associating with representativeness. Additionally, RED and Weibo are the most frequently used official websites for users, which have relatively large databases of comments [5].

Besides that, brand reputation indexes are collected from over 200 respondents through questionnaires in aspects of familiarity of brands, brand trust, brand reputation and perception of consumer sentiment. This study conduct opportunity sampling which the author publishes the questionnaire link in social media account and randomly patriated by participants who see the link because this method confirms the randomness of data collected and avoid demand characteristics [6] if using volunteer sampling. The sample structure is consisting of 217 participants. Of the

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participants, 61.01% are women and 38.99% are men. The age distribution of sample is shown in Figure 1:

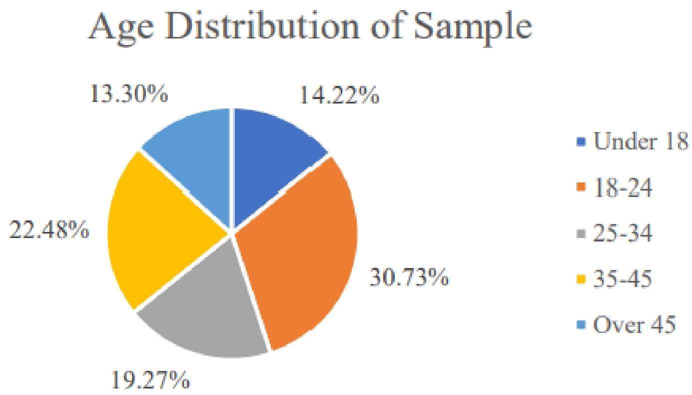

Figure 1. Age distribution of sample

The age distribution of sample indicated that relative majority is aged from 18-24, and following is 35-45 which the age group has the most purchasing power and age group 25-34 is growing, then is over 45 and under 18 which is the least likely to know about and purchase NEV.

The author collected sample that are from 17 IP addresses, and the majority is from Jiangsu, Zhejiang and Liaoning which can make the data collected generalize to population as a whole to ensure the data has generalizability. Furthermore, of the participants,41.74% of people say they familiar with Brand B most, 32.11% of people are familiar with Brand C most, 26.15% of people say they are familiar with Tesla most.

2.2. Data analysis

2.2.1. Noise removal

The original database involves many hard-to-analyze contents, like special symbols (@, #, *), emojis, extra space and numbers, etc. These contents need to be removed for analysis. This consist of advertisements, blank spaces, non-Chinese characters, emojis (prevent semantic confusion), filter out meaningless data that less than 5 words. The author only retains meaningful textual information. After cleaning the datasets, it is from 8375 comments to 5044 valid comments.

2.2.2. Word segmentation

The after-clean datasets were processed using the jieba word segmentation tool in Python. Jieba word segmentation tool is a suitable method to segment Chinese word because Chinese is not like English that it's necessary to separate words for computer identify, which also since Chinese do not have space like English, computers cannot know where to start and where to stop. In this step, each comment was tokenized into individual words to enable subsequent quantitative analyses such as word frequency statistics, sentiment scoring, and correlation/regression analysis. Common stop-words (such as filler words) were removed to ensure that only meaningful terms were retained for further processing.

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2.2.3. Word frequency analysis & part-of-speech tagging

The author uses the word frequency statistic tool to analyze the preprocessed data and count the occurrences of each word in all comment texts and sort them by frequency in descending order to generate a list of words and their corresponding frequencies like following top 30 word frequency statistics (Table 2):

Table 2. Translated word frequency and part of speech statistics

Word	Word Frequency	Part of Speech	Word	Word Frequency	Part of Speech
Tesla	596	nrt	Li Auto	95	n
NIO	457	x	Experience	87	n
Really	250	d	Highway	85	d
XPENG	236	x	Brand	82	n
XIAOMI	226	n	ADAS	80	nr
Like	151	v	Electric Vehicle	74	n
Feel	149	n	Expectation	73	v
Driver	140	n	Support	70	v
Good	131	a	Charge	69	v
Good-Looking	123	v	Users	68	n
Sales	121	n	Great	64	a
Driving	117	v	Technology	63	n
Indeed	114	ad	Endurance	62	nr
Battery	113	n	Automatic	61	vn
Vehicle	101	n	Steering Wheel	61	n

2.2.4. Comments sentiment analysis

The author uses SnowNLP to process the comments collected from Weibo and RED and set the boundaries for positive, neutral and negative: if the sentiment score is higher than 0.6, it's classified as positive; If within range between 0.4 and 0.6, it's classified as neutral; If lower than 0.4, it's classified as negative. The result shown in Table 3:

Table 3. Distribution and mean score of sentiment attitudes

Sentiment Attitudes	Count	Percentage	Sentiment Mean
Positive	2532	50.20%	0.8558
Negative	1758	34.85%	0.1661
Neutral	754	14.95%	0.4965
Total	5044	100.00%	0.5617

Positive Sentiment (50.20%) has 2,532 entries, representing the vast majority of the sample. This is the mainstream voice or dominant force (KOL) in the community. There is a strong intensity, which average of positive attitudes reaches 0.8588. This indicates that positive feedback is not only “Good” or “Just normal”, leading to “Great”, “Love so much” and “Highly recommend”. This states that supports and satisfactory users holds persistent standpoints and devote in deep emptions.

