Pol. J. Environ. Stud. Vol. 33, No. 4 (2024), 4807-4823
DOI: *10.15244/pjoes/177160* ONLINE PUBLICATION DATE: 2024-05-20

Original Research

Exploring the New Energy Vehicle Industry's Progress Path under the Carbon Peaking and Carbon Neutrality Goals: Evidence from Online Q&A Community's Emotional Analysis

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Received: 7 October 2023
Accepted: 16 December 2023

Abstract

The automotive industry's low-carbon transformation is crucial to a nation's ability to fulfill its "Carbon Peaking and Carbon Neutrality" (CPDN) commitment. However, China's automotive industry still has a number of issues that have sparked debate. Based on the fact that people use social Q&A platforms to get information, solve problems, and aid in decision-making, negative answers in massive amounts of information typically have a higher degree of information perception and are easier to spread. This work constructed the algorithm of emotion calculation and classification, negative network construction for social Q&A platforms, and carried out empirical research with Zhihu. The 175 questions and 5220 corresponding answers for new energy automobiles were organized as a database to search the development path for the new energy automobile industry. The new energy vehicle industry's development path primarily entails: resolving the issue of charging difficulty and popularizing charging heaps; attending to the battery safety issue and the head brand of new energy vehicles concentrating notably on quality control. The empirical findings also demonstrate that algorithms developed can more effectively complete the task of sentiment analysis, aid users in making decisions, and contribute to realizing the CPDN goal.

Keywords: Carbon Peaking and Carbon Neutrality, negative sentiment network construction, sentiment calculation and classification, online Q&A community, social network analysis, new energy vehicle industry

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Introduction

The President of China, General Secretary Xi Jinping, made a solemn commitment to the international community to achieve "Carbon Peaking and Carbon Neutrality" (CPCN Goals) at the general debate of the seventy-fifth session of the United Nations General Assembly. This commitment pointed out the direction of green and low-carbon development and clarified its objectives. The CPCN Goals are directing massive modifications and profound changes in China's economic structure and social style of operation, compelling all types of industries to accelerate green and low-carbon development. With its large scale, lengthy industrial chain, broad coverage, powerful driving force, and high level of internationalization, the automobile industry serves as a typical example of the manufacturing sector and holds a significant position in the industrial systems of the major economic powers in the world. In order to achieve the CPCN Goals, China's automobile industry must undergo a low-carbon transformation. This transformation is crucial for the high-quality growth of the sector and the creation of a global auto powerhouse, as well as for China's commitment to the CPCN Goals [1]. More than 120 nations have declared CPCN Goals in the world, and many of them, including the United States' Zero Carbon Action Plan (ZCAP), the European Parliament and Council's Publish Regulation (EU) 2019/631, the United Kingdom's Green Industrial Revolution Program, and 2050 Carbon Neutrality, have viewed the low-carbon transformation of the automotive industry as a key means of achieving the goal. Due to the exponential rise in the number of automobiles in the world in recent years, the escalation of climate and environmental problems, and the sharp decline in non-renewable resources like oil in the world, policies on low-carbon transformation of the automobile industry have been developed in many countries. This has accelerated the process of electrifying cars and promoted the development of new energy automobile-related research fields. [2]

The Global Electric Vehicle Outlook 2023 report notes that global electric vehicle sales surpassed 10 million units in 2022 and are projected to rise another 35% to 14 million units in 2023. Data only from January to May 2023 show that new energy vehicle sales were 2.940 million units, a year-over-year increase of 46.79%, and new energy passenger car sales were 2.810 million units, a year-over-year increase of 46.75%, of which the number of pure electric vehicles sold was 1.4 million units. Sales of new energy passenger vehicles were 2.810 million, up 46.75 percent from the previous year. Of them, 2.019 million were pure electric vehicles, up 34.61%, and plug-in hybrid vehicles sold 790,000 units, up 90.69%. [3] With the CPCN Goals, China's new energy vehicle industry is accelerating change; however, the industry still exists in the policy-driven characteristics of the obvious, imperfect infrastructure, the core technology level is not high, and the industry-standard system is not sound, and so on, many problems, caused by a lot of discussions on new energy vehicles, are widely concerned. People are progressively changing the way they transmit information and knowledge by expanding it into cyberspace as a result of the rapid development of the mobile internet. The number of Internet users in China has surpassed 1.011 billion as of 2021, and social Q&A platforms based on the Internet have emerged as one of the most efficient means for people to be exposed to new things. As forums for the automotive industry as well as others flourish, people use social Q&A platforms to learn new things, solve problems, and make decisions. Notable social Q&A platforms include Quora, Zhihu, Baidu Know, and others. Social Q&A communities' answer texts, which can be impartial, neutral, complimentary, positive, or negative with a critical intent, collect the ideas and attitudes of many people on a certain issue or topic. Unfavorable or unfavorable responses typically have a higher degree of information perception and are more likely to be widely spread when faced with a lot of information. It is possible to accurately understand users' emotions through the gathering, organizing, and processing of this information. This information can also be used to identify users' word-of-mouth, ascertain users' primary concerns, identify the development path of the new energy automobile industry from users' perspectives, and finally guide the healthy development of the new energy automobile industry.

A social Q&A website called Zhihu is referred to as "China's version of Quora", and it offers users a Q&A tool that integrates asking questions, answering questions, sharing, and disseminating knowledge, in contrast to highly structured forums like Auto News. And The internal data has strong knowledge attributes that can assist users in decision-making. Besides its more flexible Q&A format and unstructured, semantically rich data structure, among other factors, it has a wealthier type and volume of knowledge that is more suited to viewpoint mining. The overall number of questions on Zhihu has surpassed 44 million, and the number of answers has surpassed 240 million as of December 2020 [4]. Compared to other online Q&A communities, the data types in Zhihu are predominantly text-based and rich enough to be mined and analyzed with the help of text mining techniques. Since there isn't a sentiment rating system for answer texts in the Zhihu community, studies on the sentiment tendency of answers, sentiment ratings, and emotion classification of answers, as well as quantitative analysis of qualitative data, can all help the platform better understand users' points of view and mine users' opinions. On the other hand, sentiment analysis for a particular domain can help users make decisions.

This study focuses on the following issues based on the Q&A data from Zhihu: Is there a social Q&A platform with a negative sentiment network for new energy vehicles? And what traits do they possess? Are these answers helpful in determining whether purchasing a new energy vehicle is worthwhile? What are the primary issues with new energy cars? This study aims to summarize and refine the evidence in order to identify the development path of the new energy vehicle industry under the CPCN Goals, in order to provide a reference for the development of the new energy vehicle industry, and in terms of realization technology, mainly based on the evidence from the sentiment analysis of online Q&A community texts. The main contribution of this work is that the algorithms developed can more effectively complete the task of sentiment analysis, aid users in making decisions about the problems of new energy vehicles, and provide a development path for new energy vehicles that is beneficial to the achievement of the CPCN Goals.

Literature Review

Nasukawat and Yi [5] originally suggested sentiment analysis, also known as opinion mining, as a method of assessing, deducing, and summarizing subjective texts with emotional overtones in order to mine the emotional polarity of users in textual data. Sentiment analysis [6] is based on text mining techniques for online reviews that aim to determine whether a user's sentiment tends to be positive, negative, or neutral. It focuses on how to discover or mine people's feelings, opinions, or emotions expressed about a certain thing, product, or service from text [7].

