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Identifying Promising Technologies of Electric Vehicles from the Perspective of Market and Technical Attributes

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Abstract: The vigorous development of electric vehicles (EVs) can promote the green and low-carbon development of society and the environment. However, the research and development of EVs technology in China started late, and there are some problems such as relatively backward technology. In order to promote the decarbonization process of transportation systems, there is an urgent need for appropriate methods to identify promising technologies in the EVs field to guide the efficient development of innovation activities. This study proposes a novel approach to integrate the perspective of market and technical attributes to identify promising EVs technologies. Firstly, text mining tools are applied to extract review and technical keywords from online reviews and patents, and technical topics are summarized. Secondly, sentiment analysis is conducted to calculate user satisfaction based on online reviews, and then market demand of technical topics is obtained. Thirdly, social network centrality analysis, DEA–Malmquist model, and CRITIC method are employed to obtain technical features of technical topics based on patents. Finally, a portfolio map is constructed to analyze technical topics and identify promising EVs technologies. As the main driving force for the development and transformation of the automotive industry, the efficient identification of promising technologies in this field can provide strategic decision support for the development of EVs. This study aims to provide objective data and scientific guidance for related enterprises to carry out technological innovation activities.

Keywords: electric vehicles; promising technologies; patent analysis; sentiment analysis; DEA–Malmquist model

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1. Introduction

In recent years, the rapid development of industry made the problem of global energy shortage more prominent. In addition, rapid urbanization and increased fossil fuel consumption have led to excessive greenhouse gas emissions and environmental pollution, which pose a major threat to global energy efficiency [1,2]. According to the Paris agreement, the global temperature will increase by 3% in this century [3]. In this case, electric vehicles (EVs) are increasingly favored by the market for their energy-saving, clean, and environmentally friendly characteristics [4]. In addition, advances in battery technology, power grid management, and the urgent environmental need to reduce greenhouse gas emissions have led to a major shift toward the production of EVs [1]. Many countries have put forward the electric vehicle promotion goals and technology development strategies [5]. Driven by various preferential policies, electric vehicle sales have been booming recently. However, electric vehicle technology is not mature enough, and there are still some problems to be solved, such as lack of the capability of long travel range and long battery charging. Therefore, with the increasing awareness of environmental protection, technological innovation and product development of EVs have gradually become the focus of social attention.

Promising technologies refer to those with development potential that may become the main driving force for technology development in specific fields in the future. Currently, identifying promising technologies in EVs can efficiently drive the development of this field. However, they often require valuable information to assess [6]. Since patents contain abundant technical intelligence and frontier information [7], many studies aim to extract useful information based on them and then identify promising technologies from the perspective of technical attributes. For example, through the collation and analysis of patents related to EVs, technologies such as batteries, charging facilities, and power control systems are considered to be research topics of great concern in this field, and wireless charging technology and fuel cell technology are identified as promising technologies in this field [5,8]. In addition, with the booming of online shopping, online reviews contain plentiful user preference information [9]. The research and analysis of this information will help companies to understand the market dynamics of technologies and grasp the market demand trend promptly [10]. Therefore, online reviews provide a new perspective to evaluate technological superiority and then identify promising technologies.

In the existing research, through the review and analysis of EV charging methods, standards, and optimization techniques, the research status of EV charging methods in recent years was introduced, and some promising optimization techniques in the scale and layout of charging stations were identified [11]. In addition, the SPC algorithm and visualization mapping were applied to analyze the technological evolution process in the field of EVs from patent texts and to identify promising technologies in the field of EV batteries [8]. However, relatively little attention has been paid to identifying promising technologies in EVs, and there are some limitations. Firstly, most of the research on EVs has focused on specific aspects such as batteries, charging stations, and control systems [12,13]; the research methods are mainly based on experiments and investigations; and less systematic analysis of promising EVs technologies has been carried out from an overall perspective. Secondly, from the research perspective, previous studies on EVs rarely link technical attributes with market attributes for multi-perspective analysis [14,15]. This may affect the comprehensiveness and objectivity of the analysis results and make it difficult to accurately guide companies' technological innovation activities.

In response, this study combines the perspectives of market and technical attributes to identify promising EVs technologies. Online reviews and patent data are integrated to characterize the market demand and technical features of technologies. Sentiment analysis is applied to the analysis process of market demand in this study. In addition, in the analysis of technical features, social network centrality analysis and the data envelopment analysis–Malmquist (DEA–Malmquist) model are integrated to fully consider the relationship between technical keywords and the dynamic changes of them. The Criteria Importance Though Inter-criteria Correlation (CRITIC) method is applied to improve the objectivity of analytical results. The framework proposed in this study can effectively assist in identifying promising technologies in the field of EVs and guide enterprises' technological innovation.

This study is composed as follows. Section 2 reviews the literature on electric vehicles, identification of promising technologies, and methods involved. Section 3 explains the research framework and process in this study. Section 4 analyzes the identification results of promising technologies. Sections 5 and 6 provide discussions and conclusions of the research by including contributions and directions for future study.

2. Literature Review

2.1. Electric Vehicles

EVs are referred to new energy vehicles that rely on electric powertrain and plug-in charging approaches [16]. According to different forms of powertrain, EVs can be classified into battery electric vehicles (BEVs), extended-range electric vehicles (EREVs), and plug-in hybrid electric vehicles (PHEVs) [17]. Due to the increasing pressure from the environment and energy, the state and society have taken many measures to promote the development of EVs. It is worth noting that technological innovation is a key factor in the future success of the industry of EVs [12]. China, South Korea, and other countries have successively introduced policies to encourage technological innovation in EVs [18]. Therefore, industry and academia have made a lot of exploration in the technological innovation of EVs.

The existing research on the technological innovation of EVs focuses on the improvement and optimization of specific sub-fields such as batteries and charging stations in combination with quantitative analysis methods. The role of battery and charging technologies in the diffusion of EVs was explored, and an agent-based spatial integrated model (SelfSim-EV) was applied to simulate consumers' responses to these technological innovations [13]. A machine learning-based text mining model and co-occurrence network analysis were employed to analyze the impact of artificial intelligence on technological innovation in EV automation [19]. The field of EV was decomposed into subdomains, which are power electronics, battery, electric motor, and charging and discharging, and emerging topics in each subdomain were identified [12]. Field research methods and interpretive structural modeling (ISM) were adopted to study the constraints of EV charging stations [20]. These explorations have contributed to the technological innovation and development of EVs.

However, previous studies still have some limitations. These studies have given less consideration to systematically identifying promising technologies for EVs at an overall level to improve the efficiency of technological innovation. This study focuses on the field of EVs, combined with quantitative analysis methods and objective data, to accurately identify promising technologies.

2.2. Identification of Promising Technologies

Many scholars have devoted themselves to exploring the term of promising (or emerging) technology in recent years. Although there are various ways to define it, no consensus has been reached. Reference [21] defined promising technologies as those with fast-growing, novelty, untapped market potential. Reference [22] considered technologies with the features of novelty, rapid growth, coherence, prominent impact, and uncertainty as promising technologies. Based on these definitions, this study regards promising technologies as technologies with high uncertainty and high market and technology impact. Therefore, it is necessary to use suitable databases in this study to evaluate technological superiority from the perspective of market and technical attributes and then identify promising technologies.