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Negative Sentiment (34.85%) has 1758 pieces of comments, which is more than one-third. This is a very large group of opposition or dissatisfaction. It also has a strong intensity. The average score is apt to 0.1661, far below the 0.4 negative threshold, indicating these comments are not only “a little disappointed”, but also filled with strong negative emotions such as “Terrible”, “Useless” and “Never used”. This is at the exact opposite of the positive attitudes.

Neutral Sentiment (14.95%) has 754 feedback, which accounts for smallest proportion. This is a minority in the community, likely users conducting objective analysis, asking neutral questions, or expressing uncertainty. The intensity: Highly concentrated around the theoretical neutral point. The average score of 0.4965 almost perfectly falls in the middle of the author’s defined 'neutral range' (0.4-0.6).

2.2.5. TF-IDF analysis

This method helps to identify keywords. It can automatically find the most representative words from a large amount of text, reflecting the topic or focus of the comment. It’s more smart than simple word frequency because it’s not disturbed by common words.

Table 4. Translated TF-IDF statistics

Positive Sentiment		Negative Sentiment	
Word	TF-IDF Intensity	Word	TF-IDF Intensity
NIO	0.026406696	Tesla	0.028645855
Tesla	0.024866293	NIO	0.019386602
Really	0.01973149	XPENG	0.011915689
Xiaomi	0.018528417	Sales	0.010334826
Great	0.016882199	Feel	0.008424102
Like	0.015321297	Battery	0.0084135
XPENG	0.015111048	Why	0.008305573
Good-looking	0.013068611	Highway	0.008145341
Indeed	0.011365223	Really	0.008069228
Feel	0.011074821	Drivers	0.007384221
Experience	0.008982438	Vehicle	0.007134228
Vehicle	0.008151466	Charge	0.006577337
More	0.007998015	Driving	0.006558534
Support	0.007879466	Sell	0.006075034
Expectation	0.007601008	Kilometers	0.00570144

According to Table 4, Positive comments emphasize satisfaction, aesthetics, and brand appreciation, often using words like good-looking, like, support, and expectation. While Negative comments focus on performance and quality concerns, particularly issues related to battery, driving, and sales.

2.2.6. Correlation analysis

The author merges the questionnaire data and sentiment data by R and conduct correlation analysis between sentiment score and brand reputation as Table 5:

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Table 5. Result of correlation analysis

Statistics	Value
t-stat	5.5569
Degree of Freedom(df)	5042
Statistics	Value
P-value	2.887e-08
Alternative Hypothesis	True correlation is not equal to 0
95% Confidence Interval	0.05053057-0.10539107
Correlation	0.07801988

2.2.7. Regression analysis

Following the correlation analysis, the author further studies the intensity of positive sentiment and negative sentiment on brand reputation and do a regression analysis as Table 6:

Table 6. Regression analysis by R

Section	Statistic	Value	Std. Error	t value	Pr(>|t|)
Residuals	Min	-0.23849			
	1Q	-0.20917			
	Median	-0.01215			
	3Q	0.23620			
	Max	0.26813			
Coefficients	(Intercept)	3.191622	0.007519	424.493	< 2e-16 ***
	Positive dummy	0.029324	0.008565	3.424	0.000623 ***
	negative dummy	-0.002606	0.008888	-0.290	0.771850
Model Summary	Residual Standard Error	0.2065 (df = 5041)			
	Multiple R-squared	0.005678			
	Adjusted R-squared	0.005284			
	F-statistic	14.39 (df = 2,5041)			
	p-value	5.846e-07			

3. Results

3.1. Correlation analysis

The correlation analyis in r result shown that there is a linear weak positive relationship between consumer sentiment and brand reputation as the cor is 0.07801988, which shown that consumer sentiment has limited explanatory power to improve brand reputation, although this correlation is statistically significant as p-value is lower than 0.05. The reusult supports H1.

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3.2. Regression analysis

The regression analysis in Table 6 shows that positive_dummy variable and negative_dummy variable and have coefficient to decide the impacts of brand reputation, and the p-value is lower than 5% which show this model is statistically significant. The signif.codes states that postive sentiment has much more explanatory power on reputation than negative sentiment. This is in contrast of H2 for which positive sentiment has greater intensity than negative sentiment in this study.

3.3. Word map analysis

The word cloud shows that the topics the consumers currently most interested in. Of the cloud excepting brand names, “Experiences”, “Battery”, “Like”, “Beautiful”, “Technology” is the most focused topics, providing aspects for future research of NEV should concentrate, which shown in Figure 2.