Many different methods, including natural language processing, machine learning, information extraction, etc., are used in sentiment analysis [8]. Sentiment analysis consequently encompasses a variety of research goals, including "feature-versus-point-of-view" recognition [9-12], the subjective and objective detection of text [13], and sentiment analysis at various granularities [14-16]. The purpose of this study is to discover negative sentiment data using data mining techniques for Q&A in the area of new energy vehicles in the Zhihu Q&A community and to build a network of negative sentiment using social network analysis techniques. The theoretical and applied study on the value of Q&A in the online Q&A community and the accuracy of the information are the core content-related issues, and the development and use of sentiment analysis technology are the main essential technologies.

Study on the Development Path of the New Energy Vehicle Industry

At this time, the CPCN Goals are a global aim shared by more than 120 nations. Many nations view the automobile industry's transition to a low-carbon future as a critical step toward achieving the CPCN Goals. [17] Due to this, new energy automotive-related research fields have exploded, with academics increasingly concentrating on exploratory research into the future trajectory of the new energy vehicle business. The development of novel energy vehicles has received significant support and academics are increasingly focusing their attention on exploratory studies of the sector's evolutionary trajectory. Based on the method of grounded theory, Lu et al. [18] proposed the development path of the new energy automobile industry for Nanning City, Guangxi, through open coding, spindle coding, and selective coding by taking the questionnaires of 10 enterprises in the Nanning New Energy Automobile Industrial Park of Guangxi as the textual data basis. They proposed the development path for the new energy automobile industry in terms of industrial chain improvement, talent attraction, and training, and the depth of industry-academia-research fusion, increasing the government's input, and the synergistic development of upstream and downstream industries. Hu et al. [19] believe that the new energy automobile industry is an important support for the national strategic industry. Taking the web of science as the basic data source, with the help of CiteSpace software, they mined the frontier and hot topics of the research on the new energy automobile industry at home and abroad and found the important seminal literature in the field of new energy automobiles [20], and they believe that the development of China's new energy automobile industry needs to be strengthened in terms of basic research and development investment, the cooperation of the institutions, the breakthrough of scientific research, international exchanges, and so on. Tian et al. [21] proposed a dual path of technological innovation in the new energy automobile industry based on the innovation theory of duality, i.e., the combination of policy guidance and market regulation at the government level, the exploration and development of the industry level, the use of deepening the two types of innovation markets, and the flexibility of the two modes of standardized management and flexible adjustment at the enterprise level.

Sentiment Analysis of Online Q&A Communities

Users' perceptions of a product's quality are altered by product-focused affective evaluation from Q&A communities, which in turn influences their propensity to buy the product or not. The research on identifying the emotional tendency of products based on sentiment computing methods, determining the utility of sentiment analysis, and then conducting the research on users' willingness to buy, the development of online Q&A communities, and assisting vendors to carry out online marketing has been more appropriate in recent years due to the booming development of online Q&A communities and the development of natural language processing technology.

For instance, Wang and Wang [22] developed an econometric model with the aid of sentiment analysis technology to examine the relationship between the evaluation of product features and the user's willingness to purchase. This model primarily identifies the emotional polarity and its intensity with the aid of sentiment analysis technology by developing "feature-opinion pairs," which offers a theoretical foundation for word-of-mouth marketing in the process of network marketing. With the help of the NRC sentiment dictionary, Malik and Hussain [23] proposed a method to extract novel, discrete positive and negative sentiment features from the textual content of product reviews. The method then applies the results of sentiment computation to predict the usefulness of pertinent reviews for the creation of online Q&A communities. Wu et al. [24] constructed an econometric model to examine the relationship between hotel feature evaluation and user satisfaction and used Word2Vec for feature extraction and dimensionality reduction of Tripadvisor.com hotel reviews. They also combined sentiment analysis techniques to extract the sentiment corresponding to each type of feature. On the basis of analyzing and comparing the text recognition technology, Huang [25], based on the emotional weight algorithm of positive and negative vocabulary statistics as the basis for determining the emotional polarity of the text, realizes the recognition of negative word-of-mouth oriented to the automobile industry and applies it to the network risk monitoring platform of the automobile industry to guide automobile manufacturers to carry out network marketing.

In terms of sentiment analysis technology, there are primarily three types of methods for text sentiment analysis: dictionary and rule-based methods, machine learning-based methods, and deep learning model-based methods. The dictionary and rule-based method refers to the division of sentiment polarity into different granularities based on the sentiment polarity of the sentiment words provided by various sentiment dictionaries [26]. Using the HowNET emotional word set as a benchmark, Liu et al. [27] proposed a method for calculating the emotional weights of Chinese emotional words, and results showed that this method is helpful in enhancing the effect of emotion classification in the Chinese corpus. The emotion categorization of text was successfully realized when Xu et al. [28] developed an extended sentiment lexicon encompassing fundamental sentiment words, scene sentiment words, and multi-meaning sentiment words. Wang et al. [29] suggested a text sentiment classification approach based on the assignment roughness affiliation based on the text of automobile reviews, which improves outcomes by using the feature tendency strength to define the assignment roughness affiliation.

Negative Emotional Information Recognition and Application

Positive and negative affective polarities of different product types possess different effects on perceived information quality. Some researchers in the field have concentrated on studies relating to negative affective effects because it has been demonstrated that when information richness is high, negative remarks have a higher perceived information quality. Negative online reviews, according to Liu and Qiu [30] and Wu [31], are a specific form of interpersonal communication used by vocalizers to spread unfavorable information about a product in an effort to persuade other consumers to make a particular purchase. Chu et al. [32] made the point that in online review studies, the influence of negative reviews is more pronounced, the form of dissemination is richer, and the majority of Chinese consumers are more inclined than those in other foreign countries – with a percentage of more than 50% - to share negative reviews online. By combining variables like the emotional intensity of negative online reviews, perceived risk of negative reviews, perceived purchase intention of negative reviews, and degree of professionalism of recipients, Xu [33] used negative online reviews of hotels as the research object and created a statistical model of the impact of negative online reviews' emotional intensity on consumers' purchase intention, and study conclusions were devoted to providing market information. In the age of big data, sentiment analysis is not only extensively employed in online evaluations but is also the subject of more extensive research in fields including product reviews, social media, and online blogs [34]. Wu et al. [35] believe that the negative emotion of netizen groups is an important feature of online public opinion, and they created a SOAR (state, operator, and result) model of the negative emotion of netizen groups in emergencies and conducted simulation experiments for analyzing and predicting the behavioral decision-making of netizen groups in various stages of online public opinion and under various government emergency response measures. According to Chao [36], who believes that negative text in online blogs has a wider range of potential applications, a microblogging negative sentiment multi-classification method based on MAML and BiLSTM has been proposed as a solution to the problem of text sentiment multi-classification in the case of small samples.

According to the aforementioned research, machine learning-based sentiment classification and rule-based or dictionary-based sentiment identification are the key technologies used in sentiment analysis of online content in the big data era. While research on the trajectory of the new energy auto-mobile industry is primarily conducted from the perspective of policy formulation, it has been applied in online comments, microblog communities, online public opinion, etc., and the results of the application can help Internet Word of Mouth (IWOM) marketing, user purchase choice, online public opinion guidance, etc. More qualitative research, policy analysis, etc. are the foundations of the research methodology. However, the development path of the new energy automobile industry has not yet been identified from the perspective of sentiment analysis, especially negative sentiment analysis, despite the fact that the existing research has laid a strong theoretical foundation. The research on the development path of the new energy automobile industry is mostly conducted from the perspective of policy formulation, and the research methodology is based on qualitative research and policy analysis.

