Impact of user comments on the adoption of electric vehicle charging services: evidence from contextual data from the US

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ABSTRACT

This study examined user comments from individuals who utilized the charging service, and how these remarks influenced the usage of electric vehicle (EV) charging stations. The transition towards electric vehicles necessitates understanding how to optimize charging infrastructure to promote their widespread adoption. We utilized data collected from the renowned electric vehicle charging station platform PlugShare to explore various factors including user feedback, service provision, site location, and pricing. The research findings suggest that there may not be a direct correlation between user feedback and charging station utilization rates, and the impact of pricing on utilization rates is minimal. Therefore, operators should not overly focus on user ratings and pricing. Regarding site service information, operators should prioritize improving the detail and transparency of service operation systems over offering diverse but generalized service descriptions, emphasizing the provision of detailed service descriptions and usage guidelines. In terms of site selection, considering the level of activity in the surrounding environment is more critical than the type of site location. These findings provide important insights for charging station operators and the development of electric vehicles and offer new perspectives for future research.

Keywords: Electric vehicle charging stations, utilization rate, user feedback, service provision, site location, pricing strategy

1. INTRODUCTION

Excessive emission of greenhouse gases (GHGs) destroys the earth's ecological environment, leading to global warming and sea level rise, which in turn affects people's healthy life[1,2]. Transportation is one of the major sources of GHG emissions, and vehicles emit large amounts of carbon dioxide into the atmosphere during driving[3]. In order to solve this problem, replacing traditional fossil fuel vehicles with electric vehicles is considered an effective solution[4]. Various countries around the world are actively promoting this transition, and more than 20 countries and regions have announced plans to phase out traditional fossil-fueled vehicles in favor of environmentally friendly vehicles[5]. Potential barriers to the popularization of electric vehicles include high purchase prices, limited driving range, and inadequate charging infrastructure[6]. Among them, charging infrastructure plays an important role in promoting the use of EVs, and a sound and complete charging infrastructure system is a guarantee for the EV driving experience[7,8]. However, the reality is that charging demand cannot be met due to the shortage of charging facilities[9], which makes many consumers hesitant about EVs[10] and hinders the promotion and development of EVs[11]. And station utilization (i.e., the amount of electricity provided by a station over a period of time) is a key driver of charging station economics[12]. Therefore, this study will investigate the factors affecting charging station utilization and promote the construction of charging station facilities, which in turn will promote the sustainable development of the electric vehicle industry.

Trends in public EV charging stations in the United States across time and location types of utilization[10] and changes in user satisfaction with charging station setups over time[13] have been reported in the existing literature, however, relatively little research has been conducted on the impact of service provision and user comments on charging stations. Therefore, we analyzed nearly two months of site usage at 948 charging stations in 309 cities across the U.S. region, and analyzed the relationship between station utilization and station user comments, charging price, station service, and station location using statistical analysis. We also put forward corresponding optimization strategies and suggestions, hoping to

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provide effective solutions for the planning, construction, and management of charging stations, and to promote the sustainable development of the electric vehicle industry.

The structure of the follow-up research of this study is partly as follows: the second part is the theoretical analysis and research hypotheses. The third part is data presentation and data processing. The fourth part is the experimental process as well as the analysis of results. The fifth part is the conclusion of the study, related recommendations, and future research directions.

2. THEORETICAL ANALYSIS AND RESEARCH HYPOTHESIS

2.1 Charging station utilization and user feedback

Message boards, blogs, user feedback forums, and other user-generated e-feedback are becoming increasingly important to today's online consumers because they can exchange opinions and experiences about companies, products, and services with others[14]. Some studies have shown that in e-commerce, online reviews are an important factor in the influence of product sales[15]. For different products and platforms, on average, electronic word-of-mouth is positively correlated with sales[16], and improvements in reviews promote increased product sales[17]. Therefore, we propose the following hypotheses:

Hypothesis 1: Charging station utilization is significantly and positively related to the content of users' feedback on web pages.

