A Data-Driven Approach for Mining Truck User Requirements from Online Reviews

Feng Zheng [1, 2], *, Ding Liang [1,2], Zhixian Li [3], Hongyu Yin [1,2], Yifan Niu [1,2]

[1] *School of Mechanical Engineering, Qilu University of Technology (Shandong Academy of Sciences), Jinan 250353, China*

[2] *Shandong Institute of Mechanical Design and Research, Jinan 250031, China*

[3] *Jinan Heavy Industries Group Co., Ltd., Jinan 250109, China*

Abstract:
The accurate identification of user requirements is essential for successful product design. However, existing methods for extracting user needs from online reviews often face challenges due to fragmented content and implicit expressions. To address these limitations, this study proposes a comprehensive framework for mining truck user requirements from online reviews. The process begins with the collection of online reviews to form an initial dataset, which is manually filtered for relevance and processed using NLP techniques to construct a domain-specific lexicon. We leverage K-fold cross-validation and LSTM neural networks to optimize text classification accuracy. Subsequently, sentiment analysis and quantification are per-formed on both explicit and implicit sentence structures, enabling the development of a requirement prioritization model that integrates IPA, the KANO model, and the DEMATEL method to quantify inter-requirement relationships. The results demonstrate that our approach effectively transforms unstructured user feedback into actionable product design insights, provides a reliable solution for manufacturers to improve truck design and development. This research not only advances the field of user requirement mining but also provides a practical tool for data-driven decision-making in the automotive industry.

Keywords: online reviews, natural language processing, sentiment analysis, feature extraction

1.INTRODUCTION

In the context of emerging digital information technologies such as cloud computing and artificial intelligence, the growing prominence of big data has opened up new avenues for acquiring product information and extracting user requirements. Data-driven insights have emerged as a pivotal driving force for enterprise development [1]. Owing to users' significant autonomy in expressing their opinions, online reviews provide a more accurate and real-time reflection of their genuine needs, thus underscoring their increasing significance. According to a survey by Ludwig et al. [2], globally, 90% of respondents read online reviews, with 83% stating that these reviews influenced their purchasing decisions. Consequently, online reviews have been effectively utilized as a valuable data source for various decision-making analyses. However, the explosive growth of the Internet has brought with it a huge amount of information, but also the problem of "information overload" when trying to find it [3]. From a manufacturer's perspective, the selection of relevant reviews and the extraction of valuable insights for product/service enhancement are crucial [4]. Consequently, uncovering comprehensive and precise requirement elements is imperative for product designers during the development of new products [5].

From the perspective of technological innovation, the extraction of features and sentiment analysis based on online review texts constitute two crucial research directions. The objective of feature extraction is to convert the raw data into vector forms that can be expeditiously processed by the model, thereby markedly enhancing its efficacy. In the realm of feature extraction, existing technological approaches primarily include methods based on word frequency, topic probability, graph theory, and deep learning. For instance, WA Etaiwi et al. [6] proposed a method based on word frequency statistics to extract key-words from news documents. Tirunillai et al. [7] utilized the Latent Dirichlet Allocation (LDA) topic model to explore dimensions related to positive sentiment within user online reviews, monitoring the changing trends in the importance of these dimensions over time. Furthermore, Lu et al. [8] introduced a text mining algorithm called Spatio-Temporal Application Usage Pattern Mine (STAUP Mine), exhibiting strong performance in predicting user usage requirements for applications. Kurtanovic et al. [9] utilized a provided dataset of quality attributes to identify requirement types. They developed a supervised self-learning method based on lexical features and support vector machine (SVM) to enhance the accuracy of automatically classifying requirements within the dataset into functional and non-functional categories. Khan et al. [10] employed algorithms such as term frequency-inverse document frequency （TF-IDF）, logistic regression, and SVM to conduct a two-stage classification of reviews within internet user communities, extracting functional requirements, positive reviews, negative reviews. Rahman et al. [11] employed the Word2vec algorithm for text conversion into word vectors and applied three classification algorithms, revealing that long short-term memory (LSTM) yielded superior performance.

Shared information not only conveys written content but also reflects an individual's cognitive and affective response towards the conveyed information, making it imperative to evaluate social media content for a comprehensive understanding of people's sentiment [12]. From a technical standpoint, sentiment analysis primarily encompasses two approaches: lexicon-based analysis and machine learning-based analysis. Tong et al. [13] constructed a lexicon of specialized sentiments in the field of movie reviews by using extracted sentiment words and tagging their sentiment polarity. They then performed sentiment analysis using this lexicon. Zahra Ahanin et al. [14] proposed an enhanced point-wise mutual information (PMI) approach to model the correlation between emojis and sentiment categories based on a Twitter review corpus for addressing unbalanced sentiment categories, namely balanced weighted PMI (B-PMI). Pang et al. [15] employed Naive Bayes (NV), maximum entropy model, and SVM for sentiment binary classification of movie reviews. The study utilized various feature engineering techniques, with results indicating that the use of SVM for unigram model classification was optimal. Zhibo Wang et al. [16] conducted interest point mining and sentiment analysis based on online review texts from relevant users to construct user interest sequences and communities for accurate product recommendations.

Precise measurement of requirements is crucial for product design, planning, and effective marketing [17]. Additionally, online reviews provide a vast and easily accessible data source for acquiring user requirements [18]. Gebauer et al. [19] employed the structural equation model to analyze online review content and identified four significant factors (functionality, portability, performance, and feasibility) that influence user requirements. They also discussed the utilization of online reviews in evaluating user requirements. Abrahams et al. [20] developed an automatic detection and ranking method for vehicle defects by mining online reviews from popular social media platforms frequently used by car enthusiasts. The experimental results demonstrated that analyzing social me-dia reviews can support vehicle quality management. Wang W et al. [21] proposed a framework driven by online review text to determine users' preferences among various competitive products using LDA mathematical model application. They listed the competitive advantages and disadvantages of two products based on this framework. Qi et al. [22], after processing mobile phone reviews, applied the results to a joint analysis model to assess the importance of user requirements combined with KANO model analysis.

Despite the advances achieved in user requirement mining by previous studies, several limitations remain. First, the fragmentation of content and the heterogeneity of user reviews render the systematic extraction of useful information challenging [23]. Second, implicit requirements are frequently expressed through emotional expressions rather than factual narratives, complicating their identification. Third, the complexity and variability of users' affective states hinder the accurate evaluation of affective polarity [24,25]. Moreover, prevailing methodologies continue to exhibit deficiencies in processing extended sentences, optimizing classification models, and quantifying sentiment, thereby limiting their ability to meet enterprises' needs for precise demand mining [26,27,28,29]. In this context, online reviews possess significant research value and extensive application prospects within the domain of text mining. However, they are confronted with numerous challenges that necessitate further in-depth research and exploration to more effectively align with the requirements of enterprises and users.

To address the aforementioned issues, the present study aims to explore how product or service-related user requirement information can be obtained from big data from online reviews. In addition, the study will utilize advanced technologies such as natural language processing, machine learning, and deep learning to thoroughly mine and analyze the unstructured data. The ultimate aim of the study is to develop a systematic and innovative product innovation design methodology. This methodology will assist manufacturers and designers in extracting valuable hidden user requirements, identifying strengths and weaknesses of products or services in the market environment, and formulating more scientific and reasonable strategies for new product development or existing product iteration.

2.METHODS

2.1Research framework

In this section, a novel approach for identifying requirements based on online re-views is proposed.

Initially, a comprehensive collection of literature relevant to the field of trucking was conducted, along with a meticulous analysis of users' online comments. This approach was undertaken to establish an extensive and original dataset. Thereafter, a manual screening process was implemented to select effective comments that possessed practical value from a large number of comments. Thereafter, advanced natural language processing techniques are applied to pre-process the text of these effective comments. In this process, a specialized thesaurus is meticulously constructed, encompassing attribute vocabulary, sentiment vocabulary, negation vocabulary, and degree adverb vocabulary, along with other salient components.

Next， this study employs a diverse range of classic deep learning and machine learning models for online review classification in the truck field, ensuring a comprehensive analysis of the data. Additionally, K-fold cross-validation is utilised to validate the performance of different models in the classification task, ensuring reliable and robust results.