The results of sentiment analysis are typically used as one of the constituent elements for identifying the factors influencing users' purchase intentions, and they are studied from the perspective of online e-commerce. However, less is revealed about the inner mechanisms of negative sentiment generation, and this study has not yet focused on the creation of the negative sentiment network. Therefore, this study intends to expand the above two aspects, construct algorithms for emotion calculation, emotion polarity classification, and negative network construction for online Q&A community information, take the new energy automobile field in the Zhihu community as a research sample, identify the negative emotion information in the online Q&A community, construct a multidimensional negative emotion network, and excavate the deep reasons for the generation of negative emotions in the field of new energy automobiles, so as to promote the development of the new energy automobile industry.

Methodology

Emotional Calculation and Polar Classification

In the Zhihu community, answers are a collection of novel forms of comments or debates in which people participate, sometimes with objective and neutral comments, sometimes with critical and negative comments, or sometimes with complimentary comments. By computing sentiment scores to categorize emotions, sentiment analysis is primarily used in this study to discover negative sentiment response features. Sentiment analysis is a popular area in the field of natural language processing, and both domestic and international scholars have conducted in-depth research on the subject [37]. The rule-based sentiment analysis method in particular has a high level of accuracy when it comes to determining the sentiment of online comment texts [38].

Emotional Calculation Rules

The sentiment characteristics of the answer text are closely related to the words used and their sentiment polarity, the degree of word modification, whether or not they contain negative words, etc. This study uses numerical computation to determine the sentiment value of the answer text. This study develops three types of rules for the task of analyzing the sentiment of answer text based on the rule of the sentiment lexicon, the rule of the degree ad-verbs, the rule of the deletion of the words, and the rule of the negative words, along with the linguistic characteristics of Zhihu's answer text.

(1) Rule 1: Emotion Dictionary Rule

The Chinese Emotion Vocabulary Ontology [39] is utilized as an emotion word lexicon in this investigation. A total of 27,466 emotional terms are included in the dictionary, which methodically describes the Chinese language from many angles, such as lexical groups (as indicated in Table 1). The dictionary divides words' emotional potency into five groups, ranging from 1 to 9, with 9 denoting the strongest emotional potency. The four categories are 0 (neutral), 1 (positive words), 2 (depreciative words), and 3 (positive or depreciative words) and are used to classify words with varying intensities in various categories. The affective polarity values of words representing depreciative words (originally represented by 2) and words representing positive and depreciative words (originally represented by 3) were numerically changed to -1 and 1, respectively, as part of this study's attempt to quantify the affective features of the response texts. The value was modified to 1. Using the following formula for specific words, the sentiment value M of each word was determined by its

Table 1. Examples of the Chinese Affective Vocabulary Ontology's formatting.

Term	Words type	Number of words and meanings	Meaning of a word Serial number	Sentiments categorization	Dissociation Sa	Polarities J	Auxiliary Emotions categorization	Dissociation	Polarities
Bright	adj	1	1	PA	5	1	PH	1	1
Certain	adv	1	1	PG	9	0	NN	1	2
Dubious	idiom	1	1	NE	5	2	NN	3	2
Miser	noun	1	1	NN	3	2	ND	1	2
Cool	nw	1	1	PH	5	1	PB	5	1
Astute	prep	1	1	PH	9	1	PB	3	1
Dispel doubts	verb	1	1	PH	3	1	PA	1	1

Table 2. Classification of Emotions in the Ontology of Chinese Emotion Words.

NO.	Emotional Categories	Emotional Subcategories	Example Word(s)
1	Happy	Joyful (PA)	Joyful, jubilant, grinning, and joyous
2		Relieved (PE)	Grounded, relieved, reassured, and inquisitive
3	Fine	Honorable (PD)	Respectful, adoring, respectful, and awe-inspiring
4		Salutary (PH)	Handsome, brilliant, reasonable, and practical
5		Convinced (PG)	Confidence, trustworthiness, reliability,and unquestionability
6		Pet (PB)	Adore, baby, love at first sight, and love at first sight
7		Wishful (PK)	Desire, blessing, long life, and long life
8	Angry	Angry (NA)	Angry, irritated, furious, and seething with anger
9	Sad	Sad (NB)	Sadness, grief, heart-break, and sorrowfulnessl
10		Disappointed (NJ)	Regret, despair, discouragement, and disillusionment
11		Guilty (NH)	Guilt, contrition, remorse, and guilt
12		Missing (PF)	Thinking about, missing, holding on to,and thinking about
13	Fear	Flustered (NI)	Panicked, flustered, overwhelmed, and frazzled
14		Scared (NC)	Timidity, fear, trepidation, and trepidation
15		Shyness (NG)	Shy, bashful, blushing, and embarrassed
16	Evil	Gloomy (NE)	Stifled, irritable, distracted,and self-seeking
17		Hateful (ND)	Repugnant, shameful, hateful, and abhorrent
18		Derogatory (NN)	Dull, vain, disorganized, and hard-hearted
19		Jealous (NK)	Jealousy, jealousy, jealousy, and cynicism
20		Suspecting (NL)	Suspicious, skeptical, trustworthy, and doubtful
21	Surprise	Surprised (PC)	Strange, miraculous, amazed, and jaw-dropping

sentiment intensity and sentiment polarity:

Rule 1:

$$Emotion\ value\ M = \text{int}ensity\ Sa * polarity\ J \quad (1)$$

The dictionary's lexical categories are divided into seven major groups, including nouns, verbs, and adjectives. As indicated in Table 2, there are 21 subcategories within the seven basic emotional categories of happy, fine, angry, sad, fear, evil, and surprise. For instance, the major category of joy is further divided into two subcategories: happiness and peace of mind.

(2) Rule 2: Degree Adverbs Rule

In this paper, we adopt "Degree Level Words" from https://kns.cnki.net/ as the degree adverb dictionary [40], which contains six levels of degree adverbs, and the author has customized the assignment of the emotional intensity of the words under different degree levels, and the rules are defined as shown in Table 3.

These weights can be estimated using this rule:

Table 3. Dictionary of Adverbs of Degree.

NO.	Degree Level	Emotional Intensity Sb (weight)	Number of Words
1	Extreme	1.75	69
2	Very	1.5	42
3	More	1.25	37
4	Ish	0.75	29
5	Insufficiently	0.5	12
6	Over	0.25	30

Rule 2:

$$W = current\ weight\ W * emotional\ intensity\ Sb \quad (2)$$

(3) Rule 3: Negative Words Rule

In this study, we use the CSDN community's list of 71 negative words for Chinese as the negative word dictionary to conduct sentiment analysis. Since some of the negatives overlapped with sentiment words and degree adverbs, which had an impact on the calculation of the final sentiment score, a total of 60 negatives that did not contain sentiment words and degree adverbs were also filtered through text de-duplication. The negative word rule is defined as:

Rule 3: $$W = -1 * current\ weight\ W \quad (3)$$

Jieba term segmenter is mostly used in the Chinese segmentation mission. Three options are available in its word segmentation mode: accurate, search engine, and full. Every mode is unique. The accurate word segmentation approach were adopted because of the professional documents in the field of new energy vehicles that were collected for this study. The main ideas in the text will experience "noise interference" if the word vector following word division is paired with a significant number of dropped words. To increase the accuracy of the text by using keywords, stop words in the text should be eliminated. The most well-known seizures from three different categories – Baidu's stops, Harbin Institute of Technology Disable Victims, and Sichuan University Machine Intelligent Laboratory Disable Victims – are included in one article. Create a dictionary with 3137 terms after the merger and relaunch, including "About," "Ga," and other stop words. A total of 2837 stop words do not contain these three categories of words, which makes it necessary to specifically note that this technique makes it simple to filter out some emotional words, negative words, and degree adverbs that are crucial for emotion calculation.

