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Assessing Chinese user satisfaction with electric vehicle battery performance from online reviews

Lanxin Shi [a,b], Shiqi (Shawn) Ou [a,b,*], Yanzi Zhou [a], Yonglin Wu [a], Xiaolu Tan [a], Xin He [c], Daniel J. De Castro Gomez [d], Zhenhong Lin [a,b]

[a] *School of Future Technology, South China University of Technology, Guangzhou 511442 China*
[b] *Guangdong Artificial Intelligence and Digital Economy Laboratory (Guangzhou), Guangzhou 510335 China*
[c] *Aramco Americas, Aramco Research Center - Detroit, 46535 Peary Ct., Novi, Mi 48377, USA*
[d] *Technology Strategy and Planning, Saudi Aramco, P.O. Box 62, Dhahran 31311, Saudi Arabia*

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ABSTRACT

This study employs data-scraping and analysis of 11,525 Plug-in Electric Vehicle (PEV) user reviews from 2018 to 2024, focusing on users' battery performance satisfaction with electric range, battery degradation, and charging experience. Using SnowNLP, Multinomial Naive Bayes, and Bidirectional Encoder Representations from Transformers (BERT), along with an explainable machine learning algorithm, the findings identify location and vehicle price as critical factors influencing PEV perceptions. Battery Electric Vehicles (BEVs) receive consistently more positive feedback than Plug-in Hybrid Electric Vehicles (PHEVs) across the Chinese Mainland, though satisfaction for both declines with vehicle age. PEVs with an all-electric range of under 100 km get predominantly negative reviews after over four years of use. To boost PEV adoption and satisfaction, targeted incentives for PHEVs with 150–200 km and BEVs with 550–600 km range in lower-tier cities are recommended. These findings offer valuable insights for manufacturers and policymakers promoting PEV market growth in China.

1. Introduction

Plug-in Electric Vehicles (PEVs) represent the main direction for the transformation of the global vehicle industry, and constitute an important strategic choice for the high-quality development of China's automotive industry (Xin, 2024). Nowadays, China's road transport energy transition has fundamentally established a PEV development strategy that prioritizes Battery Electric Vehicles (BEVs) while concurrently developing Plug-in Hybrid Electric Vehicles (PHEVs) and Fuel Cell Vehicles (FCVs) (Wei et al., 2022). According to the latest data released by the Ministry of Industry and Information Technology of the People's Republic of China (Ding et al., 2024), in 2023, the new vehicle sales penetration rate of PEVs in China reached 31.6 %, with production and sales volumes jumping to 9.587 million and 9.495 million, respectively, maintaining a global lead for the ninth consecutive year.

As PEVs continue penetrating the market, user-centric design becomes increasingly critical in determining their success and acceptance (Li et al., 2024). Before the 2020 s, during the initial implementation phase of PEV incentive policies worldwide, PEVs had not yet achieved widespread market penetration (Ou et al., 2018). At that time, research in this field primarily focused on studying public acceptance of PEVs and analyzing the factors influencing public adoption rates through hypothetical scenarios. Existing studies

* Corresponding author at: School of Future Technology, South China University of Technology, Guangzhou 511442, China.
E-mail address: sou@scut.edu.cn (S.(S. Ou).

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indicated overarching issues such as cost (Egbue & Long, 2012; Larson et al., 2014; Skippon & Garwood, 2011; Graham-Rowe et al., 2012; Yang et al., 2018), driving range (Egbue & Long, 2012; Larson et al., 2014; Skippon & Garwood, 2011; Yang et al., 2018), charging convenience (Larson et al., 2014; Skippon & Garwood, 2011; Yang et al., 2018), vehicle characteristics (Larson et al., 2014; Skippon & Garwood, 2011; Graham-Rowe et al., 2012), and consumer individual attributes (Egbue & Long, 2012; Haustein & Jensen, 2018) are crucial for broader PEV adoption. For example, an online survey of technology enthusiasts in the US emphasized that, besides individual attributes, electric range and cost emerged as critical drivers of PEV adoption (Egbue & Long, 2012). The attitudes of Canadian residents toward electric vehicles were predominantly influenced by total cost, vehicle characteristics, and charging convenience (Larson et al., 2014). In the UK, while attributes associated with BEVs, such as acceleration, smoothness, and reduced noise, were generally viewed positively, purchase costs, driving range, and charging time are identified as the three main negative factors (Skippon & Garwood, 2011). However, although Denmark and Sweden had relatively high nationwide coverage of public charging stations (540 charging locations, including 235 fast-charging stations; 19/9/2017), the share of BEVs in new vehicle purchases was only 0.5 % in 2016. Instead, it was the individual attributes of potential consumers that had a greater influence on BEV adoption (Haustein & Jensen, 2018). According to Graham-Rowe et al. (2012), PEVs were evaluated against Internal Combustion Engine (ICE) vehicle benchmarks concerning cost, performance, convenience, comfort, and aesthetics, with purchase intentions largely dependent on PEVs meeting these criteria in the future. Similarly, a study of the Chinese market using the Stated Preferences (SP) survey method found that factors such as the coverage of charging piles, driving range, charging speed, and price influence the potential ownership and usage of PEVs (Yang et al., 2018). However, since PEVs are direct "end-user products", it might be impractical to predict user reactions based solely on pre-experience (a priori) data (Daramy-Williams et al., 2019). Furthermore, providing opportunities for consumers to gain hands-on experience with PEVs can potentially alter their attitudes toward these vehicles (Jena, 2020). Therefore, assessing firsthand evidence from users after they have experienced PEVs (a posteriori) becomes necessary (Daramy-Williams et al., 2019).

Through a field study of actual PEV users, research across different regions highlighted that electric range (Franke and Krems, 2013; Kwon et al., 2020; Su et al., 2020), charging convenience (Kwon & Jang., 2020; Su et al., 2020; Jin et al., 2021), vehicle performance (Zhao et al., 2023; Su et al., 2020; Jin et al., 2021), cost (Su et al., 2020; Zhao et al., 2023), noise (Zhao et al., 2023), and delivery time (Zhao et al., 2023) were key factors typically influencing user satisfaction with PEVs. Specially, in a large-scale electric vehicle trial in the Berlin metropolitan area, Germany, 79 participants were examined by Franke & Krems. (2013). They found that higher electric range demand, familiarity with conventional vehicles, and greater electric range anxiety experience positively influenced satisfaction with electric range. In South Korea, it was found through interviews with PEV users that two factors closely related to PEV usability—driving range and charging—significantly impact overall user satisfaction. While most BEV users were currently dissatisfied with the driving range and charging conditions, satisfaction with these factors was expected to improve as technology advances (Kwon & Jang, 2020). In the Analytic Hierarchy Process (AHP) analysis, it was found that Korean Micro Electric Vehicle (MEV) users ranked factors in order of importance as follows: user utilization, vehicle movement, and charging services (Jin et al., 2021). In China, field studies conducted in Shanghai and Nanjing revealed that user experiences related to usefulness, experience of ease-of-use, total cost, electric range, and charging infrastructure readiness were key factors influencing the satisfaction of PEV users (Su et al., 2020). An online survey was conducted to assess user satisfaction and improvement priorities, revealing that both full-sized and mini electric vehicles urgently needed improvements in noise isolation and driving range. Additionally, enhancements in delivery time, charging queue time, and purchase price were required for full-sized EVs, while mini EVs needed improvements in safety, comfort, and purchase subsidies (Zhao et al., 2023).

Recently, digital footprints such as online PEVs' user reviews and ratings have become valuable resources for understanding consumer sentiments and expectations (Li & Chen., 2022; Bian et al., 2024). Beyond merely capturing consumer emotions, the analysis of online reviews plays a dual role in shaping consumer attitudes toward PEVs and potentially influencing potential buyers (Maslowska et al., 2017). Currently, Natural Language Processing (NLP) and Machine Learning (ML) techniques are employed on these large datasets to quantify consumer satisfaction, expectations, and concerns. For instance, research on global public sentiment towards PEVs on *YouTube* indicated that positive emotions were often driven by the environmental benefits of PEVs, technological innovations, and the potential for long-term cost savings. Conversely, negative emotions were primarily focused on the high initial cost of PEVs, anxiety about battery life and range, and the inadequacy of charging infrastructure (Costello & Lee, 2020). Furthermore, in the US, Convolutional Neural Network (CNN) models were employed to analyze user sentiment in charging station reviews, examining correlations between emotions and station types (public vs. private, urban vs. rural) as well as nearby points of interest (Asensio et al., 2020). Using the same approach, consumer comments on PEVs from an Indian social media platform were analyzed, revealing widespread concerns about price, maintenance, and safety; CNNs were demonstrated as the most effective model for analyzing PEV sentiment (Jena, 2020). In China, SnowNLP and semantic network models were applied to sentiment analysis and opinion mining of *Autohome*'s online comments on Extended Range Electric Vehicles (EREVs), BEVs, and PHEVs, identifying space, energy consumption, and interior layout as the most direct factors influencing user sentiment (Li & Chen., 2022). Using "new energy vehicles" as a keyword, continuous *Weibo* posts spanning three months were collected and analyzed to assess public sentiment toward PEVs using the *NLPIR-Parser* platform. Sentiment tendencies were identified, and high-frequency keywords (e.g., safety, accident, battery life, driving range, and recharging) extracted from the comments were employed to interpret the specific reasons behind the public's diverse emotions toward new energy vehicles (Wu et al., 2023).

Although field surveys offer a more targeted approach to formulating research questions, they require specialized designs and significant time, effort, and financial resources to execute (Fowler, 2013; Nardi, 2018). In response, this study proposed a methodological framework that significantly minimizes costs by utilizing automated scripts for a sustainable approach that continuously updates with the latest reviews in real time (Baviskar et al., 2021). By integrating NLP with manual evaluation, our approach achieves

Table 1
Summary of recent studies on PEV users' reviews.

Study areas (Chronological order)	Methodology	Disadvantages of methodology[1]	Key determinants in findings[2] Electric range	Charging convenience	Cost	Vehicle characteristics	Consumer individual attributes	Others	Study subjects
UK (Skippon & Garwood, 2011)	Offline survey	①③④⑤⑥	●	●	●	●		Noise	PEV adoption & PEV satisfaction
US (Egbue & Long, 2012)	Online survey	①②⑤⑥	●		●		●		PEV adoption
UK (Graham-Rowe et al., 2012)	Offline survey	①③⑤⑥			●	●	●		PEV adoption
Germany (Franke & Krems, 2013)	Offline survey	①③④⑤	●			●	●		PEV electric range satisfaction
Canada (Larson et al., 2014)	Offline survey	①②③④⑤	●	●	●	●			PEV adoption
Denmark and Sweden (Haustein & Jensen, 2018)	Online survey	④⑥					●		PEV adoption
China (Yang et al., 2018)	Offline survey	③④⑤⑥	●	●	●				PEV adoption
China (Su et al., 2020)	Online survey	④⑤⑥	●	●	●	●	●		PEV satisfaction
South Korea (Kwon & Jang, 2020)	Offline survey	②③④⑤⑥	●	●			●		PEV satisfaction
Global (Costello & Lee, 2020)	*YouTube* platform reviews + SentimentR	④⑥⑦							PEV satisfaction
US (Asensio et al., 2020)	Mobile applications' reviews + CNN	④⑥		●				Area and POI (Point of Interest)	PEV charging satisfaction
India (Jena, 2020)	Social media platform reviews + CNN	④⑥			●	●			PEV satisfaction
South Korea (Jin et al., 2021)	Offline survey	①②③④⑤⑥		●	●	●	●		MEV satisfaction
China (Li & Chen., 2022)	*Autohome* website reviews + SnowNLP	⑥⑦				●			PEV satisfaction
China (Zhao et al., 2023)	Online survey	⑤	●	●	●	●		Noise and delivery time	PEV satisfaction
China (Wu et al., 2023)	Sina *Weibo* web page review + NLPIR-Parser	①④⑥⑦	●	●		●		Accident	PEV satisfaction
China (Bian et al., 2024)	*Autohome* and *PCauto* website reviews + perceived quality measure	①④⑥⑦						Emotional experience, defect perception, and brand/product image	PEV adoption

[1] Each number in the "Disadvantages of methodology" column repres ents specific limitations noted in these studies: ①Samples did not consist of PEV users, lacking long-term use and charging experience. ②Samples were limited to a specific type of population and did not represent a broad demographic. ③Surveys were time-consuming and required significant human and financial resources. ④Only one type of PEV was considered, or PEVs were not differentiated by type. ⑤The small sample size resulted in weak robustness of the results. ⑥No quantitative analysis was conducted on key determinants. ⑦Relied on a single NLP algorithm, the accuracy of sentiment classification was not evaluated (only applies to studies that analyzed user reviews).

[2] In the "Key determinants in findings" column, ● represents that the study found the corresponding factor to be a significant determinant of PEV adoption or satisfaction.