In the link of sentiment analysis and quantification, the screened effective comment texts are scientifically divided into explicit, implicit and other different sentence patterns. A proven implicit demand extraction method is established for different sentence types, and in-depth sentiment analysis and quantification studies are conducted on them respectively. Furthermore, it is acknowledged that natural condition factors may exert an adverse effect on the satisfaction evaluation of truck users with regard to certain design at-tributes. To this end, this study proposes the introduction of weighting coefficients influenced by environmental factors, with a view to mitigating this adverse effect.

Finally, using user attention and sentiment value as key metrics, combining IPA and KANO to provide a comprehensive perspective for mining user requirements, facilitating a deeper understanding of product or service quality characteristics. In addition, to gain a deeper understanding of the intrinsic links between requirements, this study focuses on the interrelationships and causal mechanisms of each attribute in conjunction with the DEMATEL analysis. The combination of multiple models enhances objectivity, scientific rigor, and precision in ranking results. Through comprehensive consideration of needs with data support, credibility in user requirements analysis and ranking is enhanced, fully capitalizing on the advantages provided by online reviews as a data source for mining user requirements.

Fig. 1 displays the methodology framework. displays the methodology framework. The method's framework is presented as follows, comprising four stages: data collection and processing, model construction and evaluation, sentiment analysis and quantification, and requirements priority ranking.

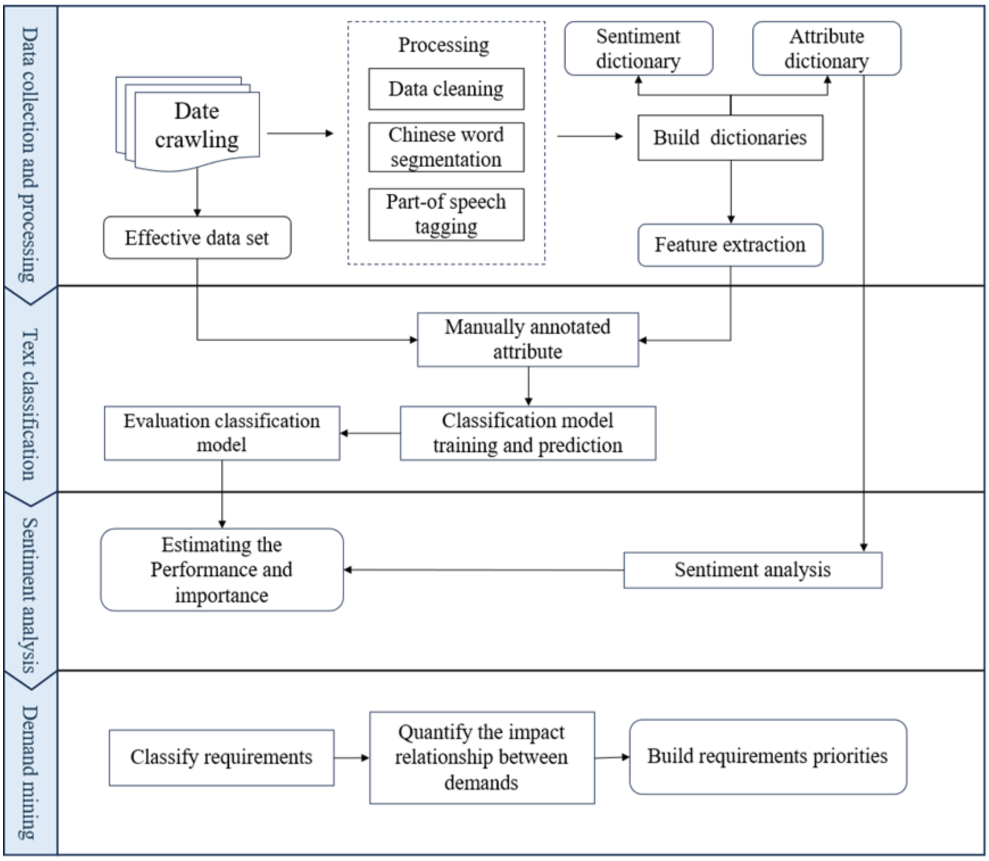


Figure 1. Research framework.

2.2. Data mining and cleaning of online reviews

2.2.1. Data collection

Data collection is of paramount importance as the inaugural step in the process of user requirement mining. The core task involves collecting relevant raw data from various sources to construct a high-quality dataset in the trucking domain. Firstly, the NLPIR-ICTCLAS Chinese word segmentation system is utilized extensively, and the theme collection mode of the dedicated collection tool is applied to gather data from 'truck market report', 'truck literature', 'truck information', 'truck news', 'truck data', 'Truck News', 'Truck Advertisement', and other relevant keywords for domestic acquisition, utilizing three distinct acquisition layers. Additionally, the Catalogue of Product Characteristics of Truck Platforms is acquired through manual search to provide a rich literature resource base for subsequent analysis and research.

To extract user requirements from online reviews on various social media platforms, we developed a Python program capable of collecting reviews from platforms such as YiChe.com, TruckHome.com, JD (a specific e-commerce platform), and Douyin (a short video platform). The collected dataset comprises crucial information, including usernames, membership levels, star ratings, review content, timestamps, likes received, and the number of reviews posted [30]. Finally, a total of 11,463 reviews are obtained. Our program harnesses multi-processor technology and the Scrapy framework, ensuring a clear architecture with minimal module coupling. Its user-friendly interface allows customization and extension using Python. With simple configurations, we efficiently extracted diverse complex datasets, reducing programming time while improving accuracy. Figure 2 illustrates the entire data processing flowchart.

The data collection process plays a crucial role in establishing a robust foundation for the construction of a high-quality dataset within the trucking domain. This dataset consists of two primary components: a knowledge base within the trucking domain and a dataset for Chinese entity recognition. These components offer a substantial and reliable data resource for subsequent in-depth studies of truck users' requirements.

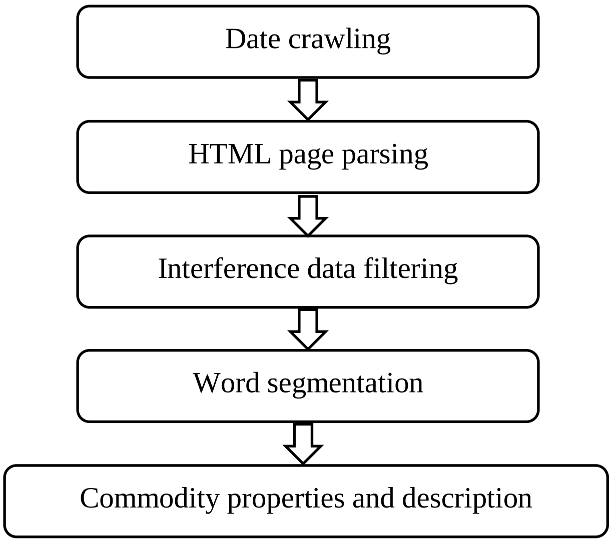


Figure 2. The procedure of conducting a systematic analysis of online reviews.

2.2.2. Mining effective information from online reviews

In terms of truck products, reference literature review defines the characteristics of effective review texts based on the relevance of the review text to the truck's design attributes, the level of detail provided, and the readability of the text [31]. Firstly, effective reviews should demonstrate a high level of relevance to the subject of the truck, with the exclusion of extraneous information. They should also contain feedback from users in the process of using the truck, as opposed to merely providing a basic introduction to the truck. Secondly, effective reviews should encompass a broader range of truck attributes and be more de-tailed. Finally, effective reviews should be universally consistent in terms of content, grammar and sentence structure, avoiding the use of archaic vocabulary or complex sentence structures. Furthermore, online reviews were segmented into individual sentences according to Chinese punctuation [32]. The characteristics of ineffective reviews contrast with those of effective ones.

To enhance the accuracy and comprehensiveness of sentiment analysis, the review text is categorized into explicit sentences and implicit sentences based on the presence of attribute words and sentiment words [33]. Explicit sentences contain both attribute words and sentiment words, while implicit sentences contain only one of the two. Implicit sentences are further divided into those that contain only attribute words and those that contain only sentiment words. Specifically, 9,251 explicit sentence patterns were determined along with 1,218 implicit sentence patterns that solely contained attribute words and 578 implicit sentence patterns that exclusively comprised sentiment words.

