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Data Drive—Charging Behavior of Electric Vehicle Users with Variable Roles

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Abstract: The global proliferation of electric vehicles (EVs) has brought forth new challenges in electric vehicle (EV) charging infrastructure. This paper utilizes operational data from the 5G real-time system of EV and traffic platforms (5gRTS-ET) in China, encompassing 12,597,109 cases and 32,259 EVs. By employing frequency density analysis, a dynamic charging behavior model is devised to address the limitations of static models in accommodating the diverse roles of EV users. Analysis reveals distinct charging behavior preferences among three urban EV operation modes, paving the way for an adaptive model for integrating charging points into networked operations on the platform.

Keywords: 5G; charging point; charging behavior; EV

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1. Introduction

Currently, the majority of research on charging behavior has focused on charger demand [1,2], a crucial aspect to consider prior to the installation of charging infrastructure. The prediction of charging behavior for these charging points is typically made during the site selection process for their construction [1]. However, the rapid evolution of electric vehicle (EV) operation modes [3], particularly with the widespread adoption of the 5G real-time system of EV and traffic platforms (5gRTS-ET), necessitates a deeper understanding of charging behavior using empirical data from 5gRTS-ET. This study proposes a method with which to infer real-time charging behavior based on empirical data derived from 5gRTS-ET, thereby establishing a dynamic model for charging behavior. Through this approach, the 5gRTS-ET platform can continuously monitor the shifting EV operation modes in real time, driven by the increasing popularity of EV operation platforms like Uber and Didi. The ability to identify EV operation modes and charging behavior in real time is essential for charging points to adapt their business strategies promptly, especially as individual EVs increasingly switch to operational modes during off-peak hours. This trend underscores the importance of real-time monitoring and adaptation in optimizing charging point operations.

The majority of research in the area of charging behavior has focused on the planning of charging point layouts [1,2], a crucial step prior to the installation of charging infrastructure. Predictions regarding charging behavior at various charging points are typically made during the site selection process [1]. However, with the widespread adoption of 5gRTS-ET technology, the operational landscape of EVs is evolving rapidly [3]. The significant growth of EVs further underscores the need for updated models (IEA, 2021). The introduction of shared platforms has introduced the possibility for EV users to assume multiple roles [4]. Despite this advancement, limited studies have explored charging behavior in relation to variable user roles or utilized actual operational data from connected vehicle platforms.

Data from the China EV Charging Infrastructure Promotion Alliance shows that, by September 2021, there were 5.52 million EVs on the road in China, which is nearly 0.2 percent of the total vehicle population (EVCIPA, 2022). The research indicates that approximately 24.2% of current EVs are private models, while 34.9% are utilized by ride-hailing services such as Uber and Didi, with the roles of these vehicles often interchangeable [3]. However, the lack of studies focusing on the dynamic role of EVs significantly diminishes the user experience and the efficiency of charging infrastructure utilization.

This research leverages operational data from 5gRTS-ET to deduce the live charging behaviors of EV users at charging stations. Employing frequency density analysis, a dynamic charging behavior model is developed to accurately depict EV users' behaviors. The model enables the 5gRTS-ET platform to monitor and analyze the evolving operational patterns of EV users in real time. As platforms for EV operations gain popularity, private EV users are increasingly transitioning to operation modes during non-working hours. This shift represents a growing trend, facilitated by platforms like Uber and Didi [5]. By addressing gaps in previous research, this study offers insights into the real-time fluctuating charging behaviors of EV operation modes and presents a mathematical model for real-time adjustments to business strategies at charging points. The results show that the performance gap of the three typical business modes (private EV, passenger operating EV, logistic distribution EV) is very heterogeneous [3].

The rest of the paper proceeds as follows: Part 2 reviews previous research, Part 3 is research design, Part 4 presents findings, Part 5 discusses conclusion and limitations.

2. Literature Review

Looking back at the literature on charging behavior, a lot of research has been undertaken on the influencing factors of charging behavior [6].

Lee et al. undertook a study regarding the choice of charging location [7], while Bi et al. undertook an analysis of three charging behaviors. These studies have shown that a more evenly distributed charging infrastructure with a grid-based approach is less effective than one with charging station placement at existing petrol stations and residential car park locations [8]. Chakraborty et al. analyzed the preference data of more than 3000 PEV drivers on charging infrastructure choices in order to understand how socioeconomic and demographic factors affect these choices [9–11]. The research results of Monios and Bergqvist also show that charging on the way is not considered in logistics operation vehicles [12]. Sadeghianpourhamami et al. undertook a quantitative analysis of EV flexibility that was data driven [13]. A path model of the process of selecting a charging point for a destination was studied using the Poisson arrival process [14]. Kang et al. have shown that private parking spaces are more in demand for charging than small community spaces [15]. The study results also show that travel charging needs should be considered. Subway stations, which are highly related to EV, are intensive charging demand points [15]. Zhang et al. analyzed the development potential of charging at the workplace [16].

With regard to the impact of charging prices, Kim et al. analyzed charging transactions for four years, finding unobserved heterogeneity and the effects of time-varying covariates [9]. Bayram et al. conducted research on price-driven charging behavior from high and low peak pricing [17], while another random dynamic pricing method is proposed by [18]. There are also research articles based on the factors of price, detour distance and waiting time [19,20].

With regard to the impact of charging type when the data time span is long enough and the amount of data is large enough, J. R. Helmus et al. used 4.9 million charging transactions and find a surprising result, wherein none of the user types displayed stereotypical behavior and the range of behaviors was more varied and subtle [21]. While the availability of home charging is the most important factor in deciding to adopt an EV, residential areas are those that are most in demand for charging, regardless of the type of charging demand or time period [5,22,23]. However, most EV owners do not have the conditions to install home charging piles. J. R. Helmus et al. expect that shifts to charging portfolios will be observed in the future [21], while the types of charging remain stable.