2.2 Charging station utilization and site service system

In the field of industrial marketing, the term "service" has two meanings: (1) When the service is at the center of the transaction, a service rather than a product being sold (i.e., transportation services or industrial cleaning services). (2) When the product is at the center of the transaction, but the service is provided with it (i.e., a guarantee that if the product breaks down it will be replaced or the speed of response to provide repair services), his main function is to reduce the buyer's workload at the time of purchase, to reduce the uncertainty associated with the purchase, and to increase the usefulness and usability of the product[18]. Services can make a significant contribution to a supplier's overall reputation in terms of delivery reliability, technical reputation, and after-sales service[19]. And strong evidence exists that users pay more for reliable services[20]. Service diversity is one of the important dimensions to measure the service of a company[21]. For charging stations, we believe that providing diverse and detailed services usually attracts more users to visit and use, thus increasing the utilization of the station. Therefore, we derive the following two hypotheses:

Hypothesis 2: The number of services is significantly and positively related to site utilization.

Hypothesis 3: Site utilization is significantly and positively related to service details on the site detail page.

2.3 Charging station utilization and site location

Store location and distribution intensity are important factors that affect store sales performance[22]. Good site location is usually the key to store success, which attracts consumers by providing them with convenient access to products or services[23]. For many retailers, the key criteria for opening a store are mainly geographic information, traffic flow, accessibility of the area, competition, distance, cost, safety of the area, local acceptance of the company, population density, etc.[24-26] As competitive pressures increase, small changes in store location (accessibility) can also have a significant impact on store performance and profitability[27]. Therefore in this study, we will explore the impact of the location of charging stations on station utilization in terms of both the type of place the station belongs to and the accessibility and busyness of the place where it is located. We propose two hypotheses:

Hypothesis 4: The type of place where the charging station belongs has a significant effect on the utilization rate of the charging station.

Hypothesis 5: The accessibility and prosperity of the place where the charging station is located have a significant positive correlation with the utilization rate of the charging station.

2.4 Charging pile utilization and price

Different types of charging piles in the same charging station charge at different prices, so for us to explore the relationship between price and charging pile utilization.

Previous research has found that the most important of a series of price, product, promotion, and location strategies used by companies to promote their brands or products in the market is price, which is the first-factor influencing customers' purchasing behavior[28]. Pricing can be used as a competitive weapon[29] to help firms capitalize on market opportunities[30]. Most of the time, consumers place more importance on price than value when making a purchase[31]. Changes in price affect demand and sales volume[32]. Appropriateness of product price is one of the marketing strategies to increase sales volume[33]. Therefore, we propose the fifth hypothesis:

Hypothesis 6: The utilization of charging piles is significantly affected by different prices.

3. DATA DESCRIPTION AND PROCESSING

3.1 Data sources and characteristics

The data for this study is derived from the Plugshare website[34], where we randomly selected 948 charging stations in 309 cities in the U.S. We used the Plugshare website to collect nearly 2.3 million real-time charging data from the above charging stations for the two-month period from mid-September to early November 2023. plugShare is an online platform that focuses on EV charging station information sharing and navigation, providing a comprehensive platform for users to find, evaluate, and share their charging station experiences, with services covering most charging stations around the world. Users can easily find the nearest charging station, view information about charging station-related facilities as well as other users' evaluations of charging stations, and share their experiences in using them[35]. In the user interface of the PlugShare website, it is possible to select and click on a specific station to navigate to that station's details page. The site details page is collected to understand and analyze the usage of charging stations. We collect information through this page because it is one of the largest communities of EV owners in the world, so the data is highly representative, and in particular, the availability of data on charging station-related reviews makes up for the lack of previous research on the impact of reviews on charging stations.