Scholars have conducted a lot of explorations on applying various databases to evaluate technological superiority. As one of the common databases of technological innovation, patents were widely used to identify promising technologies [23]. Scientific articles [24] and online community reports [25] were also employed in the process of technical analysis. Further, some studies tried to combine multi-source databases to improve the comprehensiveness of analysis results. In order to synthetically consider technological and social impacts, patents and online articles were integrated to develop a framework for identifying promising technologies [26]. Patents and government reports were also combined to analyze the matching relationship between the supply and demand of technology [27]. These databases from various sources provide abundant information and decision support in the identification process of promising technologies.

However, although the usage of these databases has made some contributions to the identification of promising technologies, there are still some limitations. In addition to the commonly used patent data, previous studies have also focused on using online articles, government reports, and online community reports to consider the market and technical impacts. These types of data may have problems such as insufficient quantity and content and difficulty in access. With the rapid development of online shopping, the number and content of online reviews have been greatly enriched [28], which can largely compensate for the deficiencies of the above database. Further, since online reviews contain abundant and diverse user preference information [29], they can be regarded as an essential source of information to identify promising technologies from the perspective of market attributes. Therefore, online reviews and patent data are applied to identify promising technologies from the perspective of market and technical attributes.

2.3. Patent-Based Evaluation of Technological Superiority

Among the existing database of technological superiority evaluation, patent data are the most frequently used data. They provide affluent and objective technical information and are widely used in the process of technical analysis [30,31]. Some studies were committed to the usage of patent citation analysis [32,33] and patent indicators analysis [34]. Some research focused on semantic analysis of patent information, such as topic modeling [35] and similarity measurement [36]. In recent years, with the rise of artificial intelligence, the combination of machine learning and patent analysis [37] has also attracted more attention.

In these patent-based studies, the construction of patent indicators can intuitively and accurately clarify the technical features. Scholars have made many attempts at applying patent indicators analysis to evaluate technological superiority. The indicators of technology impact, applicability, and sustainability were constructed and analyzed based on bibliometric information in patents [38]. A deep learning model was applied to analyze outlier patents [26], and the indicator of technology impact was measured by the number of patent forward citations [39]. Forward citations were also used to divide patents into promising and non-promising ones; then, semi-supervised learning and active learning were combined [34] to identify promising technologies. These proposed patent indicators have contributed to identifying promising technologies by providing quantitative references.

However, most of the existing patent indicators focus more on the self and static features of technologies and less on exploring their relationship and dynamic change features. It may affect the comprehensiveness and accuracy of the analysis results. The social network is introduced as an available tool to measure the relationship between nodes [40,41]. The relationship between technologies can be fully considered by calculating the centrality indicators in the network [42,43]. Moreover, in order to explore the dynamic changes of technologies, the DEA–Malmquist model is conducted in this study. DEA, as a data-driven method to provide efficiency measurement and benchmark, has been widely applied in various fields for efficiency analysis [44–46]. The commonly used DEA models include CCR, BCC, and DEA–Malmquist models [47]. Among them, the Malmquist production index can be employed to evaluate the dynamic efficiency change of decision-making units (DMUs) in continuous time [48]. Therefore, social network centrality analysis and DEA–Malmquist model are combined in this study to make up for the deficiency of existing patent indicators. Firstly, social network centrality analysis is used to consider the relationship between technologies. Then, the obtained centrality indicator values as input can be integrated into the DEA–Malmquist model to analyze the dynamic features of technologies.

2.4. Sentiment Analysis for Online Reviews

Online reviews containing plenty of user preference information can be applied to evaluate technological superiority from the perspective of market attributes. Due to its complexity, text mining techniques need to be used to effectively obtain information [49]. As a tool in natural language processing (NLP), sentiment analysis can accurately extract users' attitudes and opinions from online reviews [50]. The principle of sentiment analysis is to capture users' positive, negative, or neutral attitudes towards products or services [51] at three granularity levels, including phrase level, sentence level, and document level.

Many scholars have concentrated on the application of sentiment analysis to extract online reviews information. Sentiment analysis and an intuitionistic fuzzy TODIM method were combined to construct a product selection model [49]. The Kano model and sentiment analysis based on fine-grained were integrated to extract consumer demands for product attributes from online reviews [52]. Further, the emotion classifier based on deep learning and neural network was developed to improve the efficiency and accuracy of sentiment analysis [53,54]. As shown by the above studies, sentiment analysis has made many contributions in mining useful information from online reviews. Therefore, in the identification process of promising technologies from the perspective of market attributes, sentiment analysis is employed in this study to obtain user satisfaction based on online reviews.

3. Materials and Methods

The proposed identification method is based on a UNISON framework of data-driven innovation [55] as illustrated in Figure 1. The framework applied in this study can clearly show the path of integrating the perspective of market and technology attributes to identify promising EVs technologies. The overall research process considers the market and companies, the promising technologies, and the technical environment in six phases, including: (1) understand and define the problem, (2) identify the niche for promising technologies identification, (3) structure the objective hierarchy and influence relationship, (4) sense and describe expected outcomes, (5) overall judgments and value assessments, and (6) trade-off and decision. A detailed explanation is provided as follows.

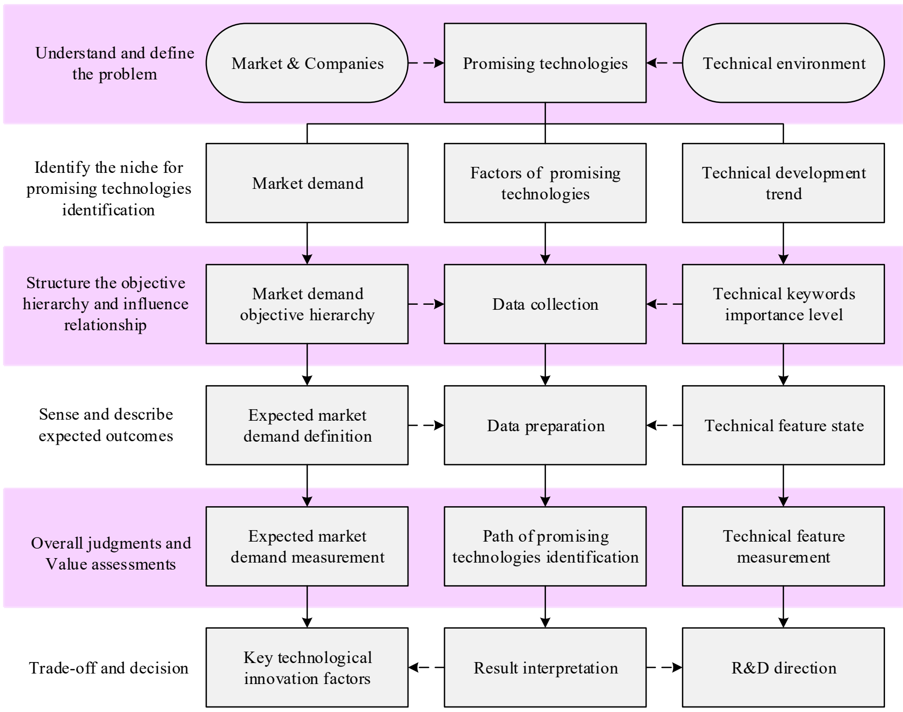

Figure 1. UNISON framework for identifying promising technologies.