With regard to the impact of an EV's state of charge (SOC), one article studied charging behavior based on EV SOC initial state distribution [19], with data that were mostly obtained from charging pile operators or EV manufacturers during the period of EV development from 2018 to 2020. However, data labels are not complete enough to study charging behavior. Complete data labels generally include charging start and end time, charging duration, battery SOC, charging speed, location information and charging cost (only available on charging pile data) [19,24,25].

With regard to research on the modeling of charging behavior, charging behavior is conceptualized as a decision model combining electric energy supplement and parking behavior [26–29]. D. Sun et al. considered the charging process as "space-time charging" and they used the latest simulation to predict EV charging behavior [30]. Modeling the charging behavior of electric taxis using a dataset of 39,372 charging events revealed that charging dynamics can be represented by the distributions of daily charging frequency, start time, and duration [31]. It is important to identify the charging behavior of EVs through the timeline of real-world data [13], and the technology acceptance model (TMA) of cognitive drive theory is studied for use in charging behavior decision-making feasibility [32]. Regarding the prediction of charging behavior, the authors gave the latest and most effective prediction scheme [30,33,34]. Y. Yang et al. used the Manhattan distance index to simulate detour distance [23] and applied a real-world road network to measure detour distance in order to improve the practicality of the proposed modeling framework. The authors additionally proposed that different user types have different preferences for time [7,14,22,25], charge amount and location, which shows heterogeneity in charging behavior. Luo et al., 2018 conducted modeling based on user behavior results [20]. The mixed logic model is appropriate when there is unobserved heterogeneity, preference difference between users or when panel data are used [19].

In summary, prior research has extensively examined charging behavior with considerations towards charging location choices, pricing, types of charging, and the initial state of an electric vehicle's SOC [35,36]. Predictive models have also been developed to understand charging patterns. The complexity of charging behavior suggests that it is challenging to accurately predict based solely on influencing factors. Furthermore, existing studies often emphasize the role of EV users [35], which may not align with the changing landscape of charging demands and behaviors due to evolving user roles, like the transition from individual ownership to shared mobility through emerging platforms [4].

3. Research Design

In this paper, probability density function forecasting, nonlinear regression, discrete selection theory, numerical modeling, numerical analysis methods, and constraint analysis research method are used to analyze the big data generated by the 5gRTS-ET platform [37,38].

3.1. Data Interpretation

According to the China EV Charging Infrastructure Promotion Alliance, the cumulative count of charging infrastructure in China reached 2.385 million units by November 2021. This total comprises 1.293 million dedicated charging piles, 1.092 million public charging piles, 450,000 direct current (DC) charging piles, 646,000 alternating current (AC) charging piles, and 406 AC/DC integrated charging piles. Over the period from December 2020 to November 2021, an average of 33,000 new public charging piles were installed every month. The Jiangsu Province New Energy Vehicle Operating Company Information Integrated Management Platform, 5gRTS-ET, was established in 2019, leading to the deployment of 874 charging stations and 12,242 charging piles by 2020, including 8618 DC charging piles and 3624 AC charging piles. The platform records crucial charging data, such as start and end times, duration, remaining state of charge, pricing, location, and frequency. Zhang et al. employed unsupervised methods to collect real operational data and conducted iterative calculations and optimizations [16].

According to the six-month data of the Nanjing downtown area from 1 March 2021 to 31 August, derived from the 5gRTS-ET operation platform, 12,597,109 cases were extracted, including charging duration, charging initiation time, EVID, charging quantity and other variables. The instructions of key parameters are shown as follows in Table 1:

Table 1. The instructions of variables from 5gRTS-ET platform data.

Related Parameters	Description	Unit
EVID	EV Identity	piece
Date	Charging service date	yyyy.mm.dd
Waiting_time	Wait time before charging	minute
Start_time	Charging start time	hh:mm:ss
End_time	Charging end time	hh:mm:ss
Charging_amount	The amount of charge during a single charge	KWh
Charging_fare	Charging paid with a fee	RMB
fast_low model	1 = fast, 2 = low	1, 2

Referring to the data processing method [16], SPSS Statistics software was used to conduct case validity identification on data such as charging speed, charging duration, charging duration, and waiting time, and 685,928 anomaly cases were identified. The effective data were 11,911,181 cases and 32,259 EVs, and the data quality met the research needs of this paper. Sampling and identification techniques are shown in Figure 1. The green star in the figure shows the real-time position of the EV, which shows that the number of EVs in the sampling area is very dense, which ensures the diversity of users in this study.

In order to meet the needs of the study, the calculation formula and description of the variables have been added, see Table 2.

Typical EV operating mode. See Table 3 [3].

Correlation analysis was conducted using the defined key variables from Tables 1 and 2, the results of which are presented in Table 4.

Table 2. Descriptions of the new variables.

Related Parameters	Calculation Formula	Description	Unit
Charging_time	Start time—end time	The length of the charging time of the EV	minute
Charging_frequency	Count EVID	The number of times the EV is charged in 6 months	times
Charging_speed	Charging Amount/charging time * 60	Average charge for one hour	kw/h
Class		1-private EV	1–4

Table 3. Classification Table of EV typical operating model.

EV Operation Model	% of Total	EV Number
Private	24.2%	7816
Uber and Didi	34.9%	11,256
Taxi	36.5%	11,762
Logistic distribution	4.4%	1425
Total	100.0%	32,259

Table 4. Correlation analysis of charging point key variables.