Sentiment Calculation and Classification Algorithm

For the online Q&A community's queries and responses, this contribution developed the Sentiment Calculation and Classification Algorithm (SCCA Algorithm). The method mostly relies on the guidelines established before and one prior work written by the authors [41]. The following actions are detailed:

Algorithm 1: Sentiment Calculation and Classification Algorithm

Input: original questions and corresponding answers. Textset Q and set A

Output: ssentiment calculation score for each question and answer, and sentiment classification

Procedure:

1. Establish the stop words dictionary, negative word dictionary, adverb degree dictionary, and emotion words, and construct a lexicon of emotion words and a lexicon of emotion categories through the Chinese Emotion Vocabulary Ontology
2. Extract original questions and answers text Q and A from database, $Q = \{q_1, q_2 ... q_i, ... q_n\}$, $A = \{a_1, a_2 ... a_i, ... a_n\}$
3. Extract sentences q_i, a_i, take "." "." "!" "!?" "?" "..." as cutting units for sentence slicing and Chinese Word Segmentation, which were mainly implemented by Python's Jieba
4. Take the results of sentence slicing as set $QSS = \{\}$ and set $ASS = \{\}$; and the results of Word Segmentation as $QSSW = \{\}$ and $ASSW = \{\}$
5. SET W = 1, **Score1** (score of single sentences from ASS) = 0; **Score2** (score of a single answer from SET A, namely a_i) = 0; and **Score3** (score of one question from set Q, namely q_i) = 0
6. for all $ASSW_j \in ASSW = \{\}$
7. match to stop words dictionary, then word removal work
8. match to the Emotion Dictionary, then Rule 1
9. match to Adverbs Degree Dictionary, then Rule 2
10. match to the Negative Words Dictionary, then Rule 3
11. end if the word is the last word in the Emotion Dictionary, the Adverbs Degree Dictionary, or the Negative Words Dictionary
12. calculate $Score1 = w*m$
13. calculate $Score2 = \sum_{i=1}^{n1} Score1 \div n1$ (n1 refers number of sentences in each answer)
14. calculate $Score3 = \sum_{i=1}^{n2} Score2 \div n2$ (n2 refers number of answers for each question)
15. else scan the next word, back to step 4
16. return sentiment calculation score: Score1, Score 2, and Score 3
17. set emotional category EC = {sad, dislike, like, surprise, fear, happy, angry, neutral}
18. run Algorithm 2 to realize emotional classification for a_i
19. return EC of a_i
20. end

Since there is no direct relationship between the scores obtained by Algorithm 1's single sentence, single answer, or single question and only one emotional classification for replies algorithm is created for this task, the scores cannot be used for the emotional classification task.

Algorithm 2: Emotional Classification for Answers Algorithm

Input: $ASSW = \{\}$ from the 4th step in Algorithm 1

Output: Emotional category of a_i (ECA_i)

Procedure:
1. read Classification of Emotions in the Ontology of Chinese Emotion Words Dictionary (*ECD*)
2. read $ASSW = \{\}$
3. for all categories EA_i in EC {} (step 17 in Algorithm 1)
4. callback to Algorithm 1
5. calculate $Score1\_EC_i$ and $Score2\_EC_i$ of each EC_i
6. record key-value pairs: $\{EC_i,\ Score1\text{-}EC_i\}$, $\{EC_i,\ Score2\text{-}EC_i\}$
7. end for all calculate min(abs($Score2\text{-}EC_i - Score2$))
8. get $EC_i = ECA$
9. return ECA_i
10. end

Net Construction Algorithm

Our study focuses on a few network properties that negative emotions reflect. This section's aim is to create negative emotional networks based on algorithms 1 and 2, and one method for building negative emotional networks is created (algorithm 3).

Algorithm 3: Negative Emotional Network Construction Algorithm

Input: $ASSW = \{\}$ from the 4th step in Algorithm 1, Score2 (score of single answer from SET A, namely a_i) from the 5th step in Algorithm 1

Output: Negative emotional network

Procedure:
1. Set key pair {$ASSW = \{\}$, Score2 of each a_i},
2. For all (Score2<0), means the emotional value is Negative
3. get corresponding $ASSW = \{\}$
4. add to set ***NAW*** ( )
5. End
6. Draw a word cloud map by R language based on word frequency in ***NAW,*** where the word frequency >N (N can be defined according to actual needs or application scenarios) after synonymous merger work
7. Set $HFW = \{\}$ where the word frequency >N
8. SET

$$WCate = \left\{ battery\ life,\ market,\ \exp erience,\ brand,\ techno\log y,\ else \right\}$$

9. For all $HFW_i \in HFW = \{\}$
10. Divide HFW_i to $WCate_j$ by manual labeling
11. Return pair $\{HFW_i,\ WCate_j\}$
12. End
13. form $matrix_{HFW} = \begin{pmatrix} hfw_{11} & hfw_{12} & \cdots & hfw_{1j} & \cdots & hfw_{1n} \\ hfw_{21} & hfw_{22} & \cdots & hfw_{ij} & \cdots & hfw_{2n} \\ \vdots & \vdots & & \vdots & & \\ hfw_{n1} & hfw_{n2} & \cdots & hfw_{nj} & \cdots & hfw_{nn} \end{pmatrix}$
14. Calculate the co-occurrence times of HFW_i in $ASSW = \{\}$, and assign it to int C
15. Generate a network based on $matrix_{HFW}$, C and $WCate_j$

To put it briefly, the input of algorithm 3 is sentence slicing the results of answers $ASSW = \{\}$ and score of single answer from SET A from algorithm 1 (the 4th and 5th steps), and the output is a negative emotional network.

First of all, based on $ASSW = \{\}$ and score 2, to get a word set for negative answers (*NAW()*);

Secondly, draw a word cloud map by R language based on word frequency in *NAW()* where the word frequency >N after synonymous merger work;

Thirdly, divide words in *NAW()* into six categories { battery life, market, experience, brand, technology, and others} by manual labeling to construct $\{HFW_i,\ WCate_j\}$ pair and form $matrix_{HFW}$;

Forthly, calculate the co-occurrence times of HFW_i as C;

At last, generate a network based on $matrix_{HFW}$, C and $WCate_j$ using the Gelphi tool.

So far, the methodology of this work can be concluded as Fig. 1.

Data Source and Its Organization

Social Q&A platforms have grown in development as a result of the rapid growth of the mobile Internet, and they now rank among the most significant sources of knowledge in the Internet era. Quora and Zhihu are the two most popular social Q&A platforms at the moment. Zhihu is referred to as "Quora in China" and creates an ecosystem of "question-answer-comment-feedback" and offers a tool for creating, sharing, and spreading information.