3.1. Understand and Define the Problem

The proposed approach begins with understanding and defining the problem. With the rapid development of technology, innovation ability has become a critical standard to measure the competitiveness of companies. In the product development stage of EVs, the correct direction of technological innovation can launch the products to meet market demand. Companies and R&D personnel urgently need to discover promising EVs technologies to improve product performance and competitiveness.

Many scholars have attempted to analyze the technical features of specific fields to achieve technological innovation in recent years. In addition, in terms of the perspective of market attributes, market demand analysis has gradually become a crucial step in assisting technological innovation. It can facilitate user purchase behavior and product or service improvement [49,56]. Therefore, this study integrates the market demand and technical features to consider this issue regarding EVs.

3.2. Identify the Niche for Promising Technologies Identification

The niche for promising technologies identification is determined in this section. Understanding current market demand can contribute to identifying the niches. Market demand is a factor that can reflect the user preference information of related products. Analysis of market demand can help to improve related products or services accurately from the perspective of market attributes. Benefited from the Internet and web 3.0 technology, users increasingly post online reviews of products or services on the Internet. Online review information can largely reflect the comparison between users' consumption experience and expectations. At the same time, with the continuous improvement of enterprise management and data monitoring, the authenticity and reliability of online reviews are also increasing. Compared with traditional market demand research, online reviews are not affected by differences in time, region, and occupation, and users' demand for products or services improvement and future demand can be greatly demonstrated [57]. Since online reviews can objectively and comprehensively reflect the market demand information of specific products or services, they are valuable for companies and R&D personnel to understand market demand. The text mining technology was used in this study to extract critical review keyword information in the field of EVs to efficiently understand the core users' preference information, and then to calculate the market demand with the help of quantitative analysis tools. Therefore, the strategic objectives can be structured.

In addition, the technical features are a factor that can reflect the current state of specific technologies. Analyzing technical features can help to clarify the development trend of technical environment. Patents are widely used in the analysis of technical fields since they contain affluent technical and frontier information [58]. By extracting and analyzing the technical keywords in patents, the core information of massive patent texts can be efficiently understood, and the technical features can be calculated by quantitative analysis methods such as social network centrality analysis. Therefore, this study focuses on obtaining technical features by analyzing the development trend of critical technical information in electric vehicle-related patents.

It is worth noting that text mining of keywords extracted from online reviews and patents is a feasible method to help understand market demand and technical features information in the field of EVs [38,59]. In terms of online reviews, the word frequency of review keywords can accurately reflect users' preferences for EVs. In terms of patents, the word frequency of technical keywords can accurately reflect the research hotspots and development directions of EVs. Therefore, review keywords and technical keywords need to be extracted from online reviews and patents. However, it is far from enough to rely only on the review keywords and technical keywords extracted from the above two data sources to analyze the market demand and technical features in the field of EVs, and some additional information needs to be obtained to provide more details. In this way, sentiment analysis is applied in this study to calculate the users' satisfaction on review keywords, and then combine user attention to comprehensively analyze the market demand in the field of EVs. In addition, in the analysis of technical features, social network centrality analysis, the data envelopment analysis–Malmquist (DEA–Malmquist) model, and the CRITIC method are integrated to fully consider the relationship between technical keywords and the dynamic changes of them.

The core issue to be addressed is to determine factors that affect promising EVs technologies. In recent years, EVs have been widely welcomed in the automotive market with their advantages of high energy efficiency and green environmental protection. There is already abundant online review data. Scholars have also conducted many explorations of EVs technology and published many related patents. Therefore, this study analyzes the market demand and technical features of EVs based on online reviews and patent data. This study chooses an automobile evaluation website that contains plenty of user online reviews—www.cars.com (accessed on 22 November 2021) as the online reviews database. The website is ranked within the top five global automobile evaluation websites and is expected to provide reliable data [39]. In terms of analyzing technical features, this study selects the DII database as the patent database. The titles and abstracts of patents related to EVs technology are extracted for further analysis.

3.3. Structure the Objective Hierarchy and Influence Relationship

Data collection is the first step in obtaining market and technology information in the EVs field. For market data, the advancement of information technology makes it easy to acquire massive reviews via web crawler. In this study, the review data collection period was set to 2017–2021, and 6571 valid review data were obtained from the website, www.cars.com. For patent data, keywords such as "electric car", "electric vehicle", or "electric automobile" were used to search related patents in the DII database. The search time range was also from 2017 to 2021, and 63,231 patents were collected after preliminary screening. Review and patent data were collected on 22 November 2021.

In this section, the objectives are structured into a hierarchy. The strategic objective of this study is to obtain market demand from online reviews. Based on previous research, user satisfaction and attention can be extracted to comprehensively measure market demand of EVs. The strategic objective can be divided into two fundamental objectives: extracting user satisfaction and attention from online reviews. The NLTK algorithm is applied in the study to extract the review keywords of EVs from collected online reviews. Then, after cleaning and pretreatment of them, review keywords that appear more than 100 times are selected as the final dataset for further analysis. The extraction results of review keywords in the EVs field are shown in Table 1.

Table 1. Review keywords in the field of EVs in 2017–2021.

	Review Keywords	Frequency of Occurrence		Review Keywords	Frequency of Occurrence
1	sound	4578	19	power	370
2	drives	1839	20	pedal	325
3	service	1597	21	acceleration	290
4	control	1459	22	save	274
5	autopilot	1068	23	bottom	266
6	styling	1002	24	locations	258
7	comfortable	989	25	fast	253
8	battery	983	26	creaks	230
9	seats	981	27	charge	204
10	back	708	28	dashboard	186
11	easy	693	29	convenient	181
12	motors	693	30	stable	146
13	high	549	31	bright	130
14	fun	542	32	congested	125
15	relax	528	33	freedom	113
16	safety	482	34	cheap	110
17	leather	406	35	panels	103
18	speed	395	36	auti-theft	101

The object of technical features is determined by comparing the importance level of technical keywords. This study applies the NLTK algorithm in python to extract technical keywords and their co-occurrence relationships from patents related to EVs. Then, the data are filtered and cleaned, and the technical keywords are sorted according to the frequency of each year. Finally, the top 40 technical keywords are determined as the object of further analysis based on expert opinions in this field. The extraction results of technical keywords in the EVs field are shown in Table 2. The importance of technical keywords is measured by the frequency of their occurrence in patents. High frequency of technical keywords will be selected for further research and analysis of their technical features.

Table 2. Technical keywords in the field of EVs in 2017–2021.