Variable	Date	Start_ Time	Charging_ Time	Charging_ Fare	Charging_ Frequency	Charging_ Amount
Date	1	0.007 **	0.000	0.006 **	−0.013 **	0.011 **
Start_ time		1	0.020 **	−0.010 **	0.017 **	−0.033 **

Table 4. *Cont.*

Variable	Date	Start_ Time	Charging_ Time	Charging_ Fare	Charging_ Frequency	Charging_ Amount
Charging_ time			1	0.813 **	−0.085 **	0.743 **
Charging_fare				1	−0.090 **	0.892 **
Charging_ frequency					1	−0.090 **
Charging_ amount						1

**. Correlation is significant at the 0.01 level (2 tailed).

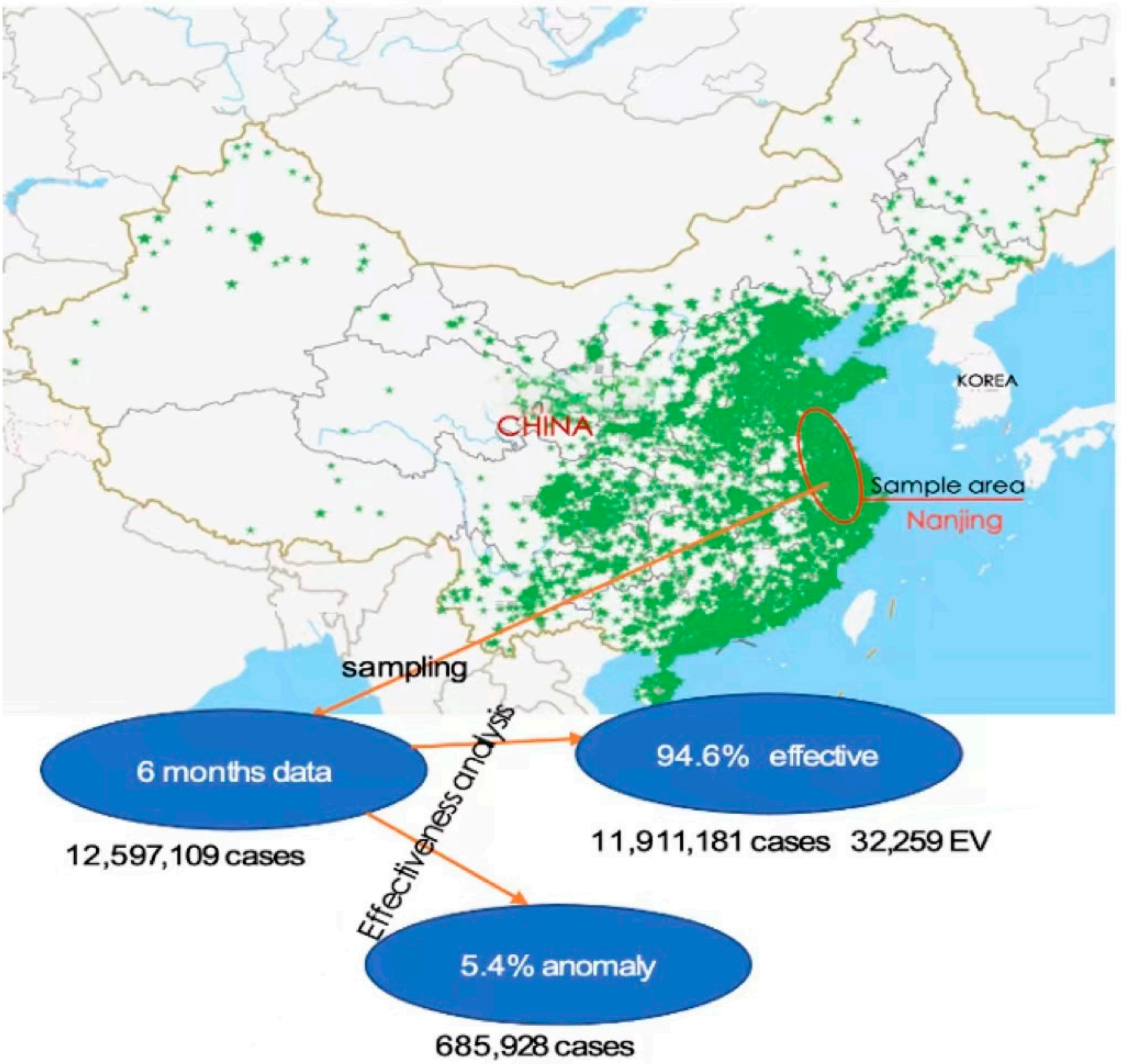

Figure 1. Data sampling filtering.

3.2. Research Models

The correlation analysis in Table 4 indicates no correlation between charging time and date. Date had a positive correlation with start time, charging fare, and charging amount, while it was negatively correlated with charging frequency. Start time showed a positive correlation with charging time and charging amount, but a negative correlation with charging fare and charging amount charging time had a negative correlation with charging frequency, and a positive correlation with charging fare and charging amount.

This paper utilizes real-time data to analyze and model the EV chargeable capacity, based on the calculation formula proposed by Sheng and Xiao in 2015 [39].

The formula for calculating the rechargeable amount when only the power of the charging pile is considered as follows [40]:

$$E = min(Pt/BC, 100\% - SOC) \tag{1}$$

The conversion formula can be calculated as follows for the charging time:

When $P < 11$ kW, any remaining SOC status has the following:

$$t = BC * (100\% - SOC)/P \tag{2}$$

When $P > 11$ kW and $80\% > SOC > 10\%$, as follows:

$$t = BC * (80\% - SOC)/P \tag{3}$$

where E indicates rechargeable amount, t indicates charging time (hours), BC represents the total capacity of electric vehicles (kWh), SOC represents the remaining SOC (%), and P represents charging pile power (kW).

The charging behavior of the three common operating modes is assumed as follows:

H1. *Private EV's choice preference is optimal for charging time periods.*

H2. *Passenger operating EV's choice preference is optimal charging speed.*

H3. *Logistic distribution EV's choice preference is the optimal charging price.*

4. Result

The following sections summarize and analyze the charging behavior of three different operating modes of urban EVs based on the 5gRTS-ET platform.

