

# Exploring user satisfaction and improvement opportunities in public charging pile resources

Licheng Xu<sup>1</sup>, Asmiza A. Sani<sup>1</sup>, Shuai Xie<sup>2</sup>, Liyana Shuib<sup>3</sup>

<sup>1</sup>Department of Software Engineering, Faculty of Computer Science and Information Technology, Universiti Malaya, Kuala Lumpur, Malaysia

<sup>2</sup>Department of Artificial Intelligence, Faculty of Computer Science and Information Technology, Universiti Malaya, Kuala Lumpur, Malaysia

<sup>3</sup>Department of Information System, Faculty of Computer Science and Information Technology, Universiti Malaya, Kuala Lumpur, Malaysia

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## ABSTRACT

The existing market of public charging pile services for electric vehicle (EV) users has occupied a particular market share. However, instead of solely focusing on pre-planning the construction of charging piles, it is crucial to address the shortcomings of the existing charging pile service and develop effective marketing strategies. This approach can help optimize the utilization of charging pile resources and minimize wastage. In this study, we explore EV users' comments on the public charging pile service and adopt a natural language pre-training model to classify comments for extracting positive and negative comments. For these two types of comments respectively, we construct the text-to-knowledge to mine the keywords from multiple dimensions. We further excavate the words correlated with the keywords by utilizing dependency parsing to create relational dependency graphs. Taken together, we identify key factors influencing EV user satisfaction or dissatisfaction and uncover the relationships among these factors. These insights provide valuable information for charging pile operators to develop targeted marketing strategies and improvement plans for the existing public charging pile resources, ultimately enhancing the overall user experience.

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## Corresponding Author:

Licheng Xu

Department of Software Engineering, Faculty of Computer Science and Information Technology

Universiti Malaya

50603 Kuala Lumpur, Federal Territory of Kuala Lumpur, Malaysia

Email: lichengderrick@gmail.com

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## 1. INTRODUCTION

Given the prominent features of energy saving and zero emissions in electric vehicles (EVs), many countries have emphasized spurring EV growth to mitigate the problem of energy shortage and environmental pollution [1], [2]. Charging piles, as indispensable facilities for EVs, play a vital role in their development encompassing aspects such as construction, distribution, and service quality [3]. As the existing public charging pile resources hold a significant market share and serve as directly accessible resources for EV users, it is imperative to thoroughly analyze EV users' comments to uncover key factors that contribute to EV user satisfaction or dissatisfaction. This analysis is crucial for developing targeted marketing strategies and improvement plans, ensuring sustainable utilization and enhancement of these resources.

Many studies on improving the charging pile service have been carried out from different perspectives, such as satisfying the ever-growing demand for the charging service by predicting the number of charging piles needed [4]–[7], finding an appropriate location for charging station construction to form an efficient charging station network [8]–[12], improving the quality and convenience of charging service by building predictive models or organizational architectures to optimize the queuing time [13]–[14], and improving the efficiency of maintenance work by using algorithms to diagnose and detect faulty of charging piles [15]–[17]. These studies have achieved fruitful results in improving the charging pile service by exploring anticipatory planning.

It can be seen that these research studies primarily concentrate on exploring anticipatory planning instead of enhancing the marketing and service aspects of the current public charging pile service. Few studies carry out research on analyzing the EV users' comments to explore the advantages and disadvantages of improving the existing public charging pile service. A tremendous amount of information in the comments is essential for mining users' needs and reflecting the service problems, thus providing targeted reference information to improve the service marketing effectiveness and quality of the charging service [18], [19].

In this context, [20] analyze EV users' comments posted on social media to reveal EV users' preferences for charging infrastructure. By conducting sentiment analysis on EV users' comments, [21] identify the key factors that trigger negative attitudes by focusing on the negative comments, while [22] predict the sale quantity of EV by combing the EV sales data. However, these studies have yet to comprehensively analyze EV users' comments to identify the essential factors influencing satisfaction or dissatisfaction with the existing charging station service, thereby limiting the availability of decision-making assistance for charging station operators in developing targeted marketing strategies and improvement plans. On the one hand, these studies do not attempt to analyze positive comments to mine the EV users' interest to increase the attractiveness and persuasiveness of marketing strategy. On the other hand, the analysis methods in these studies suffer from some serious limitations [23]–[25]. The accuracy of comment sentiment classification in [21], [22] based on factors, such as dictionaries and scores, is limited by the coverage of sentiment and scores dictionaries. This approach may face challenges in adequately processing intricate semantic and contextual information, thereby limiting its ability to classify various comment types accurately. The application of word frequency analysis, word similarity analysis, and topic analysis in [20] may inadvertently neglect crucial dimensions of keywords and limit the scope of relevant factor words identified, which fail to provide a comprehensive reflection of the issues existing within the charging pile service.

Therefore, this paper proposes a novel text analysis process for exploring marketing insights and service deficiencies by analyzing EV users' comments. We adopted the pre-training model of natural language processing (NLP) to achieve the text classification of users' comments. Focusing on the positive and negative comments, we conducted the text-to-knowledge for these comments to mine the keywords affecting the charging pile service from multiple dimensions. Moreover, we further excavated the words correlated with the keywords to draw relational dependency graphs. The results of this paper could provide both panoramic and granular views to present users' concerns and problems in the charging pile service, helping charging pile operators develop pragmatic marketing strategies and improvement plans for the existing public charging pile resources. The public charging pile station with advantages, such as a suitable fee pricing mechanism, adequate number of charging piles, high and stable performance charging piles, responsible personnel, appropriate construction location, comfortable environment, and well-equipped facilities, can be highlighted in the marketing to attract more EV users. The charging pile operators should address the problems, such as serious parking space occupation, exorbitant fee pricing mechanism, bad management environment, inadequate facilities, and abnormal operation and unstable performance of charging piles, to improve EV users' satisfaction.

