Research Article

A Study on Selection Strategies for Battery Electric Vehicles Based on Sentiments, Analysis, and the MCDM Model

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Under the goal of carbon peak and carbon neutrality, developing battery electric vehicles (BEVs) is an important way to reduce carbon emissions in the transportation sector. To popularize BEVs as soon as possible, it is necessary to study selection strategies for BEVs from the perspective of consumers. Therefore, the Latent Dirichlet Allocation (LDA) model based on fine-grained sentiment analysis is combined with the multi-criteria decision-making (MCDM) model to assess ten types of BEV alternatives. Fine-grained sentiment analysis is applied to find the vehicle attributes that consumers care about the most based on the word-of-mouth data. The LDA model is suggested to divide topics and construct the indicator system. The MCDM model is used to rank vehicles and put forward the corresponding optimization path to increase consumer purchases of BEVs in China. The results show that (a) via the LDA model based on fine-grained sentiment analysis, attributes that consumers care most about are divided into five topics: dynamics, technology, safety, comfort, and cost; (b) based on the DEMATEL technique, the dimensions in the order of importance are as follows: safety, technology, dynamics, comfort, and cost; (c) the price is the most important criteria that affect customers' satisfaction by the DANP model; and (d) based on the VIKOR model, the selection strategies present that Aion S is highlighted as the best choice, and the optimization path is discussed to promote the performance of BEVs to increase customers' satisfaction. The findings can provide a reference for improving the sustainable development of the automobile industry in China. The proposed framework serves as the basis for further discussion of BEVs.

1. Introduction

With the rapid growth of the number of vehicles, the issue of energy consumption and greenhouse gas (GHG) emissions in the transportation sector are attracting increasing attention worldwide [1, 2]. According to the International Energy Agency, the transportation sector accounts for about 24.6% of the world's energy-related carbon dioxide emissions [3]. Automobile emissions have been a major source of emissions in the transportation sector [4–6], which aggravates the deterioration of the ecological environment and causes a series of health problems [7–9]. China owns the largest automobile market in the world since 2009 [10], and car ownership has exceeded 200 million by 2020, indicating that the issue of energy security and environmental pollution will become more prominent [11, 12]. To alleviate these

problems, governments and automobile manufacturers pay more attention to develop cleaner and more efficient alternative-fuel vehicles [12, 13], which induces the upsurge of battery electric vehicles (BEVs) [14–17]. And, BEVs will become the mainstream of vehicle sales by 2035 in China [18].

However, in the early stage of the development of BEVs, only relying on market forces is not enough for the commercialization and popularization of BEVs [19]. Thus, the Chinese government has formulated a series of incentive policies for consumers and BEV manufacturers [20–23], e.g., purchase subsidies, tax exemption, free parking, and driving privileges [24, 25]. Based on the above incentives, from 2011 to 2019, the production and sales volume of BEVs increased from 5655 and 5579 to 1,020,000, and 972,000, respectively. More importantly, as a result of the reduction of subsidies,

sales of BEVs in July 2019 dropped significantly compared with June 2019, with a drop of 59.9% [26]. This means that the advantages of policy support offered by BEVs are not enough to persuade consumers [27]. Previous studies have highlighted that the low market share of BEVs is related to consumers' perceived uncertainty [28, 29], which means that exploring the selection strategies of consumers will help enlarge the market share of BEVs [30, 31].

Existing studies on vehicle selection and comparison are mainly based on life cycle assessment (LCA) [32], statistical methods [33], and multicriteria decision-making method (MCDM) [34, 35], but the influence of consumer sentiments on vehicle selection strategies is ignored. Therefore, this study attempts to use the Latent Dirichlet Allocation (LDA) model based on the fine-grained sentiment analysis, that is, to analyze the sentiment polarity of online reviews, to reveal the customer's sentiment towards the attributes of BEVs' models, and to extract the attributes that consumers care most about as evaluation criteria. The topic analysis is applied to distinguish dimensions. This method considers the index from the consumer's point of view and effectively avoids the problem of artificial selection. Based on this, quantitative cause-effect relationships among vehicle attributes are included as an important point in BEVs' assessment. It makes up for the lack of considering the correlation between attributes in the existing research. Taking ten domestic BEVs models in China as research samples, a detailed and practical optimization path is put forward, which solves the shortage that the existing research only considers evaluation and selection.

The main tasks of this study include the following aspects: (1) Using consumers' word-of-mouth data from Autohome website and LDA model based on the fine-grained sentiment analysis, a new evaluation index system of BEVs selection based on customer perspective is constructed. (2) Decision Making Trial and Evaluation Laboratory (DEMATEL) technique is utilized in this study to identify the interaction between criteria within each dimension. Analytic network process (ANP) is then employed to determine the weights of criteria and dimensions. (3) Modified Vlse Kriterijska Optimizacija I Komoromisno Resenje (VIKOR) is applied to calculate the indicator gaps and comprehensive evaluation scores for ten types of BEVs in China. Based on the above research framework, the customer selection strategies and the manufacturer optimization paths are proposed. The specific analysis process is shown in Figure 1.

The remainder of this study is organized as follows. Section 2 gives a literature review. Section 3 describes the methods. Section 4 presents the results. Section 5 conducts a discussion. Section 6 presents the conclusions.

2. Literature Review

This section briefly reviews the literature from three aspects: application of machine-learning methods in the field of electric vehicles (EVs), application of MCDM models in vehicle selection, and the factors influencing consumers' choice of BEVs.

2.1. Application of Machine-Learning Methods in the Field of EVs. With the rise of big data analysis and machine learning, many scholars have applied it in the field of EVs. Bas et al. [36] applied supervised machine-learning techniques to identify key elements influencing EVs' adoption and classify potential EVs purchasers. De Clercq et al. [37] made use of two machine-learning techniques, i.e., LDA model and multi-label classification algorithm to extract subject words from patent texts and classify patents into multiple cooperative patent categories. Yang et al. [38] evaluated and optimized relevant policies of China's new energy vehicle industry based on text mining technology. In the study of Naumanen et al. [39], LDA model was used to identify emerging research topics according to papers and patents related to heavy duty BEVs. Aguilar-Dominguez et al. [40] used a machine-learning method to evaluate the availability of five vehicles participating in the vehicle-to-home services. Basso et al. [41] applied the probabilistic Bayesian machine-learning model to solve the route selection problem and found the best route for EVs by predicting the energy consumption within the limited driving distance. Ma et al. [42] adopted big data and text-mining technologies to analyze online behavior of Chinese consumers and to identify the factors affecting consumers' preferences. Different from previous research on online comment mining, emotion analysis is not only the mining and analysis of consumers' online comments but also the extraction and interpretation of emotions expressed in texts [43]. The purpose of sentiment analysis is to investigate the emotion polarity of online texts and divide them as positive, neutral, and negative [44]. However, only a few papers in the literature apply sentiment analysis to the analysis of consumers' recognition of vehicle. Via big data platform, Deep Learning techniques were employed by Jena [44] to explore and classify consumers' sentiment towards EVs in India.

2.2. Application of MCDM Models in Vehicle Selection. According to previous studies on MCDM, MCDM models could be classified into the following two categories. The first category is applied to calculate the weights of alternatives, such as the Simultaneous Evaluation of Criteria and Alternatives (SECA) [34], Analytical Hierarchy Process (AHP) [35], ANP [45], and Stepwise Weight Assessment Ratio Analysis (SWARA) [46]. In the second category, the ranking of alternatives is based on comprehensive scores such as Measurement of Alternatives and Ranking according to Compromise Solution (MARCOS) [34], Complex Proportional Assessment (COPRAS) [46], VIKOR [47], Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [48], ELimination and Choice Expressing the REality (ELECTRE) [49], Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) [50], and so on. In addition, the combination of these methods has also attracted the attention of academic circles. To enhance the robustness, scholars have combined the single method and formed the newly developed hybrid MCDM models.

FIGURE 1: Analysis procedure of the study.

In recent years, based on the hybrid MCDM models, a series of scientific and systematic theoretical explorations have emerged, especially in vehicle evaluation and selection. For example, Li et al. [47] adopted an MCDM combining AHP and VIKOR to rank and optimize four types of vehicles, including EVs, gas vehicles, methanol vehicles, and ethanol vehicles, to provide references for decision-makers in the new energy automotive industry. Using intuitionistic fuzzy set and TOPSIS methods, Onat et al. [48] evaluated

and ranked the performance scores of alternative vehicles, which indicated that hybrid electric vehicles were the most proper choice. Das et al. [51] developed a fuzzy AHP-EVAMIX hybrid model for evaluating and comparing the performance of electric vehicles in Asia. Tzeng et al. [52] developed a hybrid approach including AHP, TOPSIS, and VIKOR for alternative fuel buses like fuel cell, electricity, and methanol. The final ranking shows that the hybrid electric bus is the most suitable choice. Liang et al. [53] presented a

fuzzy MCDM assessment model to evaluate and compare alternative-fuel vehicles, and the research results show that biodiesel vehicles are the best choice.

2.3. The Factors Influencing Consumers' Choice of BEVs. Vehicle purchasing is closely related to consumers' acceptance. Up to now, many studies have explored the possible drivers or barriers that influence consumers' choice of BEVs [54]. Liu et al. [55] found that the customer experience is the main decisive factor in buying BEVs. Kim et al. [56] concluded that customers with good driving experiences and knowledge are more likely to buy BEVs in Korea. Li et al. [57] found in their study that family factors, such as scale, income, and location, can influence consumers' choice of BEVs. She et al. [58] demonstrated that older, experienced, and environmentally conscious consumers were more interested in buying a BEV in Tianjin. Besides, safety, reliability, and range were the three key obstacles to BEV sales. Dong et al. [59] recognized that urban consumers' purchasing decisions would be changed by psychological factors such as subjective norms, feelings and emotions, personal norms, and perceived behavioural control. Li et al. [60] argued that fast charging time and battery warranty can promote consumers' adoption of BEVs. Das et al. [51] evaluated the performance of EVs based on nine attributes, such as the price, battery capacity, torque, charging time, overall weight, seating capacity, driving range, top speed, and acceleration. Nazari et al. [31] stressed that the elimination of concerns such as technical uncertainty, limited vehicle styling, and charging time will increase the utilization rate of BEVs. In addition to price and battery technology, Ma et al. [42] suggests that the design of the exterior and interior has a strong appeal to consumers. Kukova et al. [61] pointed out that internal space, operating reliability, and braking are also important attributes affecting whether consumers choose BEVs or not. Li et al. [24] believed that the implementation of financial incentives, such as purchase subsidies and tax exemption, played an indispensable role in promoting Chinese consumers to adopt BEVs. In the study of Cheng et al. [4], reduction in battery charging time and maintenance cost were the first two major measures to motivate consumers to purchase BEVs. Although existing studies have considered the influence of demographic, technological, and psychological factors on consumer purchasing behavior, researchers have shown that consumers' decision to purchase BEVs is largely determined by the vehicle's performance characteristics [62, 63]. Therefore, in this study, only the influence of vehicle attributes on BEVs selection is considered, and other factors are not considered.