	Technical Keyword	Year				
		2017	**2018**	**2019**	**2020**	**2021**
1	electric	114,810	164,112	113,612	120,331	92,792
2	charge	106,018	33,092	110,516	20,465	31,635
3	battery	12,470	48,639	54,040	37,265	7240
4	antithief	3141	95,557	38,021	16,202	2635
5	control	17,485	30,466	49,277	18,368	20,522
6	generator	437	6728	1933	3853	37,281
7	storage	6170	4533	12,435	6704	4406
8	driver	4018	2740	7325	4732	12,991
9	motor	1456	1395	6179	2275	18,433
10	energy saving	1940	2237	4536	9235	9950
11	body	4079	2495	8266	4752	1915
12	solar	319	1421	16,535	233	194
13	light	2285	701	10,720	2362	421
14	communication	1076	12,321	2123	486	317
15	panel	288	480	8992	3837	1183
16	inner	175	3086	8774	557	1813
17	automation	6006	628	4611	1237	1491
18	lock	975	4147	4297	619	3054
19	converter	220	286	5271	932	5483
20	beam	1886	1252	6444	910	261
21	rear	1385	495	2072	1392	4665
22	assembly	808	756	1543	5285	984
23	alarm	403	362	2953	3671	1754
24	brake	6441	376	1002	631	457
25	detector	1173	2191	3935	317	290
26	display	4461	257	1209	755	449
27	chassis	213	340	270	4482	1504
28	remote monitoring	160	266	5763	456	104
29	sound	238	341	5511	152	102
30	seat	668	535	847	1095	780
31	accelerator	324	200	323	2586	206
32	screen	2500	114	307	331	220
33	bms	1040	129	1724	140	187
34	damping	236	300	2093	295	231
35	gps	185	198	2354	167	127
36	head	308	590	894	589	384
37	bearing	368	515	491	553	380
38	camera	109	190	315	292	116
39	bluetooth	155	161	139	182	133
40	buzzer	143	136	178	135	122

3.4. Sense and Describe Expected Outcomes

The phase of sense and describe expected outcomes involves the definition of expected market demand, data preparation, and the description of technical features state. At the stage of data preparation, it is necessary to further process the review keywords and technical keywords of EVs identified in the last step. It can be clearly seen that these two types of keywords have great differences in semantic expression. Review keywords extracted from online reviews are more colloquial, while technical keywords obtained from patent data are more professional. These two types of keywords need to be mapped and the technical topics are summarized in combination with expert opinions, as shown in Table 3. In this way, the market demand of technical topics in the field of EVs can be represented by the market demand of corresponding review keywords. The technical features of technical topics can be represented by the technical features of corresponding technical keywords.

Table 3. Technical topics classification of review and technical keywords in the EVs field.

Technical Topics		Technical Keywords	Review Keywords	Technical Topics		Technical Keywords	Review Keywords
appearance	A1	beam	bright	power system	PS1	accelerator	pedal power
	A2	body	styling		PS2	converter	acceleration speed
	A3	head	high		PS3	driver	drives
	A4	light	bright		PS4	motor	motors
	A5	rear	back	manipulation	M1	automation	autopilot service
interior decoration	I1	assembly	freedom		M2	brake	pedal
	I2	display	dashboard		M3	control	control
	I3	seat	seats leather comfortable		M4	panel	panels
	I4	storage	convenient comfortable	communication system	C1	bluetooth	easy relax
	I5	inner	congested comfortable		C2	communication	easy convenient
System configuration	SC1	bearing	creaks stable		C3	detector	safety
	SC2	chassis	high bottom		C4	gps	locations
	SC3	damping	comfortable		C5	screen	relax fun
	SC4	generator	safety convenient		C6	sound	sound
power consumption	PC1	battery	battery	safety device	SD1	alarm	safety
	PC2	BMS	service safety		SD2	antithief	auti-theft
	PC3	charge	charge fast		SD3	buzzer	sound safety
	PC4	electric	cheap save		SD4	camera	safety convenient
	PC5	energy	save		SD5	lock	safety
	PC6	solar	convenient save		SD6	remote	easy convenient

Based on the two clarified fundamental objectives, this study aims to analyze the review keywords extracted from online review data to obtain the market demand of EVs. Specifically, user satisfaction is defined as a subjective evaluation of products or services provided based on expectations and actual performance [60]. It is usually expressed in positive and negative emotions. User attention refers to the degree of users' concern about the specific attributes of products or services [61]. If a user reviews on one attribute of a product or service, it is considered that he/she is concerned about this attribute. Therefore, the definition of user satisfaction and user attention can be determined.

After that, the sentiment analysis tool textblob is employed to calculate the sentiment score of review keywords. User satisfaction (S_j) with each review keyword is represented by the calculation result, as shown in Formula (1), where N_j refers to the number of reviews on the review keyword j. Secondly, user attention (A_j) to review keywords can be quantitatively measured by the proportion of the number of times that a user mentions a review keyword in all reviews. The specific calculation process is shown in Formula (2), where N refers to the number of all reviews. Accordingly, market demand (D_j) is calculated by the Formula (3), which means that lower user satisfaction and higher user attention will form higher market demand.

$$S_j = \frac{\sum_{i=1}^{N_j} S_{ij}}{N_j} \quad (1)$$

$$A_j = \frac{N_j}{N} \quad (2)$$

$$D_j = \left(1 - S_j\right) * A_j \quad (3)$$

In terms of the technological environment, this section presents the calculation method of technical features of EVs. Firstly, the co-occurrence matrix of each year is constructed based on technical keywords and co-occurrence relationships. Secondly, social network centrality analysis is applied to calculate the network features of technical keywords. This study uses the following three centrality indicators [43], as explained in Table 4.

Table 4. Three centrality indicators for measuring network features of technical keywords.

Centrality indicator	Formula	Description
Degree centrality ($DC_{(v)}$)	$DC_{(v)} = m$ m—the number of other nodes directly connected to node v	Apply to reflect the number of other nodes that are directly connected to a node
Betweenness centrality ($BC_{(\mathrm{v})}$)	$BC_{(v)} = \sum_{j}^{n}\sum_{k}^{n}\frac{\theta_{j,k}(v)}{\theta_{j,k}}$, $j \neq k \neq i$ and $j < k$ $\theta_{j,k}$—the total number of shortest paths between node j and k in the network; $\theta_{j,k}(v_i)$ —the number of those paths that pass through node v_i	Apply to reflect the role played by the node in the network connectivity
Closeness centrality ($CC_{(v)}$)	$CC_{(v)} = \frac{\lvert I\rvert - 1}{\sum_{i \neq v} d_{vi}}$ $\sum_{i \neq v} d_{vi}$—Sum of distances between node v and other nodes directly connected	Apply to measure the proximity of the node to the center

Thirdly, the central indicator value obtained as the input data of DEA–Malmquist model and run the model to calculate the importance and increase rate of technical keywords. Since there is no output data, an output-oriented BCC model with no inputs is adopted in this study for applying DEA [14]. This process is repeated once a year to obtain the efficiency of all years. The importance of technical keywords ($TI_{(k)}$) is calculated by averaging the efficiency scores of all years, as shown in Formula (4). The increase rate of $TI_{(k)}$ ($ROI_{(k)}$) is obtained by the average value of the ratio of importance in the current year to importance in the previous year, as shown in Formula (5), where n represents the number of years, and $effch(k)_i$ represents the technical efficiency of technical keyword k in year i. After that, the CRITIC method [62] is introduced. Its principle is to determine the objective weight of each indicator by comparing the size of the value gap between the evaluation scheme of the same indicator and the conflict between the evaluation indicators. This method is applied to objectively assign weights to the importance and growth rate of technical keywords to obtain the technical features.

$$TI_{(k)} = \frac{\sum_{i=1}^{n} effch(k)_i}{n} \tag{4}$$

$$ROI_{(k)} = \frac{\sum_{i}^{n-1}\left(\frac{effch(k)_{i+1}}{effch(k)_i}\right)}{n-1} \tag{5}$$

3.5. Overall Judgments and Value Assessments

According to the given Formulas (1) and (2), the user satisfaction and attention indicator values of review keywords are calculated. The two indicator values of review keywords in the field of EVs are shown in Table 5. The positive and negative values of user satisfaction indicate that users have positive and negative attitudes towards the corresponding review keywords.