The information we collect includes real-time usage of different types of stake point plugs in the charging station, feedback from the users of the charging station, information about the power of different stake points in the charging station, information about the charges of different power stake points in the charging station, information about the latitude and longitude of the charging station, the specific address of the charging station, the type of the place where the charging station belongs to, information about the services provided at the charging station, the hours of operation of the charging station, and the distance of the charging station from a typical nearby location, and other related information. Table 1 provides the relevant variables and descriptions considered in this paper. In order to ensure the representativeness of the charging station data, we randomly selected 948 charging stations in different cities in the U.S. region for data collection, and the distribution of the randomly selected charging stations is shown in Figure 1, with each green dot in the figure indicating a selected charging station.

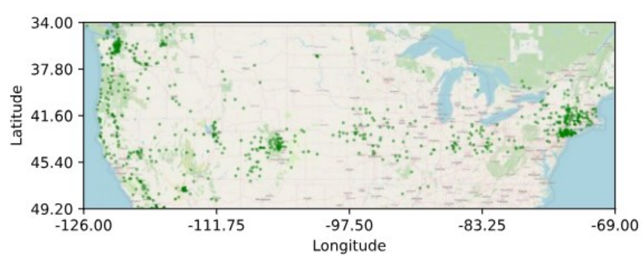

Figure 1. Distribution map of randomly selected charging stations.

In order to guarantee the timeliness and continuity of the data, we grouped these stations for a cyclic collection of stations within the group. According to the difference in the loading and collection speed of different stations, we set 40-70 stations as a group, so that each station collects other relevant information except user feedback once every thirty minutes on average. For charging station user feedback data, due to the small number of comment data and the large time span, at the end of collecting real-time data from charging stations, we crawl all the user feedback data information and feedback time of all stations at once for subsequent analysis.

Table 1. Variables and descriptions.

Independent variable	Description
Utilization rate	A continuous variable between 0 and 1, indicating the average utilization of the charging station during the collection time period
Business hours explanation	A binary variable indicating whether the station introduction details page provides information about the site's hours of operation
Additional explanation	A binary variable indicating whether the station introduction detail page has a more detailed additional description in the additional description section
Distance	Continuous variable indicating the sum of the distances to charging stations from typical locations in the neighborhood provided on the station introduction detail page
Number of services	A discrete variable from 0 to 7 indicating the number of different services offered by the service list on the station introduction details page
Prices	Continuous variable in /kWh
Number of comments	Discrete integer variable indicating the number of user comments visible on the charging station introduction page
Comments score	Continuous variable indicating the average of user review scores that can be seen on the charging station introduction page
Site rating	Continuous variable indicating the site's original station rating
Type of location	Discrete variables 1 to 7, indicating the category of the place where the charging station belongs to

3.2 Structured data processing

We summarized the data information collected from the same site at different times and calculated the variation of the utilization rate of the charging station at different times as well as the average utilization rate during the collection time period. The average utilization rate of the station during the collection time period was also used as a benchmark for data analysis.

Since each charging station contains multiple types of charging posts and each charging post may have multiple plugs. We collected charging data as the total number of plugs in each charging pile and the number of plugs in use. Therefore, we take the number of plugs in use /total number of plugs in the charging pile for each charging pile at the moment of data collection as the utilization rate of that charging pile and then average the utilization rate of each charging pile overall the collected moments as the average utilization rate of that charging pile. Finally, the average utilization rate of all the charging piles in the charging station is averaged again to arrive at the average utilization rate of the charging station in the collection time period, i.e., the final utilization rate (i.e., Utilization Rate). If the utilization rate of a charging pile in a charging station is always 0 or 1 during the collection time period, we regard it as abnormal data and remove it from the dataset. In addition, we utilize the Z-score method to identify and remove outliers, and consider observations with an absolute value of Z-score greater than 3 as outliers and remove them. With these outliers, we obtained data from 800 eligible sites for subsequent data analysis.