To sum up, although previous studies on vehicle selection have made some progress, there are still the following limitations: (1) Some studies have not clearly explained how to select indicators. In addition, some studies have pointed out that indicators are obtained through literature review, but this process is susceptible to subjective factors. (2) The indicators are interdependent, but many studies have not clearly identified the cause-effect relationship. (3) The literature does not provide beneficial guidance for consumers

to choose BEVs in China. There is no mention of the optimization paths of specific models. Therefore, this study adopts the LDA model based on fine-grained sentiment analysis to obtain indicators. The MCDM model is used to identify interrelationships, and to propose selection strategies and optimization paths for BEVs in China from the point of view of consumers.

3. Methodology

This research proposes a hybrid model combining fine-grained sentiment analysis and MCDM model to form a novel framework to study consumers' selection strategies for BEVs. Specifically, the LDA model based on fine-grained sentiment analysis is applied to identify dimensions and criteria based on the word-of-mouth data of BEVs in Autohome website. DEMATEL technique is used to construct an influential network relationship map (INRM). DEMATEL-based Analytic Network Process (DANP) is used to confirm the impact weight of each evaluation indicator based on ANP [64]. Finally, VIKOR is not only used to evaluate and obtain the selection strategies but also to find the gaps in each evaluation indicator and make optimal paths to improve consumers' adoption.

3.1. Sentiment Analysis

3.1.1. Text Preprocessing. In this study, the Scrapy framework developed in Python is used to crawl the word-of-mouth data. However, invalid data in the crawled text will affect the effectiveness of data output. If these invalid data are introduced into subsequent models, it can have a significant impact on the results of the analysis. Therefore, text preprocessing should be carried out after obtaining the word-of-mouth data of the Autohome website. In this paper, the process of text preprocessing is divided into several steps, including data splitting, data cleaning, text segmentation by jieba clauses, removing stop words, adding self-defined automobile dictionary, and data transformation.

3.1.2. Doc2vec Model. After preprocessing the data, the text data are divided into a test set and a training set based on a certain ratio. Then, we build a Doc2vec model based on the training set data, train the test set data with the Doc2vec model, and finally build a support vector machine classifier to calculate the accuracy of the test set.

3.1.3. Skip-Gram Model. Emotional granularity can be divided into two types, i.e., positive and negative emotional polarity; however, to increase the accuracy of the regression model, the emotional granularity is further refined, i.e., emotional polarity is divided into five types (very satisfied, satisfied, fair, dissatisfied, and very dissatisfied). The text preprocessed data are trained 100 times using word2vec to obtain a Skip-gram model (a method for learning high-dimensional word representations that capture rich semantic relationships between words) with a word vector dimension of 200 dimensions. The results of the text

preprocessing are used to obtain the emotion words with high word frequency, and then the Skip-gram model is used to obtain words that are similar to the emotion words to obtain a more comprehensive emotion vocabulary.

3.1.4. Clustering. The clustering algorithm divides the emotional lexicon of word-of-mouth into five categories based on the difference between the customers' expectations and the actual perception of the BEVs.

3.1.5. LDA Model. Topic models are algorithms for discovering key topics in a large and unstructured collection of text [65]. LDA is one of the topic models, which is applied to automatically discover topics in the text that consumers are most satisfied and least satisfied with. The core computational problem for topic models is to use the collected text to infer the hidden topic structure [66]. Thus, this study identifies the consumer concerns by using the LDA model, to discover key topics from the collected text.

3.2. MCDM Model

3.2.1. DEMATEL Technique. DEMATEL technique is a systematic factor analysis method to detect the cause-effect relationships between complicated indicators using graph theory and matrix tools [67], originally proposed by the Battelle Research Centre in 1972 [68]. DEMATEL has been used to solve complicated real-world problems by building an INRM [69], such as optimal online travel agencies [70], regional innovation capacity [71], and sustainable online consumption [72]. Thus, the steps of this technique are summarized as follows.

Step 1. Finding the average direct effect matrix.

The mutual direct effect among criteria is evaluated by the knowledge-based experts. The scales ranged from 0 to 4 where "0" means "absolutely no effect" and "4" means "very high effect." "1," "2," and "3" mean "low effect," "middle effect," and "high effect," respectively. By a pairwise comparison, we can obtain these groups of direct matrices by scores, where ij represents the influence from criterion i to criterion j . After that, we can calculate an average direct effect matrix G (as seen in equation (1)), where each criterion is the average of the corresponding criteria in the experts' direct matrices [73].

$$G = \begin{bmatrix} g_c^{11} & \dots & g_c^{1j} & \dots & g_c^{1n} \\ \vdots & & \vdots & & \vdots \\ g_c^{i1} & \dots & g_c^{ij} & \dots & g_c^{in} \\ \vdots & & \vdots & & \vdots \\ g_c^{n1} & \dots & g_c^{nj} & \dots & g_c^{nn} \end{bmatrix}, \quad (1)$$

Step 1. Setting up the normalized direct-influence matrix X .

The matrix X can be acquired by using equations (2) and (3).

$$X = S \times G, \quad S > 0, \quad (2)$$

where

$$S = \min i, j \left\{ \frac{1}{\max_i \sum_{j=1}^n g_c^{ij}}, \frac{1}{\max_j \sum_{i=1}^n g_c^{ij}} \right\}, \quad i, j \in \{1, 2, \dots, n\}. \quad (3)$$

Step 1. Computing the total influence matrix T_c .

The total influence matrix T_c can be derived from equation (4), where matrix I denotes a unit matrix.

$$\begin{aligned} T_c &= X + X^2 + X^3 + \dots + X^\theta \\ &= X(I + X + X^2 + \dots + X^{\theta-1})(I - X)(I - X)^{-1} \\ &= X(I - X^\theta)(I - X)^{-1} = X(I - X)^{-1}, \end{aligned} \quad (4)$$

where $X = [x_c^{ij}]_{n \times n}$, $0 \leq [x_c^{ij}] \leq 1$, $0 < \sum_{j=1}^n x_c^{ij} \leq 1$, and $0 < \sum_{i=1}^n x_c^{ij} \leq 1$, and at least the sum of one row or column (but not all) equals one; $\lim_{\theta \rightarrow \infty} X^\theta = [0]_{n \times n}$.

Step 4. Building the INRM and analyzing the results.

The sum of rows and the sum of columns of total influence matrix T_c can be, respectively, represented by vector r and vector s according to equations (5)–(6), where r_i indicates the total influence of criterion i on others, the s_i denotes the total influences received by criterion j from other criteria. When $i = j$ and $i, j \in \{1, 2, \dots, n\}$, the vector $(r_i + s_i)$ expresses the importance of criterion i in the question. Likewise, the vector $(r_i - s_i)$ identifies the degree of causality among indicators. Simultaneously, if $(r_i - s_i)$ is positive, the criterion i influences other criteria. On the contrary, if $(r_i - s_i)$ is negative, the criterion i is affected by others. Finally, draw the INRM in which the vertical axis represents $(r_i + s_i)$ and the horizontal axis represents $(r_i - s_i)$ [74].

$$T_c = [t_c^{ij}]_{n \times n}, \quad i, j \in \{1, 2, \dots, n\},$$

$$r = \left[\sum_{j=1}^n t_c^{ij} \right]_{n \times 1} = [t_c^i]_{n \times 1} = (r_1, \dots, r_i, \dots, r_n)', \quad (5)$$

$$s = \left[\sum_{i=1}^n t_c^{ij} \right]_{1 \times n} = [t_c^j]_{1 \times n} = (s_1, \dots, s_i, \dots, s_n). \quad (6)$$

The total influence matrices has two forms, one is $T_c = [t_{ij} c]_{n \times n}$ (equation (7)), where n represents the number of the criteria, and the other is $T_D = [t_{ij} D]_{m \times m}$ (equation (8)), where m represents the number of dimensions.

$$T_c = \begin{matrix} & \begin{matrix} D_1 & \dots & D_j & \dots & D_m \\ c_{11} \dots c_{1n_1} & c_{j1} \dots c_{jn_j} & c_{m1} \dots c_{mn_m} \end{matrix} \\ \begin{matrix} c_{11} \\ \vdots \\ c_{1n_{11}} \\ \vdots \\ c_{i1} \\ \vdots \\ c_{in_i} \\ \vdots \\ c_{m1} \\ \vdots \\ c_{mn_m} \end{matrix} & \begin{bmatrix} T_c^{11} & \dots & T_c^{1j} & \dots & T_c^{1n} \\ \vdots & & \vdots & & \vdots \\ T_c^{i1} & \dots & T_c^{ij} & \dots & T_c^{in} \\ \vdots & & \vdots & & \vdots \\ T_c^{m1} & \dots & T_c^{mj} & \dots & T_c^{mn} \end{bmatrix} \end{matrix} \quad (7)$$

3.2.2. DANP Method. The ANP method was first proposed by Saaty [64], to deal with the interdependence and feedback problems among indicators [75, 76]. It originates from the AHP but eliminates the deficiency of AHP, which assumes that the indicators are independent of each other [77]. However, the weighted super-matrix in the ANP method lacks rationality because it assumes that each cluster has the same weight [78]. Therefore, the DANP is an appropriate method to obtain the influential weights by improving the normalization process and addressing the interrelationships among indicators [45]. It has been used in many different fields, such as low-carbon energy planning [79], material selection [80], and renewable energy selection [81]. Thus, the process of this technique involves the following steps.

Step 1. Calculating the normalized total-influential matrix $T_{\text{nor}} D$.

According to equations (8) and (9), matrix $T_{\text{nor}} D$ is framed through normalizing the total-influential matrix T_D . First, the sum of each row in matrix T_D can be expressed as $t_D^i = \sum_{j=1}^m t_D^{ij}$, where m represents the number of dimensions. Then, the normalized total-influential matrix $T_{\text{nor}} D$ is calculated by dividing the elements in each row by the sum of the row, so that $T_{\text{nor}} D = [t_{ij} D/t_i D]_{m \times m}$. Meanwhile, the sum of each row in matrix $T_{\text{nor}} D$ equals one, so that $\sum_{j=1}^m t_D^{\text{nor}ij} = 1$.

$$T_D = \begin{bmatrix} t_D^{11} & t_D^{1j} & t_D^{1m} \\ t_D^{i1} & t_D^{ij} & t_D^{im} \\ t_D^{m1} & t_D^{mj} & t_D^{mm} \end{bmatrix} \longrightarrow \sum_{j=1}^m t_D^{ij} = t_D^i, \quad (8)$$

$$T_D^{\text{nor}} = \begin{bmatrix} \frac{t_D^{11}}{t_D^1} & \dots & \frac{t_D^{1j}}{t_D^1} & \dots & \frac{t_D^{1m}}{t_D^1} \\ \vdots & & \vdots & & \vdots \\ \frac{t_D^{i1}}{t_D^i} & \dots & \frac{t_D^{ij}}{t_D^i} & \dots & \frac{t_D^{im}}{t_D^i} \\ \vdots & & \vdots & & \vdots \\ \frac{t_D^{m1}}{t_D^m} & \dots & \frac{t_D^{mj}}{t_D^m} & \dots & \frac{t_D^{mm}}{t_D^m} \end{bmatrix}. \quad (9)$$

Step 2. Exporting the normalized matrix $T_{\text{nor}} c$ by dimensions and clusters.