4.1. Research Charging Behavior of Private EV

Analysis of data from the 5gRTS-ET platform reveals the frequency distribution of charging times for 957,392 privately owned EVs. The charging behavior of these vehicles demonstrates a concentration on Fridays, Saturdays, Sundays, and the days preceding holidays, as highlighted in Figure 2. This preference for charging EVs on holidays and the eve of holidays over walking can be attributed to various factors.

(1) In EV instead of walking mode, the weekly charging frequency can meet the power needs of an EV. It is more convenient to charge on holidays.
(2) The charging concentration on the day before the holiday is to meet the need of holiday travel.
(3) The increase in the travel distance will also increase the frequency of holiday charging.

We also analyzed the date frequency density of 10,953,789 non-private EV charging data, and there was no bias toward holiday date periods, as shown in the following Figure 3.

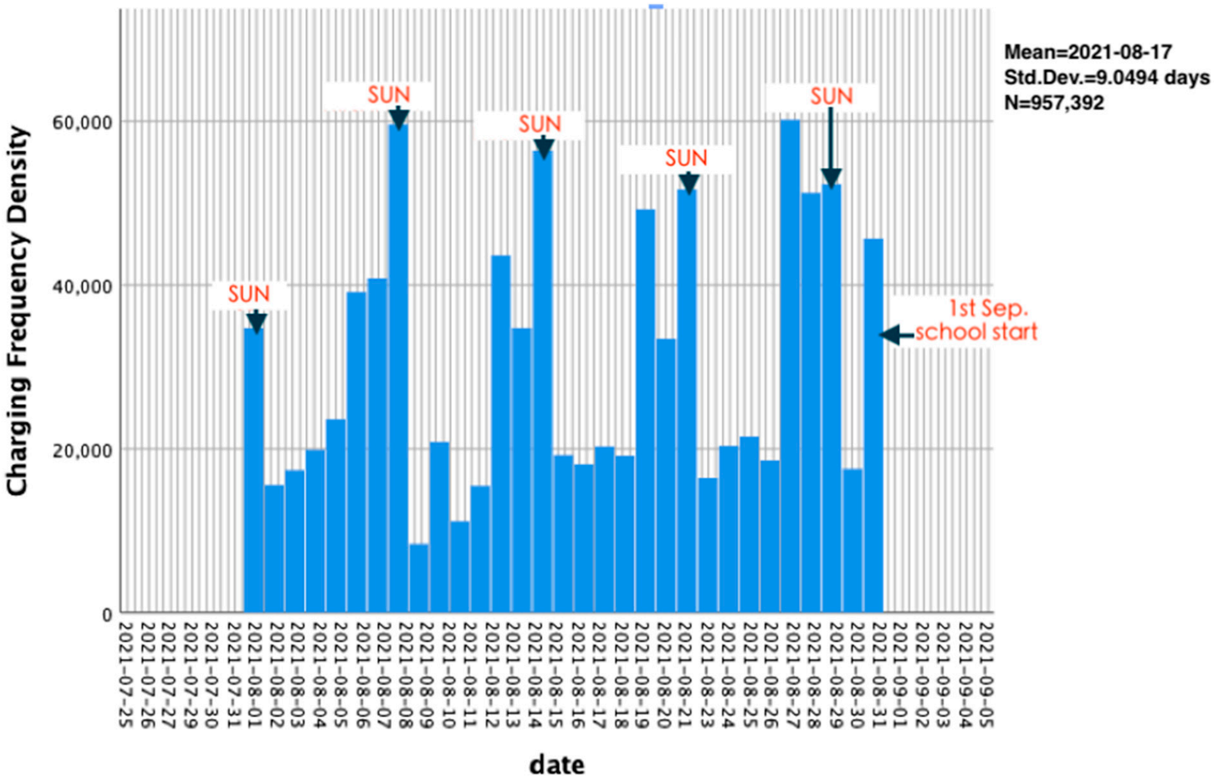

Figure 2. Private EV charging frequency density by date.