Table 5. User satisfaction and attention of review keywords in the EVs field.

Review Keywords	User Satisfaction (S_j)	User Attention (A_j)	Review Keywords	User Satisfaction (S_j)	User Attention (A_j)
acceleration	0.327	0.027	freedom	0.125	0.030
auti-theft	0.050	0.017	fun	0.335	0.084
autopilot	0.278	0.198	high	0.208	0.124
back	0.142	0.144	leather	0.250	0.027
battery	0.095	0.028	locations	0.127	0.005
bottom	−0.138	0.003	motors	0.175	0.017
brightest	0.160	0.005	panels	0.237	0.008
charge	−0.182	0.035	pedal	0.073	0.005
cheap	0.246	0.017	power	0.243	0.089
comfortable	0.376	0.504	relax	0.160	0.002
congested	0.152	0.001	safety	0.345	0.267
control	0.200	0.070	save	0.252	0.029
conveniently	0.168	0.011	seats	0.206	0.245
creaks	−0.188	0.001	service	0.260	0.026
dashboard	0.266	0.006	sound	0.357	0.037
drives	0.380	0.072	speed	0.171	0.041
easy	0.403	0.070	stable	0.246	0.007
fast	0.230	0.030	styling	0.400	0.038

Technical features are jointly determined by the importance and increase rate of technical keywords. Social network centrality analysis and DEA–Malmquist model are applied in this study to calculate the importance and increase rate of technical keywords. Firstly, a co-occurrence matrix for each year is constructed based on 40 high-frequency technical keywords, and their co-occurrence relationships are extracted from patents of EVs. Appendix A shows the technical keyword co-occurrence matrix in 2017.

Secondly, three centrality indicators of social network centrality analysis are calculated based on the constructed co-occurrence matrix in each year. The calculation results of degree centrality in each year are shown in Appendix B.

Similar to the degree centrality, the calculation results of betweenness centrality in each year are shown in Appendix C.

Similarly, the calculation results of closeness centrality in each year are shown in Appendix D.

Thirdly, DEAP2.1 software is employed in the DEA–Malmquist model of the three centrality indicators values obtained of each year. These three indicator values are used as output data for the output-oriented BCC model with no inputs, and constants are used as input data. It needs to be noted that the output data should be arranged in chronological order. The comprehensive technical efficiency change index (effch) in each year of technical keywords can be obtained after the operation. Then, according to Formulas (4) and (5), the importance and increase rate of technical keywords are calculated, as shown in Table 6.

Based on the two indicator values of market demand and technical features, the portfolio map is constructed to identify the promising EVs technologies. The identification path of promising technologies constructed in this study considers both market and technical attributes. It can identify promising EVs technologies more comprehensively and accurately.

3.6. Trade-Off and Decision

Key technological innovation factors can be obtained and analyzed in this study from the following three aspects to identify promising EVs technologies. From the market aspect, key technological innovation factors in the field of EVs can come from technological improvements that cater to market demand. From the technical aspect, the key factors in the field of EVs can also be those that occupy an essential position in technological development and can produce more technological innovation. From the comprehensive aspect, innovation factors in the field of EVs with both technological development potential and market demand can also improve the competitiveness of companies.

This study aims to use a series of quantitative analysis methods, considering the perspective of market and technical attributes, to provide accurate and objective key technological innovation factors for companies in the field of EVs. The R&D direction can be obtained from the above three aspects.

Table 6. The importance and increase rate of technical keywords in the EVs field.

Technical Keywords	TI	ROI	Technical Keywords	TI	ROI
accelerator	4.530	80.017	detector	2.270	7.429
alarm	1.969	4.734	display	5.033	3.680
assembly	2.861	18.670	driver	0.933	1.719
automation	6.694	59.114	electric	1.199	1.997
automobile	3.859	14.692	energy saving	0.869	2.546
battery	2.842	4.886	generator	0.702	4.118
beam	2.102	6.279	gps	2.986	39.029
bearing	1.669	7.159	head	0.932	1.650
bluetooth	1.105	1.472	inner	4.484	62.269
BMS	3.731	23.247	light	3.182	23.860
body	2.033	3.469	lock	1.336	2.789
brake	5.745	5.720	motor	0.754	3.361
buzzer	1.095	1.060	panel	1.371	12.729
camera	0.951	1.759	rear	1.245	2.486
charge	2.730	17.172	remote monitoring	3.383	52.379
chassis	1.657	69.277	screen	4.380	1.135
communication	2.437	14.532	seat	1.408	1.371
control	1.072	1.890	solar	3.226	16.942
converter	1.046	14.512	sound	2.378	41.215
damping	1.270	7.169	storage	1.745	2.610

4. Results

4.1. Results of Promising Technologies Identification

In terms of market demand, based on the calculated user satisfaction and attention, the market demand of review keywords in the EVs field is obtained according to Formula (3). The calculation results are shown in Table 7. The greater the indicator value of market demand, that the more the corresponding technological improvement can satisfy users.

Table 7. Market demand indicator of review keywords in the EVs field.

Review Keywords	Market Demand	Review Keywords	Market Demand
acceleration	0.018	freedom	0.026
auti-theft	0.016	fun	0.056
autopilot	0.143	high	0.098
back	0.124	leather	0.020
battery	0.025	locations	0.005
bottom	0.004	motors	0.014
brightest	0.004	panels	0.006
charge	0.041	pedal	0.005
cheap	0.013	power	0.067
comfortable	0.315	relax	0.001
congested	0.001	safety	0.175
control	0.056	save	0.022
conveniently	0.009	seats	0.195
creaks	0.001	service	0.019
dashboard	0.004	sound	0.023
drives	0.044	speed	0.034
easy	0.042	stable	0.005
fast	0.023	styling	0.023

In terms of technical features, the CRITIC method is used in this study to objectively analyze the importance and increase rate of technical keywords and assign reasonable weights to them. The weight of importance indicator is 0.4865, and the weight of increase rate indicator is 0.5135. In this way, the technical features of technical keywords can be comprehensively calculated, as shown in Table 8.

Table 8. Technical features of technical keywords in the EVs field.

Technical Keywords	Technical Features	Technical Keywords	Technical Features
accelerator	43.293	detector	4.919
alarm	3.389	display	4.338
assembly	10.979	driver	1.336
automation	33.612	electric	1.609
antithief	9.421	energy saving	1.730
battery	3.892	generator	2.456
beam	4.247	gps	21.494
bearing	4.488	head	1.300
bluetooth	1.293	inner	34.157
BMS	13.752	light	13.800
body	2.770	lock	2.082
brake	5.732	motor	2.092
buzzer	1.077	panel	7.203
camera	1.366	rear	1.882
charge	10.146	remote monitoring	28.542
chassis	36.380	screen	2.714
communication	8.648	seat	1.389
control	1.492	solar	10.269
converter	7.961	sound	22.321
damping	4.299	storage	2.189

Therefore, the market demand and technical features indicator values of technical topics are shown in Table 9.