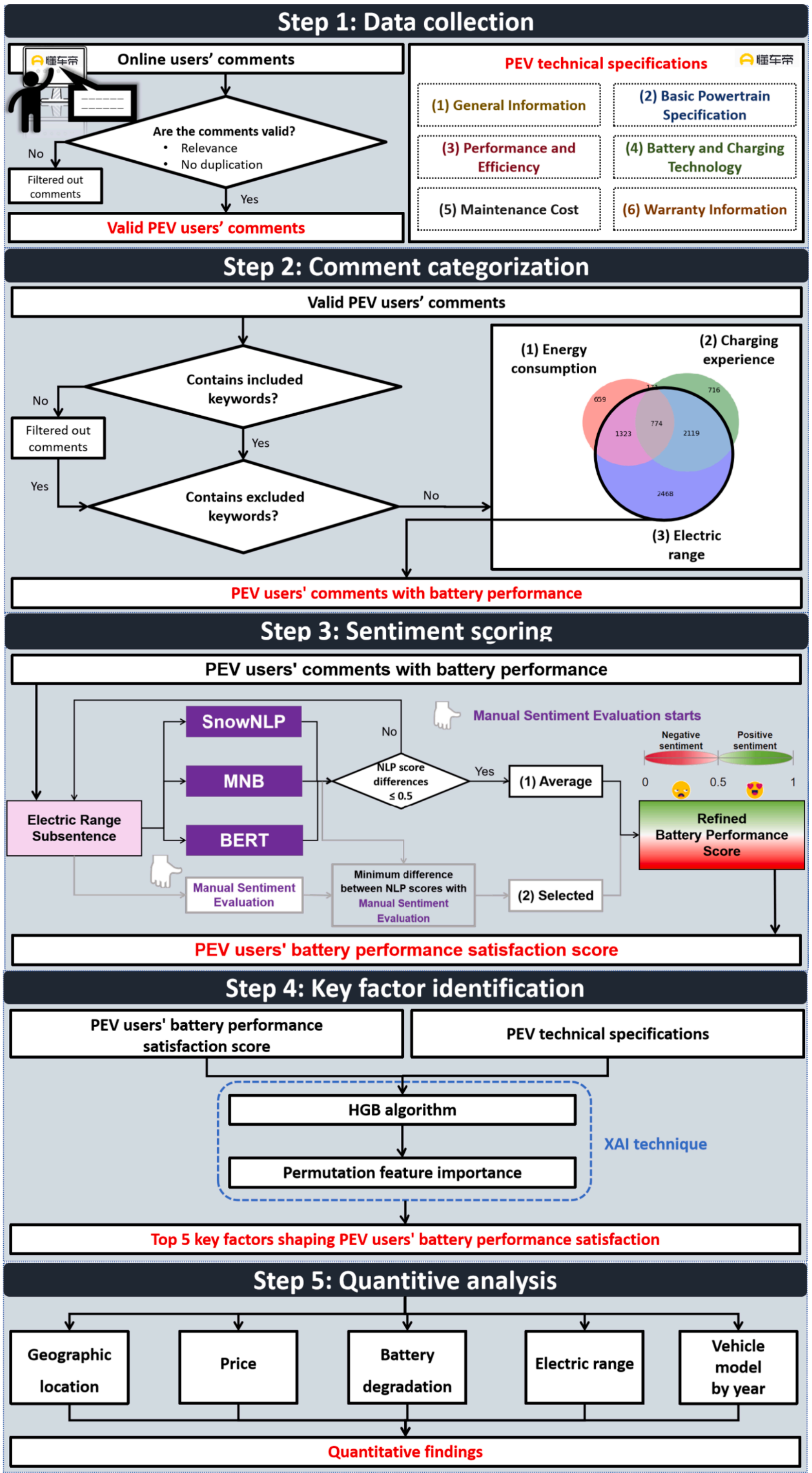


Fig. 1. Study workflow and framework.

results comparable to those of more labor-intensive methods (Li & Chen., 2022). This is particularly crucial in the era of big data and the increasing prevalence of online reviews, which offer a rich source of untapped data capable of providing more detailed insights into consumer sentiment and market dynamics (Maslowska et al., 2017; Costello & Lee, 2020).

Table 2
Descriptive statistics of PEV indicators (continuous variables).

Dimension	Indicator	Unit	Min	Mean	Max
General Information	Longitude	°	77.19	114.75	132.65
	Latitude	°	18.30	30.98	47.74
	Price	10 K (CNY)	2.36	22.06	78
	Vehicle Age	Month	0	2.67	98
Basic Powertrain Specifications	Maximum Engine Power	kW	74	90.51	120
	Maximum Motor Power	kW	107	146.84	360
	Electric Motor	HP	75	343.67	789
Performance and efficiency	Electric Range	km	43	345.50	1032
	Combined Range	km	945	1232.23	1370
	WLTC Combined Fuel Consumption (PHEVs)	L/100 km	0.7	2.23	6.3
	Electricity Consumption Per 100 km in CD Mode	kWh	9.6	14.72	27.1
	Maximum Speed	km/h	130	192.27	265
	Maximum Power	kW	55	265.93	580
Battery and Charging Technology	Battery Capacity	kWh	8.3	46.71	140.0
	Battery Energy Density	Wh/kg	115	150.18	200
	Fast Charging Time	h	0.19	0.61	1.10
	Slow Charging Time	h	1.7	6.35	12.2
Maintenance Cost	Estimated Total Maintenance Cost for 60,000 km	CNY	957	5725.64	11,975

Through a comprehensive review of related literature (Table 1), several critical gaps and the necessity for further research were identified. **(1) Insufficient focus on PEV battery preferences in China**: The Chinese Mainland holds a leading position in the global PEV market (Graham et al., 2021), underscores the critical need for targeted research on PEV consumer behavior within this key market. The substantial influence of government policies and the dominant position of domestic electric vehicle manufacturers significantly shape the decision-making processes of PEV consumers in China (Ehsan et al., 2024). Despite existing studies, there remains a compelling need for deeper, more nuanced insights into the preferences and behaviors of Chinese PEV consumers, particularly in terms of battery performance preferences. **(2) Neglect of geographic and temporal factors**: Few studies account for geographic factors that could offer deeper insights into market segmentation and consumer diversity. Additionally, there is a lack of tracking changes in PEV consumer attitudes over vehicle age as the market and technology progress. **(3) Need for advanced and comparative analytical tools**: Current studies focusing on PEV users' online comments predominantly utilize single NLP algorithms for sentiment analysis. This extreme reliance on only one NLP method may lead to misclassifications of sentiments, which fails to accurately capture the subtle nuances of PEV users' emotions. Furthermore, despite the availability of established frameworks for collecting and rating online consumer reviews of PEVs, there is still a need to develop more sophisticated analytical tools. Advanced big data analytics techniques, such as explainable machine learning (XAI), are crucial for deciphering the nuances in user feedback (Rong et al., 2023) and understanding their impact on the PEV market. XAI excels at managing the complex and non-linear relationships inherent in consumer data (Li et al., 2024), thereby enabling a more accurate and comprehensive analysis of sentiments and behavioral patterns that are often incorrectly assumed to be linear by conventional analyses.

Focusing on the Chinese market, this study analyzed textual data from user comments using NLP algorithms to quantify PEV user sentiments in battery performance. In addition, it integrated corresponding vehicle information and powertrain specifications. This study also utilized XAI to gain deeper insights into the key features that drive consumer perceptions in the PEV sector. Through big data mining and analytics, this study examined preferences both geographically and temporally. Furthermore, it provided a detailed understanding of the interplay between user experience and market dynamics, revealing how these interactions are influenced by broader societal, economic, and technological trends. These insights are able to guide strategic policymaking decisions and PEV product development.

This paper is organized as follows: Section 2 describes the study methods, including the data sources, study subject, scoring rules, the XAI model's algorithm, and the criteria for analyzing user evaluation indices across different cities. Section 3 presents the results, providing a macro-level analysis of the contributions of various important features to the model for PHEVs and BEVs, respectively. At the micro level, it primarily examines the specific impacts of geographical factors, price, vehicle age, and model year on user evaluations. This section also compares these findings with existing literature to underscore the contributions of this study. Finally, Section 4 and Section 5 conclude by summarizing the main findings and suggesting avenues for future research.

2. Data & methods

The comprehensive workflow and framework employed in this study to systematically analyze PEV users' battery performance satisfaction is illustrated in Fig. 1. This framework is organized into five key steps: data collection, comment categorization, sentiment scoring, key factor identification, and quantitative analysis. The key issues addressed at each step are highlighted in red text within the Fig. 1.

2.1. Data source

The dataset for this study was sourced from *Dong Che Di*, the most popular and influential online automotive review platform,

Table 3
Descriptive statistics of PEV indicators (categorical variables).

Dimension	Indicator	Encoding	Description	Frequency
General Information	Manufacturer	1	Domestic Brand (Chen et al., 2020)	81.43 %
		2	Foreign Brand (Tesla)	16.48 %
		3	Foreign Brand (excluding Tesla)	2.09 %
	Vehicle Model Year	2015		0.09 %
		2017		0.03 %
		2018		0.03 %
		2019		0.33 %
		2020		8.48 %
		2021		21.38 %
		2022		28.32 %
		2023		17.40 %
		2024		23.94 %
Basic Powertrain Specifications	Powertrain Type	PHEV		50.89 %
		BEV		49.11 %
	Vehicle Type	1	Sedan	43.31 %
		2	SUV	43.88 %
		3	Minivan	12.81 %
	Engine (PHEVs)	1	1.5 T	93.90 %
		2	2.0 T	6.10 %
Battery and Charging Technology	High-Voltage Fast Charging Platform	400 V		70.11 %
		800 V		29.89 %
	Fast Charge Capacity	1	10—80 %	7.89 %
		2	20—80 %	14.74 %
		3	30—80 %	73.27 %
		4	80 %	4.09 %
Warranty Information	Whole Vehicle Warranty Period	1	3 years or 100,000 km	2.09 %
		2	4 years or 100,000 km	19.51 %
		3	4 years or 80,000 km	16.49 %
		4	5 years or 100,000 km	2.33 %
		5	6 years or 150,000 km	59.58 %
	Battery Pack Warranty Period	1	6 years or 150,000 km	0.12 %
		2	8 years or 150,000 km	0.37 %
		3	8 years or 160,000 km	15.13 %
		4	8 years or 190,200 km	3.90 %
		5	No limit on time or mileage for the original owner	80.48 %

Table 4
Classification criteria for PEV user comments.

	Included keywords	Excluded keywords
Energy consumption	"energy", "electric", "energy consumption", "battery", "aging", "degradation", "electricity consumption", "energy efficiency", "power consumption", "energy saving", and "efficiency"	/
Charging experience	"charging", "fast charge", and "slow charge"	"charging piles" and "charging stations"
Electric range	"electric range", "range", "travel time", "mileage", "kilometer", "km", "meter", "distance", and "long distance"	/

known for its large and active user base, especially among young people (Zhu et al., 2024; Gao et al., 2024). All comments on *Dong Che Di* are exclusively submitted by verified PEV owners, who are required to provide specific details about their vehicle, including model, age, fuel and electricity consumption per 100 km, and total mileage traveled, before posting a review.

The initial dataset, spanning from November 14, 2018, to June 30, 2024, consisted of 20,078 user comments on PEVs, covering a wide range of topics such as exterior design, interior features, entertainment systems, pricing, and dealership experiences. It also included duplicate entries caused by multiple postings or system errors, as well as promotional or unintelligible comments. For the purpose of this study, only comments specifically addressing battery performance—such as range, charging speed, battery life, or energy efficiency—were considered valid for analysis. After filtering, 11,525 comments were identified as valid samples.

Additionally, this study collected corresponding technical specifications directly from the "specifications" section of the *Dong Che Di* platform for each PEV. The technical data covered six aspects: general information, basic powertrain specification, performance and efficiency, battery and charging technology, maintenance cost, and warranty information. In the "general information" section, the PEV purchase location was linked to the latitude and longitude of the corresponding prefecture-level city, enabling the retrieval of precise geographic coordinates. Descriptive statistics for the corresponding indicators are presented in Tables 2 and 3. To further illustrate the characteristics of the key continuous variables, distribution plots are provided in the Appendix.