Service-related data includes the types of services mentioned in the site details page, information about the charging station's operating hours, and additional supplemental descriptions of the site. It is worth noting that for the types of services mentioned on the different charging station pages, the services offered at the different sites were part of the WiFi, Shopping, Dining, Restrooms, EV Parking, Grocery, and Lodging options. From this, we hypothesize that the site web pages were designed to provide merchants with a list of services to choose from, from which the merchants selected the services offered by their charging stations as appropriate. Therefore, we calculated the number of service types in the charging stations to perform an analysis of service types and utilization. To explore the relationship between hours of operation additional station supplementation and station utilization, we transformed the data into dummy variables. Specifically, we labeled sites with hours of operation as 1 and sites without hours of operation as 0. For sites with additional supplemental instructions, we labeled them as 1, and sites without additional supplemental instructions were labeled as 0. This treatment helped us to more precisely analyze the relationship between these factors and the utilization of EV charging stations.

The information about the location of the station includes information about the type of location where the charging station is located and the level of prosperity of the location where the charging station is located. The information about the type of location where the charging station is located in the airport, Arena/Concert Hall, Bank ...... etc. In order to explore the effect of different location types on the utilization of charging stations, we classified this information into seven categories, which include: transportation facilities, recreational facilities, commercial facilities, public service facilities, accommodation facilities, religious facilities, and work and rest facilities. We coded the location type information for data analysis. Specifically, sites belonging to the transportation facility category are denoted by 1, including Airport, Street Parking, Transit Station, and Parking Garage/Lot; sites belonging to the entertainment facility category are denoted by 2, including Arena/Concert Hall, Casino, Movie Theater, Museum, Park, Tourist Attraction; commercial facilities are indicated by 3, including Bank, Car Service, Dealership, Gas Station, Restaurant, Shopping Center, Store; public services are indicated by 4. The sites belonging to the category of public service facilities are indicated by 4, including Civic, Government, Hospital/Healthcare, Library, School/University, and Visitor Center; the sites belonging to the category of lodging facilities are indicated by 5, including Campground, Lodging, and Residential; the sites belonging to the category of religious facilities are indicated by 5, including Campground, Lodging, and Lodging, Residential; sites belonging to the category of religious facilities are denoted by 6, including Place of Worship; and sites belonging to the category of work and rest facilities are denoted by 7, including Workplace, Marina, and Rest Stop. In addition, by using information about typical locations near the site (e.g., nearby restaurants or shopping centers, etc.) and the distance to the charging station, we can infer where the charging station is located. we can infer the prosperity of the geographic location where the charging station is located. Specifically, the closer these typical locations are to the charging station, the smaller the sum of the distances from these locations to the charging station will be, implying that the charging station is located in a more prosperous area. Conversely, if these typical locations are farther away from the charging station, the sum of the distances will be larger, implying that the charging station is located in a more isolated area.

During the processing of the price data, it was noted that some stations did not explicitly list price information, making this part of the data unusable for analysis. In addition, different charging stations have differentiated charging price units, such as /h, /min, and /kWh. In order to ensure the accuracy and validity of the subsequent analysis, we utilized the charging power of the charging pile to convert all the units to per kilowatt hour (/kWh) uniformly. In addition, the charging power varies between different charging piles at the same charging station, therefore, we explore the relationship between the utilization rate of charging piles (Charging data for a total of 472 stakeouts for the last two months) and the price.

3.3 Unstructured data processing

In this study, we use two methods to analyze the sentiment tendency of user comments in this study: one is through traditional natural language processing tools, and the other is through big language models[36] (in this study, we are utilizing the charm big model[37]) for the sentiment analysis of text. Traditional natural language processing tools use the sentiment vocabulary and corpus in NLTK in the Python programming language by preprocessing the text by subjecting the content of the comments to textual segmentation, removing stop words, and so on, and by identifying the sentiment words in the sentence and assigning weights to them based on the sentiment polarity and intensity of the words and the context, which are then summed together to produce an overall sentiment score for the sentence. Big language modeling is an advanced artificial intelligence technique that is capable of understanding and generating human language by learning large-scale textual data, and such models have demonstrated good performance in many domains. Therefore, in this study, we utilize the powerful features of the Big Language Model to perform sentiment analysis on review texts. We categorize the sentiment tendencies of comment texts into three types: negative sentiment (marked as -1), positive sentiment (marked as 1), and neutral sentiment (marked as 0) by these two methods, respectively.