A new matrix $T_{\text{nor}} c$ is acquired by normalizing T_c with the total degrees of effect and influence of the dimensions and clusters:

$$T_c^{\text{nor}} = \begin{matrix} & \begin{matrix} D_1 & \dots & D_j & \dots & D_m \end{matrix} \\ \begin{matrix} c_{11} \dots c_{1n_1} & c_{j1} \dots c_{jn_j} & c_{m1} \dots c_{mn_m} \end{matrix} & \\ \begin{matrix} D_1 \\ \vdots \\ c_{1n_1} \\ c_{i1} \\ \vdots \\ c_{in_i} \\ c_{m1} \\ \vdots \\ D_m \\ c_{mn_m} \end{matrix} & \begin{bmatrix} T_c^{\text{nor}11} & \dots & T_c^{\text{nor}1j} & \dots & T_c^{\text{nor}1n} \\ \vdots & & \vdots & & \vdots \\ T_c^{\text{nor}i1} & \dots & T_c^{\text{nor}ij} & \dots & T_c^{\text{nor}in} \\ \vdots & & \vdots & & \vdots \\ T_c^{\text{nor}m1} & \dots & T_c^{\text{nor}mj} & \dots & T_c^{\text{nor}mn} \end{bmatrix} \end{matrix} \quad (10)$$

Step 3. Determining the unweighted super-matrix W_c .

The unweighted super-matrix W_c is obtained by transposing the normalized matrix $T_{\text{nor}} c$:

$$W_c = (T_c^{\text{nor}})' = \begin{matrix} & \begin{matrix} D_1 & \dots & D_j & \dots & D_m \end{matrix} \\ \begin{matrix} c_{11} \dots c_{1n_1} & c_{j1} \dots c_{jn_j} & c_{m1} \dots c_{mn_m} \end{matrix} & \\ \begin{matrix} D_1 \\ \vdots \\ c_{1n_1} \\ c_{i1} \\ \vdots \\ c_{in_i} \\ c_{m1} \\ \vdots \\ D_m \\ c_{mn_m} \end{matrix} & \begin{bmatrix} W^{11} & \dots & W^{i1} & \dots & W^{m1} \\ \vdots & & \vdots & & \vdots \\ W^{1j} & \dots & W^{ij} & \dots & W^{mj} \\ \vdots & & \vdots & & \vdots \\ W^{1n} & \dots & W^{in} & \dots & W^{mn} \end{bmatrix} \end{matrix} \quad (11)$$

Step 4. Constructing the weighted super-matrix $W * c$.

The normalized total-influential matrix $T_{\text{nor}} D$ is obtained by equation (9) and the unweighted super-matrix W_c is obtained by equation (11). Thus, using equation (12), a weighted super-matrix $W * c$, which improves the traditional ANP by using equal weights to make it appropriate for the real world, can be obtained by the product of $T_{\text{nor}} c$ and W_c , i.e., $W * c = T_{\text{nor}} D * W_c$. This demonstrates that the influential level values are the basis of normalization to determine a weighted super-matrix.

$$W_c^* = T_D^{\text{nor}} W_c = \begin{bmatrix} t_D^{\text{nor}11} \times W_c^{11} & \dots & t_D^{\text{nor}1i} \times W_c^{i1} & \dots & t_D^{\text{nor}1m} \times W_c^{m1} \\ \vdots & & \vdots & & \vdots \\ t_D^{\text{nor}1j} \times W_c^{1j} & \dots & t_D^{\text{nor}ij} \times W_c^{ij} & \dots & t_D^{\text{nor}mj} \times W_c^{mj} \\ \vdots & & \vdots & & \vdots \\ t_D^{\text{nor}1m} \times W_c^{1m} & \dots & t_D^{\text{nor}im} \times W_c^{im} & \dots & t_D^{\text{nor}mm} \times W_c^{mm} \end{bmatrix}. \quad (12)$$

Step 5. Calculating the influential weights of the criteria.

The influential weights $w = (w_1, \dots, w_j, \dots, w_n)$ can be obtained according to the weighted super-matrix $W * c$, and multiplied several times until it converges a stable super-matrix, so that $\lim_{\alpha \rightarrow \infty} (W * c)^\alpha$, where α is a positive integer number.

3.2.3. VIKOR Method. The VIKOR method was first proposed by Opricovic to optimize the multiple criteria of complicated systems in 1998 [82]. It is applied to rank and select from a set of alternatives given the conflicting criteria. VIKOR is also the compromise ranking method, based on the concept of the Positive-ideal (or the aspired level) solution and Negative-ideal (or the worst level) solution [83]. So, the order of results can be compared by “proximity” to the “ideal” alternative [82, 84, 85]. In this study, the modified VIKOR method can be used to increase customers’ satisfaction in alternatives that are influenced by the interaction of various factors. All of the steps for VIKOR are presented as follows:

Step 1. Determining the positive-ideal solution, negative-ideal solution, and the gap.

According to the concepts of VIKOR, f^+j is the positive-ideal point of assessment criteria, which indicates the best value (aspiration level); In contrast, f^-j is a negative-ideal point, which means the worst value. In this study, the best value is set as $f^+j = 10$ [64]. Likewise, the worst value is set as $f^-j = 0$ with scores of criteria ranging from 0 (dissatisfied) to 10 (satisfied). This is different from the traditional VIKOR, in which the positive-ideal solution is set as the maximum of all schemes, i.e., $f^+j = \max \{f_{kj} | k = 1, 2, \dots, K\}$, and the negative-ideal solution is set as the minimum of all schemes, i.e., $f^-j = \min \{f_{kj} | k = 1, 2, \dots, K\}$. Then, we can obtain the gap ratio, as is described in equation (13).

$$z_{kj} = \frac{(|f_j^* - f_{kj}|)}{(|f_j^* - f_j^-|)}. \quad (13)$$

Step 2. Calculating the average gap E_k and maximal gap Q_k for prioritizing improvement.

The general form of the L_p -metric function is introduced as follows:

$$L_k^p = \left\{ \sum_{j=1}^n [w_j \times z_{kj}]^p \right\}^{1/p}, \quad 1 \leq p \leq \infty; k = 1, 2, \dots, k, \quad (14)$$

where w_j is the influential weight generated from the DANP. $L_k^{p=1}$ and $L_k^{p=\infty}$ are separately expressed as E_k and Q_k , which can be calculated by equations (15) and (16):

$$E_k = L_k^{p=1} = \sum_{j=1}^n w_j \times z_{kj}, \quad (15)$$

$$Q_k = L_k^{p=\infty} = \max_j \{z_{kj} | j = 1, 2, \dots, n\}. \quad (16)$$

The compromise solution $\min_k L_p k$ indicates that the synthesized gap should be minimized. The average gap is emphasized when p is equal to one. However, Q_k means the maximum gap of overall criteria in alternative k . When p is infinite, the maximal gaps should be improved by the priority.

Step 3. Exporting comprehensively evaluated values of the alternatives.

$$U_k = \lambda \frac{(E_k - E^*)}{(E^- - E^*)} + (1 - \lambda) \frac{(Q_k - Q^*)}{(Q^- - Q^*)}. \quad (17)$$

For equation (15), the best gap E^*k and the worst value E^-k is expressed as $E^*k = \min_k E_k$ and $E^-k = \max_k E_k$, respectively; For equation (16), the best gap Q^*k and the worst value Q^-k is separately expressed as $Q^*k = \min_k Q_k$ and $Q^-k = \max_k Q_k$. Furthermore, in optimal conditions, $E^*k = 0$, $Q^*k = 0$, and at worse, $E^-k = 1$, $Q^-k = 1$. Then, equation (17) can be simplified as follows:

$$U_k = \lambda E_k + (1 - \lambda) Q_k. \quad (18)$$

The range of values for λ is zero to one. $\lambda > 0.5$ means the analysis emphasizes the average gap more. $\lambda < 0.5$ indicates the analysis is more concerned about the maximum gap for priority improvement. In general, we can set $\lambda = 0.5$.

4. Empirical Results

Based on the above models, ten types of BEVs are carried out as shown in Table 1. The empirical results of the analytical process are as follows:

4.1. Building Evaluation Indicator System. The online word-of-mouth of BEVs is from the Autohome website (see <https://www.autohome.com.cn/>), which is a relatively well-known auto website in China. Word-of-mouth is the key for users to express their views. On the Autohome website, the word-of-mouth data reflect vehicle attributes that users are most concerned about. Because the website has strict requirements on the opinions, all the text information is accurate and of high quality.

4.1.1. Emotional Polarity Analysis. First, emotional lexicon is extracted from the text that has been preprocessed. Table 2 shows the emotional words with high word frequency. It can be found that the word frequency of the emotional words, such as right, fine, smooth, not bad, not so dusty, high, comfortable, stable, and so on, is very high, which indicated that consumers’ overall cognition of BEVs is relatively concentrated.

On the Autohome website, the overall image of a BEV is often measured in terms of the customers’ satisfaction with the BEV. Then, the emotional terms of customers’ satisfaction are obtained through cluster analysis, as is shown in Table 3. The overall satisfaction of customers with the BEV is measured by the emotion words that indicate emotion. 30.6% of the total number of word-of-mouth have

TABLE 1: Details of ten types of BEVs.

Alternatives	Vehicle types	Vehicle manufacturers
P1	BAOJUN E100	SGMW Company
P2	BAIC EU Series	BAIC BJEV Company
P3	Aion S	GAC NE Company
P4	MG EZS	SAIC Motor
P5	Aeolus E70	Dongfeng Passenger Vehicle Company
P6	GEOMETRY A	Geely Auto Company
P7	BYD Yuan	BYD Company
P8	BESTUNE B30EV	China FAW Group Corporation
P9	EMGRAND EV	Geely Auto Company
P10	ORA R1	Great Wall Motor Company Limited

TABLE 2: The emotional words with high word frequency.