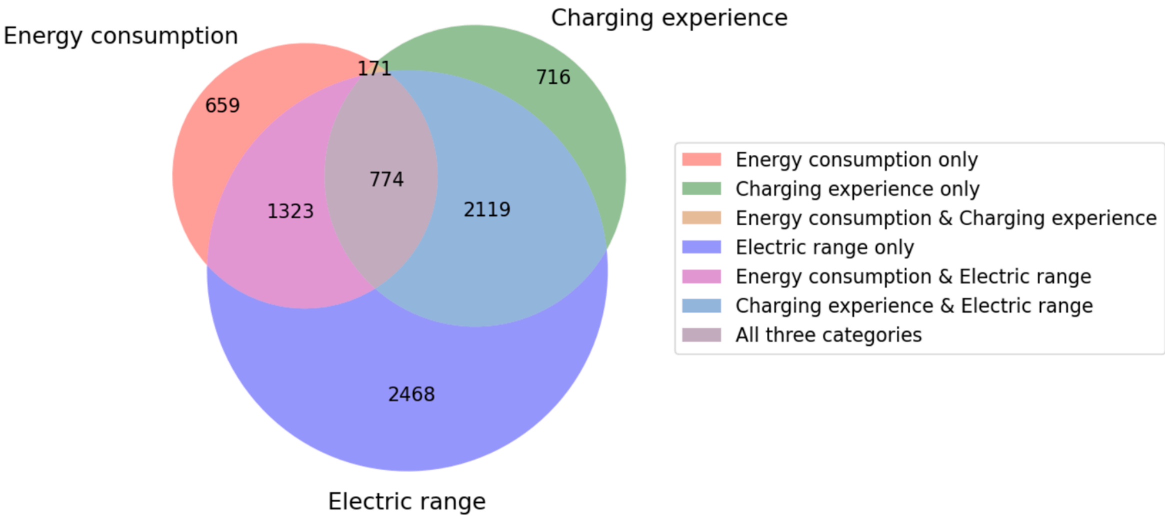


Fig. 2. Distribution of sub-sentence counts in PEV users' comments on energy consumption, charging experience, and electric range.

2.2. Study subject

In this study, a total of 11,525 valid comments were systematically categorized into three distinct groups: energy consumption, charging experience, and electric range. This categorization was automatically achieved through the meticulous identification of specific keywords within each sample sub-sentence, ensuring that the nuances of user feedback were accurately captured and appropriately classified. The detailed classification criteria and the associated keywords for each category are outlined in Table 4. Importantly, comments related to "charging piles" and "charging stations" were excluded to focus exclusively on PEV users' satisfaction with battery performance. Each numeral in Fig. 2 represents the count of sub-sentences categorized.

Obviously, PEV users predominantly discussed aspects related to the electric range, accounting for 81.22 % of all comments. While there were mentions of energy consumption and charging experience, a significant majority of these comments—71.64 % and 76.53 %, respectively—also related to the electric range, suggesting a thematic overlap where the same battery performance sentiment was expressed across different topics. Consequently, this study focused exclusively on comments related to the electric range, totaling 6,684 instances, to conduct a targeted quantitative analysis of PEV users' satisfaction with battery performance.

2.3. Scoring rules

Textual analyses of user comments were conducted by developing and comparing sentiment scoring models through the use of three distinct NLP algorithms, including SnowNLP (Tang et al., 2020; Ming et al., 2022), Multinomial Naive Bayes (MNB) (Kibriya et al., 2004; Zulfikar et al., 2023), and Bidirectional Encoder Representations from Transformers (BERT) (Alaparthi et al., 2020; Deepa, 2021). The basic principles, strengths, and weaknesses of these three NLP algorithms are summarized in Table 5.

These models targeted both PHEV and BEV categories, focusing on battery performance. Subsequently, this study used a sentiment dictionary for the sentiment analysis to classify the text as either positive or negative. It returned a probability score ranging from 0 (indicating negative sentiment) to 1 (indicating positive sentiment), with values closer to the extremes reflecting stronger sentiment intensities. Fig. 3 provides a comprehensive overview of the data structure and scoring rules used in this study.

To select the most accurate NLP algorithm among SnowNLP, MNB, and BERT for subsequent modeling and analysis, this study also incorporated manual sentiment evaluation as a calibration benchmark. Although qualitative in nature, this manual evaluation provided a reliable standard for assessing the performance of each algorithm. By using it as a reference, the errors across the three NLP algorithms can be effectively compared. Fig. 4 illustrates the framework used to compute the Refined Battery Performance Score, which integrates the performance of the three NLP algorithms.

This study initially set a score threshold, defined as the difference between any two of the three algorithms, at 0.5. When the score differences between each pair of the three NLP algorithms were all less than or equal to 0.5, the Refined Battery Performance Score was automatically set as the arithmetic mean value of the scores from the three NLP algorithms. Samples in this scenario accounted for 83.31 % of the total valid dataset.

$$Score_{Refined} = \overline{Score} = \frac{1}{N}\sum_{n=1}^{N} Score_n \tag{1}$$

Where $\overline{Score}$ is the Refined Battery Performance Score after applying the average method; N is the number of algorithms used (in this study, N=3); $Score_n$ represents the sentiment score provided by the n-th algorithm.

When the score difference between any two out of the three algorithms exceeded 0.5, this study implemented manual intervention.

Table 5
Comparative overview of NLP algorithms: SnowNLP, MNB, and BERT.

	SnowNLP	MNB	BERT
Basic principles	Based on probabilistic models, it trains a classifier to distinguish the sentiment tendencies of Chinese texts.	Based on Bayes' theorem and assumes conditional independence among features.	Based on the Transformer architecture, it utilizes the Multi-head Self-Attention mechanism to capture the relationships between words.
Strengths	Chinese-specific (Tang et al., 2020); lightweight model (Yu et al., 2019); convenience and ease of use (Zhang et al., 2023)	High computational efficiency (Kibriya et al., 2004); ease of use (Tama & Sibaroni, 2019); broad applicability (Xu, 2018)	Strong contextual understanding (Alaparthi et al., 2020); pre-trained model (Alaparthi et al., 2020); suitability for complex tasks (Li et al., 2019)
Weaknesses	Limited accuracy (Zhang et al., 2018)	Independence assumption (Harzevili & Alizadeh, 2018); sensitivity to text length (Qiang, 2010)	Resource intensive (Ji et al., 2021); high training costs (Kenton & Toutanova, 2019)

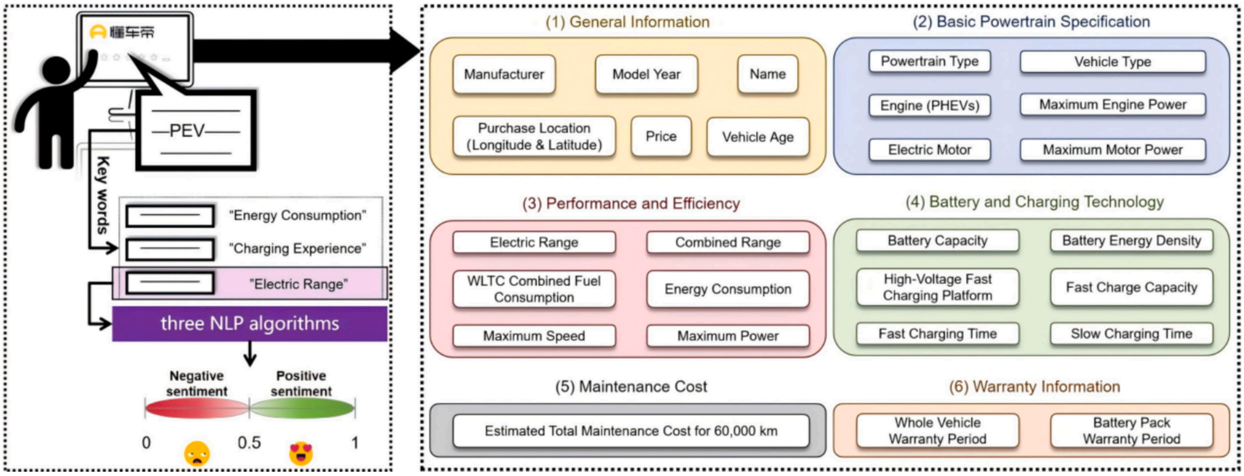


Fig. 3. Framework of PEV user sentiment score & corresponding PEV indicators.

By qualitatively scoring samples (user comment sub-sentences)—as 0 for negative sentiment, 0.5 for neutral sentiment, and 1 for positive sentiment, this study then compared these manual qualitative scores with the three NLP scores and selected the closest NLP score as the Refined Battery Performance Scores. Samples under this category accounted for 16.69 % of the total valid dataset.

$$Score_{Refined} = Score_{selected} \tag{2}$$

Finally, the scoring error for the *n*-th algorithm was defined as the mean of the absolute differences between the algorithm's scores and the standard sentiment scores:

$$Scoreerror_n = \frac{\sum_{m=1}^{M} \left| Score_n - Score_{Refined} \right|}{m} \tag{3}$$

where *m* represents the *m*-th comment sample, with a total of *M* comment samples.

2.4. XAI for understanding factors' contributions

2.4.1. Histogram Gradient boost algorithm

In this study, the Histogram Gradient Boosting (HGB) algorithm was utilized to address the demands of the big dataset. The HGB algorithm, an advanced improvement over the traditional Gradient Boosted Decision Trees (GBDT), significantly simplifies computational demands by discretizing continuous feature values into finite bins, forming the basis for constructing decision trees (Javaid et al., 2022; Nhat-Duc & Van-Duc, 2023). This method considerably reduces the number of potential split points, enhancing computational speed and decreasing memory usage (Shi et al., 2022). The discretization of feature values, $Bin(x_i)$, is given by:

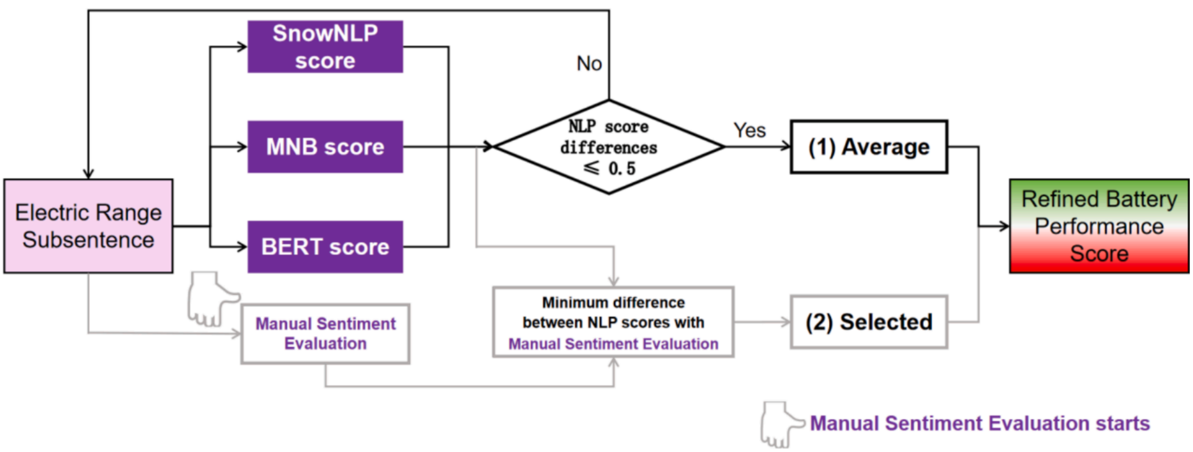


Fig. 4. Calculating framework for the Refined Battery Performance Score.

Table 6
Errors of Battery Performance Score using SnowNLP, MNB, and BERT.

	Battery Performance Score errors
SnowNLP	0.1296
MNB	0.0610
BERT	0.2925

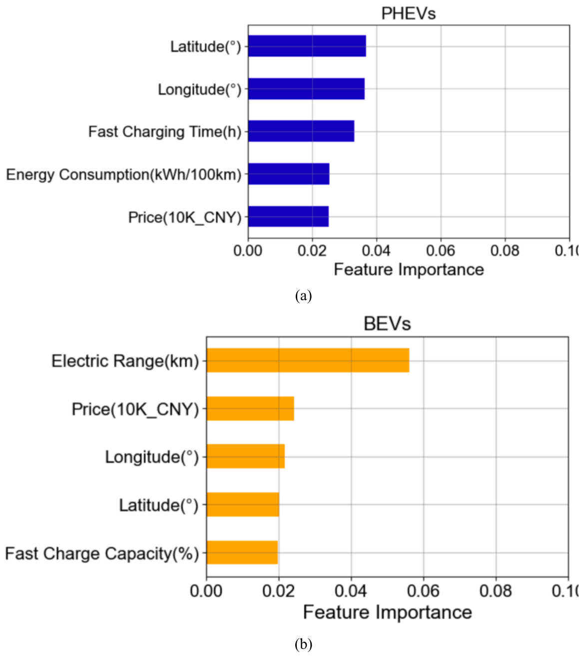


Fig. 5. Permutation feature importance for Battery Performance Score **(a)** PHEVs; **(b)** BEVs.

$$Bin(x_i) = \left\lfloor \frac{x_i - \min(x_i)}{w} \right\rfloor \tag{4}$$

where x_i is a feature value, $\min(x_i)$ is the minimum value of the feature, and w is the interval width determined by the number of bins.