The twelve graduate students with an engineering background were divided into six groups, each consisting of one male and one female, to ensure equal gender representation. Initially, the original reviews were divided into 12 equal parts and distributed among the focus group members for the first round of screening based on predetermined criteria. Subsequently, two members of the group exchanged their review texts for a second round of screening. A comparative analysis was conducted between the two sets of validity screening data, and any objectionable reviews were collectively identified by all members involved in the process. Ultimately, a total of 11,047 effective reviews were obtained, ac-counting for a 60.79% effectiveness rate.

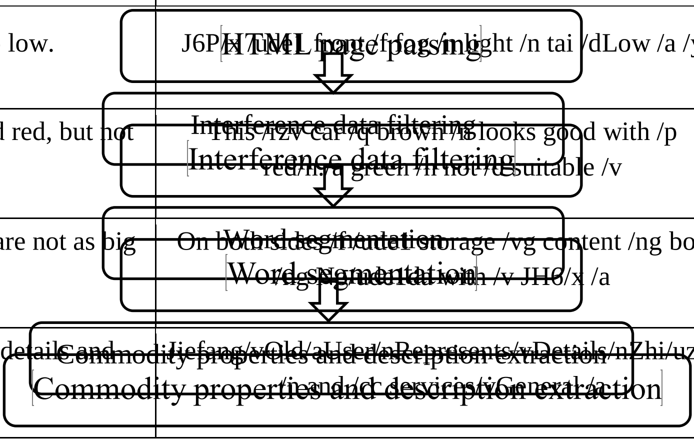
2.2.3 Date pre-processing

Before integrating textual data into machine learning models, a series of pre-processing operations must be performed to convert the raw textual data into a format compatible with machine learning models. This transformation facilitates enhanced pro-cessing and modeling of the textual data by the models, thereby optimizing their ability to interpret and utilize the textual information [34]. The initial step in this process is data cleansing, which aims to enhance the quality of the truck dataset by removing superfluous or redundant information considered noise or lacking value. This process involves the removal of HTML tags, advertisements, comments, and codes from the relevant review text, leaving only useful information. Unlike English, Chinese requires text segmentation and word splitting to divide a continuous sequence of characters into a meaningful sequence of units in preparation for subsequent processing. Next, stopword filtering is implemented, where the elimination of stopwords enhances the efficiency of the analysis and mitigates the adverse impact of noisy data on the research outcomes. Lexical annotation is a process of linguistic analysis that involves identifying the meaning of each word or phrase, as well as its positional relationship in the sentence structure. This process is integral to the analysis of textual data, with the aim of enhancing the linguistic information contained within relevant review texts. This enhanced information can then be used in subsequent studies to analyze the specific roles of these texts with respect to sentence themes and structures. The Python Jieba package [35] was used for data cleaning, lexical segmentation, stopword filtering, and lexical annotation of relevant review texts.

Concurrently, given the rapid emergence of new words, this study employs the NLPIR-ICTCLAS Chinese lexical analysis system to process truck text data for new word discovery. This process encompasses keyword and neologism extraction, aiming to automatically detect newly emerging words or concepts of potential value from a large-scale corpus. The detected words are then combined with an existing professional thesaurus to facilitate the timely updating of lexical resources. The keywords and neologisms are dis-played in Table 2 and Table 3, respectively. The attribute dictionary consists of nouns in the reviews, as well as keywords and neologisms in the trucking domain. The emotion dictionary, degree adverb dictionary, and negation dictionary are derived from the vocabulary ontology of Dalian University of Technology, the China Knowledge Network (How Net) dictionary, the Tsinghua University's Li Jun Chinese Praise and Depreciation Dictionary, and the NTUSD Simplified Chinese of the National Taiwan University, and are supplemented with adjectives, degree adverbs, and negatives in the reviews.

Table1. Effective comments on the part-of-speech tagging results of the text

Effective comment text	Part of speech tagging results
The tachometer is very textured.	Speed /n table /n very /d have /vyou texture /n
The sound insulation is quite good	Sound insulation /vi is /vshi equivalent /d good /a
J6P's front fog light is too low.	J6P /x /ude1 front /f fog /n light /n tai /dLow /a /y
This car looks good in brown and red, but not in green.	This /rzv car /q brown /n looks good with /p red/n /a green /n not /d suitable /v
The storage boxes on both sides are not as big as JH6.	On both sides /f under storage /vg content /ng box /ng [illegible] with /v JH6/x /a
Liberating old users to express details and services in general.	Jiefang/vOld/aUser/nRepresents/vDetails/nZhi/uzhi /i and/c services/vGeneral/a



Where can I buy such rearview mirrors	Where /rys can /v buy /v to /v like this /rzv/ude1 rearview mirror /n
I want to ask if the upper berth is widened.	I /rr want to/vAsk/vShop/nWiden/v./ule /y
…	…
Exterior painting is ugly.	Exterior /f painting /v very difficult /d difficult /ad look /v

Table 2. Keyword extraction results

words and expressions	part of speech
cab	n
can	v
sleeping berth	n
not have	v
air deflector	n_new
design	vn
…	…
space	n

Table3. New word extraction results.

words and expressions	part of speech
gradeability	n_new
Comfort	n_new
fault rate	n_new
seperation and reunion	n_new
airtightness	n_new
refine	n_new
…	…
list	n_new
gradeability	n_new

2.3 Refinement and evaluation of a text classification model

2.3.1 Manual marking

Before text classification, manual annotation is used to establish a set of product features from selected reviews, serving as a benchmark for evaluating text mining accuracy [36]. Specific rules and characteristics for each attribute category are then defined based on the distinctive features of the product. The implementation of lexical similarity analysis is based on the first-level functional attributes, second-level functional attributes, and the attribute vocabulary base in the Catalogue of Product Features of Truck Platforms, aiming to apply dimensionality reduction techniques. The Word2vec lexical similarity analysis model is used to conduct lexical synonym relationship analysis, with the terms included in the attribute vocabulary library grouped with the first-level and second-level functional attributes in the Truck Platform Product Feature Catalogue, as illustrated in Table 4.

Table4. Lexical similarity classification results.

First-level functional attribute	Attribute vocabulary
product quality	Engine, chassis, fault, circuit, material, workmanship …
life cycle cost	Depreciation rate, cost, price, cost performance ratio, value preservation …
Driving performance	Performance, power, deviation, horsepower, control, starting, endurance …
security	Safety, vision, sight, blind area, protection, alarm …
…	…
environmental protection	Noise, ...

In this study, three domain experts were invited to identify the primary parameters and factors associated with trucks. After analyzing truck parameter characteristics, ten representative functional attributes were selected: product quality, life cycle cost, drivability, security, comfort, suitability, maintenance convenience, design, intelligent features, and environmental impact. The 10 functional attributes of the truck are designated with letters A to J. A subset of effective reviews was extracted by the aforementioned focus group for sentence-by-sentence evaluation. The corresponding attribute class is labeled as "1", while others are labeled as "0", resulting in a total of 1275 appropriately labeled review texts, as shown in Table 5.

Table5. Manual annotation matrix.

	A	B	C	D	E	F	G	H	I	J
Space is super big	0	0	0	0	1	0	0	0	0	0
The seats are very comfortable	0	0	0	0	1	0	0	0	0	0
The interior is beautiful	0	0	0	0	0	0	0	1	0	0
Large space	0	0	0	0	1	0	0	0	0	0
Look pretty enough	0	0	0	0	0	0	0	1	0	0
The interior is full of technology	0	0	0	0	0	0	0	1	0	0
The truck has good power	0	0	1	0	0	0	0	0	0	0

…	…	…	…	…	…	…	…	…	…	…
Good comfort	0	0	0	0	1	0	0	0	0	0

2.3.2 Text Classifier Selection

In machine learning algorithms, classical models such as SVM, NB and random for-est (RF) play a prominent role in classification and prediction [37,38,39]. Weight values are obtained by training the TF-IDF model and simultaneously dividing the data into training and test sets. The feature vector is then input into the respective machine learning algorithm for training. For deep learning in sentiment analysis, basic neural networks such as convolutional neural networks (CNN), recurrent neural networks (RNN), and LSTM are commonly used. However, since the output of CNN only considers the influence of previous inputs without considering the impact of other inputs and RNNs may encounter issues such as gradient disappearance or explosion during the backpropagation process [40]. Consequently, LSTM is chosen as the foundational model due to its ability to capture information encoded from front to back. To achieve more fine-grained classification, a bidirectional long short-term memory (BiLSTM) is introduced. Additionally, an attention mechanism (Attention_BiLSTM) is incorporated to focus on crucial words that capture essential semantic information within sentences [41]. The Keras library is utilized to build and train the model, selecting the categorical cross-entropy loss function and Adam optimizer during training.