Emotional words	Frequency	Emotional words	Frequency	Emotional words	Frequency
Right	725476	Powerful	524895	Low	302589
Fine	707542	Not too bad	524123	Expensive	212587
Smooth	694575	Not very good	487256	Pretty good	128456
Not bad	675821	Uneconomic	462358	Excellent	114753
Not so dusty	658426	Loud	458697	Terrible	102475
High	654895	So-so	458241	Poor	102452
Comfortable	641257	Beautiful	458214	Reasonable	85426
Stable	607002	Super good	436248	Bad	83856
Passable	597426	Spacious	385462	Insensitive	68542
Noisy	584712	High-end	368456	Awful	62147
Cheap	548968	Accurate	325869	Small	56235

TABLE 3: Emotional terms of customers' satisfaction.

Customers' satisfaction	Emotional words
Practical feelings $\gg$ expectations	Super good, pretty good, excellent, superb, high, etc.
Practical feelings $>$ expectations	Not bad, right, fine, not so dusty, cheap, etc.
Practical feelings $=$ expectations	Passable, not too bad, etc.
Practical feelings $<$ expectations	Not very good, so-so, etc.
Practical feelings $\gg <<$ expectations	Loud, poor, bad, low, terrible, awful, expensive, noisy, etc.

customers' satisfaction far greater than customers' expectations, 27.5% of the total have customers' satisfaction greater than customers' expectations, 15% of the total have customers' satisfaction equal to customers' expectations, 10.7% of the total have customers' satisfaction less than customers' expectations, and 16.2% of the total have customers' satisfaction far less than customers' expectations.

Finally, the word-of-mouth containing the above sentiment words are calculated and scored. The actual score ranges from 1 to 5 points according to the set scoring rules (using the sentiment dictionary method, transforming and rounding the results), the scores of the word-of-mouth containing the sentiment words are obtained, and the average score containing each sentiment word is calculated (the ratio of the frequency of the sentiment word to the number of word-of-mouth containing the sentiment word). The emotional scores are shown in Table 4.

4.1.2. Topic Analysis. This study identifies the consumer concerns by using the LDA model, to discover key topics from the collected text. As is shown in Table 5, the LDA model divides keywords into five topics, including dynamics,

technology, safety, comfort, and cost. Specifically, the keywords in topic 1 mainly involve maximum power, max torque, top speed, and acceleration time, which reflect the dynamics. In topic 2, the keywords mainly involve driving range, charging time, and electricity consumption, which reflect the battery technology. The keywords of topic 3 are mainly related to three aspects, curb weight, braking, and operating stability, which represent the safety of BEVs. In topic 4, the keywords mainly involve four aspects, exterior and interior, space, suspension, and seats, reflecting the comfort of BEVs. The keywords in topic 5 involve three aspects: price, incentives, and after-sales cost, which are the embodiment of the cost factor.

Through the above analysis, five major topics are obtained, which are taken as the five dimensions in the indicator system. Seventeen criteria are identified by keyword segmentation. The details of the evaluation dimensions and criteria of BEVs are shown in Table 6.

4.2. Data Collection. Based on the evaluation indicator system, two different questionnaires are designed to collect the information required for sufficient evaluation of ten BEVs. The DEMATEL questionnaire on the relationship

TABLE 4: Average score of word-of-mouth with sentiment words.

Customers' satisfaction	Emotional words
Super good, pretty good, excellent, superb, comfortable, high, etc.	5
Not bad, right, fine, not so dusty, etc.	4
Passable, not too bad, etc.	3
Not very good, so-so, etc.	2
Loud, poor, bad, low, terrible, awful, etc.	1

TABLE 5: The word-of-mouth data analysis results.

Topics	Keywords
Topic 1: dynamics	Power, accelerate, full of power, torque, top speed, powerful, climbing
Topic 2: technology	Charge, quick charge, economy, battery capacity, range, lithium battery, electricity consumption
Topic 3: safety	Braking, stability, control, vehicle weight, sensitivity, steering, accurate, start smoothly
Topic 4: comfort	Space, seat, rear seats, seat backs, suspension, damping, fashion, high-end, face value, taillight, design, wheel, dashboard, workmanship, large screen, recorder, high beams
Topic 5: cost	Price, virtual-high, subsidies, incentives, policies, restricted licence, repair, maintenance, after-sale service, supporting facilities, market ratios, cost-efficient, quality assurance

TABLE 6: Descriptions of the evaluation dimensions and criteria of BEVs.

Dimensions	Criteria	Descriptions	Source
Dynamics (A)	Maximum power (A1)	Maximum power output that the BEVs can achieve.	[53, 86]
	Max torque (A2)	The higher the torque is, the better the vehicle acceleration.	[51]
	Top speed (A3)	Top speed that can be driven on good road.	[27, 30, 87]
	Acceleration time (A4)	Acceleration time refers to the acceleration time of 100 kilometers.	[27, 30, 88, 89]
Technology (B)	Driving range (B1)	In the standards of the new European driving Cycle, the maximum mileage the EVs can run without a recharge.	[90–93]
	Electricity consumption (B2)	Electricity consumption for 100 kilometers.	[27]
	Charge time (B3)	The time required to charge the battery to 80% of capacity using high-power direct current (DC) charging.	[90, 91, 94]
Safety (C)	Curb weight (C1)	Empty weight is one of the most important factors to check the safety of a vehicle.	[95]
	Braking properties (C2)	The shorter the braking distance is, the higher the safety.	[96, 97]
	Operating stability (C3)	It is a combination of mobility and stability.	[61]
Comfort (D)	Car space (D1)	It includes the size of the driver control space, luggage space, and passenger compartment.	[98]
	Suspension (D2)	Vibration characteristics ensure normal and comfortable driving.	[99]
	Car seat (D3)	It includes electrically adjustable, soft, and comfortable material, etc.	[87]
	Exterior and interior (D4)	Exterior involves many aspects, such as appearance and color; interior involves reasonable color matching, complete and intelligent equipment, etc.	[61, 100]
Cost (E)	Price (E1)	Whether the price is within the acceptable range.	[101–103]
	Incentives (E2)	It includes purchase tax, subsidies, etc.	[104–106]
	After-sales cost (E3)	It includes vehicle repairs, maintenance, and other expenses.	[4, 12]

between dimensions and criteria is emailed to 8 experts who are proficient in the automobile industry and have several years of experience in the BEVs field. Moreover, experts' professional and practical experience can strongly support personal interviews and questionnaires. Experts can use a five-point scale ranging from 0–4 to grade mutual influences based on pairwise comparisons [45]. Then we collect the experts' results and compute the average scores of all criteria to form the initial direct-effect matrix, as is shown in Table 7. The statistical significance confidence of scores by experts is

95.13% (greater than 95%; i.e., the gap error is only 4.87%, or < 5%), which indicates consistent responses.

The modified VIKOR questionnaire is distributed to customers who have bought BEVs or intend to buy BEVs to score the criteria, on an eleven-point scale ranging from 0–10. Of the 550 questionnaires distributed, 540 valid questionnaires are obtained. The internal consistency of customer ratings is tested using Cronbach's alpha [107]. The null hypothesis of the scores associated with each BEV is defined as no difference between customer ratings. The

alternative hypothesis assumes that the scores are different. The Cronbach's alpha values related to these ten hypotheses are 0.894, 0.882, 0.930, 0.855, 0.838, 0.823, 0.825, 0.802, 0.750, and 0.835, respectively. The null hypothesis is significant. It is hoped that this study can help the government departments and automobile enterprises' decision-makers to effectively improve customers' purchasing decisions, thereby enhancing the BEV's development and competitiveness.

4.3. Estimating the Relationships among Dimensions and Criteria. The DEMATEL technique is applied to obtain the cause-effect relationships and to construct the INRM among dimensions and criteria. According to the responses from 7 experts, the direct effect 17×17 matrix $G = [a_{ij}]$ is constructed in Table 7. The normalized direct-influence matrix X in Table 8 is derived by equations (1)–(3). The total influence matrix T_c of the criteria and matrix T_D of the dimensions are separately listed in Tables 9–10. Furthermore, the $(r_i + s_i)$ and $(r_i - s_i)$ values of indicators can be obtained from the total influence matrix, as is shown in Table 11. The implication of $(r_i + s_i)$ presents the intensity of the influence that the i th criterion plays in the problem, and $(r_i - s_i)$ presents the size of the i th criterion's direct impact on others. When $(r_i - s_i)$ is positive, i th criterion influences other criteria. On the contrary, if $(r_i - s_i)$ is negative, i th criterion is influenced by other criteria. The INRM is drawn with $(r_i + s_i)$ as the horizontal axis and $(r_i - s_i)$ as the vertical axis, reflecting the cause-and-effect relationships between dimensions and criteria as shown in Figure 2.

As shown in Table 11, the five dimensions can be prioritised as $E > A > B > C > D$ based on the $(r_i + s_i)$ values, where the cost (E) has the highest impact intensity, with a value of 0.402. The comfort (D) is the most vulnerable in its influence, with a value of 0.154. The influential relationship $(r_i - s_i)$ indicates that safety (C), technology (B), dynamics (A), and comfort (D) have the highest direct influence on the other dimensions in relationship studies, with the values of 0.084, 0.062, 0.058, and 0.052. On the contrary, cost (E) has the lowest negative value of -0.256 , which is easily affected by other dimensions. Hence, based on the causal relationships derived in Figure 2, the safety (C) affects technology (B), dynamics (A), and comfort (D), whereas cost (E) is influenced by all other dimensions.

The network relationship between criteria under each dimension can be shown in Figure 2. The $(r_i + s_i)$ and $(r_i - s_i)$ are shown in Table 11. Overall, from the $(r_i + s_i)$ values, maximum power ($A1$) is considered the most important criterion of all criteria, with the value of 0.397. From the $(r_i - s_i)$ values, max torque ($A2$), driving range ($B1$), curb weight ($C1$), suspension ($D2$), and incentives ($E2$) have a greater influence on the other criteria in the individual dimensions. According to Figure 2, specifically, in the dynamics (A) dimension, max torque (0.110) and maximum power (0.085) have the strongest influence on max speed (-0.056) and acceleration time (-0.019). This indicates that max torque should be improved first to prompt customer purchase intention. In the technology (B) dimension, the driving range (0.019) directly influences the remaining

criteria, including electricity consumption (-0.009) and charge time (-0.011). Thus, it is important to achieve a longer driving range to ease consumers' range anxiety, thereby affecting the degree of purchase. Automobile enterprises should increase technological investment and give priority for expanding driving. Under the same circumstances, consumers usually choose new energy vehicles with a high range [54]. In terms of safety (C) dimension, curb weight (0.194) exerts a direct effect on the other criteria, including braking properties (-0.093) and operating stability (-0.101). Therefore, lightweight technology should be supported and promoted to reduce curb weight and thus improve the safety of BEVs. In the comfort (D) dimension, the criterion of suspension (0.048) and car seat (0.017) strongly influence exterior and interior (-0.016), and car space (-0.050). Thus, optimizing the suspension to improve operating comfort is the most influential way to encourage a customer to purchase new vehicles. In the cost (E) dimension, incentives (0.072) exert a direct effect on the remaining criteria, including price (-0.033) and after-sales cost (-0.039). Therefore, incentives play the most important role in consumers' decisions. The general improvement priorities can be sequenced as $E2$, $E1$, and $E3$.