Subsequent tree construction relies on the gradients (g_i) and Hessians (h_i) calculated for each observation from the loss function l, with.

$$g_i = \frac{\partial l(y_i, \widehat{y}_i)}{\partial \widehat{y}_i} \tag{5}$$

and

$$h_i = \frac{\partial^2 l(y_i, \widehat{y}_i)}{\partial \widehat{y}_i^{\,2}} \tag{6}$$

Each node in the tree selects the optimal split based on the histograms of the g_i and h_i. The gain from a potential split is calculated as:

$$Gain = \frac{\left(\sum_{i\in L} g_i\right)^2}{\sum_{i\in L} h_i + \lambda} + \frac{\left(\sum_{i\in R} g_i\right)^2}{\sum_{i\in R} h_i + \lambda} - \frac{\left(\sum_{i\in S} g_i\right)^2}{\sum_{i\in C} h_i + \lambda} \tag{7}$$

where L and R are the sets of instances in the left and right child nodes post-split, C is the set of instances in the current node, and λ is the regularization term.

2.4.2. Permutation feature importance

Permutation Feature Importance assesses the importance of different features concerning the predictive power of a statistical model (Altmann et al., 2010; Kaneko., 2022). This method involves shuffling each predictor variable within the dataset individually and observing the resultant decline in the model's performance metric. The central hypothesis is that randomizing the values of a pivotal feature significantly undermines the model's accuracy, while altering a less crucial feature has minimal impact.

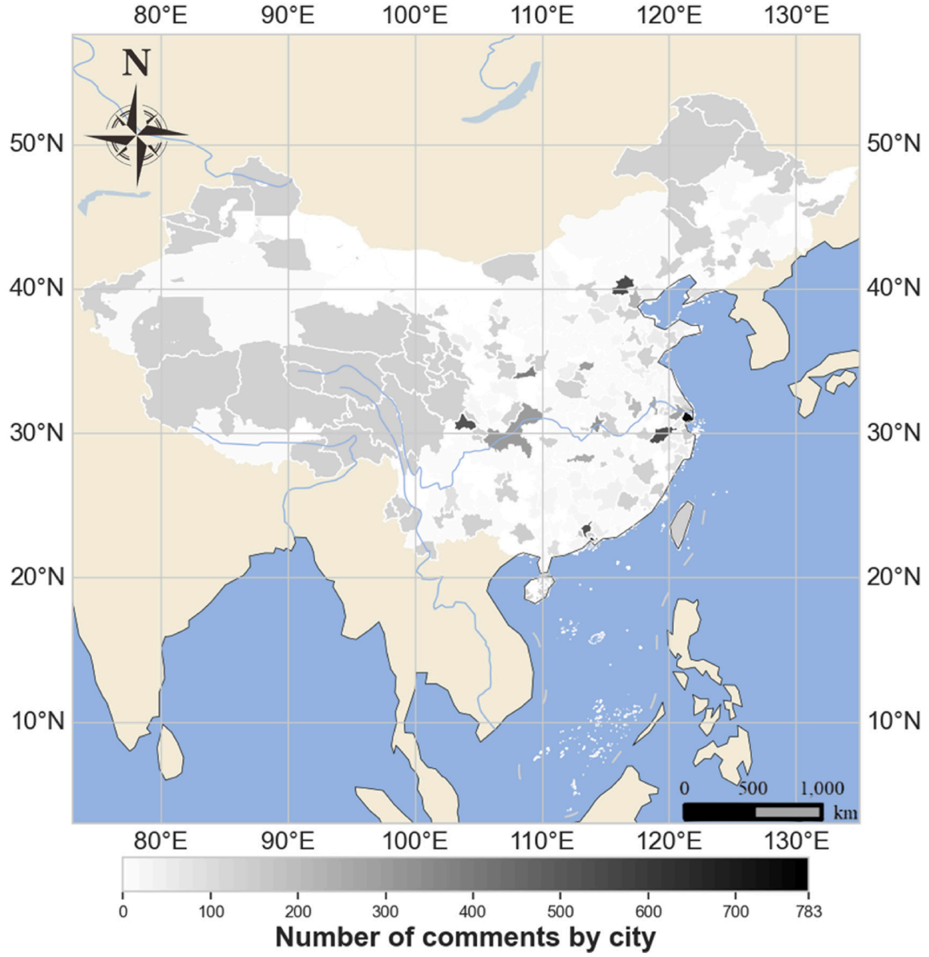


Fig. 6. Distribution of PEV user online comment hotspots.

Consider the original dataset containing features X_1, X_2, …, X_n and target variable Y. For this regression model, performance is quantified using the mean squared error, denoted as $mse_{orig}(X, Y)$.

To assess feature importance, a new dataset is generated by permuting the values of feature X_p within the dataset. Specifically, the values in column *j* are shuffled randomly, breaking any correlation between X_p and Y. The model's performance is then recalculated on this permuted dataset, noted as $mse_{perm}(X_{perm}, Y)$.

The importance of feature X_p is quantified as the change in performance due to this permutation:

$$Importance(X_p) = mse_{orig}(X, Y) - mse_{perm}(X_{perm}, Y) \tag{8}$$

A larger decrease in performance signifies a higher importance of the feature. This method provides a direct and intuitive measure of each feature's impact on the model's accuracy (Debeer & Strobl, 2020).

2.5. PEV users' evaluation index

Due to varying levels of PEV adoption and market acceptance across different regions in the Chinese Mainland, such disparities can significantly influence the interpretation of user sentiment scores derived from comments. To equitably and comprehensively study battery performance sentiment scores regarding prefecture-level city *j*, this study have developed standardized evaluation indices, denoted as ${EI_j}^{norm}$. The evaluation index ${EI_j}^{norm}$ for electric range are calculated separately based on their corresponding scores.

$$\overline{S_j} = \frac{\sum_{k=1}^{N_j} S_{jk}}{N_j} \tag{9}$$

where S_j is the battery performance satisfaction evaluation score of prefecture-level city *j*; S_{jk} is the battery performance satisfaction score of the *k*-th sample in prefecture-level city *j*; N_j is the number of sample reviews corresponding to prefecture-level city *j*.

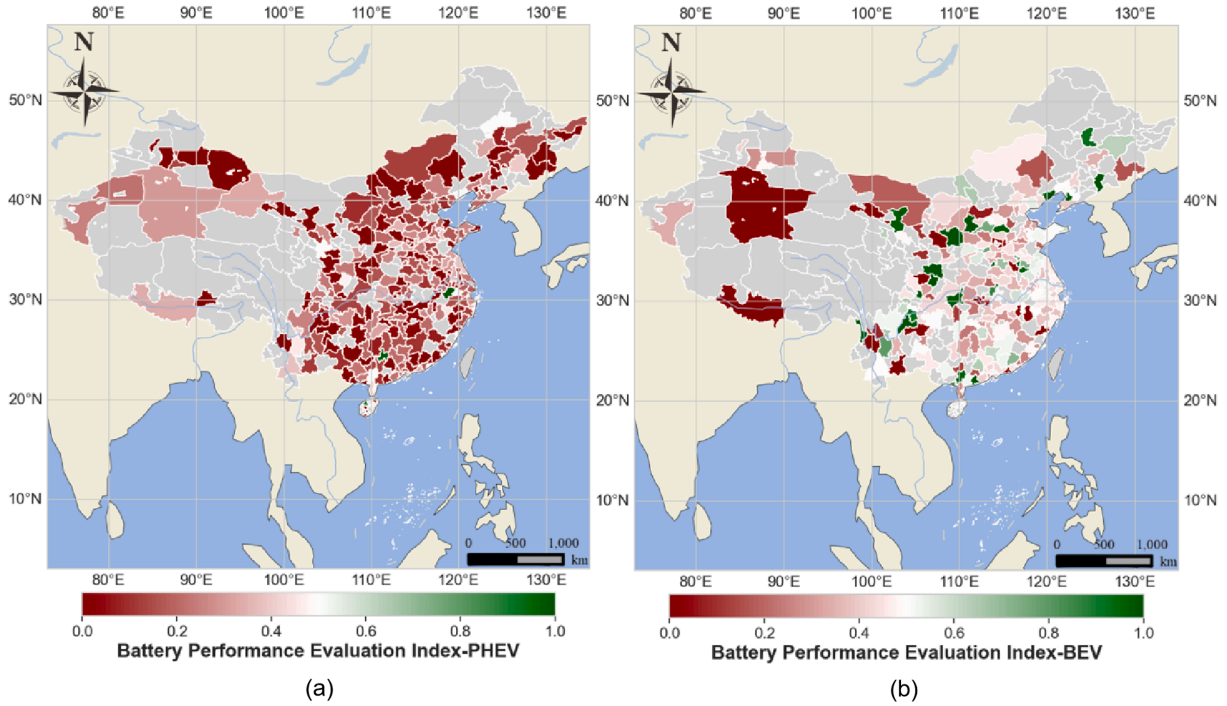


Fig. 7. Geographic distribution of the **(a)** Battery Performance Evaluation Index – PHEV and **(b)** Battery Performance Evaluation Index – BEV.

Each city j associated with its corresponding province $p(j)$ and the province p's total PEV stock $V_{p(j)}$ by the end of 2023 (Ministry of Public Security's Traffic Management Bureau, 2023), $\sum_{p=1}^{P} V_p$ is the sum of PEV ownership across the Chinese Mainland. The evaluation index EI_j^{norm} for a prefecture-level city, j is calculated by normalizing the average sentiment score EI_j relative to the total PEV stock of its province, allowing it to range from 0 to 1, thereby forming a comparable metric across all cities:

$$EI_j = \frac{\overline{S_j} \bullet V_{p(j)}}{\sum_{p=1}^{P} V_p} \tag{10}$$

$$EI_j^{norm} = \frac{EI_j - \min(EI)}{\max(EI) - \min(EI)} \tag{11}$$

where $\min(EI)$ and $\max(EI)$ are the minimum and maximum values of EI_j across all cities, respectively.

3. Results analysis

In total, this study collected user comments on PEVs from 268 prefecture-level cities across the Chinese Mainland. After scoring these comments, this study discovered a pronounced polarization in user evaluations. The proportion of Battery Performance Scores greater than 0.9 or less than 0.1 amounted to 74.79 %. This polarization can be attributed to the structure and dynamics of online environments, such as social media and review platforms, where psychological tendencies often amplify extreme sentiments, leading to a scarcity of neutral opinions in online reviews. This phenomenon is typically explained by underlying network structures and group dynamics that form echo chambers, reinforcing strong group identities and more extreme viewpoints (Phillip et al., 2023; Wankhade et al., 2022).

3.1. NLP models' performance

Concentrating on the satisfaction with battery performance attributes, this study quantified the sentiment score errors across three different NLP algorithms: SnowNLP, MNB, and BERT. The results of the scoring error are detailed in Table 6. These results reveal that MNB models demonstrated the highest accuracy and reliability in analyzing battery performance sentiment of texts pertaining to specific terminologies within the PEV domain. Consequently, for subsequent studies, the scores for both types derived from the MNB models were utilized.

3.2. HGB models' performance

The HGB algorithm was employed to model the scores for PHEVs and BEVs across two aspects, constructing a total of four HGB models. The Mean Squared Error (MSE) for these models were as follows: Battery Performance Score for PHEVs: 0.1949; and Battery Performance Score for BEVs: 0.1791.

3.3. Top 5 important features

The permutation feature importance for each of the four models was subsequently calculated. Fig. 5 evaluates the importance of the top five features across two scores for both PHEVs and BEVs.

It reveals the considerable influence of geographic location and price on the battery performance of both PHEVs and BEVs. Moreover, specific vehicle attributes, such as fast charging capabilities and energy efficiency, prove to be critical in shaping consumer preferences and vehicle usability. For BEVs, the electric range also emerges as a crucial factor, influencing the practicality and appeal of these vehicles.

Consequently, subsequent analyses in this study will focus on the three most influential factors—geographic location, price, and electric range—while also examining vehicle age and model year to elucidate their impact on consumer preferences further.

3.4. Geographic location

Significant regional disparities in the volume of comments are depicted in Fig. 6. This indicates a pronounced urban–rural divide and east–west gradient in PEV adoption rates and user engagement levels across the Chinese Mainland. Economically developed cities, such as Beijing, Shanghai, Hangzhou, Guangzhou, and Chengdu, are centers of concentrated feedback from PEV consumers and have the highest sales of PEVs (Zheng et al., 2020). In comparison, there are considerably fewer comments from China's inland and western regions. This distribution may be influenced by a variety of factors, including regional economic disparities, differences in infrastructure such as charging stations, and varying levels of government incentives for PEVs.