The goal of this study is to gather data on concerns or conversations surrounding new energy vehicle quality standards, after-sales service, key technologies, etc. in the Zhihu community and to gather negative emotional data on this basis to conduct mining research. The main steps in the data collection process for this study are:

Seed Words for Data Collection

In this study, we gather pertinent inquiries on new energy vehicles on the Zhihu platform using the web crawler program "Octopus Collector". The well-known domestic and international new energy vehicle brands include BYD Auto, Tesla China, SAIC Motor Corporation (Shanghai Automobile Works), GAC Yi'an, Great Wall Motors, and Azure Auto, among others, according to the "2020 China New Energy Vehicle Industry White Paper" published by Ai Rui Consulting and the "January-November 2020 New Energy Vehicle Sales Data" from the Trolley Resource Institute of the Passenger Vehicle Association. As a result, in order to create an initial dictionary for Q&A acquisition in the field of new energy that takes into account the search rate and accuracy during the information retrieval

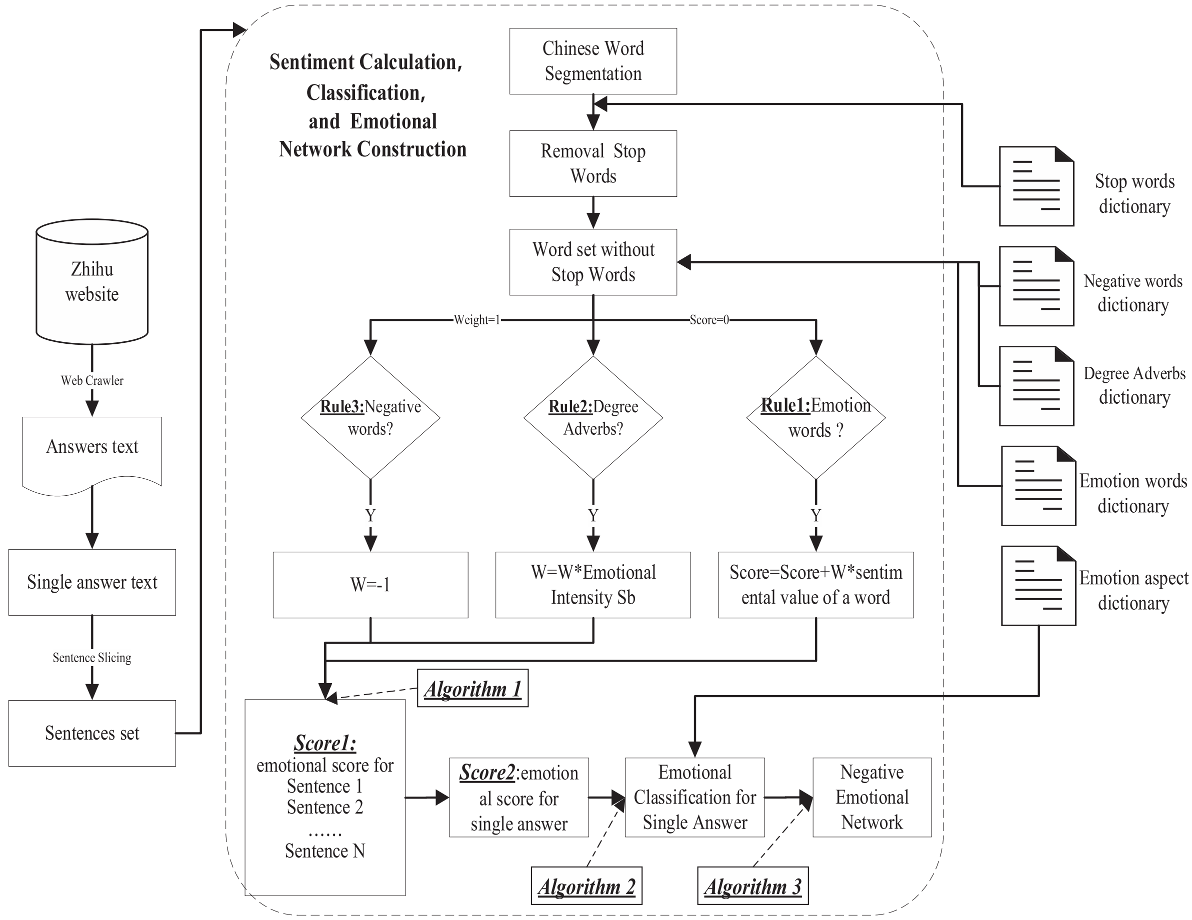

Fig. 1. Flow Chart of the methodology (including Algorithms 1, 2, and 3).

process, the data collection is carried out step by step using a trial search strategy, with a total of four sets of search terms that each contain 16, 21, 32, and 40 search terms, respectively (Table 4). The increase in the number of search terms and the corresponding collection results is combined with a manual review process. The experimental findings reveal that on March 21, 2021, the network environment was the same case for data collection operations, collecting 1636, 2687, 4168, and 4278 pieces of data, respectively. The last collection in the search terms increased by 8 cases; the incremental increase in the set related to the match is smaller; and it was ultimately decided that the fourth collection of the 40 search terms would be set up as a final collection of data for retrieval.

With the aid of the Octopus data collector, the data collection task was completed at 15:30 on March 21, 2021, based on the dictionary created in Step 1 that contained 40 new energy-electric vehicle domains. Since each Q&A in Zhihu is saved on its own webpage, the manual extraction stages during data collection are as follows:

(1) Type the first 40 search terms from the list;

(2) Go to the related Q&A page by clicking on each question's link, then copy the question's title, its description, its text response, etc.

(3) Click on each user who responds in turn to record their basic contact information, such as how many followers they have, how many questions they've been asked, and other details (user information).

Table 4. List of search terms for data collection.

NO.	Number of Seed Words	Words Increased	Records Matched	Records Increased	Records Increased / Words Increased
1	16	0	1636	0	0
2	21	5	2687	1051	210.20
3	32	11	4168	1481	134.64
4	40	8	4278	110	13.75

Table 5. Types and quantities of problems in the field of new energy vehicles.

Question type	Quantity	Examples of questions
Direct evaluation	101	What do you think of Xiaopeng Motors?
Brand Comparison	36	Esla Model 3 or Mercedes C260?
Suggestions for Selection	38	How to choose a new energy vehicle in 2020?

Table 6. Answer types and word count of questions in the field of new energy vehicles.

	Number of answers	Number of words	Average number of words
Text only	3926	948856	242
Text and pictures	1278	1708289	1337
Pictures only	16	0	0

(4) The study's initial dataset consisted of 441 questions and 14,581 corresponding answers.

In order to identify the new energy vehicle industry's influencing factors in Q&A platforms, this study focuses on the sentiment tendency of users toward new energy vehicles, necessitating the screening of questions that are directly related to the new energy vehicle reviews. However, a lot of the first data that was already gathered in Step 2 includes inquiries that have nothing to do with the evaluations of new energy vehicles, such as "Is it embarrassing for young people to drive a Wuling Hongguang?" "How is the work environment at Geely?" This study therefore performed data cleaning on the initial data source, which was jointly completed by three team members. Two of the team members initially screened the 441 questions to see if they related to the evaluation of new energy vehicles, and if there were any discrepancies, the other one joined the screening work. Ultimately, 175 questions related to the evaluation of new energy vehicles were identified after many iterations of validation and team judgment. As indicated in Table 5, the research team eventually identified 175 questions (with a total of 5,220 answers) about the evaluation of new energy vehicles that may be classified into three categories: direct evaluation, brand comparison, and purchasing suggestions.

In the responses to questions about the new energy vehicle industry, 3926 out of 5220 responses were of the text-only variety (totaling 948856 words, with an average of 242 words per Q&A); 1278 responses were text accompanied by pictures (totaling 1708289 words, with an average of 1337 words per Q&A); and 16 responses contained only pictures, which were disregarded because the current study focused on the text for sentiment analysis (Table 6). Although there were 3926 responses with only text, or 75% of the total, the average number of words in a text-only response is far lower than that of a response with images.