The text of manually annotated effective reviews is converted into a numerical representation using the Word2vec algorithm. Subsequently, the training set and test set are randomly partitioned. The performance of the experimental comparison each model was evaluated by developing a text classification model using both machine learning and deep learning algorithms.

2.4 Analysis of evaluation results

To compare the learning-based classifiers fairly, their performance is evaluated using ten-fold cross-validation experiments on each dataset, with K=10. Specifically, the datasets are initially divided into ten equally-sized subsets using a random partitioning procedure. The experimental procedure involves reserving one of the ten folds for testing in each fold experiment, while utilizing the remaining nine folds for training. This process is repeated ten times, each time using a different fold as a test set. Finally, the average result obtained over the 10-folds is calculated.

The model's reliability was assessed using precision, recall, and F1-score metrics [42]. Precision refers to the proportion of samples correctly predicted by the classifier as the positive class out of the total number of samples predicted as the positive class. It serves as a metric for quantifying the classifier's misclassification rate. The recall rate denotes the ratio of correctly predicted positive samples by the classifier out of all actual positive sam-ples, serving as a metric for evaluating the classifier's ability to accurately identify positive examples. The F1-score represents the weighted average of the aforementioned metrics, providing a comprehensive measure for evaluating classifier performance. A higher F1-score value indicates a more effective classifier. The F1-score for each request category is computed using Equation (1):

$$F1_{score} = 2 * \frac{precision * recall}{precision + recall} \quad (1)$$

Table 6 presents the assessment data. The data results were depicted in a column analysis chart, as illustrated in Figure. 3. The LSTM model demonstrated superior performance with an F1-score of 87.32%, outperforming the SVM (76.32%) and Random Forest (78.29%) models. This is attributed to the LSTM model's ability to capture contextual relationships in textual data, making it particularly suited for analysing complex user reviews. Consequently, the classification outcomes obtained from the LSTM model serve as foundational data for future research endeavours. The trained model is employed for the classification prediction of truck reviews, and the corresponding results are presented in Table 7.

Table 6. Model evaluation result.

Classification algorithm	Precision/%	Recall/%	F1
LSTM	91.03	84.21	87.32
Attention_BiLSTM	91.14	81.74	85.61
BiLSTM	85.61	81.12	81.73
Random Forest	83.16	77.43	78.29
SVM	80.13	74.38	76.32
Naive Bayes	76.4	69.17	72.83

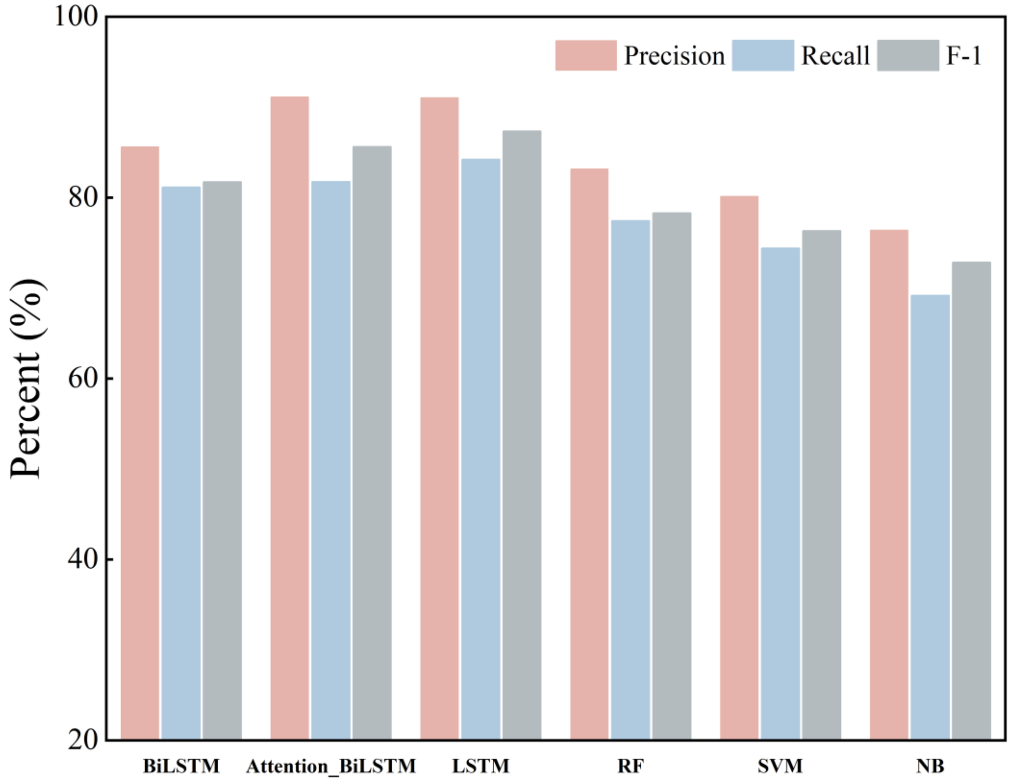


Figure 3. Histogram depicting the evaluation results for each classification model.

Table 7. The result of LSTM-based partial classification

Text contents	Tokenization	Prediction tag
隔音是相当不错 (Sound insulation is pretty good.)	sound insulation, pretty, good	Comfort
前雾灯可以改成和大灯一体的	front fog light, can be, headlight	Modelling

(The front fog light can be converted into one with the headlight.)		
外部涂装很难看 (The exterior paint is very ugly.)	exterior, paint is, very, ugly	Modelling
我们应该对比一下哪个省油 (We should compare which one is more fuel-efficient.)	more, fuel-efficient	Life cycle cost
细节之处和服务一般 (Details and service are mediocre.)	details, service, mediocre	Quality
以后把上铺能再加宽就好了 (It would be nice to widen the top bunk later.)	top bunk, widen	Comfort
动力总成才是关键 (The powertrain is the key.)	Powertrain, key	Driveability

2.5 Sentiment analysis and quantification

The Chinese language is characterised by its intricate structure, which contributes to its richness in terms of connotation and denotation. In different contexts, the same emotion word may vary in emotional intensity [43]. The emotional intensity of online reviews pertaining to specific attributes reflects the users' perception of these attributes in relation to the product or service in question. This can be viewed as an indication of the product's or service's true performance in relation to these specific attributes. Consequently, the performance of the product/service can be estimated based on the emotional intensity exhibited by users for each attribute [44].

In this study, the classification results of the Long Short-Term Memory Network (LSTM) model were used as the foundation for sentiment polarity analysis employing the Sentiment Orientation Point Mutual Information Algorithm (SO-PMI), followed by quantitative assessment of positive and negative sentiments, degree adverbs, and the assignment of negative words. For implicit sentence patterns consisting only of attribute words, sentiment polarity is determined based on the attribute word with the highest proportion in the corresponding explicit sentence pattern. Similarly, for implicit patterns containing only sentiment words, sentiment polarity is determined based on the attribute word with the highest weight in the corresponding explicit patterns. Values are then assigned based on the results of the SO-PMI, as illustrated in Figure 4.

To account for the moderating effect of degree adverbs on sentiment tendencies, sentiment words containing degree adverbs were weighted based on the HowNet degree adverbial lexicon. The degree adverbs were categorized into four classes based on their levels of sentiment intensity. The intensity of a sentiment word is "1" if it is not preceded by a degree adverb. If a negative word exists, it is labelled with the opposite sentiment polarity [45]. The results of sentiment polarity assessment, degree adverbs, and negative words are em-ployed to establish a standardized table for quantifying sentiment, as illustrated in Table 8.