Fig. 7(a) and (b) illustrate the regional distributions of the Battery Performance Evaluation Index across different areas in the Chinese Mainland. The gray-shaded regions represent cities without available data or comments, which reflect the lower adoption rates of PEVs in China's western and northern regions. The market development for PEVs in these areas is relatively slow, whereas the western region, often characterized by complex terrain and sparse populations, has impacted the construction of electric vehicle infrastructure. This has resulted in the western region having the lowest density of EV charging stations (Chen et al., 2023; Wu et al., 2015). Differences between the northern and southern regions have been identified due to temperature variations (Wu et al., 2023) and GDP (Qiu et al., 2024; Li et al., 2019).

The Battery Performance Evaluation Index reveals widespread dissatisfaction with battery performance among PHEV users. In contrast, BEV users generally report higher satisfaction with battery performance, especially in the Central Plains region of China. This discrepancy can be attributed to several factors: Firstly, the battery capacity of PHEVs is significantly smaller than that of BEVs. PHEV users often opt to operate in electric mode to save on fuel costs, using the battery whenever possible. However, the electric range of PHEVs is often insufficient to fully meet these needs. Secondly, this frequent cycling between charging and discharging results in a higher number of battery cycles for PHEVs compared to BEVs, accelerating battery degradation as more cycles lead to faster aging (Hu et al., 2017). Thirdly, the driving habits of PHEV drivers may also differ from those of BEV drivers. For example, PHEV drivers are more likely to deeply charge and discharge the battery, leading to more inaccurate predictions of the remaining battery range and more severe battery degradation.

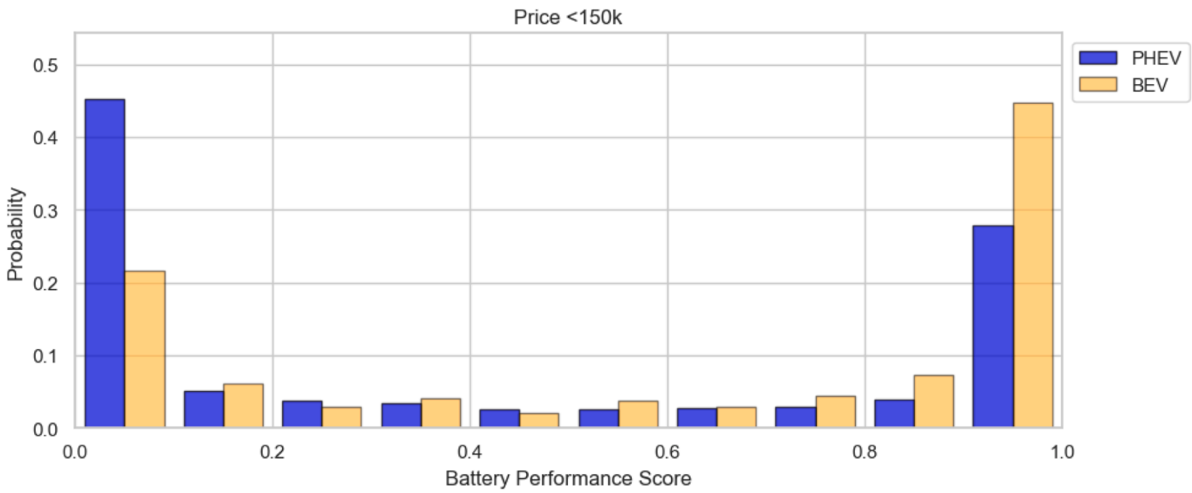
Furthermore, this study intriguingly found that on a prefecture-level city scale, third and fourth-tier cities often receive higher evaluations than first-tier cities such as Beijing and Shanghai. For instance, in the evaluation of PHEV battery performance, only third and fourth-tier cities such as Xuancheng, Hezhou, and Danzhou displayed positive feedback, see Fig. 7(a). This trend may be attributed to several factors: First, compared to the larger first and second-tier cities, the smaller geographic areas of third and fourth-tier cities make the electric driving range of PHEVs more suitable and sufficient for daily travel needs (Xiong et al., 2023). Second, the total costs associated with PHEVs are generally lower than those for gasoline-powered vehicles, offering a cost-effective alternative for residents (Alanazi., 2023). Thirdly, reduced traffic congestion in these areas leads to more efficient battery use and less strain on PHEV systems, alleviating a common source of dissatisfaction. Lastly, relatively lower expectations in smaller cities may lead to greater satisfaction when these expectations are met or exceeded. This observation is supported by the findings of Asensio et al. (2020), which also revealed that the highest incidence of negative sentiments in the US is not in rural areas or smaller urban clusters, but rather in densely populated urban centers.

3.5. Price

Distinct consumer satisfaction disparities in battery performance evaluations across different vehicle price categories for PHEVs and BEVs are highlighted in Fig. 8. Across all price categories, BEV users consistently report higher satisfaction compared to PHEV users, with this trend becoming more pronounced at a higher price.

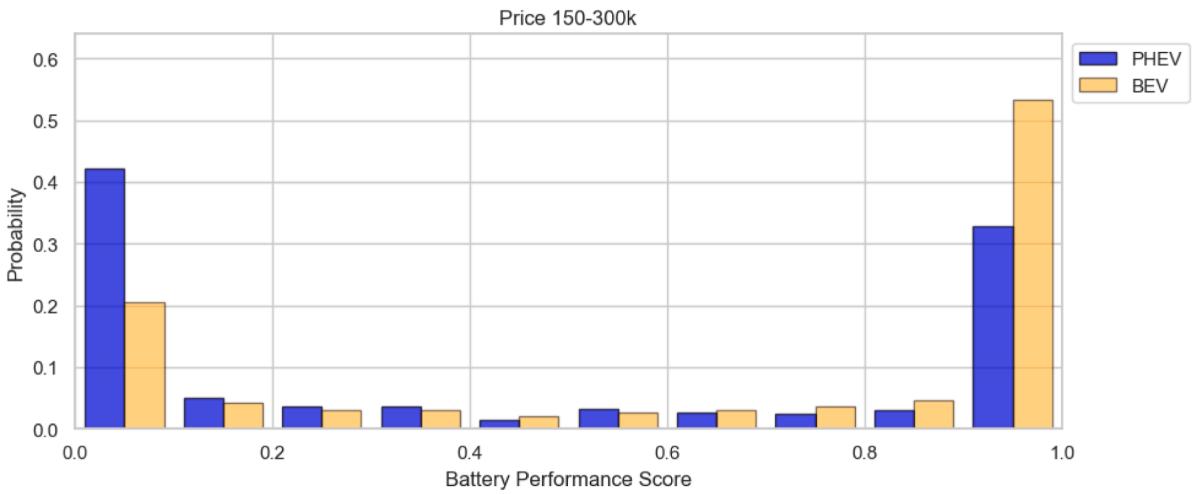
At a price point below 150,000 CNY, PHEVs demonstrated a predominantly negative response rate on battery performance satisfaction, with 60 % negative evaluations compared to 40 % positive. Conversely, BEVs exhibited more favorable responses, with only 37 % negative and 63 % positive evaluations. In the mid-price category, ranging from 150,000 to 300,000 CNY, negative evaluations for PHEVs slightly decreased to 57 %, while positive evaluations increased to 43 %. BEVs continued to show improved satisfaction, with 32 % negative and 67 % positive evaluations. For vehicles priced above 300,000 CNY, the trend in improved satisfaction persisted, with PHEVs showing a further decrease in negative evaluations to 51 % and an increase in positive evaluations to 49 %, while BEVs recorded the lowest level of negative evaluations at 29 % and the highest level of positive evaluations at 71 %.

In this study, the average electric range for PHEVs is 78.74 km in the price category below 150,000 CNY, 104.66 km in the 150,000 to 300,000 CNY range, and 173.49 km for vehicles priced above 300,000 CNY. For BEVs, the average electric range is significantly



	0.0 - 0.1	0.1 - 0.2	0.2 - 0.3	0.3 - 0.4	0.4 - 0.5	0.5 - 0.6	0.6 - 0.7	0.7 - 0.8	0.8 - 0.9	0.9 - 1.0
PHEV	0.45	0.05	0.04	0.03	0.03	0.03	0.03	0.03	0.04	0.28
BEV	0.22	0.06	0.03	0.04	0.02	0.04	0.03	0.04	0.07	0.45

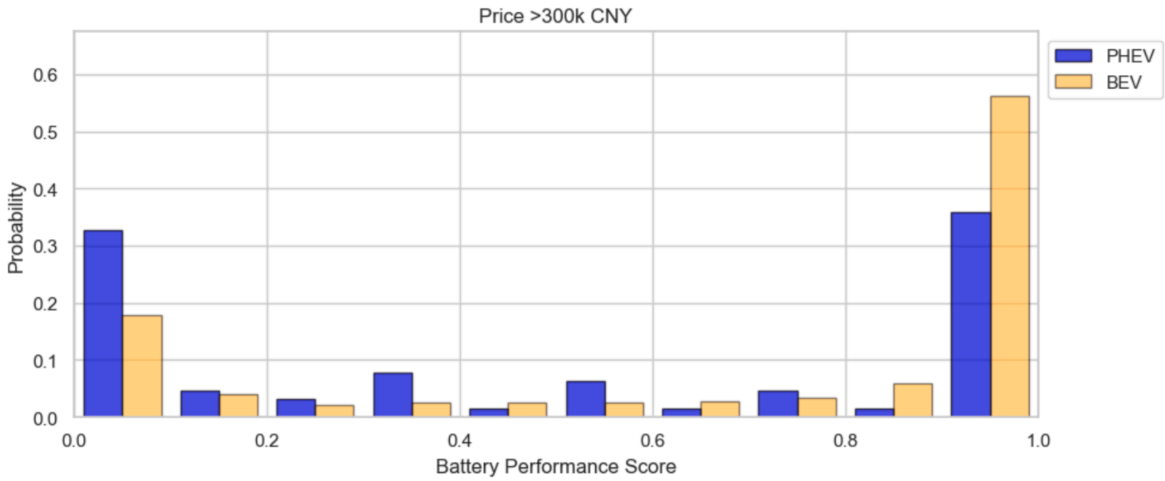
(a)



	0.0 - 0.1	0.1 - 0.2	0.2 - 0.3	0.3 - 0.4	0.4 - 0.5	0.5 - 0.6	0.6 - 0.7	0.7 - 0.8	0.8 - 0.9	0.9 - 1.0
PHEV	0.42	0.05	0.04	0.04	0.02	0.03	0.03	0.02	0.03	0.33
BEV	0.2	0.04	0.03	0.03	0.02	0.03	0.03	0.04	0.05	0.53

(b)

Fig. 8. PEV users' evaluation by price categories for Battery Performance Score for **(a)** prices less than 150 K CNY, **(b)** prices between 150 K and 300 K CNY, and **(c)** prices over 300 K CNY.



	0.0 - 0.1	0.1 - 0.2	0.2 - 0.3	0.3 - 0.4	0.4 - 0.5	0.5 - 0.6	0.6 - 0.7	0.7 - 0.8	0.8 - 0.9	0.9 - 1.0
PHEV	0.33	0.05	0.03	0.08	0.02	0.06	0.02	0.05	0.02	0.36
BEV	0.18	0.04	0.02	0.02	0.03	0.03	0.03	0.03	0.06	0.56

(c)

Fig. 8. (*continued*).

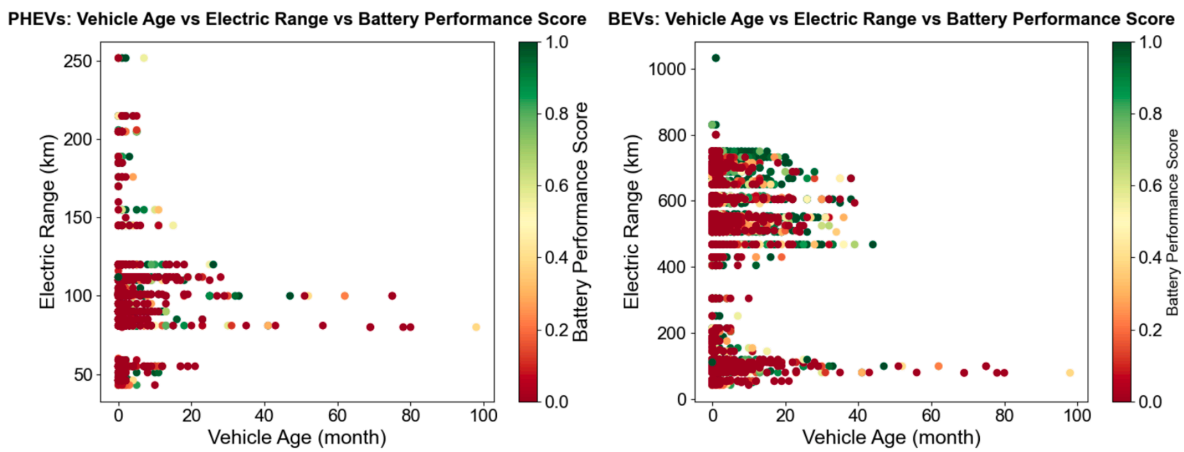


Fig. 9. Battery Performance Score under the interaction of vehicle age and electric range.