4.4. Determining the Influence Weights. After identifying the relationships among indicators through the DEMATEL technique, the influence weights of those indicators can be obtained by the DANP method. Initially, the unweighted super-matrix W_c in Table 12 can be derived by equation (11). The weighted super-matrix $W * c$ in Table 13 can be obtained using equation (12). Finally, the weight of each criterion is acquired by limiting the power of the weighted super-matrix.

According to the influence weights shown in Table 14, in terms of dimensions, the cost (0.400) is ranked as the most important weight, while the comfort (0.062) is ranked as the least important one. Based on the influence weights (global weights) associated with seventeen criteria, empirical results reveal that price ($E1$), incentives ($E2$), and after-sales cost ($E3$) are ranked as the top criteria. Concretely, price gains the highest point of 0.191, followed by incentives (0.106) and after-sales cost (0.103). Moreover, the influence weights of suspension (0.010), car seat (0.010), exterior, and interior (0.009) are relatively low, which means that these criteria have the least impact.

4.5. Obtaining the Selection Strategies and Optimal Path. This study aims to propose the most effective strategies to improve customers' decisions for BEVs in China. In this section, the Modified VIKOR method is employed to evaluate ten models based on the opinion of customers. The range of f_{ik} is defined from 0 to 10, where 0 is the worst level, and 10 is the desired level in the evaluation. By introducing the relative weight versus each criterion, the average gap E_k and maximal gap Q_k is derived. U_k is also derived by setting v as 0.5. Thus, each BEV could be evaluated and ranked, and the results are shown in Table 15. The key to solving the problem can be identified according to this integrated index from the dimension perspective or the criteria perspective.

TABLE 7: Initial direct-effect matrix G.

	A1	A2	A3	A4	B1	B2	B3	C1	C2	C3	D1	D2	D3	D4	E1	E2	E3	Total
A1	0.000	0.286	3.429	1.857	3.286	1.857	2.429	0.000	2.143	1.286	0.000	0.143	0.000	0.000	2.429	0.429	1.571	21.143
A2	0.714	0.000	1.000	3.429	1.143	0.286	0.000	0.000	2.714	1.143	0.000	0.429	0.000	0.000	2.286	0.429	2.429	16.000
A3	1.286	1.286	0.000	0.571	1.286	2.857	0.429	0.000	1.714	1.429	0.000	0.143	0.000	0.000	1.714	3.286	0.143	16.143
A4	1.143	0.429	0.286	0.000	0.429	1.143	0.286	0.000	1.429	1.000	0.000	0.286	0.000	0.000	2.571	0.571	2.429	12.000
B1	1.286	0.000	2.857	2.571	0.000	3.714	0.857	0.143	0.000	0.000	0.000	0.000	0.000	0.000	3.571	3.714	2.857	21.571
B2	0.714	0.143	1.571	0.429	3.571	0.000	0.714	0.000	0.143	0.000	0.000	0.000	0.000	0.000	3.429	3.714	2.714	17.143
B3	0.429	0.000	0.000	0.286	0.429	0.714	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	3.429	2.857	1.857	10.000
C1	1.286	1.286	1.286	1.857	2.571	1.857	0.000	0.000	2.857	2.714	0.286	0.000	0.143	1.143	1.714	3.429	0.286	22.714
C2	1.143	1.571	0.714	1.429	0.000	0.143	0.000	0.000	0.000	2.857	0.143	0.571	0.000	0.286	3.571	0.143	2.286	14.857
C3	1.000	0.857	0.571	0.571	0.000	0.000	0.000	0.000	2.571	0.000	0.143	0.429	0.000	0.286	3.571	0.143	1.857	12.000
D1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.571	0.857	0.143	0.000	0.143	2.286	1.571	0.429	0.000	0.143	6.143
D2	0.000	0.000	1.429	1.286	0.000	0.286	0.000	0.714	2.714	3.429	0.571	0.000	0.571	0.714	2.429	0.143	1.571	15.857
D3	0.000	0.000	0.000	0.000	0.000	0.143	0.000	0.857	0.000	0.000	2.429	0.286	0.000	1.286	0.857	0.000	0.714	6.571
D4	0.429	0.000	0.143	0.286	0.714	0.143	0.000	0.286	0.000	0.000	2.429	0.143	0.571	0.000	0.571	0.000	0.286	6.000
E1	1.857	0.714	1.429	1.286	1.286	0.714	0.000	0.143	0.429	0.429	1.571	0.143	0.143	0.000	0.000	0.857	0.143	11.143
E2	0.000	0.000	0.000	0.000	0.571	0.000	0.143	0.286	0.000	0.000	0.000	0.000	0.000	0.000	2.714	0.000	1.143	4.857
E3	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.571	0.143	0.000	0.714
Total	11.286	6.571	14.714	15.857	15.286	13.857	4.857	3.000	17.571	14.429	7.571	2.714	3.714	5.286	35.857	19.857	22.429	

Note. $1/(n(n-1)) \sum_{j=1}^n (|t_{ij}^p - t_{ij}^{p-1}|/t_{ij}^p) \times 100\% = 4.87\% < 5\%$, i.e., significant confidence is 95.13%, where $p = 7$ denotes the number of experts, t_{ij}^p is the average influence of i criterion on j , and n denotes number of criteria, here $n = 17$ and $n \times n$ matrix.

TABLE 8: The normalized direct-influence matrix X .

	A1	A2	A3	A4	B1	B2	B3	C1	C2	C3	D1	D2	D3	D4	E1	E2	E3
A1	0.000	0.008	0.096	0.052	0.092	0.052	0.068	0.000	0.060	0.036	0.000	0.004	0.000	0.000	0.068	0.012	0.044
A2	0.020	0.000	0.028	0.096	0.032	0.008	0.000	0.000	0.076	0.032	0.000	0.012	0.000	0.000	0.064	0.012	0.068
A3	0.036	0.036	0.000	0.016	0.036	0.080	0.012	0.000	0.048	0.040	0.000	0.004	0.000	0.000	0.048	0.092	0.004
A4	0.032	0.012	0.008	0.000	0.012	0.032	0.008	0.000	0.040	0.028	0.000	0.008	0.000	0.000	0.072	0.016	0.068
B1	0.036	0.000	0.080	0.072	0.000	0.104	0.024	0.004	0.000	0.000	0.000	0.000	0.000	0.000	0.100	0.104	0.080
B2	0.020	0.004	0.044	0.012	0.100	0.000	0.020	0.000	0.004	0.000	0.000	0.000	0.000	0.000	0.096	0.104	0.076
B3	0.012	0.000	0.000	0.008	0.012	0.020	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.096	0.080	0.052
C1	0.036	0.036	0.036	0.052	0.072	0.052	0.000	0.000	0.080	0.076	0.008	0.000	0.004	0.032	0.048	0.096	0.008
C2	0.032	0.044	0.020	0.040	0.000	0.004	0.000	0.000	0.000	0.080	0.004	0.016	0.000	0.008	0.100	0.004	0.064
C3	0.028	0.024	0.016	0.016	0.000	0.000	0.000	0.000	0.072	0.000	0.004	0.012	0.000	0.008	0.100	0.004	0.052
D1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.016	0.024	0.004	0.000	0.004	0.064	0.044	0.012	0.000	0.004
D2	0.000	0.000	0.040	0.036	0.000	0.008	0.000	0.020	0.076	0.096	0.016	0.000	0.016	0.020	0.068	0.004	0.044
D3	0.000	0.000	0.000	0.000	0.000	0.004	0.000	0.024	0.000	0.000	0.068	0.008	0.000	0.036	0.024	0.000	0.020
D4	0.012	0.000	0.004	0.008	0.020	0.004	0.000	0.008	0.000	0.000	0.068	0.004	0.016	0.000	0.016	0.000	0.008
E1	0.052	0.020	0.040	0.036	0.036	0.020	0.000	0.004	0.012	0.012	0.044	0.004	0.004	0.000	0.000	0.024	0.004
E2	0.000	0.000	0.000	0.000	0.016	0.000	0.004	0.008	0.000	0.000	0.000	0.000	0.000	0.000	0.076	0.000	0.032
E3	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.016	0.004	0.000

TABLE 9: The total influence matrix of criteria.

	A1	A2	A3	A4	B1	B2	B3	C1	C2	C3	D1	D2	D3	D4	E1	E2	E3	r_i
A1	0.024	0.021	0.120	0.076	0.114	0.082	0.076	0.002	0.078	0.053	0.006	0.008	0.001	0.002	0.128	0.055	0.082	0.241
A2	0.037	0.011	0.045	0.112	0.045	0.025	0.006	0.001	0.092	0.049	0.006	0.016	0.001	0.002	0.103	0.030	0.094	0.204
A3	0.051	0.044	0.021	0.036	0.058	0.094	0.020	0.002	0.063	0.052	0.005	0.007	0.001	0.001	0.096	0.116	0.036	0.152
A4	0.043	0.019	0.023	0.013	0.026	0.042	0.013	0.001	0.050	0.038	0.005	0.010	0.001	0.001	0.099	0.030	0.085	0.098
B1	0.055	0.010	0.101	0.088	0.031	0.125	0.033	0.006	0.016	0.013	0.007	0.002	0.001	0.001	0.149	0.138	0.110	0.189
B2	0.036	0.011	0.064	0.030	0.116	0.023	0.027	0.002	0.014	0.008	0.006	0.002	0.001	0.001	0.134	0.131	0.099	0.166
B3	0.020	0.003	0.010	0.016	0.023	0.027	0.003	0.001	0.005	0.004	0.005	0.001	0.001	0.000	0.113	0.090	0.062	0.053
C1	0.059	0.049	0.063	0.079	0.096	0.076	0.010	0.003	0.102	0.094	0.017	0.005	0.006	0.035	0.113	0.127	0.050	0.199
C2	0.047	0.052	0.036	0.057	0.015	0.016	0.005	0.001	0.021	0.091	0.011	0.019	0.002	0.010	0.131	0.017	0.084	0.113
C3	0.041	0.032	0.030	0.031	0.012	0.010	0.004	0.001	0.083	0.014	0.011	0.015	0.002	0.010	0.124	0.015	0.068	0.099
D1	0.004	0.003	0.004	0.004	0.004	0.003	0.001	0.018	0.028	0.009	0.009	0.005	0.065	0.048	0.021	0.004	0.010	0.127
D2	0.017	0.012	0.053	0.051	0.013	0.020	0.003	0.022	0.094	0.111	0.024	0.004	0.018	0.024	0.105	0.019	0.066	0.071
D3	0.004	0.002	0.004	0.004	0.005	0.007	0.001	0.026	0.006	0.004	0.073	0.009	0.006	0.040	0.031	0.005	0.024	0.127
D4	0.016	0.002	0.010	0.013	0.025	0.010	0.002	0.010	0.006	0.004	0.071	0.005	0.021	0.004	0.026	0.007	0.014	0.101
E1	0.062	0.026	0.055	0.050	0.051	0.036	0.007	0.006	0.026	0.022	0.046	0.006	0.007	0.003	0.031	0.042	0.024	0.097
E2	0.006	0.003	0.006	0.006	0.021	0.005	0.005	0.009	0.003	0.003	0.004	0.001	0.001	0.001	0.082	0.007	0.036	0.125
E3	0.001	0.000	0.001	0.001	0.001	0.001	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.017	0.005	0.001	0.022
s_i	0.156	0.094	0.208	0.236	0.169	0.175	0.064	0.005	0.207	0.200	0.177	0.024	0.110	0.116	0.130	0.054	0.061	

TABLE 10: The total influence matrix of dimension.