The main contributions of this paper are:

- (i) By leveraging a pre-training model, we achieve a remarkably accurate classification of EV users' comments, even with limited sample data, eliminating the need for manual dictionary updates or rating criteria. Notably, our comment classification extends beyond the binary classification of positive and negative sentiments, effectively filtering out irrelevant and promotional comments, thereby avoiding the potential impact on the mining analysis process.
- (ii) Based on the text-to-knowledge and dependency parsing in our proposed EV users' comment analysis process, the keywords mined from each dimension and relational dependency graphs focus on positive and negative comments respectively, pertinently and holistically revealing the key factors that satisfy or dissatisfy EV users when using charging piles service. Charging station operators could identify EV users'

concerns and charging service deficiencies to develop marketing strategies and make targeted improvements, helping to improve the utilization rate of existing public resources and alleviate the poor quality of the service that jeopardizes the overall development of EVs.

- (iii) As the charging pile adoption increases, more EV users' comments will accumulate in the transaction. The proposed novel text analysis process for analyzing the EV users' comments in this paper would provide a basic sketch for attaining improvement and marketing information to make the practicable course of action, ensuring the all-around development of charging pile service.

The rest of this paper is structured as follows: section 2 describes the data source, data pre-processing and methods. Section 3 analyzes and discusses the results of the experiment. The conclusion and future work are shown in section 4.

## 2. METHOD AND DATA

Aiming to enhance the sustainable utilization of existing charging pile resources, it is necessary to pertinently uncover the key factors that could be perceived as strong incentives in the marketing strategy or major obstacles to using the public charging pile service. In this section, we propose a novel text analysis process to analyze EV users' comments for exploring marketing insights and service deficiencies, as shown in Figure 1. We first use Python script to crawl EV users' comments on the charging pile service application and manually label a small portion of comments through preliminary browsing (section 2.1 and 2.2). Then, we use the labeled data to train, test, and evaluate the pre-training model in the PaddleNLP framework to obtain the optimal model parameters, then use the optimal model parameters to classify the unlabeled data (section 2.3). Next, we introduce how to adopt the text-to-knowledge to mine the keywords from multiple dimensions (section 2.4) and adopt the dependency parsing to excavate the words related to the keywords to draw dependency graphs (section 2.5).

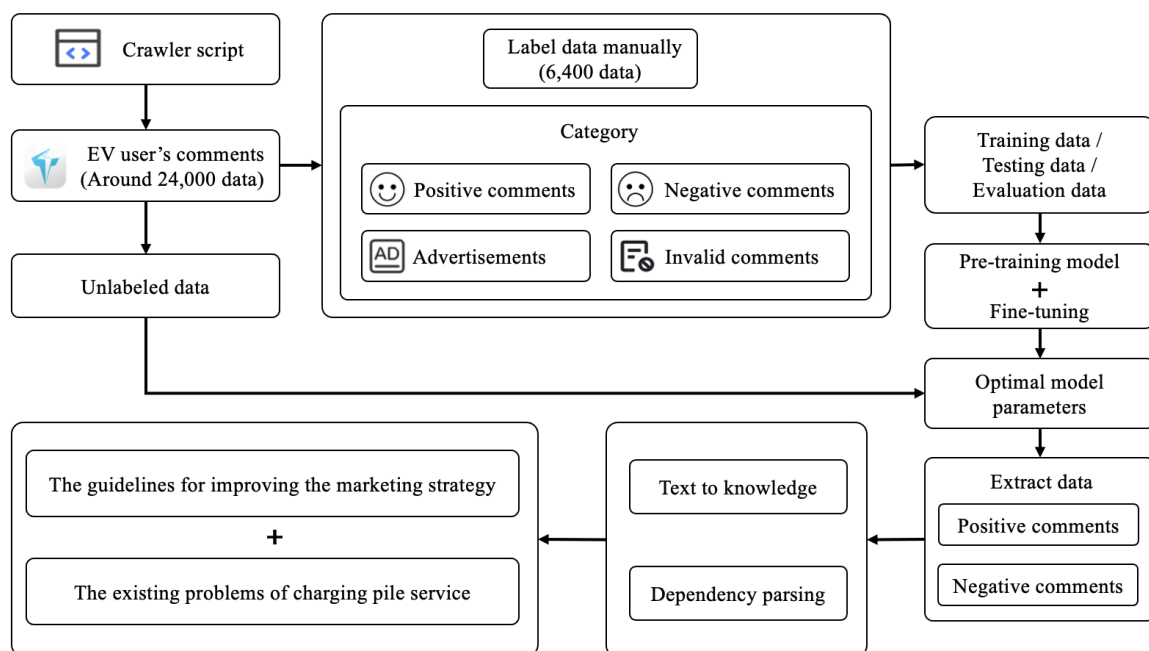


Figure 1. The experimental processes

### 2.1. Data source

The data of EV users' comments in this paper was collected by using Python crawler script from charging stations in the TELD application [26]. A total of 24,694 pieces of data were collected. Each piece of data includes the name of the charging station, user name, vehicle brand, score, comment time, and comment content. Part of the data can be seen in Table 1.

Table 1. Examples of EV users' comments on using the charge pile service

Charging station name	User name	Vehicle brand	Score	Comment time	Comment content
Guangzhou Yuexiu Dongshan Haide Mansion Charging Station	150****0157	Tesla	3	2022-07-01 21:47:08	Service fees are too expensive.
Guangzhou Yuexiu Dongshan Haide Mansion Charging Station	136****7327	BYD	1	2022-04-21 01:42:14	Every day, many fuel vehicles are parked in the charging post so I have no parking place to charge.
Guangzhou Guangxinghua Building Charging Station	135****1983	Tesla	1	2022-03-25 19:17:47	It's so bad that the security guard still won't give access to use the charging pile
Guangzhou Guangxinghua Building Charging Station	159****0188	BYD	1	2018-05-07 06:21:59	Convenient and close to residence community. Preferred by high-rise residents.