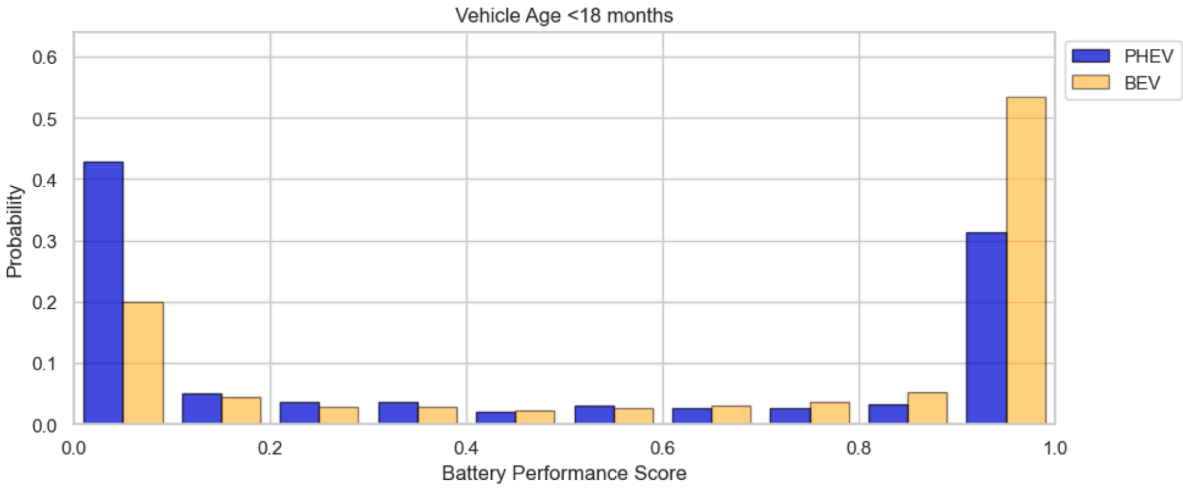
higher, with 425.24 km in the under 150,000 CNY category, 584.34 km in the 150,000 to 300,000 CNY range, and 641.94 km for vehicles priced above 300,000 CNY.

This pattern underscores the significant influence of vehicle type and pricing on user satisfaction concerning battery performance. The consistently lower negative evaluations among BEVs across all price brackets suggest that PHEV users preferred having a longer electric range. As vehicle prices increase, both PHEVs and BEVs tend to exhibit improved satisfaction levels, which can be attributed to the inclusion of higher-capacity batteries and more advanced range-enhancing technologies in higher-end models. Moreover, the diminishing negative evaluations in higher-priced PHEVs suggest that as investment in hybrid technology increases, the gap in range satisfaction between PHEVs and BEVs could narrow.

3.6. Battery degradation

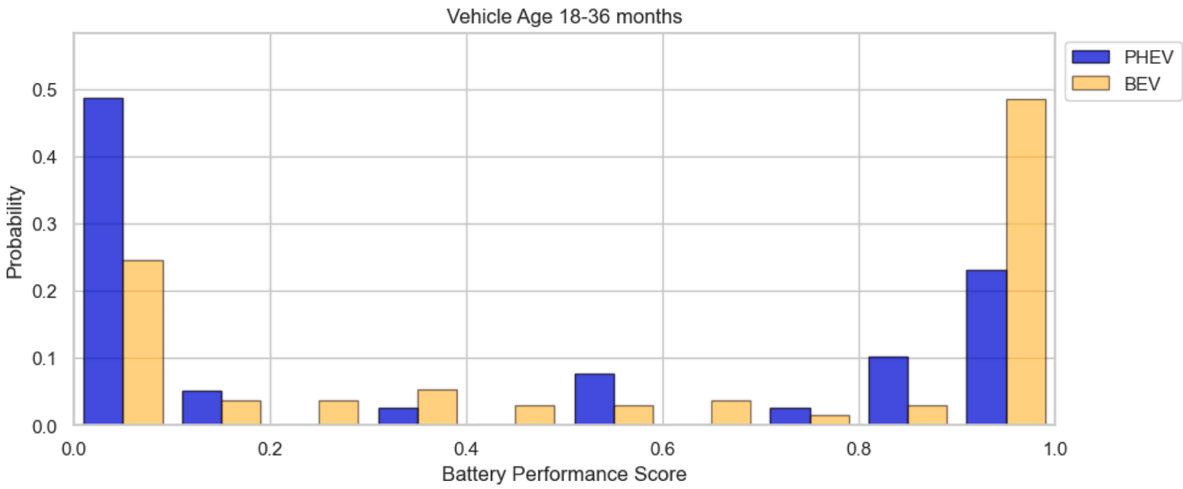
The interactions of vehicle age and battery degradation on user evaluations of battery performance for PHEVs and BEVs are illustrated in Fig. 9. It's important to note that the points in Fig. 9 do not represent individual user comments but are clustered data points. This study found that the electric range of PHEVs is primarily concentrated between 50 and 125 km, while BEVs exhibit a bimodal distribution, with most ranges clustered within two distinct intervals: 0–300 km and 400–800 km. This distinct distribution underscores the significant diversity in range capacities among BEV models, which reflects differing design priorities and consumer requirements—some are tailored for urban, short-distance travel, while others are designed for long-range, intercity travel. This extensive range capability in BEVs contrasts sharply with the more confined range of PHEVs, which generally depend on an internal combustion engine for longer journeys.

Over a longer time, particularly beyond 4–5 years, PEVs garner predominantly negative user sentiments, particularly as the majority of these vehicles demonstrate an electric range of 100 km or less. Such limited range severely constrains the vehicle's utility,



	0.0 - 0.1	0.1 - 0.2	0.2 - 0.3	0.3 - 0.4	0.4 - 0.5	0.5 - 0.6	0.6 - 0.7	0.7 - 0.8	0.8 - 0.9	0.9 - 1.0
PHEV	0.43	0.05	0.04	0.04	0.02	0.03	0.03	0.03	0.03	0.31
BEV	0.2	0.04	0.03	0.03	0.02	0.03	0.03	0.04	0.05	0.53

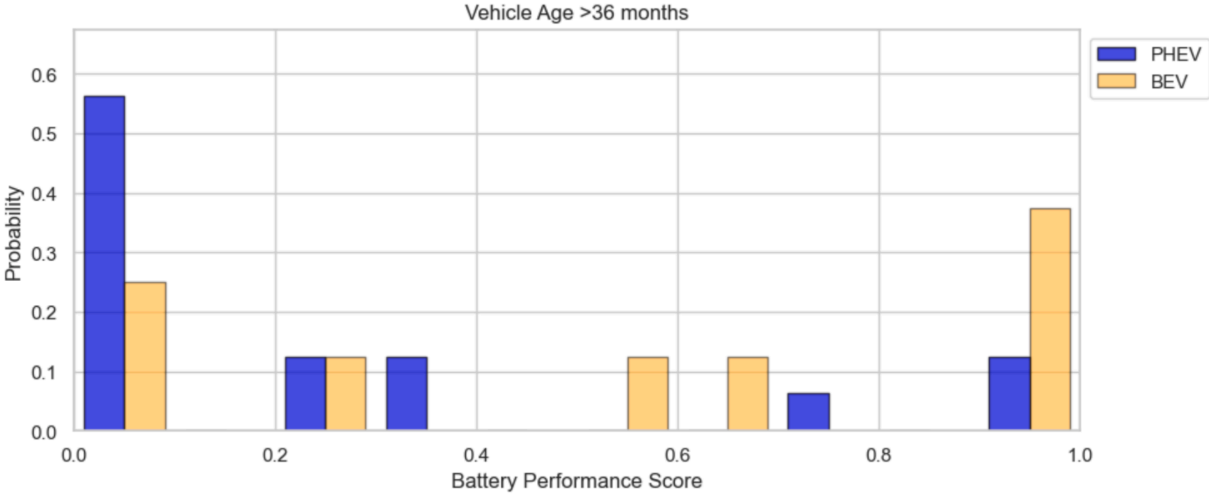
(a)



	0.0 - 0.1	0.1 - 0.2	0.2 - 0.3	0.3 - 0.4	0.4 - 0.5	0.5 - 0.6	0.6 - 0.7	0.7 - 0.8	0.8 - 0.9	0.9 - 1.0
PHEV	0.49	0.05	0.0	0.03	0.0	0.08	0.0	0.03	0.1	0.23
BEV	0.25	0.04	0.04	0.05	0.03	0.03	0.04	0.01	0.03	0.49

(b)

Fig. 10. PEV users' evaluation by vehicle age.



	0.0 - 0.1	0.1 - 0.2	0.2 - 0.3	0.3 - 0.4	0.4 - 0.5	0.5 - 0.6	0.6 - 0.7	0.7 - 0.8	0.8 - 0.9	0.9 - 1.0
PHEV	0.56	0.0	0.12	0.12	0.0	0.0	0.0	0.06	0.0	0.12
BEV	0.25	0.0	0.12	0.0	0.0	0.12	0.12	0.0	0.0	0.38

(c)

Fig. 10. (*continued*).

impacting daily usability and convenience. This negative sentiment is more pronounced in older PEVs, where the limitations imposed by battery wear and reduced range overshadow the anticipated benefits of electric mobility.

Furthermore, this study compared the user experiences of PHEVs and BEVs over three vehicle age periods: under 1.5 years, 1.5 to 3 years, and over 3 years, highlighting the differences between these two vehicle types in terms of battery performance satisfaction, shown in Fig. 10. Notably, this study uncovered an intriguing trend: in the Chinese Mainland, user reviews of BEVs consistently rate higher than those of PHEVs, particularly after three years of use.

Vehicles under 18 months old displayed distinct patterns for battery performance: PHEVs registered a significant 58 % in negative evaluations, compared to 42 % positive, indicating prevalent dissatisfaction. BEVs, on the other hand, showed predominantly favorable outcomes, with just 32 % negative against 68 % positive evaluations. As the vehicle age bracket increased to between 18 and 36 months, the trend persisted, though slightly less pronounced; PHEVs received 57 % negative versus 43 % positive evaluations, while BEVs had 41 % negative versus 59 % positive evaluations. Most notably, for vehicles older than 36 months, PHEVs showed a significant spike in negative evaluations at 80 %, with merely 20 % positive feedback, whereas BEVs maintained a more stable satisfaction profile with 37 % negative and 63 % positive evaluations.

This trend observed across different vehicle ages may be attributed to several factors influencing user experience and vehicle performance. PHEVs, which integrate both electric and combustion engine systems, may experience more pronounced degradation in electric performance over time, exacerbated by the dual strain on their power systems, leading to increased negative evaluations as the vehicle ages (Hu et al., 2017). Conversely, BEVs, which rely solely on their electric systems, tend to maintain a more consistent performance, reflecting in relatively stable positive evaluations even as the vehicle ages. This suggests that the singular focus on electric technology in BEVs might offer better long-term electric range reliability compared to PHEVs, whose hybrid nature might compromise their performance over extended use.

3.7. Electric range

This study also examined user perceptions of battery performance across various electric ranges in PHEVs and BEVs. As illustrated in Fig. 11, the box plot utilizes box plots to categorize Battery Performance Scores by electric range segments. Each box plot delineates the interquartile range (IQR), encapsulating the middle 50 % of the dataset, extending from the 25th percentile (Q1) to the 75th percentile (Q3), with the median value (Q2) marked by a horizontal line within each box. Whiskers on the plots indicate the full range of the data, stretching from the minimum to the maximum values observed. Furthermore, the mean battery performance scores are visually emphasized through a red line connected with markers.