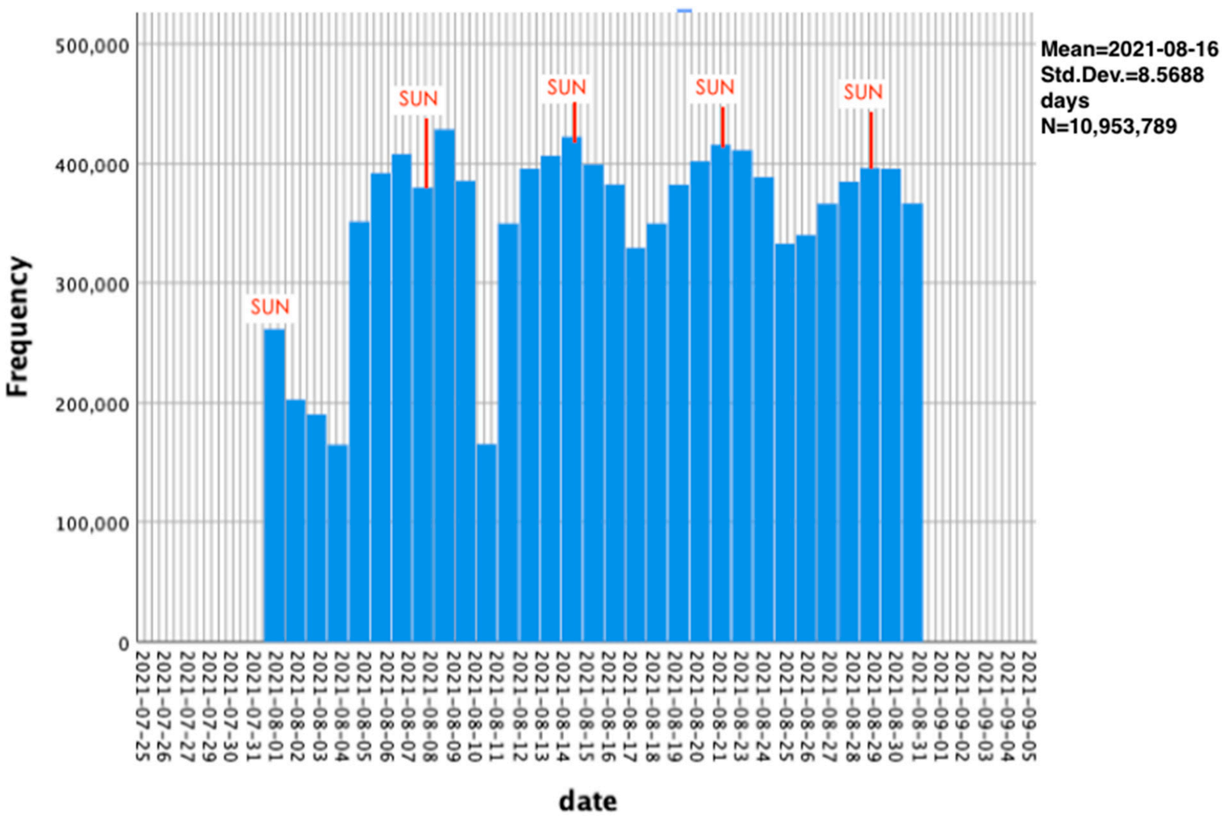

Figure 3. Non-private EV charging frequency density by date.

Chi-square testing is used to enable comparison of two types: goodness-of-fit tests and independence tests s [5,12,41,42]. We use chi-square tests here to test the independence (correlation) between two sets of private cases and other cases to determine the charging preference of the private cases group. According to the data and test requirements, the date data for the two groups are calculated in Table 5.

Table 5. Group and date type crosstabulation.

		Date Type		Total	Holiday and Day before Holiday of Total %
		Weekdays	Holiday and Eve		
Group	Other cases	6,102,083	5,809,098	11,911,181	48.77%
	Private cases	304,114	653,278	957,392	68.24%
Total		6,406,197	6,462,376	12,868,573	

Assuming that the private cases group of H0 and the other cases group variables are independent of each other, it can be seen from the test results in Table 6 that $p = 0.000 < 0.05$, accepting the null hypothesis. We can also see from the Figure 4 frequency bar chart of private and other cases that the holiday and the day before a holiday in the private cases group accounted for 68.24%, which is significantly greater than the 48.77% in the other cases group.

Table 6. Result of Chi-Square tests.

	Value	df	Asymptotic Significance (2-Sided)	Exact Sig. (2-Sided)	Exact Sig. (1-Sided)
Pearson chi-square	134,305.252 a	1	0.000		
Continuity Correction b	134,304.473	1	0.000		
Likelihood ratio	137,288.194	1	0.000		
Fisher's exact test				0.000	0.000
Linear-by-linear Association	134,305.241	1	0.000		
N of valid Cases	12,868,573				

a. 0 cells (0.0%) have an expected count that is less than 5. The minimum expected count is 476,606.21. b. Computed only for a 2 × 2 table.

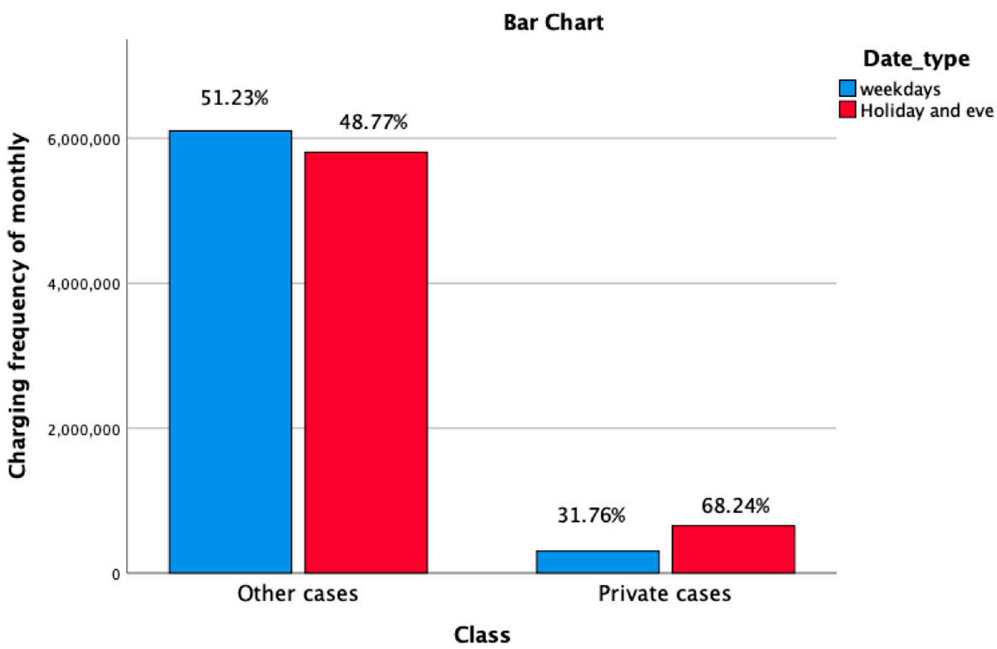

Figure 4. Frequency bar chart of private cases and other cases.

Conversely, the analysis of Figure 5 reveals that, among the different EV operating models considered, the private EV model exhibits a notably higher average daily charge, indicating an effort to fully charge the EV each time, and with an average of 80–90 kWh. However, Figure 6, which illustrates the cumulative charging amounts over a month, indicates that the total charging amount for a private EV is comparatively minimal when compared with the three other EV operating models.