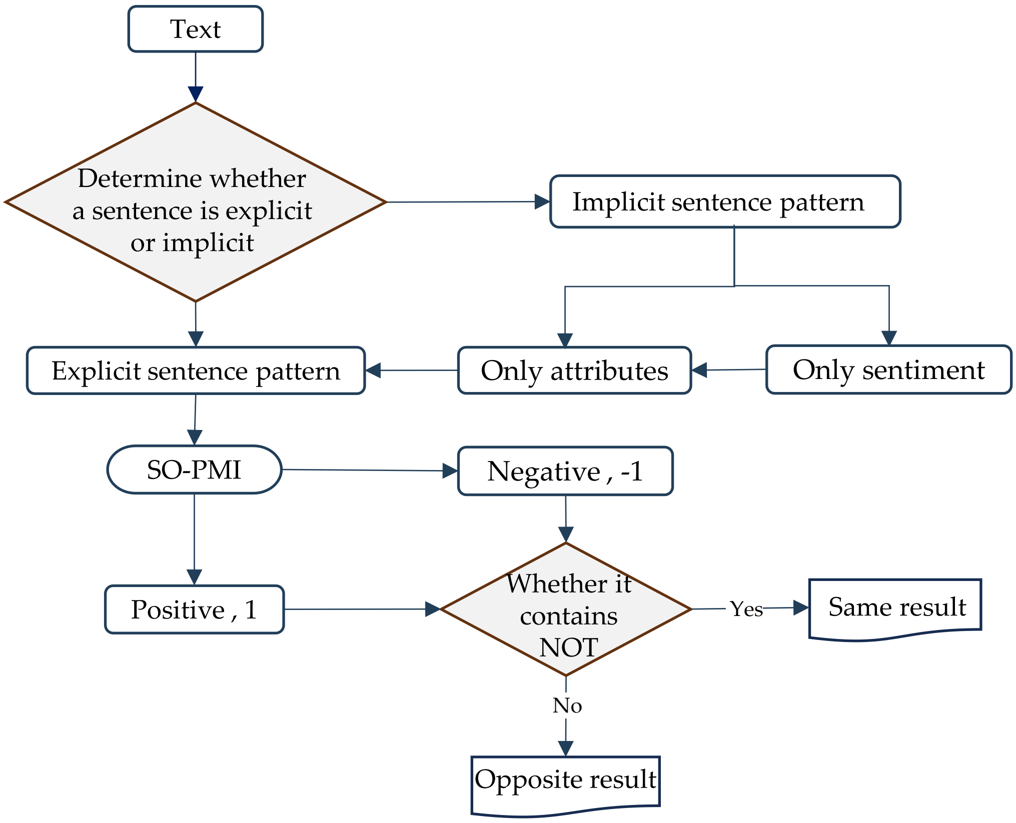


Figure 4. Process for initial polarity evaluation.

Table 8. Quantitative indicators of sentiment.

Parts of speech	Sort	Quantized value
Sentiment words	positive	1
	negative	-1
Degree adverbs	neutral	null
	“extremely”, “too”	2
	“very”, “quite”	1.5
	exclude	1
	“somewhat”, “hardly”	0.5
Negative words	contain	-1
	exclude	1

Considering the impact of natural conditions on user satisfaction regarding specific functional attributes of the truck, we propose incorporating a weighting coefficient to ac-count for environmental factors. The truck attributes identified in the effective reviews were categorized into three distinct groups during the focus group discussion: "unaffected," "less affected," and "more affected." Affective values of 1, 0.8, and 0.6 were assigned to these categories, respectively. The attributes "Brake functionality quality" and "Battery life" are assigned a weightage of 0.8. Thus, the final sentimental extreme value is calculated.

It is well-established that natural conditions can influence user satisfaction with the functional attributes of trucks. In light of this, a weighting factor for the impact of environmental factors was proposed. The truck attributes involved in the valid reviews were classified into three categories (not affected, less affected, and more affected) based on a focus group discussion. The following values were assigned to each category, respectively: 1, 0.8, and 0.5. Sentiment values of 1, 0.8, and 0.6 were assigned to the 'Functional Quality of Brake Pads' and 'Battery Life' attributes, respectively, while 'Battery Life' received 0.8 and 'Tyre Functional Quality' 0.6. The final sentiment poles are then determined. The 69 attributes of the experiment are labelled in the order of 'a1, a2, a3...a69', and combined with word frequency analysis to obtain the user's attention [46]. The calculation results are shown in Table 9, and further details can be found in Table A1.

Table 9. Sentiment analysis results

Attribute	ID	Performance	Importance
1 Quality	a1	-1.19	0.41
	a2	-1.1	1.24
	a3	-1.42	0.98
	a4	-1	0.36
	a5	-1.21	1.96
	a6	-0.8	0.1
……	……	……	……
10 Environment	a68	-0.6	0.52
	a69	-1.21	0.36

2.6 Truck User Requirements Identification and Ranking

2.6.1 Mining truck user requirements based on conjoint analysis

This section employs a systematic approach to prioritize requirements, emphasizing their significance and impact on user experience. The initial step involves constructing the IPA requirement attribute analysis model, which is based on the importance and attention of users. Subsequently, the weights are calculated based on user attention for classifying each requirement in the KANO model. Concurrently, DEMATEL analysis is employed to quantify the interaction relationship between the requirement elements. This interaction relationship is then ranked based on quadrant position and centrality to form a require-ment priority ranking table [47]. The construction of the requirement model is illustrated in Table 10.

Table 10. Construction of truck user demand sequencing model

Specific content	Research method	Concrete objectives
Requirement classification.	IPA analysis.	Divide the functional areas of the requirements.

Demand classification and sequencing.	KANO model.	Classify and sort the demand attributes.
Quantification of demand influence relationship.	Demetal analysis.	Quantify the influence relationship between demand items, Identify the priority of each requirement.

When applying the IPA analysis model, the mean performance ($\overline{P}$) and mean importance ($\overline{Imp}$) are computed using Equation (2) and (3). To establish the vertical and horizontal axes, with $\overline{P}$ = -0.62 and $\overline{Imp}$ =1.44 as reference points, the entire image is divided into four quadrants to allocate each attribute in the IPA quadrant, as depicted in Figure 5. The quadrant labelled 'Keep up the good work' indicates higher levels of user attention and satisfaction. Attributes in this area represent the most valued needs of users, and enterprise manufacturers should strive to excel in these areas. The quadrant labelled 'Concentrate here' indicates that the user does not place a high value on the elements in this area but is still content with them. The quadrant labelled as 'Low priority' belongs to the double low region and is suggested to be classified as the 'last priority'. The quadrant labelled 'Possible overkill' is an important area for improvement, as users have expressed high levels of concern but low levels of satisfaction [48].

$$\overline{P} = \frac{1}{K}\sum_{k=1}^{K} P_k \tag{2}$$

$$\overline{Imp} = \frac{1}{K}\sum_{k=1}^{K} Imp_k \tag{3}$$

where P_k denotes the customer satisfaction index for the k-th attribute. Imp_k denotes the importance of the k -th attribute.