Table 9. Technical features and market demand of technology topics.

	Market Demand	Technical Features		Market Demand	Technical Features
A1	0.014	4.247	PS1	0.047	43.293
A2	0.023	2.770	PS2	0.026	7.961
A3	0.098	1.300	PS3	0.044	1.336
A4	0.014	13.800	PS4	0.014	2.092
A5	0.124	1.882	M1	0.081	33.612
I1	0.026	10.979	M2	0.027	5.732
I2	0.016	4.338	M3	0.056	1.492
I3	0.177	1.389	M4	0.026	7.203
I4	0.162	2.189	C1	0.022	1.293
I5	0.015	34.157	C2	0.025	8.648
SC1	0.003	4.488	C3	0.175	4.919
SC2	0.056	36.380	C4	0.025	21.494
SC3	0.315	4.299	C5	0.029	2.714
SC4	0.092	2.456	C6	0.023	22.321
PC1	0.025	3.892	SD1	0.175	3.389
PC2	0.097	13.752	SD2	0.016	9.421
PC3	0.032	10.146	SD3	0.100	1.077
PC4	0.017	1.609	SD4	0.092	1.366
PC5	0.022	1.730	SD5	0.175	2.082
PC6	0.158	10.269	SD6	0.025	28.542

In order to identify promising technology of EVs, this study takes technical features as abscissa and market demand as ordinate to construct a portfolio map. Based on the average value of technical features and market demand indicators, 9.402 is set as the median of x axis, and 0.064 is set as the median of y axis. The technical topics in the EVs field can be divided into four types by quadrants in Figure 2.

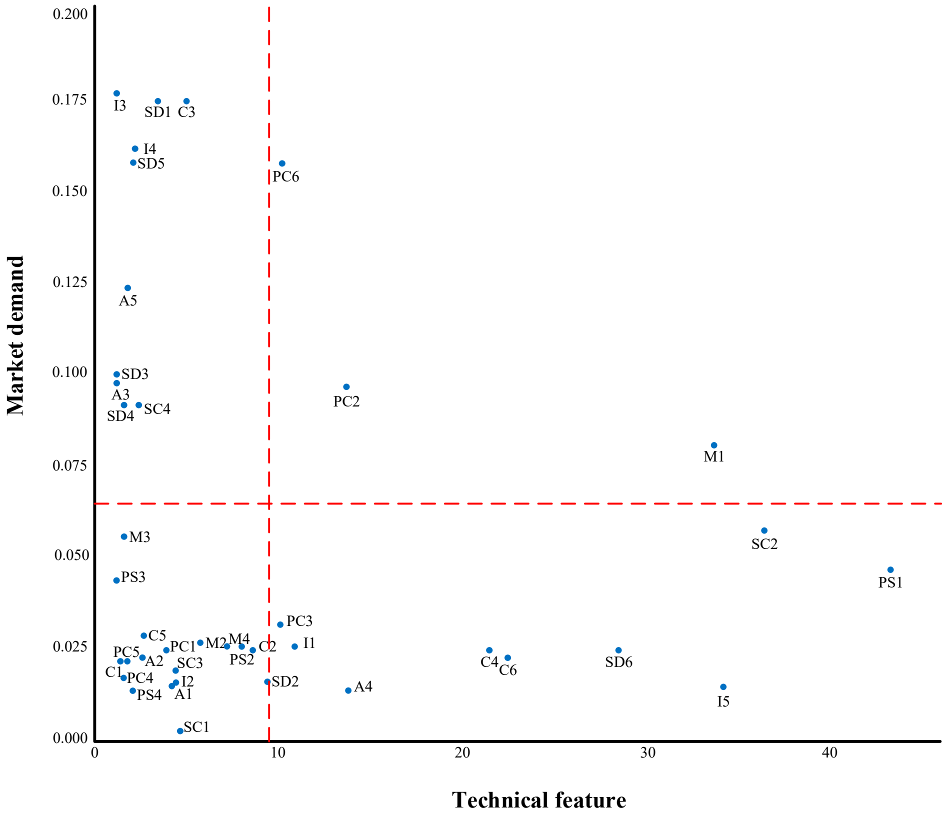

Figure 2. Portfolio map in the EVs field.

As shown in Figure 2, technical topics in the first quadrant are promising technologies from the comprehensive perspective. Because of their relatively high market demand values and technical features values, they can be considered as technologies that are important and have high market demand in the EVs field. Improvements and innovations in these technologies will enhance the market competitiveness and technological superiority of companies. The technical topics in the second quadrant are promising technologies from the perspective of market attributes. For companies that focus on gain market, emphasis on improving such technologies can accurately develop EVs that meet market demand. The technical topics in the third quadrant are relatively unpromising technologies. Since their market demand values and technical features values are relatively low, they will not be analyzed and considered in this study. The technical topics in the fourth quadrant are promising technologies from the perspective of technical attributes. For companies in the field of EVs that focus on technological development, innovation of such critical technologies can achieve better innovation effects.

4.2. Analysis of Promising Technologies

The findings from the constructed portfolio map can provide some useful insights into the innovation in the EVs field. From the perspective of market attributes, innovation can come from improving the key areas where the users are troubled and thus want improvements. In this study, those areas include: (1) seat (I3); (2) alarm (SD1); (3) detector (C3); (4) storage (I4); (5) lock (SD5); and so on. Based on the above analysis, the two technical topics with the highest market demand are interior decoration and safety devices, especially in the seat, internal storage space, alarm system, and lock system. In addition, the detector is also a technology that needs to be urgently improved. Targeted optimization of these aspects can greatly improve user satisfaction and help obtain market superiority. Therefore, from the market perspective, the identified promising technologies are as follows. First of all, in terms of interior decoration, lightweight and high-strength new composite materials are used as much as possible in the body structure manufacturing process, with less body mass and increased internal space, thereby improving user comfort and improving the overall performance of the vehicle. Secondly, in terms of safety devices, when the vehicle is running normally, the vehicle terminal device establishes a communication connection with the integrated monitoring platform, sets up a multi-level alarm mechanism at the terminal, and performs different levels of alarm prompts according to different information anomalies.

From the perspective of technical attributes, further technology development is expected to emerge to yield more subsequent innovation in such areas as (1) accelerator (PS1); (2) chassis (SC2); (3) inner (I5); (4) remote monitoring (SD6); and so on. Firstly, the technologies of accelerator and chassis have occupied an important position in EVs in recent years. Companies focusing on technology development should give priority to improving these two technologies. In addition, the upgrading of Internal placement and remote monitoring functions can also improve the technical impact of EVs. Therefore, from the market perspective, the identified promising technologies are as follows. In terms of power systems, first of all, new synthetic materials can be used to further reduce the quality of the cooling system and control device of the drive motor. Secondly, a wide range of speed adjustments can be completed in the case of only setting the first-stage reducer to obtain a higher driving speed. In terms of safety devices, the vehicle equipment is composed of a communication module and a Bluetooth module, which has the function of obtaining real-time operation data of EVs and transmitting the data to smartphones.