Results and Discussion

New Energy Vehicle Domain Q&A Sentiment Analysis

The Overall Analysis of Questions & Answers

This study calculates the sentiment scores of 175 questions about new energy vehicles (Fig. 2), as well as the sentiment scores of the 5,220 corresponding answers (Fig. 3) and their categorization (Fig. 4), based on the

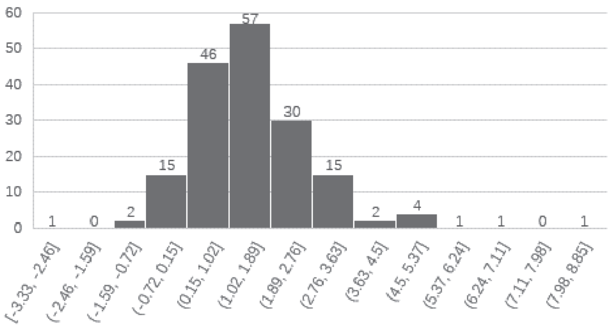

Fig. 2. Histogram of sentiment scores for 175 questions in the field of new energy vehicles.

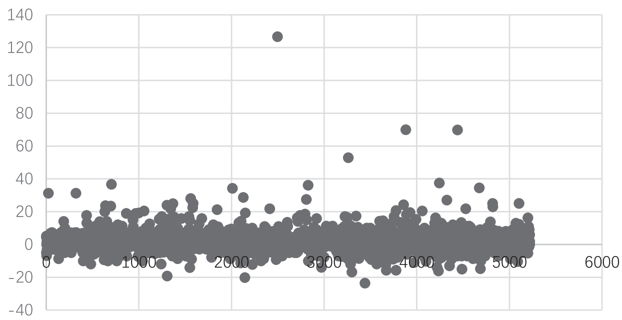

Fig. 3. Scatterplot of sentiment scores for 5220 answers in the field of new energy vehicles.

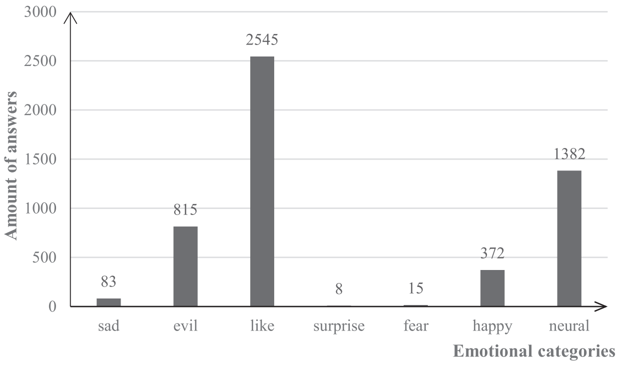

Fig. 4. Cluster Bar Chart for 5220 answers Sentiment Classification in New Energy Vehicles.

algorithm for calculating and categorizing the sentiment scores of answer texts on new energy vehicles proposed in the methodology section. In Fig. 2, the horizontal axis shows the interval of the sentiment score, while the vertical axis shows the number of responses. In Fig. 3, the horizontal axis shows the respondent's ID, and the vertical axis shows the score of a specific response.

Fig. 3's sentiment analysis of questions in the new energy vehicle field reveals that the 175 questions' overall sentiment scores followed a normal distribution, and 90% of the questions have positive sentiment scores, which suggests that Zhihu comments have a favorable attitude toward questions about new energy automobiles in general and are more favorable toward the new energy automobile industry's state of development.

The mean sentiment score of the 5220 answers in the field of new energy vehicles is 1.27, and the overall trend is a horizontal straight line, with the positive score responses and negative score responses symmetrically distributed along the trend line while there are individual extremes, indicating that the response users have a more positive and generally tend to be consistent with the comments related to the responses. The sentiment calculation for one response text results in a score of 126.62, which is "The experience was very good, the handling was very good, the acceleration was very good, and it was perfect for driving around the city."

As demonstrated in Fig. 4, Zhihu has the most responses to the evaluation of new energy vehicles, with 2,545 responses classed as "like" and 372 responses categorized as "happy", which is similar to "like". Together, these 2,545 and the 372 responses labeled as "happy" account for 55.88% of all the answers. Which means that more than half of the answers to the questions related to new energy vehicles are more positive, indicating that the online Q&A community users are generally optimistic and affirmative, but at the same time there are some users who expressed their dissatisfaction with new energy vehicles. The more negative emotional categorization mainly included "sad," "evil," "fear," and "surprise" in a total of 921 (17.64%). The users' opinions of new energy vehicles are varied, according to the results of the answer text's sentiment classification, and no one follows the herd's affirmative or negative sentiments blindly. The specifics of each user's opinion will be discussed in the answer text individual analysis.

Answer Text Individual Analysis

This study extracted the response texts with sentiment scores at extreme values in order to further explore the fine-grained characteristics of user comments in the area of new energy vehicles. The 3 responses with higher or lower sentiment scores are provided in Tables 7 and 8, respectively. While the responses with lower emotional scores summarize the possible causes for the lower emotional scores, which mainly lie in the range of new energy vehicles and charging trouble, etc., and some users have some criticisms about the trouble

Table 7. Examples of response content with high sentiment scores for Zhihu new energy vehicle evaluation responses.

NO.	Content of the answer	Emotional Score	Emotional categories
A_068_20210723_083	The handling, acceleration, and overall driving experience were all excellent, making it ideal for city driving.	126.62	Happy
A_138_20210723_017	Let's simply discuss my emotions. Ideal ONEA: the overall style is mature and stable, new and stable, add-on program no mileage pressure; both experiences down are not awful, style is slightly different. Azera ES6: features closer to the trend of the middle and high-end young people, voice control is more aesthetically pleasing.	70	Fine
A_146_20210723_059	When you go outside to play, you are aware of the advantages of Tesla supercharging stations and Azera's one and only power exchange station. However, these facilities are few and far between, and many locations only have a pit. Since this is the case, the line will be longer if you choose to do so. Tesla's long range of 668 kilometers is 340,000 kilometers, and the Azalea 420 range ES6 will be 350-370,000 kilometers or more, adding 58,000 kilometers to the battery out of 100 degrees. If you want to get an azalea, you must be able to charge it at home, as there are super charging stations in large cities all over the place.	37.52	Fine

Table 8. Examples of response content with low sentiment scores for Zhihu new energy vehicle evaluation responses.

NO.	Content of answers	Emotional Score	Emotional categories
A_064_20200914_157	The price of the contempt chain is actually the brand of the chain, which stands for imports despise joint venture and joint venture despises domestic. Millions despite tens of thousands, hundreds of thousands despite tens of thousands, hundreds of thousands despite hundreds of thousands, hundreds of thousands despite hundreds of thousands, hundreds of thousands despite hundreds of thousands, and hundreds of thousands despite tens of thousands, and then discovered that the Azera is more than 500,000, is the same as the Phaeton, there is a fool to buy this car.	-31.72	evil
A_117_20210723_089	Although an electric car has a good range, driving outside of the city is not recommended because if you get too far from a power source, it won't be any better than burning oil. However, what if there are no power outlets available and there aren't any charging stations nearby?	-16.81	sad
A_099_20210723_058	In the end, I wouldn't contemplate purchasing one because new energy vehicles lack the same sense of power as conventional vehicles, as well as having poor mileage, inconvenient charging, and batteries that don't perform any better in the winter.	-15.75	evil

of charging new energy vehicles, the responses with higher emotional scores reflect the user's own driving experience, and the answers to the questions based on driving new energy vehicles have a strong infectious force and authenticity. The charging issues and short driving range of the new energy vehicles have drawn harsh criticism from some users.

Characterization of Negative Responses to New Energy Vehicles

When compared to positive sentiment, the examination of negative sentiment can disclose information that is more helpful and likely to include important influencing variables that will have an impact on the growth of the new energy vehicle market. There were 941 unfavorable comments out of 5220 total responses (18.03%). These comments were subjected to word frequency statistics in order to create a word cloud map, based on algorithm 3: Negative emotional network development method. Fig. 5 displays the outcomes that were attained using the R tool.