## 2.2. Data pre-processing

For the crawled data, we dropped the comments with null values. Based on the preliminary browsing, we divided the comments into four main categories, namely invalid comments, advertising comments, positive comments and negative comments.

- i) Invalid comments: after using the charging pile service, some users are not willing to spend time writing comments, thus inputting a random string of characters as a comment to submit. Invalid comments consist of three main categories: pure numbers, pure symbols, and illogical text.
- ii) Advertising comments: some charging station operators consider the comments section as an effective publicity channel to attract more users to use their charging pile services. Their comments contain specific information about their own charging stations, such as the name of the charging station, charging price, description of nearby facilities, and so on.
- iii) Positive comments: the comments denote a positive attitude towards the service provided, meaning users are satisfied with the experience of using the charging pile service. The comments cover phrases such as fast charging, reasonable price, free parking, and convenient facilities nearby, reflecting the critical advantages of the service.
- iv) Negative comments: the comments reflect a negative view of the charging pile service, meaning that users are unsatisfied with the experience of using the charging pile service. Their comments contain information about shortcomings of the charging pile service, covering phrases such as slow charging, expensive fees, and austere environment.

Based on the above categories of comments, we classified the 6,400 data items with manual tagging instead of using the score as a single criterion for categorizing data. These data were divided into the training set, testing set, and evaluation set for the experiment.

## 2.3. Adoption of pre-training model of NLP

Regarding the classification of EV user comments, the conventional classification methods utilized by [21] and [22] entail the need for manual updates of dictionaries and rating standards, where the coverage of the dictionaries and incorrect ratings can influence the accuracy of the classification. The process of original text classification entails a massive amount of sample data, requiring much time and energy to label data. The resulting model is also challenging to adapt to new business scenarios [27], [28]. To respond to the above problems, the pre-training model is applied to NLP. Pre-training models aim to provide helpful feature representations for subsequent specific tasks by learning a wide range of semantic and contextual information. These models typically use unsupervised learning algorithms to train on large amounts of unlabeled data to learn the underlying structures and patterns of the data. The pre-training models can be used for fine-tuning or transfer learning specific tasks. By further training on labeled data for particular tasks, the models can adapt to new tasks' specific requirements and data features, improving their performance and accuracy on particular tasks [29]. Therefore, based on the pre-training model, we use manually labeled data to fine-tune the model and establish the comment classification model.

This paper used the PaddleNLP framework to call the ERNIE 3.0 pre-training model and the corresponding text transformation model. For manually labeled data, we extract their comment content and

corresponding labels and divide them into training, testing, and evaluation sets. By importing dependency packages related to the PaddleNLP framework, we called 'AutoModelForSequenceClassification.from\_pretrained()' to select the 'ernie3.0mediumzh' as the classification model and set the value of 'num\_classes' to four, which denotes that there are four types of comments needed to be classified in this task. Then, we called 'AutoTokenizer.from\_pretrained()' to select the corresponding model's tokenizer to convert raw input text into an input data format acceptable to the model, and defined the data reading and pre-processing functions and the iterator definitions for each data set. For the fine-tuning optimization strategy and scoring metric, we adopted the 'paddle.optimizer.AdamW()' to implement the fine-tuning optimization strategy where  $learning\_rate = 2 \times 10^{-5}$ ,  $warm\_up\_proportion = 0.1$  and  $weight\_decay = 0.01$ , and called 'paddle.nn.loss.CrossEntropyLoss()' and 'paddle.metric.Accuracy()' as the loss function and evaluation metric. Then, setting the number of training rounds to 12, we evaluated the results of each round against the evaluation set and compared the accuracy obtained to select and store the optimal model parameters, as shown in Algorithm 1. After that, we called 'paddle.load()' to load the stored optimal model parameters from Algorithm 1, and called 'model.set\_dict()' to set the parameters into the model. Next, we can define the model prediction function to process all the unlabeled comment data.

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**Algorithm 1:** Training text classification model based on pre-training model
 