Figure 2. Word map of collected comments

4. Discussion

H1 is partially supported by the authors’ data analysis which show a quite weak positive relationship between consumer sentiment and brand reputation. This can be explained by that the brand reputation in NEV market is not largely determined by consumer sentiment on social media platforms, instead NEV market in China now has evolved marketing strategy to improve brand reputation and sales, like patriotism and fan nationalism [7]; Beside that, other researchers found that economic environment, pricing and government policy are the priority to influence consumers’ decisions, which shown that management of consumer sentiment is not an effective way to promote consumers’ purchasing behavior [8].

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H2 is in contrast to the author's findings as the result shown that negative sentiment is not have greater impact on brand reputation than positive one. One possible cause is limited sampling and overly subjective thoughts, which is easier to shade respondent-specific impression on scoring the survey, leading to shortage of generalizability. In addition, participants in questionnaires are like to fall in social desirability bias to cause them more likely to answer based on general impression about the three brands, instead of personal first-hand knowledge [4].

Although H1 and H2 were not fully confirmed, the results still provide valuable insights. The study found no significant linear relationship between consumer emotions and brand reputation, indicating that more complex factors may influence their interaction, such as brand trust or social media context [9]. Companies should not rely on single indicators to assess brand image or sentiment. Instead, a comprehensive monitoring system using surveys, social media analysis, and sentiment models is recommended to better understand consumer perceptions. Future research should explore the mechanisms driving these differences, possibly using longitudinal or mixed-methods approaches to examine how emotions affect brand reputation over time, the difference between consumers' sentiment online and in-store also should be investigated whether it has impacts on sales and brand reputation [10]. While the hypotheses were not fully supported, the findings highlight the complex relationship between emotions and brand reputation, offering new directions for research and practice.

5. Conclusion

This study finds no clear link between consumer emotions and brand reputation. Social media sentiment scores do not consistently match survey-based reputation measures, which suggest that factors like brand trust and online context can't fully interpret the relationship and there is difference in consumers' behavior online and in real life. Relying on a single data source can't fully explain how sentiment and reputation interact. Also, the gap between real consumer sentiment and online sentiment reflected by social media platform may result in inconsistencies of hypotheses and results. The study's main contribution is combining sentiment analysis and brand management, offering new insights to understand how consumer perception influence brand reputation which help company get to know how to manage customers' relationship more effective in daily operations context. Companies should use multiple tools, such as surveys, sentiment analysis, and context studies to better capture real consumer emotions. The study has limitations of short time frame and insufficient sample size. Future research could use long-term and cross-platform analysis to investigate deeply how factors like brand trust and emotion spread affect brand reputation online and further examine whether difference in consumers' behavior between social media and in-store have impacts on the sales.

References

[1] Chowdhury, R.H. (2024) Sentiment analysis and social media analytics in brand management: Techniques, trends, and implications. World Journal of Advanced Research and Reviews, 23(2), 287–296.
[2] Li, Z. (2022) Research on brand image evaluation method based on consumer sentiment analysis. Computational Intelligence and Neuroscience, 2022(1), 2647515.
[3] Liu, Y., Zhang, M., Chen, X., Li, K. and Tang, L. (2024) The impact of consumer sentiment on sales of new energy vehicles: Evidence from textual analysis. World Electric Vehicle Journal, 15(7), 318.
[4] Kwak, D.H.A., Ma, X. and Kim, S. (2021) When does social desirability become a problem? Detection and reduction of social desirability bias in information systems research. Information & Management, 58(7), 103500.
[5] Pu, Y., Ma, R., Li, J., Wei, Y., Pan, X. and Zhang, X. (2025) The impact of social media information dissemination on consumer brand perception: An empirical study based on Weibo and Xiaohongshu data. Journal of

DOI: 10.54254/2754-1169/2026.LD31119

Organizational and End User Computing (JOEUC), 37(1), 1–33.
[6] Orne, M.T. (1996) Demand characteristics. In Introducing Psychological Research: Sixty Studies That Shape Psychology, 395–401. London: Macmillan Education UK.
[7] Cao, Z. (2025) Fan nationalism: A study on consumers' willingness to buy NEVs in China's NEV sales process. Advances in Economics and Management Research, 13(1), 632–632.
[8] Leng, J., Hao, D., Guo, M. and Liu, X. (2024) Research on the factors influencing consumer purchase intentions for new energy vehicles using the DEMATEL-ANP method. Advances in Consumer Research, 1(1), 1–16.
[9] Açikgöz, F.Y., Kayakuş, M., Zăbavă, B.-Ș. and Kabas, O. (2024) Brand reputation and trust: The impact on customer satisfaction and loyalty for the Hewlett-Packard brand. Sustainability, 16(22), 9681.
[10] Díaz, A., Gómez, M. and Molina, A. (2017) A comparison of online and offline consumer behaviour: An empirical study on a cinema shopping context. Journal of Retailing and Consumer Services, 38, 44–50.