In order to validate and compare the accuracy of the two methods, we randomly selected 500 comments from all the comments and manually labeled the comment sentiment by three different researchers to reduce subjective bias. We filtered out the data with consistent values of the three people's labeled sentiments and compared them with the sentiments using the two methods mentioned above. The experimental results show that the large model exhibits better performance relative to traditional natural language processing tools, with more than 90% similarity to the manually labeled data. Therefore, in this study, the big language model (chatglm) is utilized for the analysis of the sentiment values of comment texts. We averaged all the comment sentiment score values of the site as the sentiment score value of the site for the study.

4. EXPERIMENTAL PROCESS AND RESULT

4.1 Charging station utilization in relation to user feedback

User feedback on the charging pile is mainly reflected in two aspects, one is the Site Score, expressed in the site details page provided by the site's comprehensive score, the score distribution interval is 1 to 10, 10 means the site scores the highest, 1 means that the site scores the lowest; the other is the Comment Score, the site user comments on the sentiment of the average value.

We performed a correlation analysis of these two scores with Utilization Rate separately, and since the final utilization rate of the site did not conform to a normal distribution, we assessed the relationship between the variables through Spearman's rho. Spearman's rho calculation is shown in equation (1):

$$\rho = \frac{\frac{1}{n}\sum_{i=1}^{n}\left(R(x_i)-\overline{R(x)}\right)\cdot\left(R(y_i)-\overline{R(y)}\right)}{\sqrt{\left(\frac{1}{n}\sum_{i=1}^{n}\left(R(x_i)-\overline{R(x)}\right)^2\right)\cdot\left(\frac{1}{n}\sum_{i=1}^{n}\left(R(y_i)-\overline{R(y)}\right)^2\right)}} \tag{1}$$

Among them, $R(x), R(y)$represent the positions of x and y, respectively, and $\overline{R(x)}$, $\overline{R(y)}$represent the average positions.

The results of Spearman's rho are shown in Table 2, and the results of the correlation analysis between Site Score and Utilization Rate show that although there is a significant positive correlation between the two, the correlation coefficients are relatively low. The correlation analysis between Comment Score and Utilization Rate shows a significant negative correlation between Comment Score and Utilization Rate as shown in Table 2. This indicates that the lower the rating of the charging station, the higher the utilization rate. This is not in line with the common perception that the better the reputation of a product, the higher its sales. Why is this the case? We suspect that this may be due to the fact that charging stations are different from other products in the "consumer experience" domain, such as restaurants and apparel. In the "consumer experience" sector, people are often willing to take the time to write positive reviews when they enjoy a good experience, and in these sectors, people are more focused on the quality of the service and the quality of the product, and the ratings are more likely to influence decision-making. For charging stations, however, most users only choose to post a review when they have had a very poor experience. Also, as an infrastructure, users may not be as demanding of the service quality of charging stations as they are in the "consumer experience" domain, and few users pay attention to the ratings before using them. This means that the user feedback received by charging stations is more skewed towards the negative. Therefore, the more utilized a charging station is, and the more users it has, the more likely it is that users will leave reviews, and the lower the review score. To verify this conjecture, we further analyzed the relationship between the number of station reviews, review scores, and station utilization. The experimental results are shown in Figure 2, where the number of comments is significantly positively correlated with the utilization rate, and the number of comments is significantly negatively correlated with the comment score, confirming our conjecture. Therefore, synthesizing the above two analyses, hypothesis 1 is rejected.

Table 2. Correlation analysis table of charging station utilization rate with site rating, distance, business hours explanation, supplementary explanation, number of services, prices, and comments score.

	Site rating	**Distance**	**Business hours explanation**	**Supplementary explanation**	**Number of services**	**Comment score**
Spearman's rho	0.082*	-0.98**	0.077*	0.143**	-0.09	-0.081*
P-value	0.021	0.006	0.029	0.000	0.0801	0.021

Note: **p*<0.05; ***p*<0.01.