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**Data:** pre\_accuracy, accuracy  
**Result:** optimal model parameters

```

1 for epoch in range(1, epochs+1) do
2   for step, batch in enumerate(train_data_loader, start=1) do
3     obtain text number, text content, and text label from batch;
4     call the model and pass in the text number and content to obtain probability logits;
5     use criterion() to calculate the loss between model output logits and labels;
6     use F.softmax() to calculate the probs of logits;
7     use metric.compute() to calculate the correct number of predictions between the probability probs and labels labels
      predicted by the model;
8     accumulate the correct predicted number of the current batch into the indicator;
9     calculate the accuracy of accumulation;
10    adopt back-propagation and calculate gradients;
11    update parameters based on gradient and adjust learning rate based on current steps;
12    clear the gradient information in the optimizer to prepare for the next iteration;
13  end
14  call the evaluate function to evaluate the model on the validation set;
15  if accuracy > pre_accuracy then
16    save the model parameters;
17    pre_accuracy ← accuracy;
18  end
19 end

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## 2.4. Text to knowledge

The text-to-knowledge offers a linkage approach from text to the knowledge tree, providing comprehensive and rich knowledge annotations for text parsing. Traditional lexical analysis methods start with part-of-speech, such as verbs and nouns, but ignore the label of the type to which its vocabulary belongs. The significant keywords from other dimensions would be curtailed solely depending on word frequency and part-of-speech, leading to incomplete further analysis for obtaining decision-making reference information. This paper adopts WordTag to conduct the text-to-knowledge for EV users' comments. WordTag is the first-word knowledge annotation tool that covers all Chinese words WordTag [30], containing 91 lexical and proper name category labels, such as scenario events, biologicals and location direction, which improve the precision of text parsing and mining. Compared with traditional Chinese parsing of word segments, part-of-speech tagging and named entity recognition, WordTag is based on the term tree TermTree [31] to implement knowledge annotation. It annotates the part-of-speech sequence of sentences and associates the collected words to the term tree. We translate the comments into English to illustrate its processing mechanism, as shown in Figure 2. It is assumed that the comment is "Charging piles charge quickly". WordTag splits the comment into words and figures out the corresponding WordTag labels and other attributes.

Based on the 91 vocabulary and proprietary name category labels included in WordTag, such as the scenario event and the modifier, we selected the labels with higher proportions as the primary directions for keyword mining. Then, we selected the words with the highest proportions within each label as the keywords from positive and negative comments separately. The code for this process is presented in Algorithm 2.

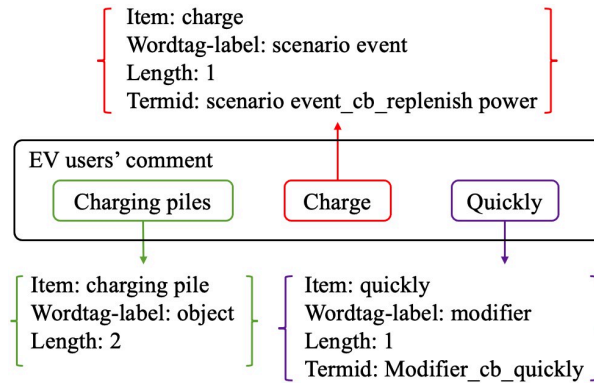


Figure 2. Example of WordTag processing data

**Algorithm 2:** Mining the keywords from multiple dimensions

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Data: positive comments, negative comments
Result: keywords list from multiple dimensions

1 initialize label_dict;
2 for comment in positive comments or negative comment do
3     result_wordtag ← comment passed as a parameter to the WordTag function;
4     temp ← obtain annotation results for each word by result_wordtag[0][items];
5     for i in range(len(temp)) do
6         if temp[i]["wordtag_label"] is in label_dict then
7             the frequency corresponding to the label++;
8         else
9             add the new label to the label_dict;
10            the frequency corresponding to the label++;
11        end
12    end
13 end
14 Sort the frequency of labels in the label_dict from high to low;
15 Select labels with high frequency to mine keywords, and initialize a certain number of lists according to the needs to store the
    mined keywords;
16 for comment in positive comments or negative comment do
17     result_wordtag ← comment passed as a parameter to the WordTag function;
18     temp ← obtain annotation results for each word by result_wordtag[0][items];
19     for i in range(len(temp)) do
20         wordtag_label ← temp[i]["wordtag_label"];
21         if temp[i]["wordtag_label"] is in corresponding list then
22             store in the corresponding list and count the frequency;
23         end
24    end

```

**2.5. Dependency parsing**

Dependency parsing is concerned with the dependencies between words in a sentence. The term “dependency” refers to the relationship between the word and the dominated word, which is a partial sequence relationship. Dependency parsing considers the predicate as the central core of the sentence to analyze its

dependency with other words directly or indirectly associated with it. [32], [33]. It explores the subject-verb relationship, verb-object relationship, and preposition-object relationship. Between words, which is helpful to reflect the prominent features in the keywords to make decisions from different perspectives. Based on the keywords mined from the text-to-knowledge, we further excavate the correlative words to draw relational dependency graphs, reflecting the various facets of them. For example, in the positive comments, we assume the “Charge” is the keyword in the WordTag of scenario events. The words correlative with it are “Quick”, “Smooth” and “Stable” by using dependency parsing as shown in Figure 3. The correlative words could indicate that the event of “Charge” could evoke a positive response in EV users owing to the fast, smooth and stable charging pile performance.

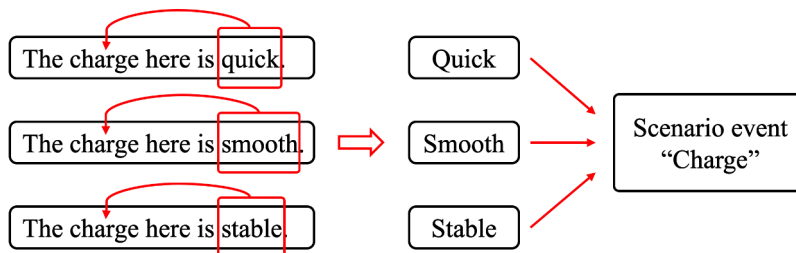


Figure 3. The example of using dependency parsing to mine correlative words

### 3. RESULTS AND DISCUSSION

#### 3.1. Comment classification

The highest accuracy of 95.12% is achieved within 12 training epochs of the experiment, which is selected as the optimal parameter mode as shown in Figure 4. The accuracy of the obtained optimal parameter model is 95.11% and 94.12% in the evaluating and testing sets respectively. The model with the optimal parameters was utilized to classify the remaining unlabeled 18,731 data. Among the collected EV users' comments, there are 11,688 positive comments and 12,294 negative comments as shown in Figure 5. The classification results highlight the presence of issues within the existing charging pile service, leading to a significant proportion of negative comments. Identifying and rectifying these service deficiencies are essential components of formulating a comprehensive improvement plan, ensuring the sustainable utilization of charging pile resources and effectively catering to EV users' needs. Furthermore, mining important information from positive comments also could reveal specific concerns of EV users regarding the public charging pile service, laying the foundation for developing targeted marketing strategies and enhancing the overall service experience.