From the comprehensive perspective, companies and R&D personnel can also improve competitiveness by innovating in areas that have technical prospects and meet market demand, including the following areas: (1) solar (PC6); (2) BMS (PC2); and (3) automation (M1). Accordingly, the technical topic of power consumption is the most promising. The application of clean energy such as solar energy of EVs and the battery management system (BMS) should be particularly concerned. In addition, the automation level of EVs should be improved. Therefore, from the comprehensive perspective, the identified promising technologies are as follows. Firstly, the battery pack technology should be developed to produce a battery pack with a larger capacity and larger charging current to improve charging efficiency. Secondly, creating a fully automatic battery swapping process, increasing the construction of battery swapping stations, automatically collecting the disassembled feed batteries to the designated location for charging, and cycling to complete the battery swapping work are future research directions. Finally, optimizing the automotive circuit system, reducing the energy consumption of electronic components, introducing energy recovery and storage technology, and improving energy efficiency are also future research directions.

It is worth noting that the identification results in this study are different from the results of direct statistics of keywords extracted from online reviews and patents. The reasons are as follows. In terms of review keywords, the higher the word frequency, the higher the users' preference for specific components of EV products. However, it is difficult to analyze users' satisfaction with specific components only based on attention preference. The market demand should be measured by users' satisfaction and attention. In terms of technical keywords, the higher the word frequency, the more frequently these keywords are mentioned in the patents. However, it is not comprehensive and objective enough to measure their technical features only by the times of occurrence. Social network centrality analysis is introduced in this study to fully analyze the relationship between keywords. In addition, the DEA–Malmquist model and CRITIC method are applied to improve the objectivity of the calculation results of technical features. Therefore, compared with the results of direct statistics of keywords, the identification results are more accurate, comprehensive, and objective.

Companies can carry out innovation activities in the field of EVs based on the above identification results to improve technological innovation capability and product competitiveness. The R&D direction can be developed based on three important perspectives of market, technical, and comprehensive attributes.

5. Discussion

This study combines the perspectives of market and technical attributes to identify promising EVs technologies. Market demand and technical features in specific fields are obtained from online reviews and patent data to provide more sufficient evidence and richer research perspectives for identifying promising technologies. The research framework proposed is based on a recursive decision analysis process, which aims to identify the problem essence and clarify the problem from different aspects. The data-driven innovation method proposed can provide sufficient information for companies and R&D personnel. Meanwhile, the research framework proposed in this study is a dynamic system process. Since this study is based on the analysis of existing information on market and technical aspects, the identification of promising technologies may be less practical over time. With the new inputs of online reviews and patent data, the identification results can be improved and updated to provide the latest insights for companies and R&D personnel in the field of EVs.

This study identifies promising technologies from the market perspective, technical perspective, and comprehensive perspective, and describes them in detail. In general, promising technologies mainly involve technical topics such as interior decoration, safety devices, power systems, and power consumption. Different EV manufacturers can choose different perspectives to carry out technological innovation activities according to their focus. Specifically, manufacturers that focus on market attributes and focus on key areas that are troublesome to users should combine promising technologies identified from the market perspective with improvements and innovations in interior decoration and safety devices. Manufacturers that focus on technical attributes and are committed to promoting technological development through innovation should combine promising technologies identified from the technical perspective to improve and innovate from aspects such as power systems and safety devices. In addition, manufacturers considering both market and technical attributes should combine promising technologies identified from the comprehensive perspective to improve and innovate in the aspects such as power consumption and automation.

The research on identifying promising technologies for EVs from the perspective of market attributes and technical attributes in this study extends the research of Song et al. [38]. Their research mainly focused on measuring the prospect degree and technical features of patents using the accumulated patent bibliometric information and the patent bibliometric information as its first appearance and paid less attention to the text information of patents. In addition, a technology is represented by a patent in their research, and the identified promising technology is represented by a patent title and application in the field of automobile door systems. They emphasized the combination of a retrospective technological features analysis and a prospective market-needs analysis to identify promising technologies. It provides a reference for us to integrate market and technical attributes to identify promising technologies. Based on existing research, the text information of patent data was fully considered in this study, and social network centrality analysis and the DEA–Malmquist model were applied to fully consider the correlation between technical keywords and their dynamic changes. The promising technologies identified in this study have been more specifically explained to provide clearer innovation guidance for EV manufacturers. In addition, the research framework proposed is based on a recursive decision analysis process, which aims to identify the essence of the problem and clarify the problem from different aspects. Therefore, this study provides more sufficient evidence and richer research perspectives for identifying promising technologies.

In terms of research methods and techniques, in order to illustrate the feasibility and advantages of the methods and techniques used in this study, their comparative analysis with other methods needs to be discussed. In the existing literature, patent maps [63], abnormal value detection [64], and index analysis are often applied to identify promising technologies from the technical perspective. Among them, the patent map and abnormal value detection method intuitively present the identification results, and the index analysis method measures the identification results quantitatively and objectively. However, the above methods focus on the self and static features of technologies and less on the relationship between them and dynamic change features. To our best knowledge, social network centrality analysis can fully consider the relationship between technologies by calculating the centrality indicators of each technical node in the network. The DEA–Malmquist model can be used to evaluate the dynamic efficiency changes of centrality indicators in continuous time, and the CRITIC method can objectively assign weights to multiple output indicators of the DEA–Malmquist model. Therefore, these methods and techniques are applied in this study to improve the comprehensiveness and accuracy of the analysis results.

6. Conclusions

This study develops a novel approach to identify promising EVs technologies from the perspective of market and technical attributes. The review and technical keywords are extracted from online reviews and patent data using text mining tools. Further, a series of quantitative analysis methods such as sentiment analysis and the DEA–Malmquist model were applied to analyze and calculate market demand and technical features values. Promising technologies were identified by constructing a portfolio map based on these two indicators. The identification results can provide innovative ideas for companies and R&D personnel in the field of EVs.

The contributions of this study are as follows. From the aspect of perspective, this study attempts to integrate the market attributes into the process of identifying promising EVs technologies, while most of the existing literature on EVs only relies on a single perspective of technical attributes, and less systematically analyzes the promising EVs technologies from the overall level. Meanwhile, the UNISON framework developed provides a systematic approach for promising technology identification by integrating market and technical attributes. From the aspect of methodology, in the stage of technical features analysis, social network centrality analysis and the DEA–Malmquist model are employed. This can compensate for the previous studies focusing on the self and static technical keywords while ignoring their correlations and dynamic changes. In addition, the application of the CRITIC method enhances the objectivity of technical features calculation results. From the perspective of application, the method proposed in this study can provide an objective and comprehensive reference for EV-related enterprises to analyze technology trends and opportunities. In addition, the promising technologies identified in this study can provide relevant enterprises with innovative improvement directions for EVs, thus contributing to global energy efficiency and environmental protection.