This study found that the assessments of PEV battery performance generally exhibited a positive correlation with electric range, indicating that higher electric range PEVs tend to receive more favorable evaluations from users. This finding underscores the importance of enhancing electric range capabilities in shaping user perceptions of PEVs, consistent with Delmonte et al. (2020). It

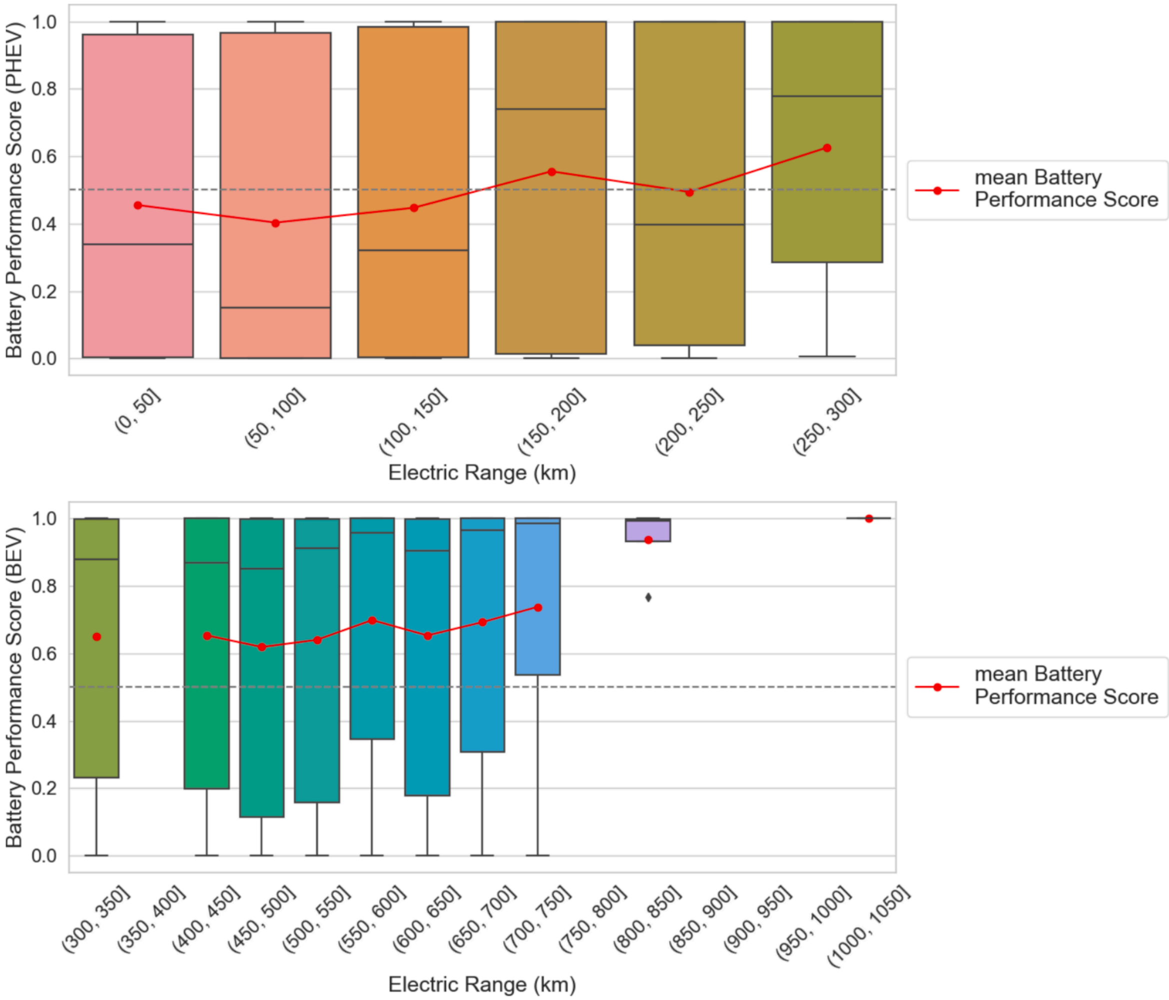


Fig. 11. Distribution of Battery Performance Scores by electric range categories.

reflects a growing user expectation for PEVs to not only match but exceed the convenience and reliability of traditional internal combustion vehicles.

The findings also indicate that perceptions of battery performance in PHEVs are mixed, with a more dispersed distribution of reviews. In contrast, BEVs consistently scored higher across most electric range categories, exhibiting a narrower IQR, which suggests that evaluations from BEV users are more concentrated and generally more positive. This discrepancy in user feedback is likely attributable to differences in battery usage patterns. PHEVs operate with a combination of a battery and a combustion engine, resulting in a hybrid system that can complicate the modes of battery usage and charging. This complexity might lead to inconsistencies in battery performance, as different users experience varied driving conditions (such as urban versus highway driving). On the other hand, BEVs rely solely on electrical power, typically featuring more optimized and consistent charging and usage patterns.

User evaluations of battery performance in PHEVs with an all-electric range of less than 150 km are notably poor, with average Battery Performance Scores all falling below 0.5. This may be due to the limited range forcing vehicles to frequently switch to gasoline mode, thereby diminishing the perceived advantages of the electric mode. Such frequent transitions can lead to concerns regarding battery reliability, lifespan, and the overall utility of the vehicle as an electric option, resulting in lower performance scores. However, when the all-electric range of PHEVs is between 150–200 km, user ratings reach a local maximum. Beginning with the 150–200 km electric range, the average battery performance evaluations by PHEV users shift from a negative to a positive perspective. This reflects that PHEVs begin to offer a more seamless electric driving experience at this electric range, capable of meeting a broader spectrum of daily travel needs without the need to activate the combustion engine. This range is likely viewed as an optimal point where the benefits of electric driving can be fully enjoyed without concerns about limited range, thereby leading to higher satisfaction and, correspondingly, higher performance scores. In the current highest all-electric range bracket for PHEVs (250–300 km), the average rating surpasses 0.6, marking the highest evaluations across all ranges.

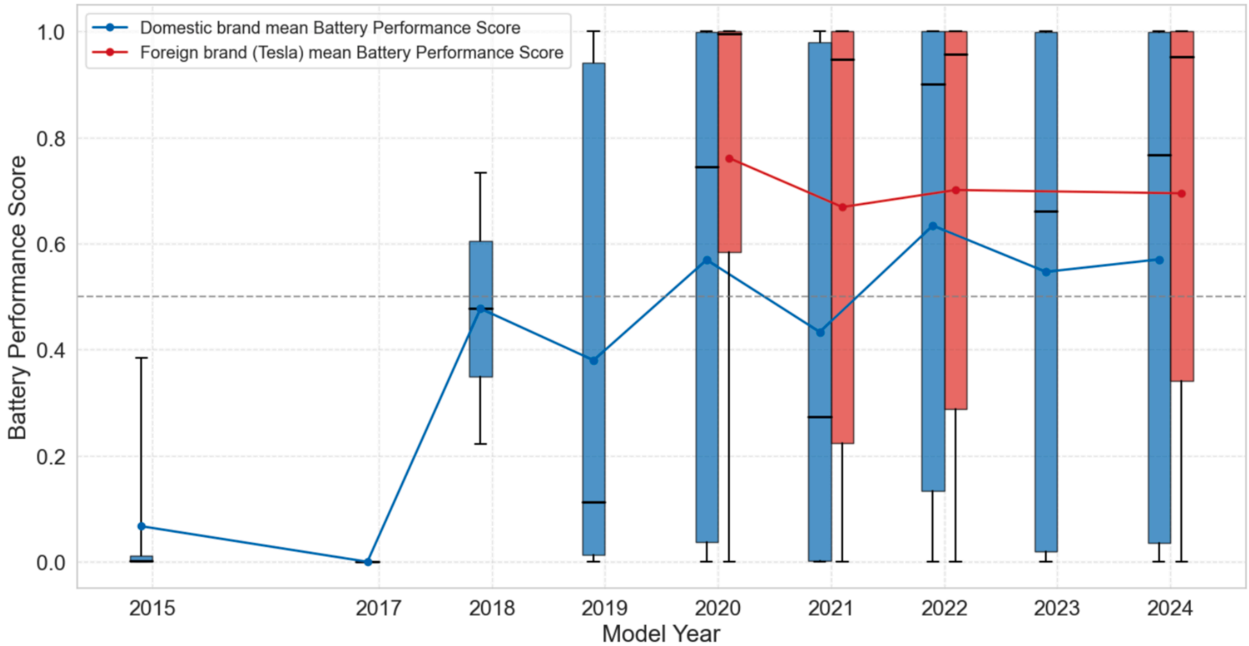


Fig. 12. Domestic and foreign brand (Tesla) PEVs' Battery Performance Scores by model year.

3.8. *Vehicle model by year*

In the realm of PEVs, Tesla stands out as a leading company, with the Chinese Mainland being its largest international market (Yang, 2024). Tesla is at the forefront of electric vehicle technology and business innovation, significantly shaping the dynamics of the PEV industry. Thus, this study focused on Tesla as an international benchmark and investigated prominent Chinese manufacturers such as BYD, Geely, and Zeekr to compare user satisfaction with battery performance across various model years. Fig. 12 displays this comparison using box plots to represent Battery Performance Scores for both domestic brands and Tesla, along with a line plot indicating their average performance scores.

Several trends and observations are evident. Tesla's battery performance evaluation from users exhibits a consistently high trend across model years, maintaining an average Battery Performance Score above 0.6 from 2020 to 2024, which underscores a high and consistent level of user satisfaction. Tesla's scores started relatively high in 2015, saw a dip in 2017, but subsequently stabilized to sustain an excellent level of performance over the following years. The slight fluctuations observed indicate minor variances in battery performance across different model years but generally depict Tesla as maintaining a competitive edge. However, from 2022 onwards, the gap in performance scores between Tesla and domestic brands narrows, indicating that domestic brands have substantially caught up in terms of battery performance.

Domestic brands have demonstrated substantial improvements in Battery Performance Scores over time. Starting from a very low score in 2015, there was a marked increase, especially notable from 2018 onwards. By 2022, the scores had improved substantially and remained relatively stable. Since then, the overall average battery performance satisfaction for all domestic brand models has generally been within the satisfactory range, with users' Battery Performance Scores commonly exceeding 0.5. This variability is likely a consequence of the rapid advancements in the PEV industry, which include the development of more efficient battery technologies, batteries with higher energy density, and advanced motors and control systems, all of which have significantly enhanced the performance of these vehicles (Xin, 2024).

However, compared to Tesla, the box plots of domestic brands show a larger IQR, indicating that consumer satisfaction with the battery performance of domestic brands has been mixed. This may be due to differences in the quality of battery production among different domestic PEV brands, leading to inconsistent battery performance. As a result, consumers always have varied opinions on the reliability and durability of batteries from domestic brands.

4. Discussions & Implications

4.1. *Feedback for BEVs is consistently more favorable than for PHEVs*

The scoring analysis shows that users have a more negative perception of battery performance in PHEVs compared to BEVs. Several potential factors may contribute to this sentiment. Firstly, in contrast to BEVs, which prioritize battery energy management and larger battery capacities, PHEVs may lack similarly robust battery management systems by manufacturers. Additionally, user driving behaviors may lead to more frequent deep charging and discharging cycles in PHEVs, adversely affecting battery health over time (Hu et al., 2017). Another possible factor is that PHEV buyers might have overly high expectations regarding battery efficiency's impact on fuel savings, leading to lower satisfaction scores. In any case, this finding warrants further investigation to uncover underlying causes.

Furthermore, perceptions of battery performance in PHEVs are mixed, with a more dispersed distribution of reviews, likely due to the hybrid nature of these vehicles. Offering both electric and combustion options, PHEVs result in diverse user experiences influenced by individual driving habits, range expectations, and usage patterns. In contrast, BEV reviews are more concentrated and generally positive, as BEVs provide a fully electric experience that aligns closely with user expectations for all-electric functionality and longer range, leading to more consistently favorable feedback.

4.2. Key factors shaping user perceptions of PEV battery performance include location, price, fast charging capabilities, energy efficiency, and electric range

Latitude and longitude as geographic factors are crucial in influencing user evaluations of PEVs, especially in terms of PEV adoption. However, while geographic location remains important in the post-purchase battery reviews of PEV users, there is no clear monotonic and consistent pattern of variation with longitude or latitude. Instead, the level of urban development appears to be a more decisive factor in shaping the opinions of PEV owners in a city. Moreover, price often dictates the quality and capability of the battery management systems that manufacturers opt to install, influencing overall battery longevity and performance.

Furthermore, fast charging capabilities are increasingly influencing consumer preferences, as they allow quicker turnaround times and greater convenience, particularly for consumers with demanding schedules. Energy efficiency also plays a crucial role, as more efficient vehicles can travel longer distances on a single charge, reducing the frequency and cost of recharges for users. Lastly, the electric range of PEVs, particularly BEVs, remains a critical determinant of vehicle attractiveness. Longer ranges are perceived as more versatile and reliable, diminishing range anxiety and making these vehicles more suited for various uses, from daily commutes to extended road travels (Delmonte et al., 2020).

4.3. City characteristics and regional development influence PEV user satisfaction across various city tiers in the Chinese Mainland

City characteristics and regional development play significant roles in PEV user adoption and satisfaction, with economically developed cities such as Beijing and Shanghai having a concentration of reviews. These cities not only have advanced economic development and charging infrastructure, which contribute to the highest sales of PEVs (Zheng et al., 2020), but also host tech-savvy populations with high adoption rates of new technologies, leading to more active participation in online PEV review platforms. In contrast, the PEV market penetration in western and northern China has developed more slowly, with the western region having the lowest density of charging stations (Chen et al., 2023; Wu et al., 2015). Regional temperature differences (Wu et al., 2023) and GDP (Qiu et al., 2024; Li et al., 2019) also contribute to disparities between southern and northern China.