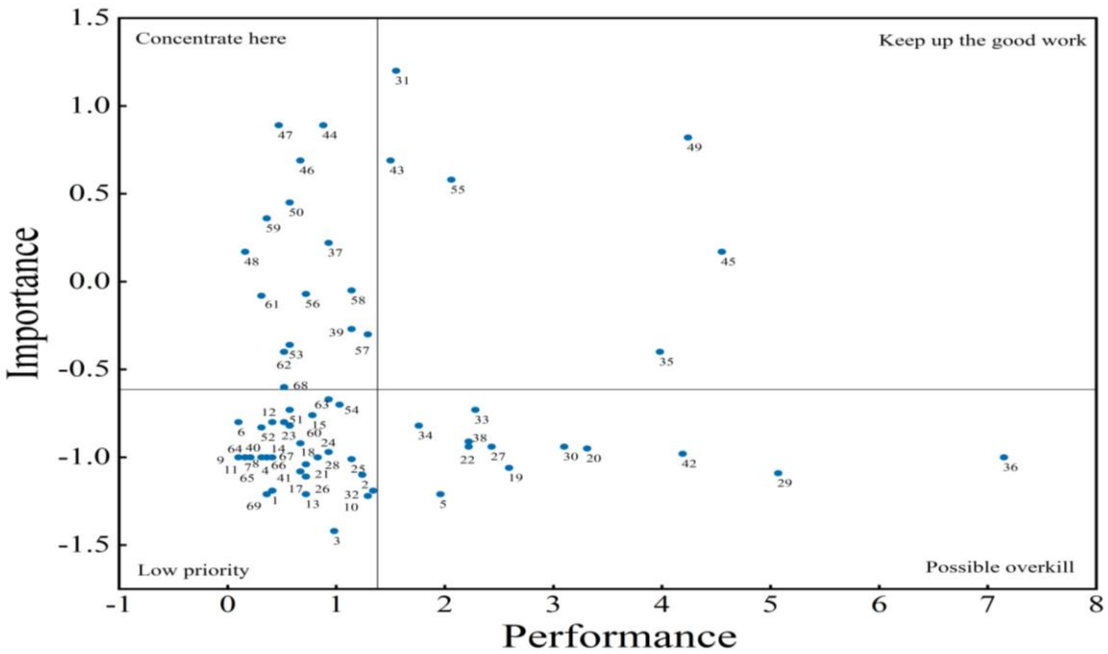


Figure 5. IPA results.

In terms of functional priority, the IPA quadrant diagram analysis is ranked as Possible Overkill (P) > 'Low Priority' > 'Concentrate Here' > 'Keep Up the Good Work', while the KANO model is ranked as 'Must-be Quality (M)' > 'One-dimensional Quality (O)' > 'At-tractive Quality (A)' > 'Indifferent Quality (I)'. The KANO model is ranked by calculating the weighted values based on user attention [49], and the results are shown in Table 11. Using KANO's attribute categories as reference points, each requirement element is mapped onto the IPA analysis quadrant, as depicted in Figure 6.

Table11. Attribute Classification and Sorting of KANO Model

Attribute Classification	ID
Must-be quality	a36, a16, a29, a42, a35, a20, a30, a19, a27, a33, a22, 38, a5, a34
One-dimensional quality	a32, a10, a57, a2, a25, a39, a58, a54, a3, a24, a63, a28, a15, a13, a21, a26, a56, a17, a18, a51, a53, a60, a23, a62, a68, a1, a12, a41, a4, a40, a66, a69, a52, a61, a67, a65, a7, a8, a11, a14, a64, a6, a9
Attractive quality	a37, a44, a46, a50, a47, a59, a48
Indifferent quality	a45, a49, a55, a31, a43

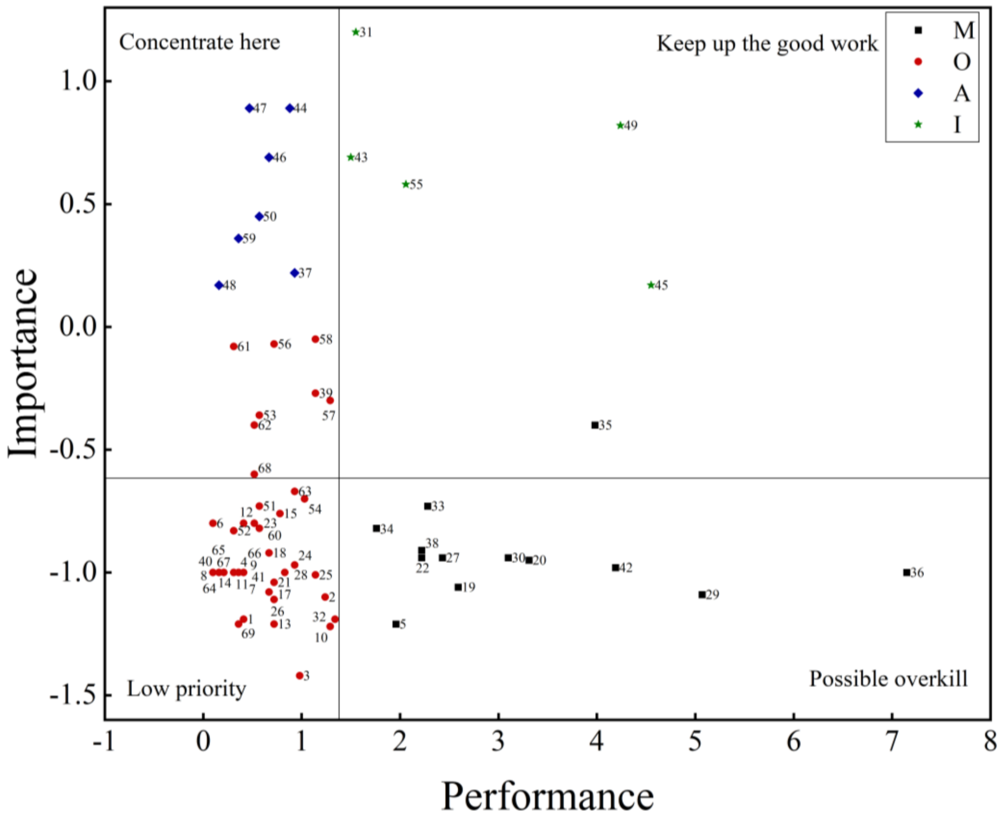


Figure 6. Mapping the attributes according to the KANO model.

Despite the KANO model's ability to effectively allocate design resources, it is unable to capture the interactions between design attributes, which negatively impacts the effi-ciency of product development. The present study employs DEMATEL analyses to lever-age complementary strengths, reduce time and resource costs, and offer decision makers more effective strategies for product development and iteration.

Initially, expert opinions were used to assess the influences among different requirements to establish the initial relationship matrix. For this study, a focus group comprising 7 in-dustrial design graduate students and 3 truck drivers was assembled, including 6 males and 4 females. They were invited to evaluate the relationship matrix table comprising 69 attribute dimensions items, resulting in the creation of the original relationship matrix (O), as presented in Table 12.

Table12. Original scoring matrix

	a1	a2	a3	a4	a5	a6	a7	…	a69
a1	0	0	0	0	0	0	0	…	0
a2	0	0	10	10	10	10	10	…	10
a3	0	70	0	0	0	0	0	…	0
a4	0	20	0	0	0	0	0	…	0
a5	0	50	0	0	0	0	0	…	0
a6	0	20	0	0	0	0	0	…	0
a7	0	10	0	0	0	0	0	…	0
…	0	0	0	0	0	0	0	…	0
a69	0	0	0	0	0	0	0	…	0

The direct impact matrix (M) is obtained by quantifying the causal relationship between the requirements using the row and maximum value method, as described in Equation (4)-(6):

$$M = \left(a_{ij}\right)_{n\times n} \tag{4}$$

$$Maxvar = max\left(\sum_{j=1}^{n} a_{ij}\right) \tag{5}$$

The original relation matrix can be normalized using (13) to obtain the normalized direct influence matrix (N):

$$N = \left(\frac{a_{ij}}{Maxvar}\right)_{n\times n} \tag{6}$$

where a_{ij} denotes the impact of requirement i on requirement j.

The normal-direct influence matrix (N) is self-multiplied as depicted in Equation (7) and represents the indirect impact between elements. When all indirect effects are aggregated, the integrated impact matrix is obtained, denoted as (T):

$$T = N(I - N)^{-1} \tag{7}$$

where N is the normalized direct impact matrix, I is the identity matrix, $(I - N)^{-1}$ is the inverse matrix of $(I - N)$.

The degrees of impact, affected, centrality and causality are determined using the comprehensive influence matrix based on (8)-(11), denoted as $\{D|C|M|R\}$. The results of the calculations are presented in **Error! Reference source not found.**. The specific procedure is illustrated in **Error! Reference source not found.**.

$$D_i = \sum_{j=1}^{n} a_{ij}\ (i = 1,2,3, \dots, n) \tag{8}$$

$$C_i = \sum_{j=1}^{n} a_{ji}\ (i = 1,2,3, \dots, n) \tag{9}$$

$$M_i = D_i + C_i \tag{10}$$

$$R_i = D_i - C_i \tag{11}$$

D_i means the degree to which a factor has a direct effect on other factors. C_i means a factor is the cause of something else. M_i means the mutual effect between two factors. R_i is the result of a factor being affected by other factors.