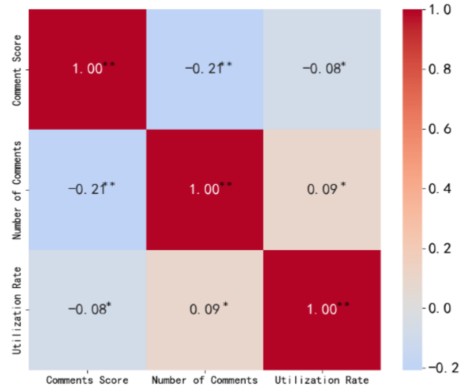

Figure 2. Correlation between number of comments, comments score, and utilization rate Symbols in cells indicate statistical significance of the estimated parameter.

Note: **significant at 1%, * significant at 5%.

4.2 Relationship between charging station utilization and site service system

The relationship between the charging station's service operation system is analyzed in three ways: first, the relationship between the number of service types and the utilization rate; second, the relationship between the additional supplemental descriptions and the utilization rate; and third, the relationship between the hours of operation descriptions and the utilization rate. The first two of these analyze the correlation between the two, and the third is explored using the point-two-column correlation method. The results, as shown in Table 2, show that there is no significant correlation between the final utilization rate of the charging station and the number of service types, rejecting Hypothesis 2. However, there are significant positive correlations between the presence or absence of additional supplemental descriptions, the presence or absence of business hours descriptions, and the final utilization rate. This indicates that the details and transparency of the service operation system of the charging station have a significant effect on its utilization rate, and Hypothesis 3 is valid. Therefore, for charging station operators, providing as much detail as possible on service descriptions and usage guidelines relative to increasing the number of services may be an effective strategy to increase utilization.

4.3 Charging station utilization in relation to site location characteristics

We use Kruskal-Wallis to test whether there is a significant difference between the utilization rate of charging stations and the type of location to which the station belongs, and the results are shown in Table 3, there is no significant difference between the utilization rate of charging stations and the type of location to which the station belongs, and Hypothesis 4 is rejected.

Table 3. Kruskal-Wallis test.

	Utilization rate
Kruskal-Wallis H (K)	10.855
Degrees of freedom	6
*P*_value	0.093

Note: Grouping variable: Type of location.

The results are shown in Table 2, the utilization rate of the site is significantly negatively correlated with the sum of distances from typical locations near the site, i.e., the further away (the more remote) the charging station is from the sum of distances from typical locations near the site, the lower the utilization rate is, and Hypothesis 5 holds. This suggests that the location choice of charging stations needs to take into account not only the type of location but also, more importantly, the degree of prosperity of the surrounding environment. Therefore, operators of charging stations, should prioritize sites in busy areas with high population density or high traffic flow rather than focusing too much on the type of location in which the site is located.

4.4 Charging pile utilization and price relationship

In conducting the correlation analysis between pile point utilization and pile point price, the result was a significant negative correlation (Spearman's rho=-0.096*, P_value=0.037) and Hypothesis 6 was established. However, the correlation coefficients are relatively low, which suggests that the degree of correlation between the two is limited, and even if a relationship exists, the impact may be less significant or complicated by the involvement of multiple factors. In this scenario, a single price change at the staking point may not be sufficient to significantly affect the utilization of the staking point. Operators should therefore consider a combination of factors when developing their pricing strategy, rather than focusing solely on price itself.