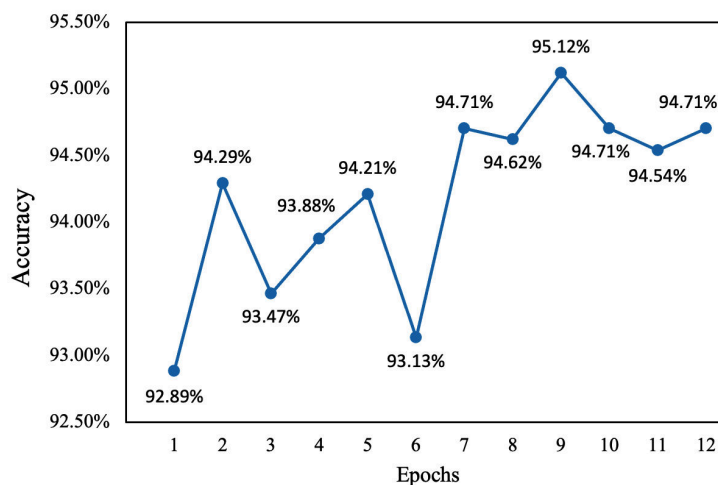


Figure 4. Twelve training epochs of the experiment

### 3.2. Keywords from text to knowledge

Utilizing the 91 vocabulary and proper noun category labels from WordTag, we analyzed both positive and negative comments to assign the corresponding WordTag labels to each vocabulary term present in the comments. We identified and manually selected the labels that account for a significant proportion, including “Scenario event,” “Modifier,” “Vocabulary term,” “Place category,” “Personality characteristic,” and “Object.” Before presenting the analysis results, we initially describe the meaning associated with these labels. The “Scenario event” label reveals the specific events EV users encounter during the charging pile service, shedding light on which events prompt users to express positive or negative feedback. The “Modifier” label reveals the emotional coloring and attitude in comments, describing aspects such as service quality, efficiency, reliability, and user satisfaction. The “Place category” and “Object” labels reflect the specific locations and objects in the charging station that EV users are most concerned about. The “Vocabulary Terms” label provides an additional perspective to uncover user concerns and can be considered as a supplementary dimension for exploration. In contrast to keyword extraction that solely relies on frequency statistics used in existing research, the keywords we obtained resulted from a multidimensional exploration. Exploring the keywords that constitute a substantial proportion under these labels can offer valuable insights to enhance marketing strategies and improve service quality for charging pile operators.

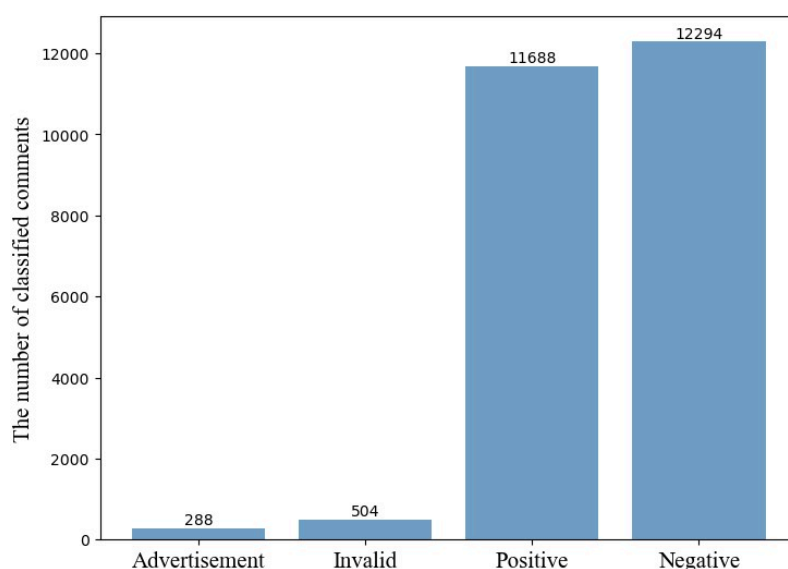


Figure 5. The number of classified comments

Based on the selected labels mentioned above, the result of keywords in the positive comments is shown in Figure 6. The events encountered by EV users are “Charge,” “Park,” and “Queue.” The characteristics of these events are the principal reasons for the positive attitude of users. In terms of marketing, the charging pile operator could make the benefits of their services at these events highly conspicuous to attract users. The adjectives in the “Modifier” label reflect the advantages of the charging pile service that appeal to users. For instance, “Cheap” reveals EV users’ opinions about affordability. Setting a reasonable charging price range could lay a solid foundation for improving service satisfaction and promoting price marketing. The users’ sentiments after using the charging pile service are figured out in the “Personality characteristic” label, namely “Comfort,” “Like,” “Satisfy,” and “Recommend.” The users’ concerns about other factors of the charging pile service are presented in remaining labels, such as “Environment,” “Service,” “Lounge,” and “Air conditioner”, which could be highlighted in the content marketing. We chose these keywords for dependency parsing analysis to identify the words associated with them, thus offering specifically pertinent information on developing marketing strategies.

The result of keywords in the negative comments is shown in Figure 7. In the “Personality characteristic” label, “Dissatisfy,” “Regret,” “Reluctance,” “Disappoint,” and “Depress” are the visible signs of negative attitudes of users. An exception to the “Charge,” users emphasized the issues in the “Scenario



event” label, such as “Occupy,” “Fully Charge,” “Park,” “Stop,” and “Jump gun,” meaning that users have great dissatisfaction with the charging pile service being hampered by these events. As shown in the “Modifier” label, “Expensive” demonstrates that there are partial price-sensitive users. The unreasonable fee pricing mechanism could reduce the degree of users’ satisfaction. “Slow” and “Faulty” point out that the charging pile service is defective in performance and operation, which could be further deduced by “Breakdown” and “Problem” in the “Lexical” label. In the “Place category” label, it can be found that some charging stations have problems with the environment, construction location, and supporting facilities. If there is deficient or unreasonable construction and management, the charging pile service might restrict the capacity to provide high service standards to meet market requirements. We chose these keywords for dependency parsing analysis to uncover the words associated with them, thereby providing a comprehensive perspective to help charging pile operators improve and solve problems in a targeted manner. Aiming to show the contributing factors to pertinently point out and demonstrate the user concerns and problems in the public charging pile service, we manually select the keywords from section 3.2 to excavate the correlative words to draw relational dependency graphs. The relational dependency graph of positive and negative comments are shown in Figure 8 and 9 respectively.