According to the findings of the word cloud, in Fig. 5, among the responses with unfavorable sentiment scores, those with higher word frequencies are primarily related to Tesla, NIO NEXTEV, BYD, and other automakers,

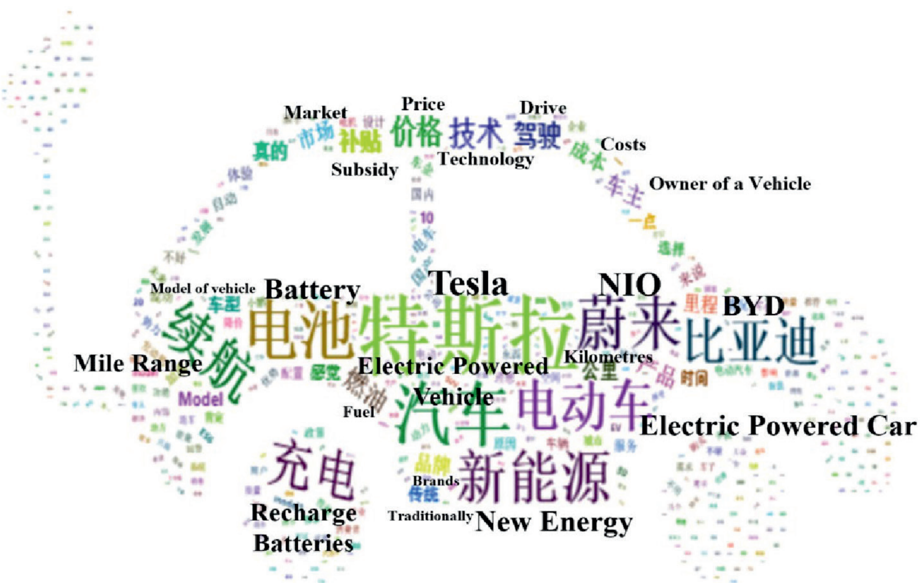

Fig. 5. Negative Sentiment Score Response Text Word Cloud.
Note: Fig. 5 shows the word cloud map in Chinese because it is the original language of the corpus. The important data in Fig. 5 is translated and presented in English.

as well as to price, subsidies, technology, driving, and other fundamental user concerns. The range, battery, and charging of new energy cars, as well as their pricing, driving experience, and subsidy programs, are the key causes of the negative sentiment scores, according to further analysis of the comments. According to some studies, users are more likely to comment positively on the power and appearance of new energy vehicles, which may be due to the fact that these vehicles typically have good power and a technologically advanced appearance, while users are more likely to comment negatively on the space and power consumption of these vehicles [42]. This study analyzes the features in the responses with negative sentiment scores based on algorithm 3 (set N = 30) and builds the negative sentiment network of answers for new energy vehicles proposed in the methodology section in order to further explore the intrinsic mechanism of the formation of negative responses for new energy vehicles. Based on the social network analysis technique, semantic network graphs are created by Gephi 0.92 to assess the features in answers with low emotion ratings. The 941 replies with low sentiment scores were grouped into six categories: battery life, market, experience, brand, technology, and others. Words were used as the building blocks for the co- occurrence matrix. Each node in the semantic network of negative responses corresponds to a keyword, and each edge corresponds to the aggregation relationship between two keywords (the occurrence of two keywords in the same response text indicates the existence of an aggregation relationship). The more the keywords are aggregated, the more closely they relate to one another. Fig. 6 depicts the drawn and formed keyword co-occurrence network graph of negative sentiment responses in the field of new energy vehicles. Each node is represented by a circle, and the larger the circle, the more words that co-occur with it. Each edge is a representation of an aggregation relationship, and it should be noted that the edges in the semantic network graph are directed line segments that point from the source node to the target node. In the semantic network graph, the direction is hidden, but it is visible through the edges' color, which matches the color of the target node.

In Fig. 6, through the dynamic semantic network diagram, it can be found that consumers are more concerned about the range of new energy vehicles, market, experience, brand, and technology-related areas in the negative sentiment semantic network, and the results of this study are more consistent with the actual situation: the keyword "problem" related to the experience, the keyword "Tesla" related to the brand, and the keyword "battery" related to the range of the top three links with high frequency of occurrence. According to this, among the energy vehicle brands, "Tesla" has generated a lot of conversation in the online community, and consumers are also more worried about the battery, which is directly tied to the range of new energy vehicles. Additional research into the correlation between these three links shows that:

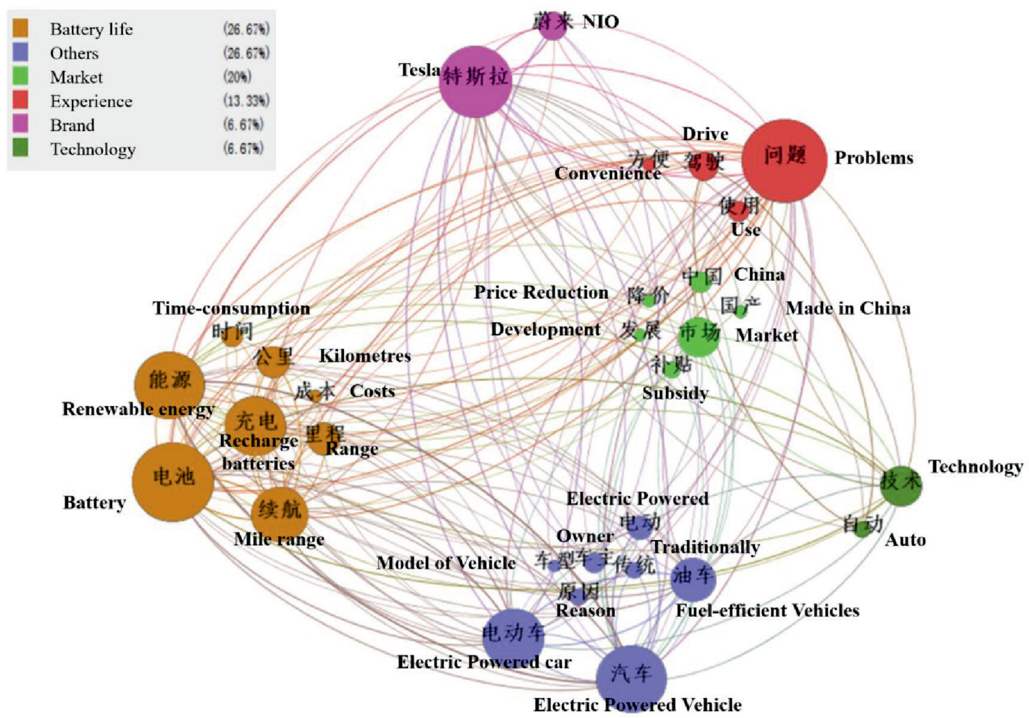

Fig. 6. Semantic network diagram for negative sentiment score answers.

Note: The negative sentiment score replies semantic network diagram (Fig. 6) is in Chinese because that is the original language of the corpus; the important details of Fig. 7 are translated and provided in English.

(1) The keywords most closely connected with the word "problem" mainly include "Tesla", "charging", "battery", etc., showing that consumers are more concerned about the battery problem, the charging problem, and the concerns of Tesla as a car brand. This demonstrates that people are more worried about the issues with Tesla, the battery issue, and the charging issue for new energy vehicles.

(2) The terms "battery" and "range", which are most frequently connected with "Tesla," indicate that Tesla's battery and range issues may have negatively impacted customer reviews.