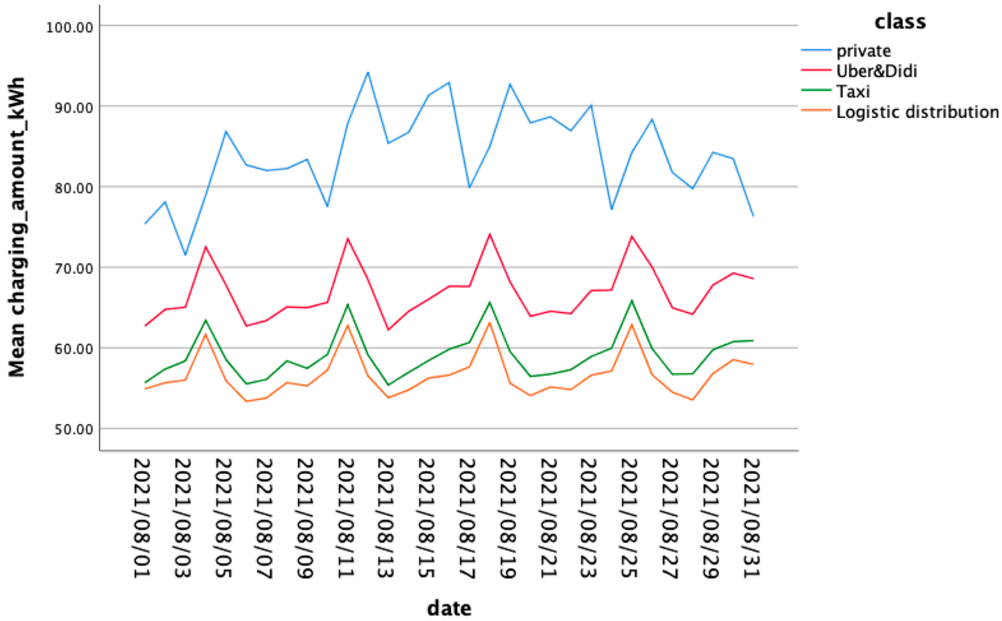

Figure 5. Average daily charging amount.

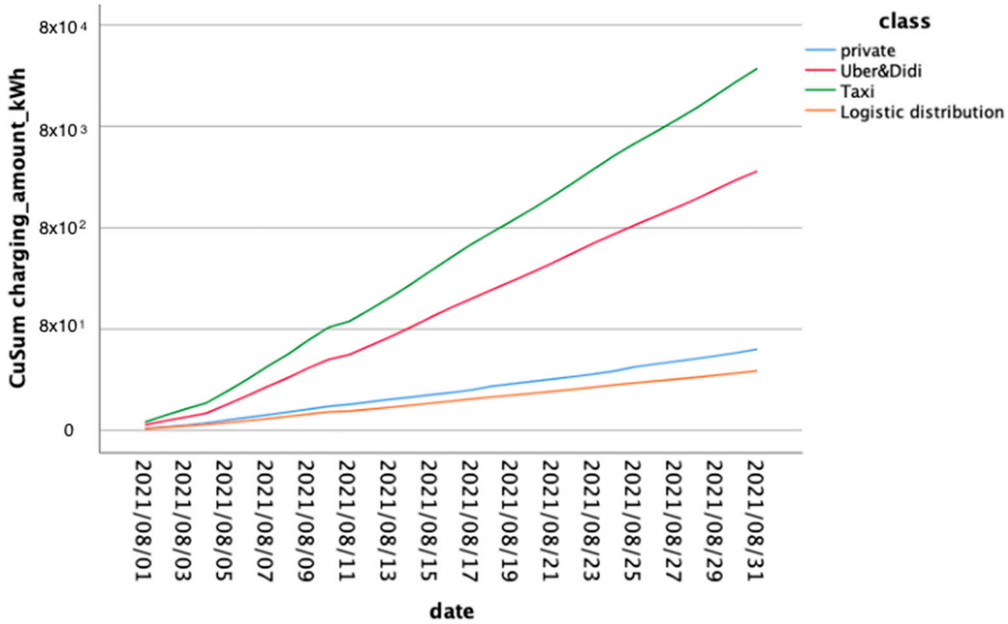

Figure 6. Sum charging amount over each month.

In summary, the charging preference for a private EV is the charging date period and full charge.

4.2. Research Charging Behavior of Passenger Operating EV

Frequency density of EV charging frequency has been analyzed in 6 months of 5gETS-ET data.

It can be seen in Figure 7 that the overall data is in an approximately normal distribution and that $p = 0.000 < 0.05$ is obtained by K–S test. The 0 hypothesis is not accepted, so it is not a normal distribution. A separate K–S test was conducted for a passenger operating EV and $p = 0.200 > 0.05$ was obtained, which is in line with normal distribution. The comparison of the test data is in Table 7, as follows:

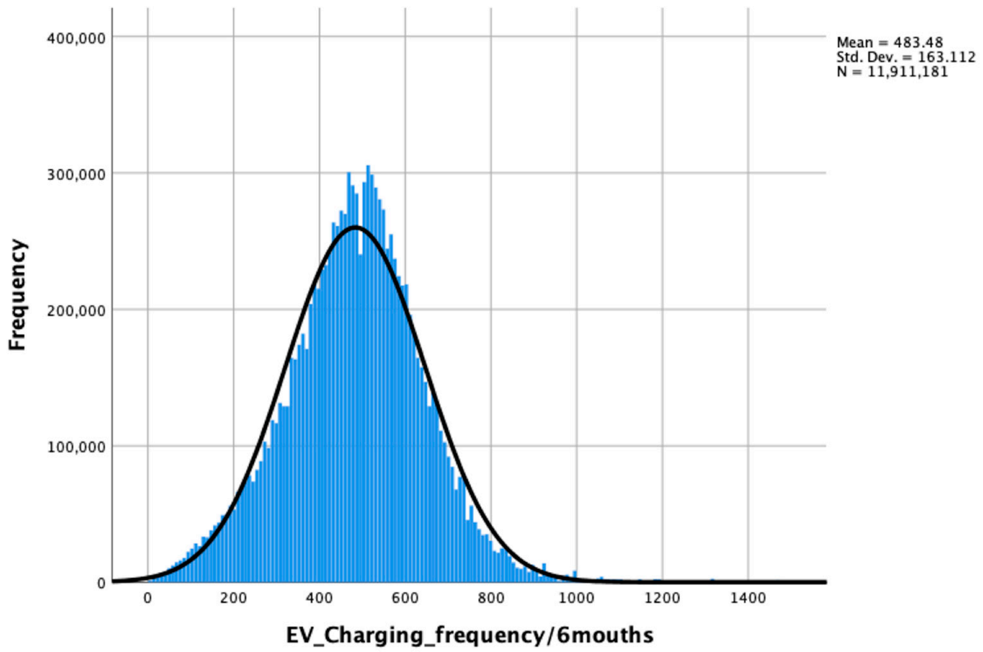

Figure 7. Frequency density distribution of EV charging frequency.