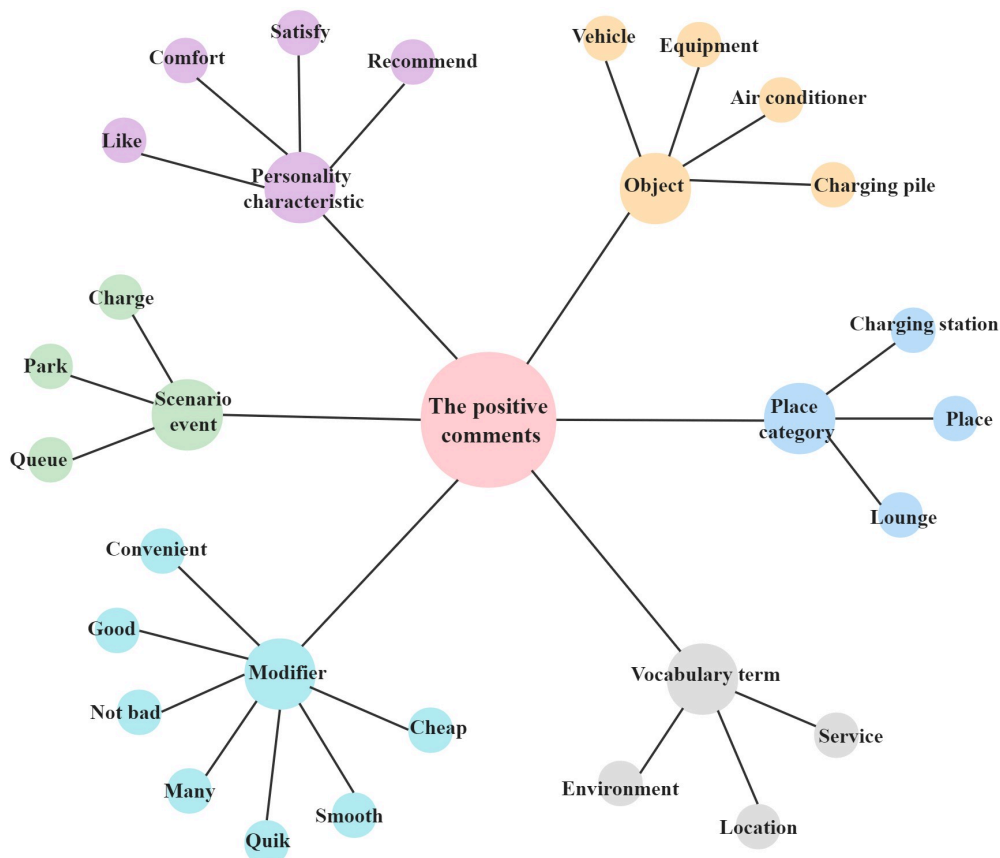


Figure 6. The WordTag result of positive comments

The findings in the positive comments: i) the event “Charge” entails the “Park” and “Queue” events (Figure 8(a)). The convenience, smoothness, and affordability of these events affect the users’ charging experience to a certain extent. The charging pile’s high speed and stable performance are conducive to reducing user waiting time and ensuring smooth charging. A sufficient number of charging piles and a good charging parking plan help ensure the capability of charging pile service offerings and finding the parking space smoothly and conveniently, enabling users to use the service efficiently without waiting in line or finding the parking space for a long time. In addition, if the charging station has an affordable charging and parking fee mechanism, this price advantage could be used as a competitive advantage to improve users’ satisfaction;

ii) users also consider additional factors related to their charging experience (Figure 8(b)). There may need to be more than just the baseline requirements of users to compete in the market as an advantage. Adding value to users' perceptions is necessary to enhance their satisfaction and loyalty [34], [35]. In addition to the three main scenario events mentioned above, we deduce that the outstanding service from the security guards and staff could prevent users' patience from being drained by assorted issues during the service, adding value to the charging pile service. Furthermore, "Convenient," "Easy to find," "Traffic," and other words correlated with "Location" infer that the appropriate construction location could make it more convenient for users to find the charging station. The words correlated with "Environment" indicate that users are attracted to the charging pile service with well-equipped facilities and a clean environment due to the long charging time of EVs. Therefore, all these advantages in the existing public charging pile service could be perceived as strong incentives to attract more users when developing the marketing strategy.