Third and fourth-tier cities often report higher levels of PHEV satisfaction compared to first-tier cities. This may be attributed to several intertwined factors. Firstly, the compact size of these lower-tier cities matches well with the electric driving ranges of PHEVs, making them ideal for daily commutes (Xiong et al., 2023). Secondly, the costs associated with owning and operating PHEVs are generally lower than gasoline vehicles, offering a more economical alternative in these areas (Alanazi, 2023). Thirdly, the lower levels of traffic congestion in these smaller cities improve battery efficiency and lessen the strain on PHEV systems, thereby mitigating a common dissatisfaction factor. Lastly, the relatively modest expectations of residents in these less developed areas often translate into higher satisfaction levels when their expectations are fulfilled or surpassed, further contributing to favorable evaluations.

4.4. Higher-priced PEVs show increased user satisfaction in battery performance

As the price of PEVs increases, there is a notable improvement in user satisfaction concerning battery performance. Specifically, for PHEVs, satisfaction improves from 40 % (below 150,000 CNY) to 43 % (150,000–300,000 CNY) and 49 % (above 300,000 CNY). For BEVs, it rises from 63 % (below 150,000 CNY) to 67 % (150,000–300,000 CNY) and 71 % (above 300,000 CNY). This trend is largely because higher-priced PEVs are often equipped with more advanced technologies and higher-quality battery components and management systems, which are crucial for maintaining battery health and longevity.

4.5. Positive correlations between PEV battery performance and electric range, with distinct local optimum, influence user satisfaction

In the current Chinese market, the electric range for PHEVs typically spans from 50 to 125 km, whereas BEVs demonstrate a bimodal distribution, predominantly clustering in the ranges of 0–300 km and 400–800 km. This diverse range spectrum underscores the varied design objectives and consumer demands, with some BEV models designed for urban, short-distance commuting and others for extended, intercity travel. In contrast, PHEVs, which primarily rely on their internal combustion engines for extended travel distance, offer a more limited all-electric range.

A general positive correlation emerges between PEV battery performance and electric range, suggesting that a longer electric range may be an essential factor in shaping favorable user experiences (Delmonte et al., 2020). Users tend to express dissatisfaction with battery performance in PHEVs with an all-electric range below 150 km, as evidenced by Battery Performance Scores consistently falling below 0.5. This trend may be attributed to user expectations for greater electric autonomy, as short-range capabilities fall short of their demands for more sustained electric driving. Consequently, low-range PHEVs frequently rely on the combustion engine, possibly leading to lower user satisfaction among those expecting a predominantly electric driving experience. Interestingly, when the all-electric range of PHEVs extends to 150–200 km, user evaluations reach a local maximum, indicating a shift from predominantly negative to more positive attitudes. This improvement suggests that a range within this bracket may meet a crucial threshold, offering sufficient electric driving capacity for daily commutes or city trips, reducing dependency on the combustion engine, and aligning more closely with user expectations. As such, this range may provide an optimal balance for users seeking a blend of electric and hybrid functionality in their PEVs. At the upper limit of PHEV capabilities, within the 250–300 km all-electric range, user satisfaction peaks, with average ratings exceeding 0.6. This represents the highest evaluations across all PHEV electric ranges and implies that users value an electric range close to that of entry-level BEVs, as it offers a near-complete electric driving experience without frequent recharging. Similarly, for BEVs, user satisfaction reaches a peak at the 550–600 km range, with exceptionally high satisfaction levels reported when the electric range exceeds 800 km, indicating a strong preference for extended range capabilities among BEV users.

4.6. PEV battery satisfaction declines with prolonged usage, particularly notable in PHEVs

After over 4–5 years of use, PEVs tend to receive predominantly negative user feedback, especially those with an electric range of 100 km or less. This pattern suggests that limited electric range becomes a critical source of dissatisfaction over time, as users' initial expectations of convenience and efficiency wane in the face of frequent recharging requirements. Notably, PEV models with shorter electric ranges appear to fall short in terms of performance durability, failing to meet the long-term expectations of users and resulting in a significant decline in positive evaluations as the vehicles age.

Battery performance satisfaction declines significantly with vehicle age, particularly for PHEVs. For PHEVs, positive evaluations change from 42 % (under 1.5 years old) to 43 % (1.5–3 years old) and then significantly drop to 20 % (over 3 years old). In contrast, BEVs maintain relatively stable satisfaction levels, with positive evaluations of 68 % (under 1.5 years old), 59 % (1.5–3 years old), and 63 % (over 3 years old). This greater resilience of BEVs to aging effects can be attributed to their typically larger battery capacities and advanced battery management systems, which together reduce the frequency of range reduction and support greater battery longevity.

4.7. Tesla upholds high battery performance ratings, while Chinese domestic brands progressively narrow the gaps

User evaluations reveal consistently high Tesla battery performance across model years, with an average score above 0.6 from 2020 to 2024, highlighting its reputation for advanced battery technology and innovation (Yang, 2024). However, while Tesla's performance scores remain robust, the gap between Tesla and domestic Chinese EV brands has narrowed since 2022. Domestic brands have demonstrated significant improvements in Battery Performance Scores over time. Beginning with very low scores in 2015, there was a notable increase, particularly from 2018 onwards. By 2022, the scores had improved substantially and remained relatively stable. Subsequently, the overall average battery performance satisfaction for all domestic brand models has generally been within the satisfactory range, with users' Battery Performance Scores consistently exceeding 0.5. These rapid gains in battery performance among domestic brands likely result from increased government support, enhanced investment in battery R&D, and a competitive push to match or surpass Tesla's standards in the Chinese market. Domestic manufacturers have strategically focused on producing high-quality, locally optimized batteries at more accessible price points, broadening PEV access for Chinese consumers.

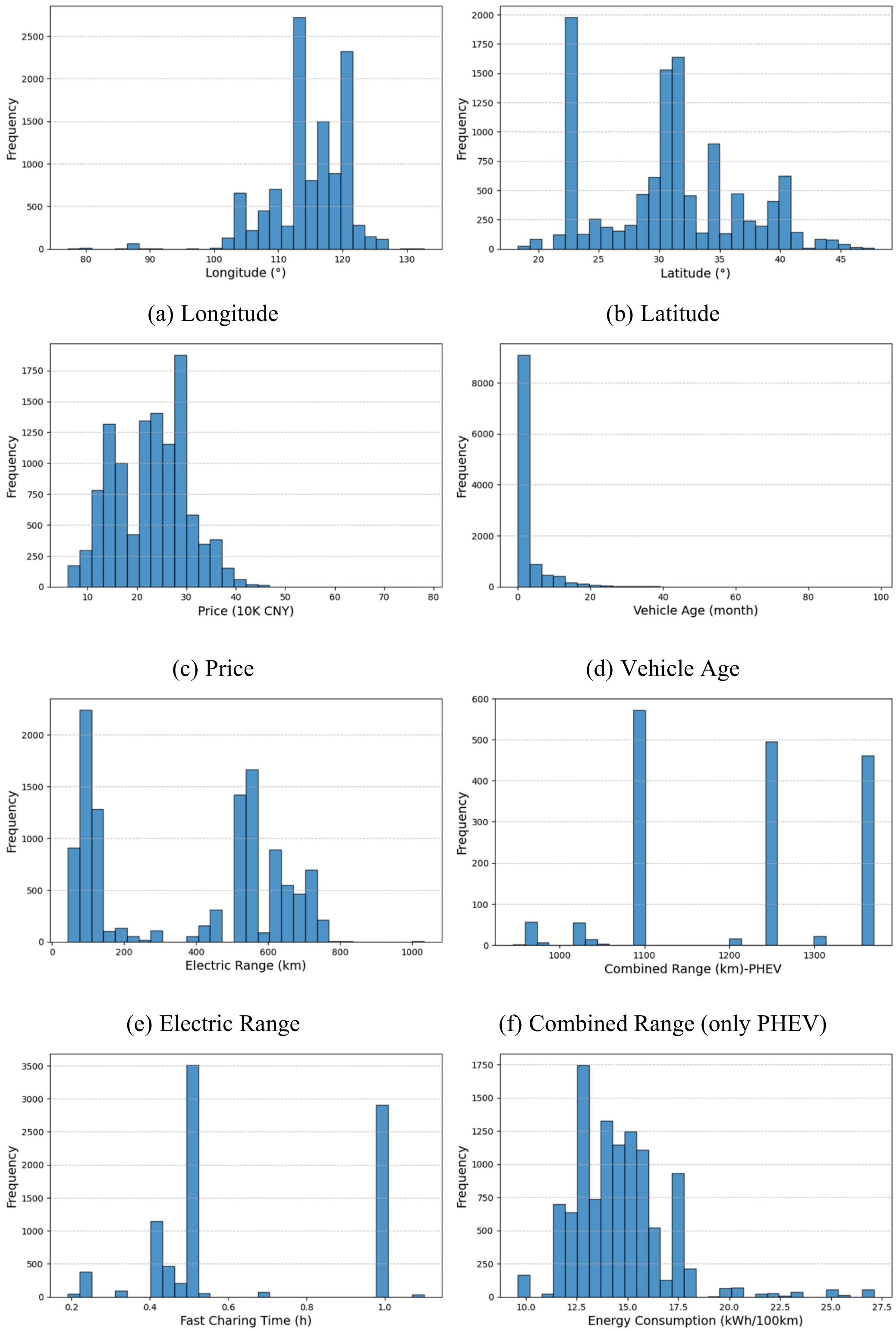
Despite these improvements, consumer satisfaction with domestic brands' battery performance remains somewhat mixed compared to Tesla's consistently high ratings. While many users' express satisfaction with the advancements in domestic PEVs, some remain concerned about long-term battery reliability and degradation. Nonetheless, as domestic brands continue to focus on enhancing their battery technologies and management systems, it is likely that the performance gap will continue to close, potentially increasing competition and consumer options within the Chinese Mainland's expanding PEV market.

5. Conclusions

This study developed a systematic method to process and quantify online PEV user comments on battery performance using three NLP algorithms—SnowNLP, MNB, and BERT—with MNB chosen for its low error margin in sentiment analysis. By linking these sentiment scores with each PEV's technical specifications, the study applied the HGB machine learning algorithm and explainable AI techniques, focusing on permutation feature importance to uncover the top five factors influencing user sentiments: geographic location, price, fast charging capabilities, energy efficiency, and electric range. This comprehensive approach offers valuable insights into the key factors shaping consumer evaluations of PHEVs and BEVs.

To enhance PEV satisfaction, this study recommends strategic interventions targeting identified challenges. First, improving PHEV battery performance is crucial for reliability and satisfaction. Second, capitalize on favorable PHEV feedback in third- and fourth-tier cities by implementing targeted financial incentives, such as tax reductions or subsidies, to boost adoption. Third, extend PHEV ranges to 150–200 km and support BEV advancements to achieve optimal ranges of 550–600 km through increased funding for battery research and incentives for manufacturers. Finally, establish a trade-in program for PEVs older than 4–5 years or with ranges under 100 km to encourage upgrades to models with advanced battery technology, promoting a more sustainable and satisfying user experience. Addressing these issues will help minimize adoption barriers, maximize satisfaction, and support a sustainable automotive future.

Several avenues remain for advancing PEV market insights. One important consideration is the potential sampling bias introduced by online reviews (Phillip et al., 2023), as individuals who leave reviews may systematically differ from those who do not, due to varying levels of engagement with EVs or demographic differences (Zhao et al., 2022). Addressing this issue in future research could



(a) Longitude (b) Latitude

(c) Price (d) Vehicle Age

(e) Electric Range (f) Combined Range (only PHEV)

(g) Fast Charging Time (h) Electricity Consumption in CD Mode

Fig. A1. Distribution of the key continuous variables.

involve incorporating additional data collection methods, such as broader surveys or interviews, to complement the findings from online reviews. Furthermore, integrating socio-economic factors, such as income, education, and environmental awareness, can enhance understanding of adoption drivers, supporting tailored strategies for varied consumer segments. Given the rapid technological advancements in PEVs, it is also crucial to investigate how these innovations influence consumer perceptions and drive market dynamics. Also, expanding our research to key markets in Europe and the U.S., along with ongoing platform updates, will enable comparative international analyses, providing valuable insights into global trends and regional differences.

CRediT authorship contribution statement

Lanxin Shi: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Formal analysis, Conceptualization. **Shiqi (Shawn) Ou:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Conceptualization. **Yanzi Zhou:** Software, Resources, Data curation. **Yonglin Wu:** Software. **Xiaolu Tan:** Software. **Xin He:** Writing – review & editing, Supervision, Project administration, Investigation. **Daniel J. De Castro Gomez:** Supervision, Project administration, Investigation. **Zhenhong Lin:** Supervision, Project administration.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Data availability

Data will be made available on request.

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