Dimension	A	B	C	D	E	r_i
A	0.043	0.050	0.040	0.005	0.079	0.217
B	0.037	0.045	0.008	0.002	0.114	0.206
C	0.048	0.027	0.046	0.012	0.081	0.214
D	0.013	0.008	0.028	0.027	0.028	0.103
E	0.018	0.014	0.008	0.006	0.027	0.073
s_i	0.159	0.144	0.129	0.051	0.329	

The order of priority for achieving the desired level can be determined by the weights of the performance values, from high to low, and the gap values, from high to low.

As indicated in Table 15, Aion S ($P3$) produced by GAC NE company presents the smallest gap (0.276) and therefore ranks first, followed by the BAIC EU Series ($P2$; 0.296), MG EZS ($P4$; 0.297), BESTUNE B30EV ($P8$; 0.304), GEOMETRY

A ($P6$; 0.305), EMGRAND EV ($P9$; 0.340), Aeolus E70 ($P5$; 0.341), BYD Yuan ($P7$; 0.344), ORA R1 ($P10$; 0.471), and BAOJUN E100 ($P1$; 0.694) in this regard. Integration of the scores of Aion S ($P3$) further demonstrates that the gap for the dynamics (A) dimension is 0.191 and that for the suspension (D2) criterion is 0.367, constituting the largest gaps, which Aion S should improve as a priority. The integration

TABLE 11: Sum of influences given/received on dimensions/criteria.

Criteria	r_i	s_i	$r_i + s_i$	$r_i - s_i$
Dynamics (A)	0.217	0.159	0.376	0.058
Maximum power (A1)	0.241	0.156	0.397	0.085
Max torque (A2)	0.204	0.094	0.298	0.110
Max speed (A3)	0.152	0.208	0.361	-0.056
Acceleration time (A4)	0.098	0.236	0.334	-0.139
Technology (B)	0.206	0.144	0.351	0.062
Driving range (B1)	0.189	0.169	0.358	0.019
Electricity consumption (B2)	0.166	0.175	0.341	-0.009
Charge time (B3)	0.053	0.064	0.116	-0.011
Safety (C)	0.214	0.129	0.343	0.084
Curb weight (C1)	0.199	0.005	0.205	0.194
Braking properties (C2)	0.113	0.207	0.320	-0.093
Operating stability (C3)	0.099	0.200	0.299	-0.101
Comfort (D)	0.103	0.051	0.154	0.052
Car space (D1)	0.127	0.177	0.304	-0.050
Suspension (D2)	0.071	0.024	0.095	0.048
Car seat (D3)	0.127	0.110	0.238	0.017
Exterior and interior (D4)	0.101	0.116	0.217	-0.016
Cost (E)	0.073	0.329	0.402	-0.256
Price (E1)	0.097	0.130	0.227	-0.033
Incentives (E2)	0.125	0.054	0.179	0.072
After-sales cost (E3)	0.022	0.061	0.083	-0.039

FIGURE 2: The INRM of each dimension and criterion.

of the scores of the BAIC EU Series (P2) in the DANP shows that the gap of the safety (C) dimension is 0.267 and that of the alliance with operating stability (C3) criterion is 0.383, constituting the largest gaps, which the BAIC EU Series should improve as a priority. The integration of the scores of BAOJUN E100 (P1) in the DANP shows that the gap of the comfort (D) dimension is 0.467 and that of the charge time

(B3) criterion is 1.000, constituting the largest gaps, which BAOJUN E100 should improve as a priority. The integration of the scores of MG EZS (P4) in the DANP shows that the gap of the vehicle comfort (D) dimension is 0.276 and that of the suspension (D2) criterion is 0.367, constituting the largest gaps, which MG EZS should improve as a priority. The integration of the scores of Aeolus E70 (P5) in the

TABLE 12: The unweighted super-matrix W_c .

		A1	A2	A3	A4	B1	B2	B3	C2	C3	D1	D2	D3	D4	E1	E2	E3
A	A1	0.101	0.182	0.337	0.442	0.218	0.256	0.412	0.245	0.305	0.272	0.129	0.274	0.392	0.322	0.294	0.321
	A2	0.087	0.052	0.288	0.190	0.039	0.075	0.069	0.271	0.240	0.186	0.093	0.149	0.046	0.133	0.120	0.133
	A3	0.497	0.219	0.141	0.231	0.397	0.454	0.200	0.188	0.223	0.242	0.398	0.280	0.242	0.287	0.304	0.287
	A4	0.314	0.547	0.234	0.137	0.346	0.215	0.320	0.296	0.233	0.299	0.380	0.297	0.320	0.258	0.281	0.259
B	B1	0.421	0.601	0.338	0.322	0.163	0.696	0.431	0.415	0.465	0.530	0.355	0.393	0.675	0.541	0.666	0.551
	B2	0.300	0.325	0.548	0.519	0.660	0.141	0.511	0.450	0.385	0.402	0.562	0.558	0.268	0.381	0.171	0.365
	B3	0.279	0.075	0.114	0.160	0.177	0.163	0.058	0.135	0.149	0.068	0.084	0.049	0.058	0.078	0.163	0.085
C	C1	0.013	0.009	0.015	0.012	0.172	0.091	0.144	0.012	0.013	0.333	0.095	0.713	0.520	0.105	0.597	0.135
	C2	0.588	0.647	0.539	0.566	0.469	0.575	0.480	0.183	0.843	0.505	0.415	0.164	0.289	0.485	0.217	0.469
	C3	0.399	0.344	0.446	0.422	0.360	0.334	0.376	0.805	0.144	0.162	0.490	0.122	0.190	0.410	0.186	0.396
D	D1	0.380	0.230	0.346	0.289	0.609	0.656	0.712	0.267	0.293	0.070	0.343	0.570	0.702	0.738	0.691	0.737
	D2	0.463	0.654	0.500	0.591	0.220	0.177	0.124	0.459	0.405	0.043	0.062	0.069	0.049	0.099	0.102	0.099
	D3	0.064	0.044	0.059	0.052	0.098	0.104	0.112	0.041	0.043	0.513	0.258	0.044	0.206	0.115	0.113	0.115
	D4	0.093	0.073	0.095	0.069	0.072	0.062	0.053	0.233	0.260	0.374	0.337	0.317	0.043	0.048	0.094	0.049
E	E1	0.483	0.455	0.387	0.462	0.375	0.369	0.427	0.564	0.601	0.613	0.552	0.519	0.551	0.320	0.657	0.763
	E2	0.209	0.131	0.468	0.141	0.349	0.360	0.339	0.074	0.070	0.107	0.102	0.087	0.143	0.432	0.055	0.213
	E3	0.309	0.414	0.144	0.396	0.276	0.271	0.234	0.362	0.329	0.280	0.346	0.393	0.306	0.248	0.288	0.024

TABLE 13: The weighted super-matrix $W * c$.

		A1	A2	A3	A4	B1	B2	B3	C1	C2	C3	D1	D2	D3	D4	E1	E2	E3
A	A1	0.020	0.036	0.067	0.088	0.039	0.046	0.074	0.053	0.055	0.068	0.034	0.016	0.034	0.048	0.080	0.073	0.079
	A2	0.017	0.010	0.057	0.038	0.007	0.013	0.012	0.044	0.061	0.054	0.023	0.011	0.018	0.006	0.033	0.030	0.033
	A3	0.099	0.044	0.028	0.046	0.071	0.081	0.036	0.057	0.042	0.050	0.030	0.049	0.035	0.030	0.071	0.075	0.071
	A4	0.063	0.109	0.047	0.027	0.062	0.039	0.057	0.071	0.067	0.052	0.037	0.047	0.037	0.039	0.064	0.070	0.064
B	B1	0.097	0.138	0.078	0.074	0.036	0.153	0.095	0.067	0.053	0.059	0.040	0.027	0.030	0.051	0.105	0.130	0.107
	B2	0.069	0.075	0.126	0.119	0.145	0.031	0.112	0.053	0.057	0.049	0.030	0.042	0.042	0.020	0.074	0.033	0.071
	B3	0.064	0.017	0.026	0.037	0.039	0.036	0.013	0.007	0.017	0.019	0.005	0.006	0.004	0.004	0.015	0.032	0.016
C	C1	0.002	0.002	0.003	0.002	0.006	0.003	0.005	0.003	0.003	0.003	0.091	0.026	0.195	0.142	0.011	0.063	0.014
	C2	0.108	0.119	0.099	0.104	0.017	0.021	0.018	0.110	0.039	0.181	0.138	0.113	0.045	0.079	0.051	0.023	0.050
	C3	0.073	0.063	0.082	0.078	0.013	0.012	0.014	0.101	0.172	0.031	0.044	0.134	0.033	0.052	0.043	0.020	0.042
D	D1	0.008	0.005	0.007	0.006	0.007	0.007	0.008	0.015	0.015	0.016	0.018	0.089	0.148	0.182	0.058	0.055	0.058
	D2	0.010	0.014	0.010	0.012	0.002	0.002	0.001	0.005	0.025	0.022	0.011	0.016	0.018	0.013	0.008	0.008	0.008
	D3	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.005	0.002	0.002	0.133	0.067	0.011	0.053	0.009	0.009	0.009
	D4	0.002	0.002	0.002	0.001	0.001	0.001	0.001	0.031	0.013	0.014	0.097	0.087	0.082	0.011	0.004	0.007	0.004
E	E1	0.176	0.166	0.142	0.169	0.207	0.204	0.236	0.148	0.214	0.228	0.165	0.149	0.140	0.148	0.119	0.245	0.285
	E2	0.076	0.048	0.171	0.052	0.193	0.199	0.187	0.166	0.028	0.027	0.029	0.027	0.024	0.039	0.161	0.021	0.079
	E3	0.113	0.151	0.053	0.145	0.153	0.150	0.129	0.065	0.137	0.124	0.075	0.093	0.106	0.082	0.093	0.107	0.009

TABLE 14: Influential weights of criteria based on DANP.