Table 13. DEMATEL indicator value

ID	Impact degree	Affected degree	Centrality	Causality
a1	0.536	0.031	0.567	0.505
a2	1.185	1.042	2.227	0.144
a3	1.077	0.058	1.135	1.019
a4	0.125	0.058	0.183	0.067
a5	0.63	0.058	0.688	0.571
a6	0.929	0.058	0.988	0.871
…	…	…	…	…
a68	0	0.058	0.058	-0.058
a69	0	0	0	0

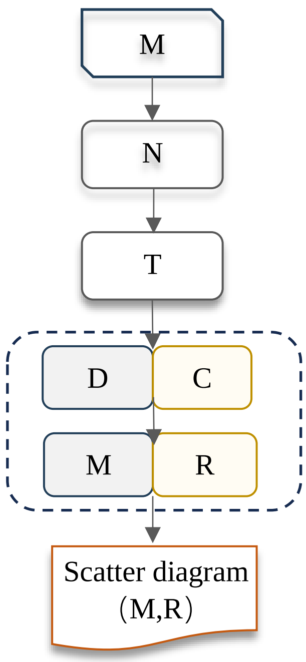


Figure 8. DEMATEL calculation process.

According to the average values of horizontal vector centrality and vertical vector causality degree, the analysis of interaction between various factors is conducted by dividing them into four quadrants, as illustrated in Figure 9. The driver elements are located in the first quadrant and hold significant importance and influence over the development and impact of the system. The second quadrant is usually dependent elements that are influenced or controlled by other factors. The third quadrant is typically characterized by independent elements that are not significantly influenced by other factors and can function relatively independently. The fourth quadrant typically contains the linkage elements that facilitate the relationships between the other elements.

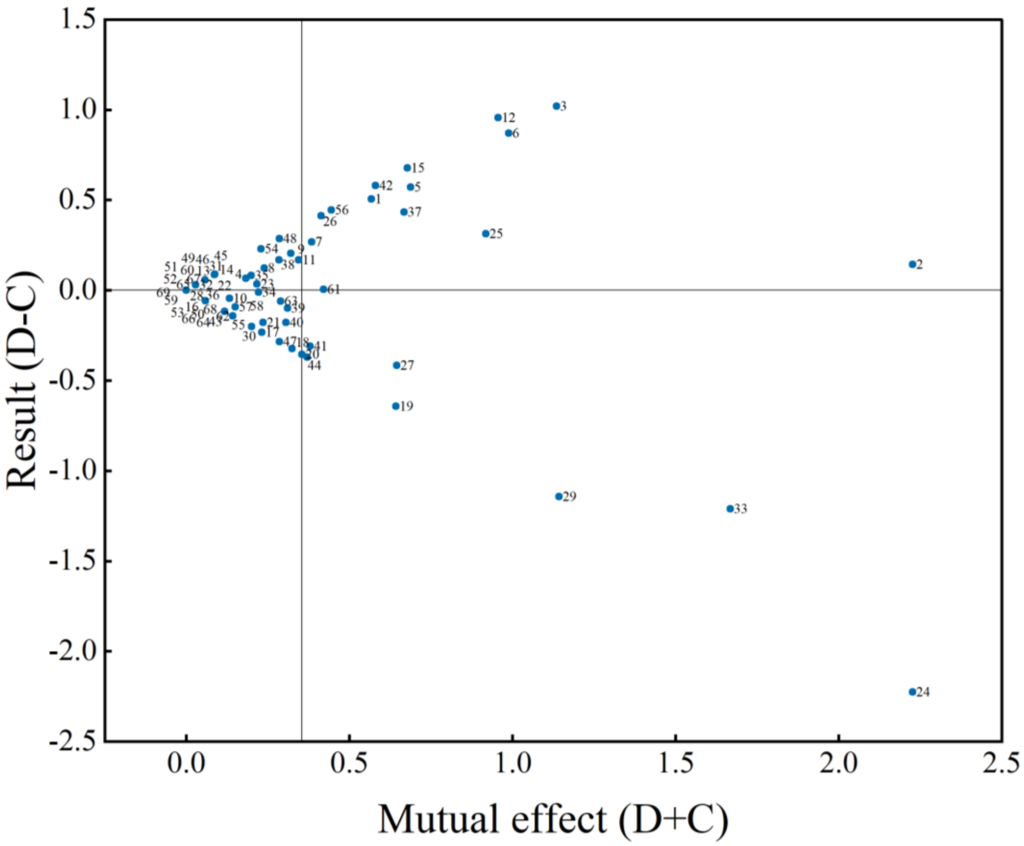


Figure 8. INRM.

3.RESULTS

Considering that Indifferent qualities (I) are improbable to exert a significant impact on user satisfaction, precedence should be accorded to researching and analyzing the pri-oritization of two categories of requirements: Attractive qualities (A) and One-dimensional qualities (O). As depicted in Fig. 11, maintenance strategies should be formulated for re-quirement factors in quadrants I and II, while improvement strategies should be devised for requirement factors in quadrants III and IV. Taking into account the importance of quadrants, the priority for maintenance in quadrant I surpasses that in quadrant II, whereas the priority for improvement in quadrant IV exceeds that in quadrant III. Fur-thermore, adhering to the classification rules of requirements in the KANO model, the prioritization sequence is as follows: M> O> A> I.

Ultimately, the connections between the elements are discerned using the Impact and Relation Map (INRM). The INRM is subsequently ranked in order of importance: I, II, III, and IV, and the requirements within each quadrant are prioritized based on the centrality of each element, from high to low. Lastly, the INRM is utilized to confirm the link between each element. The elements are categorized into I, II, III, and IV, and the requirements within each quadrant are prioritized based on the centrality of each element, from high to low. The detailed procedure is presented in Table14. Table15 shows the prioritization of the needs of truck users based on the conjoint analysis. More details can be found in Table A2.

The benefits of employing this set of methods for requirement prioritization are evident when comparing the data provided in Table 15 above. The requirement item 'Multimedia display quality (a61)' is ranked relatively low in the KANO model, classified as 'One-dimensional quality'. Consequently, according to DEMATEL, this specific require-ment falls into the 'driver elements' category and should be prioritized for enhancement. Likewise, in the KANO model, 'Driving stability (a26)' is categorized as 'One-dimensional quality' and ranks relatively high. Nevertheless, in the DEMATEL, it is categorized as 'Linkage elements'. Hence, to enhance its functionality, it is crucial to initially improve the source requirements that influence it. This might necessitate reordering it in the actual development process.

Table 14. Requirements prioritization model

Target layer	Prioritization of requirements			
Kano criterion layer	M	O	A	I
DEMATEL criterion layer	I	II	III	IV
Requirement layer	M-I,M-II, M-III,M-IV	O-I,O-II, O-III,O-IV	A-I,A-II, A-III,A-IV	I-I,I-II, I-III,M-IV

Table 15. Results of prioritizing user requirements for trucks

KANO Classification	KANO Sorting	Combination Sorting	DEMATEL Classification
M	a36	a33	I
	a16	a29	II
	a29	a27	
	a42	a19	
	a35	a20	
	a20	a30	
	a30	a34	III
	a19	a35	
	a27	a22	
	a33	a35	
	a22	a16	
	a38	a5	IV
	a5	a42	

	a34	a38	
…	…	…	…
I	a45 a49 a55 a31 a43	a55 a31 a49 a45 a43	III

4.DISCUSSION

4.1 Theoretical and practical significance

This study focuses on the field of truck products and services, utilizing online reviews as a foundational data source to deeply explore user feedback and expectations, thereby providing data-driven insights for product optimization and service enhancement. The research methodology encompasses several key aspects: (1) employing advanced information extraction techniques to precisely extract valuable content from reviews; (2) utilizing explicit and implicit demand mining methods to comprehensively identify potential user needs; (3) integrating sentiment analysis and quantification techniques to accurately assess users' emotional tendencies and demand intensity; and (4) constructing a demand prioritization model to scientifically determine the importance of different requirements.