(3) The terms that are most closely related to "battery" are "range," "mileage," "energy," etc., suggesting that users may be unsatisfied with the energy performance of new energy vehicles due to issues with range after charging. Since power batteries are an essential component of new energy vehicles, one of the main directions for the industry's development in the academic world is toward high-performance, low-cost power batteries.

(4) The high frequency of words like "price reduction," "domestic production," "subsidies," and "market", etc. in the semantic network may be related to the fluctuating costs of new energy vehicles, energy subsidies, automobile purchase taxes, automobile origin, and other hot-button issues. In addition, more community discussions revolve around topics such as comparing electric and fuel vehicles to each other, choosing an electric vehicle model, comparing powertrains, etc., and there is more negative sentiment generated on such topics.

The two major brands, Tesla and Azure, should be noted, particularly because they appear more frequently in the negative sentiment network while other new energy vehicle brands do not appear in the semantic network graph. This could be because these two major brands are currently the top sellers in the domestic electric vehicle market in China, with a high degree of hotness in Zhihu and a greater number of discussions on the existence of problems by users of the online Q&A community. However, in the word cloud diagram (Fig. 5), the number of responses related to BYD is comparable to those related to Tesla, Azera, and other brands, indicating that BYD has a good reputation in Zhihu. The brand BYD does not appear in the semantic network diagram of the negative sentiment score. Similar to Tesla and Azera, BYD received a similar number of answers.

This study suggests the following development paths for the new energy vehicle industry under the CPCN Goals based on the findings of word cloud mapping and semantic network construction of the answer texts in the new energy vehicle area with negative sentiment scores: First and foremost, we must keep advancing energy-saving technologies to support the growth of the new energy automotive sector; we must also solve the energy density and material structure of batteries through technological research and development; and we must resolve other crucial issues pertaining to the field of new energy automobiles, such as issues with vehicle battery energy storage, range, and charging. According to the CPCN Goals, it is especially crucial to concentrate on improving the use of green renewable energy in the energy supply of new energy vehicles, developing a system of electrified production in line with it, reducing reliance on conventional energy sources – such as enhancing the use of hydrogen energy in the supply of automotive power – and investigating distinctive paths and solutions for independent characteristics in the energy supply.

Secondly, the automobile industry needs to fully electrify in order to meet the CPCN Goals. In response to the negative perceptions of "subsidies" and "price reductions" in the online Q&A community, we should investigate the creation of a green tax system that would apply to the entire life cycle of automobiles in order to improve the greening of the new-energy automobile industry chain; and should clarify as soon as possible and effectively promote the subsidies for new-energy vehicles, the reduction and waiver of the purchase tax, and other policy measures.

Thirdly, we should carry out research on green transformation for the head enterprises in the new energy vehicle industry chain, so as to take the lead and promote the development of enterprises.

Fourthly, we should carry out technological research on key technologies in the industry chain, such as charging technology and high-power charging integrated equipment, to help realize the CPCN Goals.

Conclusions

Based on the fact that people in the Internet era use social Q&A platforms to obtain information, solve problems, and aid in decision-making, as well as the fact that in the mass of information negative answers typically have a higher degree of information perception and are easier to spread, we find a path for the development of a new energy automobile industry with the CPCN Goals. By using Zhihu, one social Q&A platform, as a representative, this study implements a negative sentiment feature recognition algorithm for social Q&A platforms and realizes the construction of a negative sentiment network based on social network analysis. The Q&A texts in the field of new energy vehicles are identified through the processes of determining seed words for data collection, the implementation of retrieval strategies, data crawling, data cleansing, and organizational techniques. In order to determine the development path of the new energy vehicle industry, this study used an experimental sample of 175 high-relevance questions in the field of new energy vehicles and 5220 answers to those questions. The study's findings reveal that:

(1) Users of the online Q&A community are more worried about the charging issues with new energy

vehicles, the battery issues, and potential issues with Tesla, which may have led to negative user reviews for its battery and range issues; the battery and range issues may have resulted in the users' negative evaluation of the brand; users are also worried about the range of new energy vehicles after charging. The three car brands with the most Q&A questions and user interest are Tesla, Azure, and BYD. However, BYD has not yet appeared in the brand's negative sentiment network, indicating that BYD is less negatively regarded in the Zhihu community.

(2) Technically speaking, the data collection strategy developed in this study has a high search rate and accuracy rate, and it can be used to direct the collection and screening of data in other fields that are related. Additionally, the online Q&A community answer text sentiment calculation, classification, and construction of a negative sentiment network developed in this study can identify the sentiment of the question and answer, as well as the division of sentiment polarity.

The new energy vehicle industry's growth trajectory, as based on the negative emotional network:

First of all, we must address the issue of challenging charging, popularize charging heaps, and address challenging charging at its source.

Secondly, focus on the battery issue and enhance battery security, because since the emergence of new energy vehicles, "new energy vehicles spontaneous combustion", "electric car explosions", and other news frequently, triggering a variety of concerns for prospective users of new energy vehicles prospective users, so the production should openly and transparently respond to the voices of doubt, improve the battery technology, reduce the negative impact of spontaneous combustion and, explosion incidents, and enhance the trust of car owners.

Thirdly, in order to encourage the growth of the new energy vehicle industry, new energy vehicle manufacturers should focus on quality control. Social Q&A platforms can integrate user sentiment analysis into the platform's functional modules in the context of big data to help users make decisions in real-time and with accuracy, assist automakers with word-of-mouth promotion, and advance the growth of the new-energy automotive industry.

Last but not least, the findings of this study can help to further improve the answer recommendation algorithm of socialized Q&A platforms like Zhihu, which can add the answer time interval and the number of answers as control variables into the sorting algorithm while taking into account the answer text characteristics, the answer user characteristics, and other factors, in order to further provide a more scientific answer sorting, screen out high-quality answers for the information receivers, and promote the use of answers that are both accurate and helpful.

What needs to be further discussed are the following:

(1) The social Q&A platforms based on this study only include Zhihu, which is not yet a comprehensive representative of social Q&A platforms; (2) The data analyzed in the study can only be cut off at a specific time, which prevents real-time updating and real-time analysis of the data of social Q&A platforms in order to provide more timely decision-making. In the task of sentiment analysis, images, English abbreviations, etc., similarly to Chinese text, can characterize users' emotional tendencies to some extent; however, this study has not yet taken into consideration the semantic features of images, English abbreviations, etc.; in addition, the identification of purposefully false comments is also a challenging problem in the task of sentiment analysis, which needs to be further solved; (3) The proposed development path for the new energy automobile industry under the CPCN Goals is based on the sentiment scores of the current Q&A data in social Q&A platforms, focusing on the Q&A information with negative sentiment scores, and has not yet revealed the intrinsic mechanism between negative sentiment scores and negative emotions; the aforementioned issues form the main research direction of this study.

Acknowledgments

The authors are very grateful to the respected editor and the anonymous referees for their insightful and constructive comments. The research was funded by: Eexcellent Young Backbone Teachers Project funding under the "Qing Lan Project" for higher education institutions in Jiangsu province; Jiangsu Provincial Social Science Foundation Project (21TQC003, 22GLB003); Ministry of Education Humanities and Social Science Fund Youth Project (22YJC870012); Innovation Fund General Project I of Nanjing Institute of Technology (CKJB202003), The Teaching Reform and Construction Project Of Nanjing Institute of Technology (JXGG2021031); and Jiangsu Province Education Science "14th Five-Year Plan" 2021 Annual Project (C-C/2021/01/62) AND and the Open Research Fund Of Njit Institute Of Industrial Economy And Innovation Management (JGKA202202).

Conflict of Interest

The authors declare no conflict of interest.

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