Dimensions/Criteria	Local Weights	Global Weights
Dynamics (A)	0.214	—
Maximum power (A1)	0.289	0.062
Max torque (A2)	0.143	0.031
Max speed (A3)	0.293	0.063
Acceleration time (A4)	0.274	0.059
Technology (B)	0.190	—
Driving range (B1)	0.479	0.091
Electricity consumption (B2)	0.388	0.074
Charge time (B3)	0.133	0.025
Safety (C)	0.134	—
Curb weight (C1)	0.139	0.019
Braking properties (C2)	0.478	0.064
Operating stability (C3)	0.383	0.051
Comfort (D)	0.062	—
Car space (D1)	0.527	0.032
Suspension (D2)	0.156	0.010
Car seat (D3)	0.163	0.010
Exterior and interior (D4)	0.154	0.009
Cost (E)	0.400	—
Price (E1)	0.477	0.191
Incentives (E2)	0.265	0.106
After-sales cost (E3)	0.258	0.103

TABLE 15: The performance evaluation of the BEVs using VIKOR.

Dimensions/ criteria	Local weight	Global weight	P1		P2		P3		P4		P5		P6		P7		P8		P9		P10	
			Scores	Gap	Scores	Gap	Scores	Gap	Scores	Gap	Scores	Gap	Scores	Gap	Scores	Gap	Scores	Gap	Scores	Gap	Scores	Gap
A	0.214		5.618	0.438	8.446	0.155	8.088	0.191	8.301	0.170	7.669	0.233	7.860	0.214	7.448	0.255	6.892	0.311	7.545	0.245	5.648	0.435
A1	0.289	0.062	5.833	0.417	8.167	0.183	7.833	0.217	7.500	0.250	7.167	0.283	7.833	0.217	6.000	0.400	6.667	0.333	7.333	0.267	6.000	0.400
A2	0.143	0.031	6.500	0.350	8.500	0.150	8.333	0.167	8.833	0.117	7.667	0.233	7.333	0.267	6.500	0.350	6.833	0.317	7.833	0.217	6.667	0.333
A3	0.293	0.063	6.333	0.367	8.333	0.167	7.833	0.217	8.333	0.167	8.167	0.183	8.167	0.183	8.667	0.133	7.667	0.233	7.500	0.250	6.500	0.350
A4	0.274	0.059	4.167	0.583	8.833	0.117	8.500	0.150	8.833	0.117	7.667	0.233	7.833	0.217	8.167	0.183	6.333	0.367	7.667	0.233	3.833	0.617
B	0.190		6.285	0.371	7.742	0.226	8.159	0.184	7.442	0.256	7.425	0.258	8.124	0.188	7.306	0.269	7.856	0.214	7.986	0.201	7.635	0.237
B1	0.479	0.091	6.500	0.350	8.500	0.150	8.833	0.117	7.333	0.267	7.833	0.217	8.667	0.133	7.500	0.250	8.333	0.167	8.333	0.167	7.333	0.267
B2	0.388	0.074	8.167	0.183	6.833	0.317	7.667	0.233	7.500	0.250	6.667	0.333	7.667	0.233	7.000	0.300	7.333	0.267	7.667	0.233	8.167	0.183
B3	0.133	0.025	0.000	1.000	7.667	0.233	7.167	0.283	7.667	0.233	8.167	0.183	7.500	0.250	7.500	0.250	7.667	0.233	7.667	0.233	7.167	0.283
C	0.134		6.037	0.396	7.329	0.267	8.125	0.188	7.938	0.206	7.709	0.229	7.584	0.242	7.115	0.289	8.486	0.151	6.881	0.312	6.259	0.374
C1	0.139	0.019	6.500	0.350	6.500	0.350	6.833	0.317	7.667	0.233	7.167	0.283	6.500	0.350	6.333	0.367	8.167	0.183	6.833	0.317	6.833	0.317
C2	0.478	0.064	6.333	0.367	8.500	0.150	9.000	0.100	8.500	0.150	8.167	0.183	7.833	0.217	7.167	0.283	8.833	0.117	7.333	0.267	6.167	0.383
C3	0.383	0.051	5.500	0.450	6.167	0.383	7.500	0.250	7.333	0.267	7.333	0.267	7.667	0.233	7.333	0.267	8.167	0.183	6.333	0.367	6.167	0.383
D	0.062		5.328	0.467	7.499	0.250	8.595	0.141	7.244	0.276	6.886	0.311	7.361	0.264	6.795	0.321	8.161	0.184	6.202	0.380	6.791	0.321
D1	0.527	0.032	5.833	0.417	7.500	0.250	9.500	0.050	7.667	0.233	7.333	0.267	7.500	0.250	6.500	0.350	8.500	0.150	6.333	0.367	7.333	0.267
D2	0.156	0.010	4.333	0.567	6.667	0.333	6.333	0.367	6.333	0.367	5.833	0.417	7.667	0.233	7.167	0.283	7.500	0.250	5.667	0.433	5.167	0.483
D3	0.163	0.010	4.333	0.567	7.667	0.233	9.500	0.050	6.667	0.333	6.500	0.350	6.333	0.367	7.667	0.233	8.167	0.183	6.167	0.383	7.500	0.250
D4	0.154	0.009	5.667	0.433	8.167	0.183	6.833	0.317	7.333	0.267	6.833	0.317	7.667	0.233	6.500	0.350	7.667	0.233	6.333	0.367	5.833	0.417
E	0.400		6.466	0.353	7.947	0.205	8.115	0.188	7.554	0.245	7.105	0.289	7.154	0.285	6.916	0.308	7.410	0.259	7.714	0.229	7.052	0.295
E1	0.477	0.191	6.167	0.383	8.333	0.167	8.500	0.150	8.167	0.183	6.667	0.333	6.667	0.333	7.000	0.300	6.667	0.333	7.667	0.233	7.833	0.217
E2	0.265	0.106	5.833	0.417	8.500	0.150	8.833	0.117	6.667	0.333	7.833	0.217	8.667	0.133	7.333	0.267	8.333	0.167	8.333	0.167	6.833	0.317
E3	0.258	0.103	7.667	0.233	6.667	0.333	6.667	0.333	7.333	0.267	7.167	0.283	6.500	0.350	6.333	0.367	7.833	0.217	7.167	0.283	5.833	0.417
Total	1.000	1.000	6.123	0.694	7.904	0.296	8.148	0.276	7.725	0.297	7.354	0.341	7.560	0.305	7.123	0.344	7.575	0.304	7.525	0.340	6.740	0.471
			10		2		1		3		7		5		8		4		6		9	

TABLE 16: The results of the two MCDM methods.

Alternatives	DANP-VIKOR		CRITIC-VIKOR	
	U_k	Rank	U_k	Rank
P1	0.694	10	0.726	10
P2	0.296	2	0.295	2
P3	0.276	1	0.284	1
P4	0.297	3	0.300	4
P5	0.341	7	0.340	6
P6	0.305	5	0.305	5
P7	0.344	8	0.345	7
P8	0.305	4	0.299	3
P9	0.340	6	0.353	8
P10	0.471	9	0.478	9

DANP showed that the gap of the comfort (D) dimension is 0.311 and that of the alliance with suspension ($D2$) criterion is 0.417, constituting the largest gaps, which Aeolus E70 should improve as a priority. The integration of the scores of GEOMETRY A ($P6$) in the DANP shows that the gap of the cost (E) dimension is 0.285 and that of the car seat ($D3$) criterion is 0.367, constituting the largest gaps, which GEOMETRY A should improve as a priority. Integration of the scores of BYD Yuan ($P7$) in the DANP showed that the gap of the comfort (D) dimension is 0.276 and that of the maximum power ($A1$) criterion is 0.400, constituting the largest gaps, which BYD Yuan should improve as a priority. The integration of the scores of BESTUNE B30EV ($P8$) in the DANP shows that the gap of the dynamics (A) dimension is 0.311 and that of the alliance with acceleration time ($A4$) criterion is 0.367, constituting the largest gaps, which BESTUNE B30EV should improve as a priority. The integration of the scores of EMGRAND EV ($P9$) in the DANP shows that the gap of the vehicle comfort (D) dimension is 0.380 and that of the suspension ($D2$) criterion is 0.433, constituting the largest gaps, which EMGRAND EV should improve as a priority. The integration of the scores of ORA R1 ($P10$) in the DANP shows that the gap of the dynamics (A) dimension is 0.435 and that of the acceleration time ($A4$) criterion is 0.617, constituting the largest gaps, which ORA R1 should improve as a priority. Furthermore, the gap values obtained by the customers reveal that improvement priority schemes are unique and comprehensive for each separate dimension as well as for the overall range of criteria. Decision-makers in government departments and automobile enterprises can easily understand the gaps where improvements are prioritised.

5. Discussion

The study uses fine-grained sentiment analysis and MCDM model to explore the BEVs from the customers' point of view based on five dimensions, namely, safety, technology, dynamics, comfort, and cost. The LDA model based on fine-grained sentiment analysis has been applied to obtain dimensions and criteria based on the word-of-mouth data. The DANP method combining the DEMATEL technique with ANP has been used to create an INRM to identify the causal relationship and compute the influence weights of all

indicators. The Modified VIKOR is not only used to rank and determine selection strategies but also to propose the optimized path for ten BEVs.

The empirical results are discussed as follows: First, using the LDA model based on fine-grained sentiment analysis, the comprehensive evaluation indicator system is constructed, including five dimensions and seventeen criteria. According to the DEMATEL cause-and-effect model, the interrelationships between each dimension and criterion are determined by INRM. In Figure 2, the degree of the dimension effect indicates that improvement priorities should be established in the following order: safety, technology, dynamics, comfort, and cost. The results further illustrate that the decision-makers should improve safety first because it has the greatest immediate network effect on the other dimensions. The structural design, materials used in collision sites, safety equipment, and other aspects may cause accidents [108, 109], such as battery explosions and physical damages [57]. So, most people are concerned about safety when driving BEVs [58]. The findings also imply that a full understanding of the relationships among dimensions can enable automobile companies to grasp the main direction of the future revolution, thus enhancing consumers' recognition and enthusiasm for BEVs.

Second, after describing the dimensions, the study also discusses the criterion considered in each dimension. They provide a higher-level mode for the improvement of BEV attributes [110]. In terms of the results for the safety (C) dimension, consumers are more concerned with the curb weight of BEVs. Combining lightweight designs with BEVs can further reduce environmental impacts [52]. In addition, the application of lightweight materials in the BEVs can improve functionality and safety [111]. Moreover, details on the causal relationship between technology, dynamics, comfort, and cost can also be derived from Figure 2. Each of the evaluation dimensions and criteria play an essential role in customers' choices of BEVs. Therefore, relevant departments should evaluate all the dimensions and criteria for promoting customers' attitudes and willingness. The subsequent evaluation model can be used for the automobile industry in China.