This study offers an innovative approach to user demand mining for products with complex attribute hierarchies. By combining qualitative and quantitative analysis of online reviews, it transforms users' natural language into actionable design elements, enriching the theoretical foundation of text mining research. Additionally, a high-quality dataset specific to the truck domain was constructed, and the feasibility and effectiveness of the proposed methods were validated through case studies. The research outcomes provide efficient product development strategies for enterprise decision-making, laying a practical foundation for future research on user demand mining using review data. This work holds significant implications for enhancing user satisfaction and market competitiveness in the truck industry.

4.2 Limitations and future work

This study also has certain limitations, which can serve as a valuable reference for future research endeavors. It is important to note that the raw data was sourced solely from mainstream trucking websites and social media platforms, constituting a limited dataset. Future research should consider expanding the scope to include other online communities and foreign platforms, with the aim of obtaining a more extensive range of user feedback. Secondly, in the analysis of text effectiveness, the focus group manual screening method is employed, which reduces subjectivity but remains labor intensive and time-consuming. To enhance efficiency, future research can explore the use of machine learning or deep learning for effective review screening. Furthermore, the sentiment polarity and strength of user evaluation are affected by multiple factors, including syntax, vocabulary, and punctuation. In this study, the focus is primarily on vocabulary expression, and the text classification model utilized is limited by the knowledge base. It is acknowledged that different algorithms possess distinct strengths and weaknesses, and prefeature processing of textual data is paramount. Some algorithms may necessitate preprocessing operations such as word form reduction. Lastly, this study focuses mainly on proposing strategies for optimizing product design with a focus on assisting, while considering cost effectiveness and technical feasibility in practical development.

5.CONCLUSION

Addressing the shortcomings of existing research on user demand mining based on review texts, this study leverages online reviews to explore the multifaceted demands of truck users. By integrating qualitative and quantitative analysis methods, it transforms users' natural language into product design metrics, offering an innovative approach for demand mining in products with complex attributes. The key contributions of this re-search are summarized as follows:

(1) Innovative Demand Mining Method: A truck user demand mining method based on social media review texts was proposed, with four key strategies to enhance comprehensiveness and accuracy: (1 segmenting long sentences for improved analysis precision; (2 selecting the text classification model with the highest F1 score from six candidate models; (3 conducting sentiment analysis and quantification separately for explicit and implicit sentence structures; and (4 introducing environmental weighting coefficients to mitigate the impact of natural conditions on user satisfaction.

(2) High-Quality Dataset Construction: Utilizing a Chinese entity recognition dataset, a high-quality truck-specific dataset was constructed, including a domain knowledge base and Chinese entity recognition data, providing a robust foundation for in-depth research on truck user requirement.

(3) Requirement Prioritization Model: An innovative demand prioritization model was developed, integrating user attention and sentiment values. By combining the IPA quadrant analysis, KANO model, and DEMATEL method, it provides a competitive enterprise perspective for analyzing user demands, offering scientific support for product development and service improvement.

This study not only provides an efficient demand mining tool for the truck industry but also serves as a valuable reference for research and practice in other fields involving products with complex attributes.

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APPENDIX

Table A1. Attribute words, Performance and Importance sets

Attribute	ID	Words	Performance	Importance
Quality	a1	Complete vehicle refinement	-1.19	0.41
	a2	Overall vehicle functional quality	-1.1	1.24
	a3	Engine functional quality	-1.42	0.98

	a4	Transmission functional quality	-1	0.36
	a5	Chassis functional quality	-1.21	1.96
	a6	Brake pad functional quality	-0.8	0.1
	a7	Sensor functional quality	-1	0.16
	a8	Clutch functional quality	-1	0.16
	a9	Airbag functional quality	-1	0.1
	a10	Vehicle wiring system	-1.22	1.29
	a11	Component quality	-1	0.16
	a12	Battery endurance	-0.8	0.41
	a13	After-sales service	-1.21	0.72
	a14	Warranty	-1	0.16
	a15	Tire functional quality	-0.76	0.78
Life cycle cost	a16	Purchase price	-0.93	8.74
	a17	Depreciation rate	-1.08	0.67
	a18	Maintenance cost	-0.92	0.67
	a19	Repair cost	-1.06	2.59
	a20	Energy consumption cost	-0.95	3.31
	a21	Payload capacity	-1.04	0.72
	a22	Vehicle weight	-0.94	2.22
Drivability	a23	Acceleration performance	-0.8	0.52
	a24	Subjective driving feel	-0.97	0.93
	a25	Braking performance	-1.01	1.14
	a26	Driving stability	-1.11	0.72
	a27	Power performance	-0.94	2.43
Security	a28	Fuel tank safety	-1	0.83
	a29	Passenger protection	-1.09	5.07
	a30	Visibility	-0.94	3.1
	a31	Long-nose truck	1.2	1.55
	a32	Cab-over truck	-1.19	1.34

Comfort	a33	Driving comfort	-0.73	2.28
	a34	Driving noise	-0.82	1.76
	a35	Cabin space	-0.4	3.98
	a36	Sleeper space	-1	11.74
	a37	Seat comfort	0.22	0.93
	a38	Air conditioning comfort	-0.91	2.22
	a39	Cabin sealing	-0.27	1.14
	a40	Indicator recognition	-1	0.36
	a41	Humanized central control design	-1	0.41
	a42	Steering wheel angle	-0.98	4.19
Suitability	a43	Climate adaptability	0.69	1.5
	a44	Rough road adaptability	0.89	0.88
	a45	Rough road adaptability	0.17	4.55
Design	a46	Repair/maintenance operability	0.69	0.67
	a47	Repair/maintenance Replacement Convenience	0.89	0.47
	a48	Spare parts availability	0.17	0.16
Design	a49	Exterior overall design	0.82	4.24
	a50	Exterior lighting	0.45	0.57
	a51	Air deflector design	-0.73	0.57
	a52	Window design	-0.83	0.31
	a53	Rear window design	-0.36	0.57
	a54	Side mirror design	-0.7	1.03
	a55	Interior design	0.58	2.06
	a56	Centre console design	-0.07	0.72
Intelligentize	a57	Fault indication function	-0.3	1.29
	a58	Warning notification function	-0.05	1.14
	a59	Advanced driver assistance system	0.36	0.36

	a60	Seat adjustment memory function	-0.82	0.57
	a61	Multimedia display quality	-0.08	0.31
	a62	Refrigerator	-0.4	0.52
	a63	Air conditioning	-0.67	0.93
	a64	Power supply	-1	0.16
	a65	Dashcam	-1	0.21
	a66	Shoe cabinet	-1	0.36
	a67	Vehicle power supply	-1	0.31
Environment	a68	Degree of fulfilment of emission regulations	-0.6	0.52
	a69	Application of scrap batteries	-1.21	0.36

Table A2. Results of Prioritizing User Requirements for Trucks

KANO Classification	KANO Sorting	Combination Sorting	DEMATEL Classification
M	a36	a33	I
	a16	a29	II
	a29	a27	
	a42	a19	
	a35	a20	
	a20	a30	
	a30	a34	III
	a19	a35	
	a27	a22	
	a33	a35	
	a22	a16	
	a38	a5	IV
	a5	a42	
	a34	a38	

O	a32	a2	I
	a10	a25	
	a57	a61	
	a2	a24	II
	a25	a41	
	a39	a18	
	a58	a39	
	a54	a40	
	a3	a63	
	a24	a21	
	a63	a17	
	a28	a8	III
	a15	a23	
	a13	a4	
	a21	a58	
	a26	a57	
	a56	a10	
	a17	a62	
	a18	a14	
	a51	a68	
	a53	a13	
	a60	a32	
	a23	a69	
	a62	a67	
	a68	a66	
	a1	a65	
	a12	a64	
	a41	a60	
	a4	a53	

	a40	a52	
	a66	a51	
	a69	a28	
	a52	a3	IV
	a61	a6	
	a67	a12	
	a65	a15	
	a7	a1	
	a8	a56	
	a11	a26	
	a14	a7	
	a64	a11	
	a6	a9	
	a9	a54	
A	a37	a44	II
	a44	a47	
	a46	a59	III
	a50	a50	
	a47	a46	
	a59	a37	IV
	a48	a48	
I	a45	a55	III
	a49	a31	
	a55	a49	
	a31	a45	
	a43	a43	