Despite the contribution, this study has some limitations, and further study is required. Firstly, in order to map the review keywords and technical keywords and summarize the technical topics, this study has employed the opinions of experts in the field of EVs. However, the mapping relationship between the two can be determined by combining quantitative and qualitative analysis to improve the efficiency and objectivity of the analysis process. In addition, since the market demand in this study is analyzed based on online reviews, it can work well only in the field where enough user reviews have accumulated to offer reliable and trustworthy information on market demand. Finally, the proposed framework based on the perspective of market and technical attributes focuses on short-term technological innovation. A rolling collection of online reviews and patent data in specific fields should be required to update and improve the innovation ideas in time.

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Appendix A

Table A1. Co-occurrence matrix for technical keywords in the EVs field in 2017.

	Accelerator	Alarm	Assembly	...	Converter	Damping	...	Solar	Sound	Storage
accelerator	534	18	46	...	25	2	...	2	7	80
alarm	18	536	13	...	18	2	...	19	42	84
assembly	46	13	1301	...	55	27	...	24	3	172
...	...	...	...	...	...	...	...	...	...	...
converter	25	18	55	...	1048	4	...	51	4	274
damping	2	2	27	...	4	236	...	5	1	31
...	...	...	...	...	...	...	...	...	...	...
solar	2	19	24	...	51	5	...	319	2	178
sound	7	42	3	...	4	1	...	2	118	16
storage	80	84	172	...	274	31	...	178	16	2560

Appendix B

Table A2. Degree centrality of technical keywords in the EVs field in 2017–2021.

Technical Keywords	Year				
	2017	2018	2019	2020	2021
accelerator	3479	2859	1799	2645	1625
alarm	3321	3056	2298	9516	9480
assembly	7196	7873	7940	8293	5270
automation	8447	10,894	8407	9243	6229
automobile	23,598	29,182	21,351	23,231	16,103
battery	30,860	34,863	31,369	33,420	21,140
beam	1779	1948	2143	2504	1347
bearing	2115	3082	2780	3251	2001
bluetooth	445	455	391	342	239
BMS	1284	1010	1202	1088	673
body	14,671	18,277	14,647	16,573	10,894
brake	6948	7978	7276	2826	1830
buzzer	409	341	231	255	166
camera	1053	1479	1243	1230	810
charge	43,634	49,799	25,189	49,709	31,128
chassis	1942	2349	1709	1855	1167
communication	5933	6853	6440	6007	4323
control	65,536	74,072	60,994	62,840	40,636
converter	6174	4636	8387	8355	4865
damping	1271	1801	1588	1677	1263
detector	24,822	16,383	13,266	13,939	4770
display	6006	5671	4843	5694	3492
driver	33,644	41,925	34,145	40,558	24,249
electric	67,342	77,120	68,448	75,602	48,075
energy saving	15,213	18,079	15,441	16,037	10,760
generator	6533	17,121	12,729	19,884	14,572
gps	734	764	562	509	216
head	2763	3839	3099	3675	2269
inner	2847	3576	2205	2163	1742
light	4122	4812	4174	4626	2804
lock	25,869	27,698	27,909	28,466	18,901
motor	24,152	26,474	23,362	22,949	14,381
panel	3303	4487	3290	3372	2237
rear	5738	6991	6063	7076	3824
remote monitoring	1999	2022	1469	1625	933
screen	2871	3839	2328	2489	1601
seat	4093	5029	4935	6524	4494
solar	5902	10,557	9650	13,056	9532
sound	851	1131	825	1087	757
storage	14,658	20,444	18,800	19,092	16,055

Appendix C

Table A3. Betweenness centrality of technical keywords in 2017–2021.

Technical Keywords	Year				
	2017	2018	2019	2020	2021
accelerator	0.526	0.237	0.361	0.422	0.416
alarm	0.526	0.679	0.851	0.884	0.893
assembly	0.439	0.458	0.664	0.536	0.513
automation	0.526	0.679	0.547	0.884	1.018
automobile	0.526	0.679	0.851	0.884	1.018
battery	0.526	0.679	0.851	0.884	1.018
beam	0.174	0.168	0.029	0.137	0.263
bearing	0.116	0.111	0.215	0.286	0.639
bluetooth	0.114	0.027	0.342	0.061	0.254
BMS	0.204	0.083	0.147	0.286	0.231
body	0.526	0.679	0.851	0.884	1.018
brake	0.526	0.679	0.851	0.238	0.355
buzzer	0.176	0.028	0.059	0.109	0
camera	0.173	0.466	0.404	0.661	0.666
charge	0.526	0.679	0.851	0.884	1.018
chassis	0.201	0.195	0.361	0.286	1.018
communication	0.377	0.679	0.851	0.884	1.018
control	0.526	0.679	0.851	0.884	1.018
converter	0.526	0.382	0.851	0.536	0.472
damping	0.41	0.339	0.087	0.256	0.199
detector	0.526	0.679	0.851	0.884	1.018
display	0.526	0.679	0.851	0.884	1.018
driver	0.526	0.679	0.851	0.884	1.018
electric	0.526	0.679	0.851	0.884	1.018
energy saving	0.526	0.679	0.851	0.884	1.018
generator	0.526	0.679	0.664	0.884	1.018
gps	0.231	0.557	0.503	0.789	0.332
head	0.526	0.382	0.392	0.661	0.665
inner	0.526	0.679	0.459	0.512	0.859
light	0.526	0.679	0.851	0.884	1.018
lock	0.526	0.679	0.851	0.884	1.018
motor	0.526	0.679	0.851	0.884	1.018
panel	0.526	0.679	0.851	0.792	0.859
rear	0.289	0.679	0.851	0.884	1.018
remote monitoring	0.526	0.592	0.69	0.634	0.393
screen	0.526	0.679	0.851	0.884	0.893
seat	0.526	0.679	0.851	0.884	1.018
solar	0.526	0.679	0.851	0.884	1.018
sound	0.377	0.324	0.663	0.477	0.703
storage	0.526	0.679	0.851	0.884	1.018

Appendix D

Table A4. Closeness centrality of technical keywords in 2017–2021.

Technical Keywords	Year				
	2017	2018	2019	2020	2021
accelerator	40	43	42	43	44
alarm	40	40	40	40	41
assembly	41	41	41	41	42
automation	40	40	41	40	40
automobile	40	40	40	40	40
battery	40	40	40	40	40
beam	45	43	45	44	44
bearing	44	44	44	43	42
bluetooth	44	49	46	50	46
BMS	44	44	46	47	46
body	40	40	40	40	40
brake	40	40	40	45	45
buzzer	44	47	49	45	50
camera	43	42	43	41	42
charge	40	40	40	40	40
chassis	43	42	42	43	40
communication	41	40	40	40	40
control	40	40	40	40	40
converter	40	41	40	41	42
damping	41	43	45	43	44
detector	40	40	40	40	40
display	40	40	40	40	40
driver	40	40	40	40	40
electric	40	40	40	40	40
energy saving	40	40	40	40	40
generator	40	40	41	40	40
gps	43	41	43	41	46
head	40	41	42	41	41
inner	40	40	42	43	41
light	40	40	40	40	40
lock	40	40	40	40	40
motor	40	40	40	40	40
panel	40	40	40	41	41
rear	42	40	40	40	40
remote monitoring	40	41	41	42	44
screen	40	40	40	40	41
seat	40	40	40	40	40
solar	40	40	40	40	40
sound	41	42	41	42	42
storage	40	40	40	40	40

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