Third, the study uses the DANP to confirm the weight of the 17 influential criteria. As shown in Table 14, price ($E1$) is the largest relative weight of seventeen criteria with the value

TABLE 17: Optimal path.

Formula		Path (sequence of improvement priorities)
Total optimization path	F1: influential network of dimensions of DEMATEL	C, B, A, D, E C: C1, C2, C3 B: B1, B2, B3
	F2: influential network of criteria within individual dimensions	A: A2, A1, A3, A4 D: D2, D3, D4, D1 E: E2, E1, E3
Specific optimization path	F3: BAOJUN E100 (by gap value, from high to low)	D, A, C, B, E D: D2/D3, D4, D1 A: A4, A1, A3, A2 C: C3, C2, C1 B: B3, B1, B2 E: E2, E1, E3 C, D, B, E, A C:C3, C1, C2
	F4: BAIC EU Series (by gap value, from high to low)	D: D2, D1, D3, D4 B: B2, B3, B1 E: E3, E1, E2 A: A1, A3, A2, A4 A, C/E, B, D A: A1, A3, A2, A4 C: C1, C3, C2 E: E3, E1, E2 B: B3, B2, B1
	F5: Aion S (by gap value, from high to low)	D: D2, D4, D1, D3 D, B, E, C, A D: D2, D3, D4, D1 B: B1, B2, B3 E: E2, E3, E1 C: C3, C1, C2 A: A1, A3, A2/A4 D, E, B, A, C D: D2, D3, D4, D1 E: E1, E3, E2 B: B2, B1, B3
	F6: MG EZS (by gap value, from high to low)	A: A1, A2/A4, A3 C: C1, C3, C2 E, D, C, A, B E: E3, E1, E2 D: D3, D1, D2/D4 C: C1, C3, C2 A: A2, A1/A4, A3 B: B3, B2, B1 D, E, C, B, A D: D1/D4, D2, D3 E: E3, E1, E2 C: C1, C2, C3 B: B2, B1/B3
	F7: Aeolus E70 (by gap value, from high to low)	A: A1, A2, A4, A3 A, E, B, D, C A: A4, A1, A2, A3 E: E1, E3, E2 B: B2, B3, B1 D: D2, D4, D3, D1 C:C1/C3, C2 D, C, A, E, B D: D2, D3, D4/D1 C: C3, C1, C2 A: A1, A3, A4, A2 E: E3, E1, E2 B: B2/B3, B1 A, C, D, E, B A: A4, A1, A3, A2 C: C3/C2, C1
	F8: GEOMETRY A (by gap value, from high to low)	D: D2, D4, D1, D3 D, B, E, C, A D: D2, D3, D4, D1 B: B1, B2, B3 E: E2, E3, E1 C: C3, C1, C2 A: A1, A3, A2/A4 D, E, B, A, C D: D2, D3, D4, D1 E: E1, E3, E2 B: B2, B1, B3 A: A1, A2/A4, A3 C: C1, C3, C2 E, D, C, A, B E: E3, E1, E2 D: D3, D1, D2/D4 C: C1, C3, C2 A: A2, A1/A4, A3 B: B3, B2, B1 D, E, C, B, A D: D1/D4, D2, D3 E: E3, E1, E2 C: C1, C2, C3 B: B2, B1/B3 A: A1, A2, A4, A3 A, E, B, D, C A: A4, A1, A2, A3 E: E1, E3, E2 B: B2, B3, B1 D: D2, D4, D3, D1 C:C1/C3, C2 D, C, A, E, B D: D2, D3, D4/D1 C: C3, C1, C2 A: A1, A3, A4, A2 E: E3, E1, E2 B: B2/B3, B1 A, C, D, E, B A: A4, A1, A3, A2 C: C3/C2, C1
	F9: BYD Yuan (by gap value, from high to low)	D: D2, D4, D1, D3 E: E3, E2, E1 B: B3, B1, B2
	F10: BESTUN EB30EV (by gap value, from high to low)	
	F11: EMGRAND EV (by gap value, from high to low)	
	F12: ORA R1 (by gap value, from high to low)	

of 0.191, which indicates that the price of BEVs is the most important criterion that affects the customers' decision. Generally, the cost of BEVs is higher than that of Internal Combustion Engine Vehicles (ICEVs), which is mainly due to the high research and development (R&D) expense and production costs, especially batteries. Hence, in addition to technology improvements, automakers can develop dedicated platforms and modular production platforms for BEVs to reduce costs as much as possible. The lowest priority is exterior and interior (0.009). Consequently, the design of the exterior and interior has the least impact on consumers' decisions. The results indicate that the priority of criterion improvement from top to bottom and the improvement of the most influential criteria would provide the largest effects. It is possible that improving different criteria will strongly influence the results directly and indirectly, and improving the most influential criteria provides the most substantial effects.

Fourth, the comparison results of ten BEVs in Table 15 show that Aion S (P3) is the best choice. In order to verify the feasibility and validity of this hybrid method, we combine the criteria importance through inter-criteria correlation (CRITIC) method with modified VIKOR for ranking the ten BEVs. The CRITIC method, proposed by Diakoulaki et al. [112], is used to calculate attributes' weights by standard deviation. As derived in Table 16, although the sorting of the BEVs based on different MCDM methods varies partly, Aion S (P3) is still the optimal choice. This means that the proposed method is effective at ranking and selecting BEV alternatives.

Finally, from the perspective of dimension, the comfort (D), featuring the largest gap value (0.467, 0.276, 0.311, 0.321, 0.380) with cars of BAOJUN E100 (P1), MG EZS (P4), Aeolus E70 (P5), BYD Yuan (P7), and EMGRAND EV (P9), should be the priority for improvement if banking managers wish to enhance service innovation. The dynamics (A) dimension, constituting the largest gap value (0.191, 0.311, 0.435) with cars of Aion S (P3), BESTUNE B30EV (P8), and ORA R1 (P10), should improve as a priority. In the BAIC EU Series (P2), the safety (C) dimension features the largest gap with the value of 0.267, which should be a top priority for improvement to achieve aspiration levels. In the alternative of GEOMETRY A (P6), the cost (E) dimension constitutes the largest gap with the value of 0.285. According to the same rule, the priority improvement following sustainable development context can be sequenced in the criteria for each BEV. Given these critical empirical findings, our analysis results, as holistically formulated in Table 17, present the optimized path for different BEV models. Hence, relevant departments can not only use this method to define gaps but also enhance customers' purchase willingness in China based on the priorities of influence weights or gap values.

6. Conclusions

BEVs are not only the mainstream of the future automobile industry but also the top priority for implementing national energy policy and achieving sustainable development of the automobile industry. However, a large proportion of

consumers still hold a wait-and-see attitude [58, 60], China's BEV market has always been a policy-oriented model. There is still much room for improvement in consumers' purchase willingness. This study creates a novel hybrid model combining fine-grained sentiment analysis and an MCDM model to assess BEV alternatives from the customers' point of view. In summary, the main results of this study are as follows:

- (1) The comprehensive evaluation indicator system, including five dimensions (dynamics, technology, safety, comfort, and cost) and seventeen criteria, is obtained by the LDA model based on fine-grained sentiment analysis.
- (2) Safety (C) is the most influential dimension, followed by technology (B), dynamics (A), comfort (D), and cost (E). Safety improvements can lead to changes in other dimensions. Thus, government and providers can improve BEV attributes more flexibly and accurately based on the identification of cause-effect relationships between the dimensions and the actual situation of BEVs.
- (3) The DANP analysis shows that price (E1), incentives (E2), and after-sales cost (E3) are ranked as the top criteria, and they all belong to the cost dimension. Moreover, the lowest influential weights involve suspension (D2), car seat (D3), exterior, and interior (D4), and they all belong to the comfort dimension. Government and providers can determine the order of improvement based on the weight.
- (4) The modified VIKOR results indicated that the selection strategies of ten BEVs are $P3 > P2 > P4 > P8 > P6 > P9 > P5 > P7 > P10 > P1$, which presented that P3 (Aion S) is the best choice. In addition, there is still room for improvement in vehicle attributes, and the indicator gaps and optimized path are different for each BEV. Taking the BEV named Aion S as an example, it has the highest integrated scores, but it still falls short of aspiration levels. According to the gaps ranging from large to small, the first step of the optimized path should improve the dynamics.
- (5) In this study, we find some attributes that have been neglected in previous studies, such as maximum power, max torque, and after-sales cost, affect customers' satisfaction. With the gradual maturity of BEV technology, the effects of more detailed vehicle attributes should be considered [30]. Therefore, the widespread promotion of BEVs cannot rely solely on policy incentives and the government should take active measures to promote automobile companies to achieve the urgent improvements of BEV attributes [113, 114].

However, there are some limitations in this study, which need to be solved in future research. First, due to the differences in consumption concepts and the influence of psychological factors, consumers can be divided into different levels for further analysis. Second, based on the

complexity of things and the ambiguities of subjective judgments, interval numbers and fuzzy numbers can be introduced in future research on consumers' adoption of BEVs. Finally, some forecasting methods can be used to predict the motivation of consumers.

Abbreviations

AHP:	Analytic hierarchy process
ANP:	Analytic network process
BAIC BJEV:	Beijing Automotive Industry Corporation Beijing Electric Vehicle
BEVs:	Battery electric vehicles
BYD:	Build your dreams
COPRAS:	Complex proportional assessment
CRITIC:	Criteria importance through intercriteria correlation
DANP:	DEMATEL-based analytic network process
DC:	Direct current
DEMATEL:	Decision-making trial and evaluation laboratory
ELECTRE:	ELimination and Choice Expressing the REality
EVs:	Electric vehicles
FAW:	First automobile workshop
GAC NE:	Guangzhou Automobile Group Co., Ltd
GHG:	Greenhouse gas
ICEVs:	Internal combustion engine vehicles
INRM:	Influential network relationship map
LCA:	Life cycle assessment
LDA:	Latent Dirichlet Allocation
MCDM:	Multicriteria decision-making method
MARCOS:	Measurement of Alternatives and Ranking According to Compromise Solution
PROMETHEE:	Preference Ranking Organization Method for Enrichment Evaluation
R&D:	Research and Development
SAIC:	Shanghai Automotive Industry Corporation
SECA:	Simultaneous Evaluation of Criteria and Alternatives
SGMW:	Shanghai General Motors Wuling
SWARA:	Stepwise Weight Assessment Ratio Analysis
TOPSIS:	Technique for Order of Preference by Similarity to Ideal Solution
VIKOR:	Vlse Kriterijuska Optimizacija I Komoromisno Resenje.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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