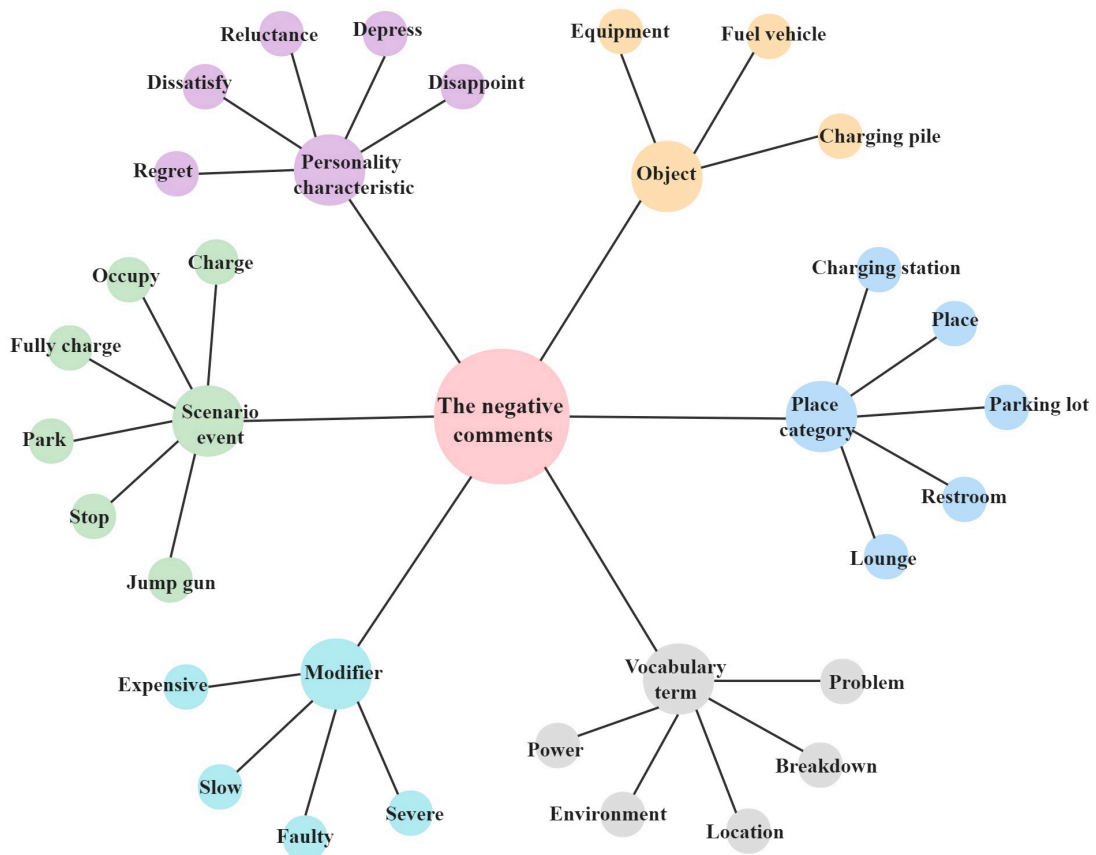


Figure 7. The WordTag result of negative comments

The findings in the negative comments: i) "Expensive," "Price," and "Fee" are associated with "Charge" as shown in Figure 9(a). A possible explanation for this might be that affordability becomes one of the most important problems in some charging stations. The charged price set by the operator should be combined with the local consumption situation and the national grid policy. Moreover, charging pile service charges are divided into charging and parking fees. The problem may be aggravated if the standard setting on parking fees is unreasonable. Excessive charges reduce the overall utilization rate of charging piles, which is not beneficial to the development of the EV industry [36]; ii) the words correlated with "Fully charge" and "Jump gun" reveal the operational problems of the charging pile, meaning users can not use the charging pile normally. The phenomenon that the charging pile suddenly or automatically stops during the charging process is called the "Jump gun." It leads to a situation where the EV is not fully charged, which could have a detrimental influence on the travel plan [37]. Meanwhile, "Slow" and "Power" correlated with "Charge" also reflect

the performance problems of charging piles. Charging pile operators have an inescapable responsibility for regularly checking and upgrading charging piles to ensure their normal and efficient operation; iii) the nodes connected with “Occupy” demonstrate that the parking spaces paired with charging piles are heavily occupied by fuel vehicles. “Always” and “Nobody manages” demonstrate that the relevant person in charge of the charging station does not make a point of this problem. The occupancy of charging spaces could force users to spend much time being queued or find another charging pile with idle parking space, which is undoubtedly one of the most important problems for reducing the utilization rate and satisfaction of charging piles; iv) the nodes connected with “Lounge” and “Restroom” imply that the equipment with lounge and restroom and a clean and tidy environment form an integral part of the charging service as shown in Figure 9(b). Improving the charging station environment and facilities could offer better charging pile service to enhance users’ satisfaction. Overall, these factors would be neglected by charging pile operators, causing inefficient and inferior quality service and significantly detracting from the value of existing public charging pile resources.



Figure 8. The dependency parsing result of the key information in positive comment; (a) the event “Charge” entails the “Park” and “Queue” events and (b) users also consider additional factors related to their charging experience