Table 7. EV charging frequency K–S Test.

One-Sample Kolmogorov–Smirnov Test			
Project		**All Data**	**Passenger Operating EV Data**
N		984	441
Normal parameters a,b	Mean	25,603.88	19,922.88
	Std. deviation	401,340.611	4711.837
Most extreme differences	Absolute	0.483	0.061
	Positive	0.483	0.060
	Negative	−0.475	−0.061
Test statistic		0.483	0.061
Asymp. Sig. (2 tailed)		0.000 c	0.200 c,d

a. The test results are normally distributed. b. Calculated based on data. c. Lilliefors significance correction. d. This is a lower bound of the true significance.

We analyzed the charging duration over a period of 6 months and examined the relationship between charging frequency and charging duration, revealing a positive linear correlation. To handle the large dataset, nonlinear regression of discrete selection theory and constraint analysis were applied to generate the scatter diagram depicted in Figure 8, demonstrating that increased charging frequency is associated with longer charging times.

We summarized six months of data based on the charge amount and examined the correlation between charge frequency and charge amount. The analysis revealed a positive linear correlation. By employing nonlinear regression techniques, such as discrete selection theory and constraint analysis, Figure 9 was obtained, which illustrates that an increase in charging frequency is associated with a higher charging amount.

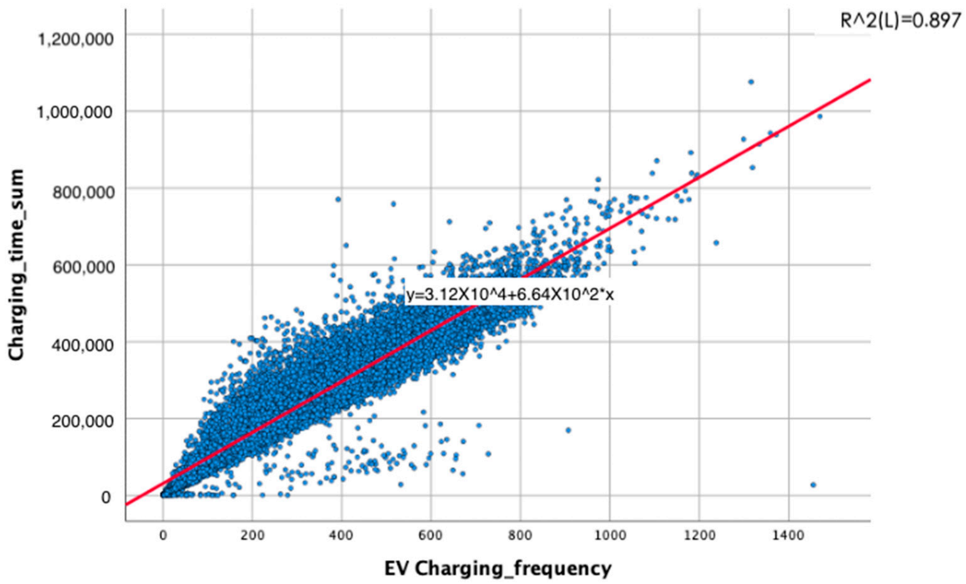

Figure 8. EV charge frequency and charge duration scatter plot.

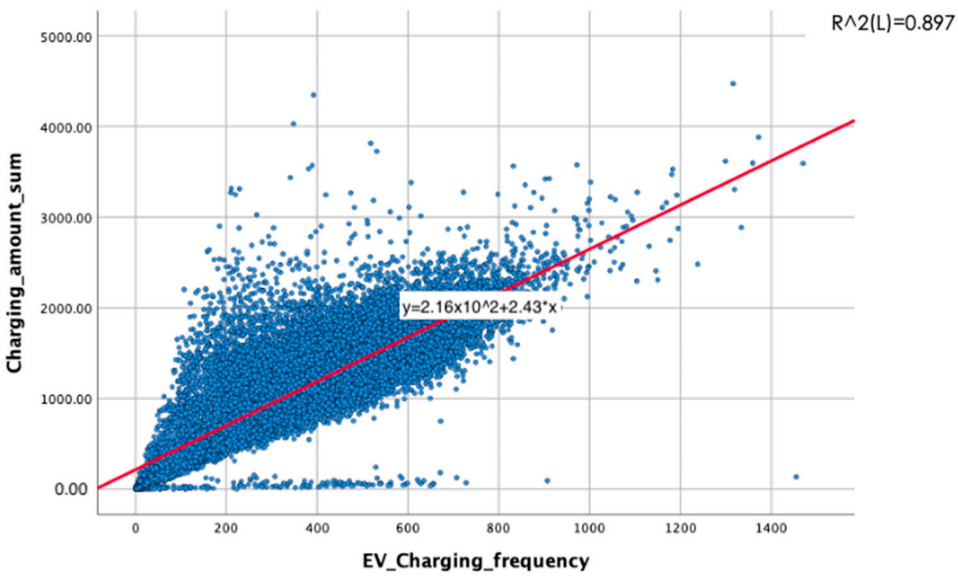

Figure 9. Scatter plot of charge frequency and charge amount.