4.5 Comprehensive analysis of factors affecting charging station utilization

In order to comprehensively analyze the influence of each factor on the utilization rate of charging stations, we use multiple linear regression to analyze, and the proposed linear model is constructed as shown in equation (2):

$$y = c + a_1x_1 + a_2x_2 + a_3x_3 + a_4x_4 + a_5x_5 + u \tag{2}$$

where c denotes the intercept; $a_1, a_2 \dots \dots a_5$ denote the correlation coefficients, which were determined by least squares (OLS) regression; the u-value reflects the difference between the expected value and the measured value and denotes any external factors that were not taken into account; $x_1,\ x_2 \dots \dots x_5$ denote the independent variables, where x_1 denotes the presence or absence of additional instructions, x_2 denotes the sum of the distances between a typical location and a charging station, x_3 denotes the website rating, x_4 denotes the number of services, and x_5 denotes the presence or absence of hours of operation instructions. Due to the small sample size of the data containing prices, the fact that prices are broken down by stake, the high degree of correlation between different stakes at the same site, and the fact that the above analysis indicates that prices do not have a significant effect on utilization, prices were not considered in this analysis. Based on the results of the analyses shown in Table 4, we found the following two variables to have the greatest statistically significant (0.05 level) relationship with site utilization: the presence of additional supplemental instructions (*a*=0.039, *p*=0.001), and distance (*a*=-0.001, *p*=0.000).

Table 4. OLS regression results: utilization rate.

<table>
<tr><th>Dependent variable</th><th>R</th><th colspan="2">R square</th><th>Adjusted R square</th><th>Standard error of the estimate</th><th colspan="2">Durbin-Watson</th></tr>
<tr><td>Utilization rate</td><td>0.181</td><td colspan="2">0.033</td><td>0.027</td><td>0.148113498582051</td><td colspan="2">1.801</td></tr>
<tr><th rowspan="2">Predictor variable</th><th colspan="2">Unstandardized coefficients</th><th>Standardized coefficients</th><th rowspan="2">t</th><th rowspan="2">Significance</th><th colspan="2">Collinearity statistics</th></tr>
<tr><th>B</th><th>Standard errors</th><th>Beta</th><th>Tolerance</th><th>VIF</th></tr>
<tr><td>(Constant)</td><td>0.167</td><td>0.027</td><td></td><td>6.180</td><td>0</td><td></td><td></td></tr>
<tr><td>Score</td><td>0.001</td><td>0.003</td><td>0.011</td><td>0.322</td><td>0.748</td><td>0.994</td><td>1.006</td></tr>
<tr><td>Number of services</td><td>-0.004</td><td>0.003</td><td>-0.039</td><td>-1.087</td><td>0.277</td><td>0.957</td><td>1.045</td></tr>
<tr><td>Business hours explanation</td><td>0.013</td><td>0.012</td><td>0.041</td><td>1.155</td><td>0.248</td><td>0.970</td><td>1.031</td></tr>
<tr><td>Additional explanation</td><td>0.039</td><td>0.012</td><td>0.114</td><td>3.239</td><td>0.001</td><td>0.989</td><td>1.011</td></tr>
<tr><td>Distance</td><td>-0.001</td><td>0</td><td>-0.130</td><td>-3.714</td><td>0</td><td>0.999</td><td>1.001</td></tr>
</table>

5. CONCLUSION AND FUTURE RESEARCH

This study delves into the relationship between the utilization rate of charging stations and various factors. The research findings reveal that user feedback on charging stations is not always directly correlated with their utilization rates, and although pricing does have an impact on utilization rates, the effect is minimal. Therefore, operators should not overly focus on user ratings and pricing. Regarding station services, operators should emphasize improving the details and transparency of service operation systems rather than providing diverse but generalized service introductions. They should pay attention to providing detailed service descriptions and usage guidelines. Additionally, in site selection, it is more important to consider the level of prosperity in the surrounding environment rather than overly focusing on the type of location where the station is located.

Future research could further deepen and expand by obtaining data from multiple dimensions for analysis. For example, conducting separate studies on fast charging and slow charging, exploring whether the utilization rates of charging stations exhibit different trends in different seasons and weather conditions, and analyzing the influencing factors of charging stations in other regions to understand the impact of regional characteristics on charging demand. From various other perspectives such as the design of charging stations, the performance and reliability of charging equipment, and the quality-of-service personnel, explore their impact on the utilization rate of charging stations.

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