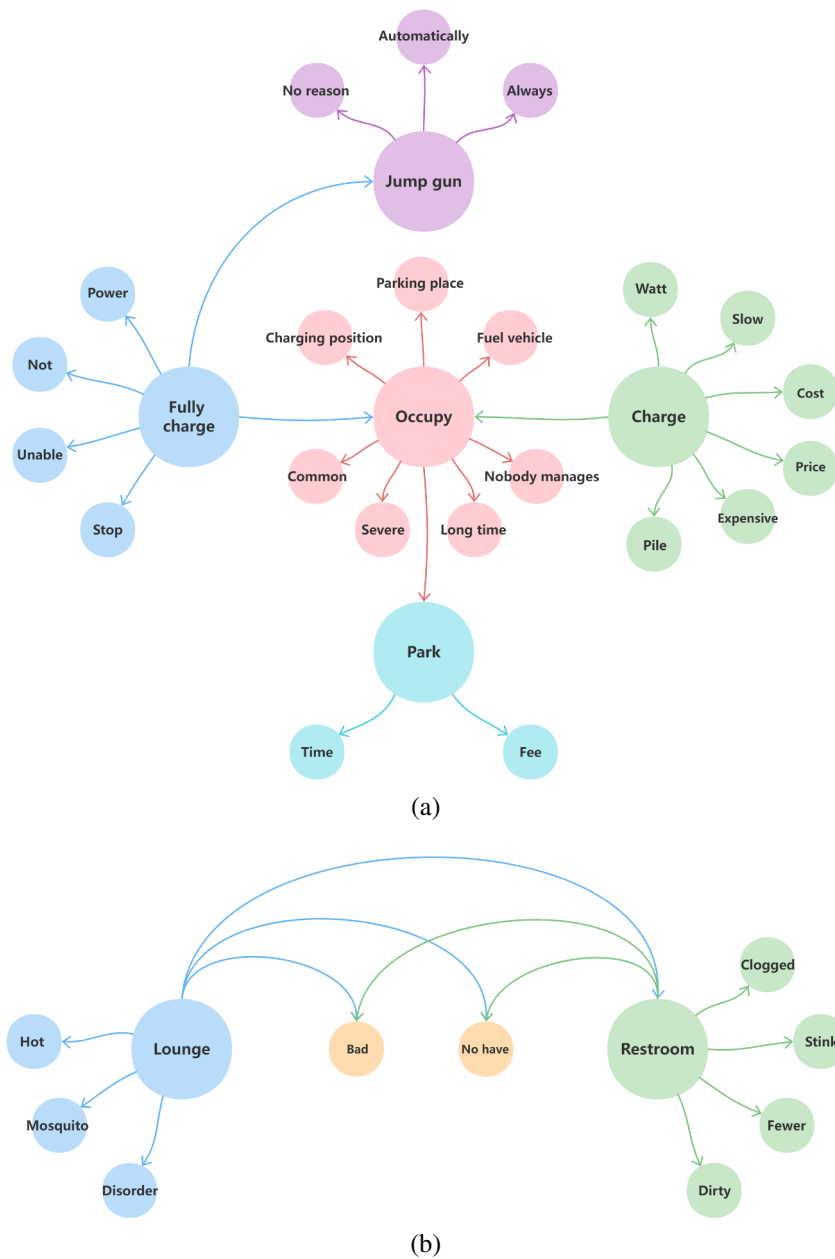


Figure 9. The dependency parsing result of the key information in negative comments; (a) “Expensive,” “Price,” and “Fee” are associated with “Charge” and (b) the nodes connected with “Lounge” and “Restroom” imply that the equipment with lounge and restroom

#### 4. CONCLUSION

The charging pile has been on such a gigantic scale to meet the charging needs of EV users in the market. These existing charging pile resources are directly accessible to users and have significant implications for the harmonious development of charging services and electric vehicles. This study proposes a novel text analysis process for mining the advantages and disadvantages of improving the existing public charging pile service. Our analysis process adopts the pre-training model to improve the accuracy of comment classification, avoiding the limitations of traditional text classification that require manual updating of sentiment lexicons and imposing restrictions on classification types. Additionally, we incorporated the text-to-knowledge to explore keywords from multiple dimensions and used dependency parsing to identify related words for

constructing relationship graphs. From the results provided by our analysis process, charging pile operators can gain an understanding of EV users' concerns and the benefits of their services through positive comments. Incorporating these factors and their interrelationships into the marketing of charging pile services allows operators to optimize their marketing strategies. Furthermore, by assessing negative comments, charging pile operators can identify areas requiring improvement in their existing services and take appropriate measures to enhance their offerings.

Based on the analysis of EV users' comments we have collected, the following features in the charging pile service can elicit a positive response from EV users: i) a suitable fee mechanism; ii) an adequate number of charging piles and parking spaces; iii) high and stable performance charging piles; iv) responsible personnel; v) an appropriate construction location; and vi) a comfortable environment and well-equipped facilities. These factors can be considered the starting point for further improving the service and developing the marketing strategy. According to features in different public charging stations, the charging pile operator can develop corresponding marketing strategies to highlight the service advantages, which is beneficial for attracting more EV users to improve the utilization of the existing charging pile resources. It was found that the negative comments on the existing charging pile service have a high proportion. There are some major problems in the existing charging station: i) serious parking space occupation; ii) exorbitant fee pricing mechanism; iii) lousy management environment; iv) inadequate facilities; and v) abnormal operation and unstable performance of charging piles, which can exert a considerable adverse influence on EV users' attitude towards the service. The charging pile operator can make a coherent plan to tackle these problems of different charging stations, avoiding waste of charging pile resources.

We have demonstrated a novel text analysis process for mining EV users' comments, which is not provided to the charging pile operators interactively. During the experiment, we filtered out some low-frequency keywords and related words which were not included in the discussion. However, these words may have important guiding significance for the charging pile operators to improve their marketing strategies and improvement plans based on their actual operational situation. In future research, we aim to present this analysis process to the charging pile operators in an interactive system, enabling them to better explore the decision-making reference information according to their specific needs.





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## BIOGRAPHIES OF AUTHORS






**Licheng Xu**     received his Master of Software Engineering (Software Technology) at the Universiti Malaya, Malaysia in 2023 and his Bachelor of Computer Science and Technology at the Lingnan Normal University in 2020. During his semester, he received a national scholarship and some awards in programming competitions in China. His research interests include decision support, smart grids, visual analysis, and information system. He can be contacted at email: lichengderrick@gmail.com.






**Asmiza A. Sani**    is a Senior Lecturer at the Department of Software Engineering, Faculty of Computer Science and Information Technology, University of Malaya. Her recent work focuses on IoT frameworks and her research interest includes formal software specifications and model-driven engineering. She is also currently looking into blockchain modeling and specifications. She can be contacted at email: [asmiza@um.edu.my](mailto:asmiza@um.edu.my).



**Shuai Xie**    is currently pursuing his Ph.D. at the Universiti Malaya, Malaysia. He received his Master's degree in Computer Science (Applied Computing) at the Universiti Malaya, Malaysia, from 2020 to 2023. His research interests include large language model (LLM), explainable AI (XAI) and counterfactual inference. He can be contacted at email: [s2012529@siswa.um.edu.my](mailto:s2012529@siswa.um.edu.my).



**Liyana Shuib**    (Senior Member, IEEE) obtained her Master of Information System (Data Mining) from Universiti Kebangsaan Malaysia in 2005 and a Ph.D. degree from the University of Malaya, Malaysia, in 2013 respectively. She is an Associate Professor at the Department of Information Systems, Faculty of Computer Science & Information Technology, University of Malaya, Malaysia. She has published a number of journal papers and proceedings locally and internationally. Her research interests include personalization, e-learning, analytics, recommender systems, data science, data mining, artificial intelligence application, and educational technology. She has won more than 20 awards from reputable innovation competition internationally. She is also a senior member of IEEE Computing Society, an active blogger and presently, the principal investigator of multiple research grant in the Faculty. She can be contacted at email: [liyanashuib@um.edu.my](mailto:liyanashuib@um.edu.my).