Frequency density analysis was performed on the charging duration of passenger-operating EVs in fast charging mode, excluding cases where, due to instances where the charging plug-in was not uninstalled post-charging, there is a charging duration exceeding 120 min. The analysis indicates that the timeframe between 20 min and 90 min accounted for the highest proportion of charging durations in this mode, refer to Figure 10. For a detailed summary of the analysis results, refer to Table 8.

Frequency density analysis was performed on the charging capacity of a passenger operating EV mode in Figure 11. For this analysis, only fast charging data were considered, and instances where the charging capacity exceeded 200 kWh were excluded. The results indicate that the range between 10 kWh and 40 kWh comprised more than fifty percent of the total charging capacity for this mode, as shown in Table 9 regarding the frequency density distribution of charging amount.

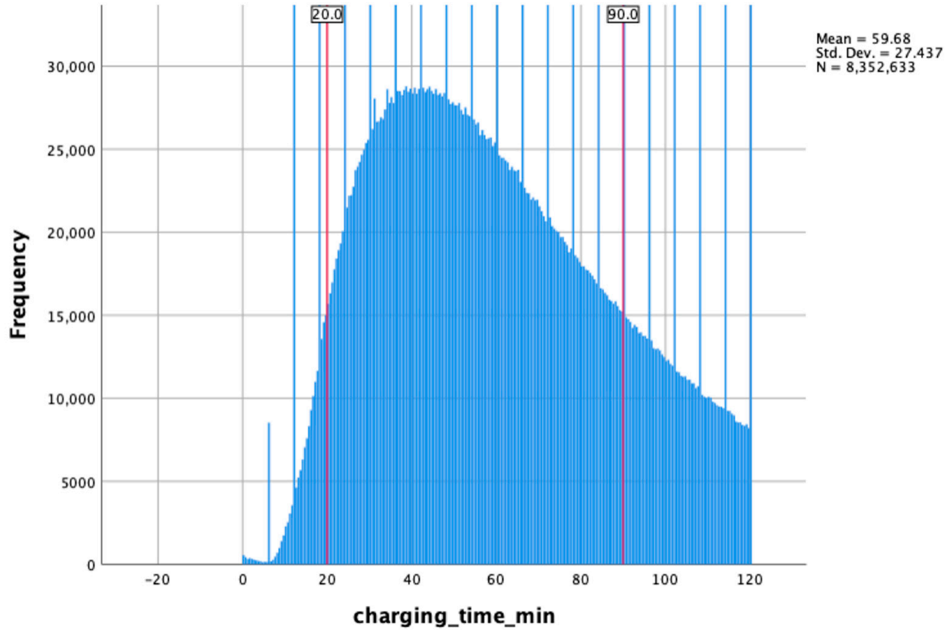

Figure 10. Frequency density analysis of charging duration.

Table 8. Frequency density ratio distribution of charging time.

Charging Time (min)	Charging Time Frequency Sum	% of Total Sum
<20	400,127	4.8%
20–90	6,647,523	79.6%
>90	1,304,983	15.6%
Total	8,352,633	100.0%

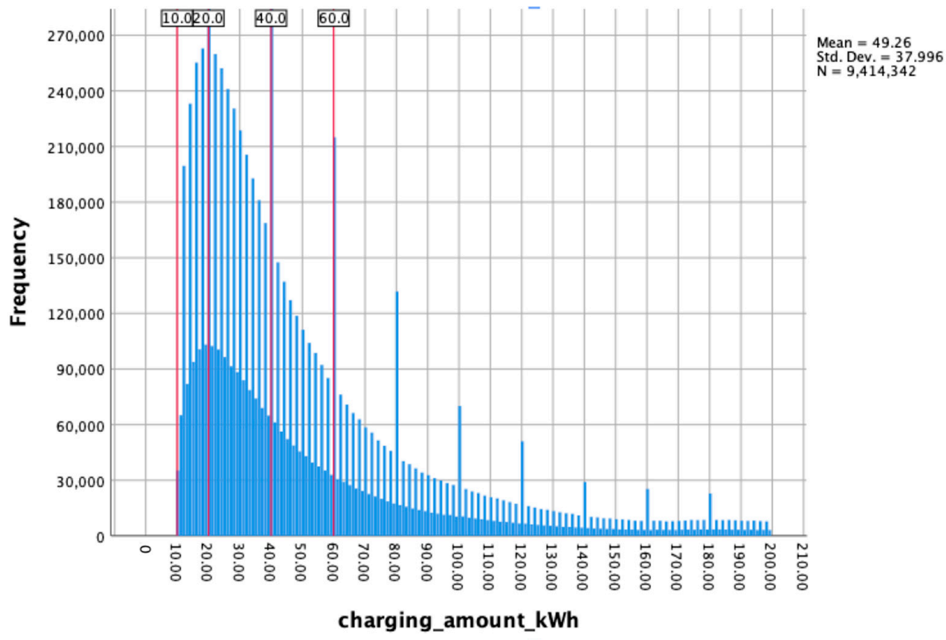

Figure 11. Frequency density of charging amount.

In summary, the charging preference of a passenger operating EV is charging speed.

Table 9. Frequency density distribution of charging amount.

Charging Amount (kWh)	Charging Amount Frequency Sum	% of Total Sum
<10	35,243	0.4%
10–20	1,416,372	15.0%
20–40	3,896,355	41.4%
40–60	1,707,807	18.1%
60–90	1,173,346	12.5%
>90	1,185,219	12.6%
Total	9,414,342	100.0%

4.3. Research Charging Behavior of Logistics Distribution EV

Refer to Table 10 for the time segment pricing model of charging unit price in order to determine the pricing model for charging points.

Table 10. Time segment pricing model of charging unit price.

No	Time	Electricity CNY/kWh	Service Charge CNY/kWh	Charging Price CNY/kWh
1	00:00–8:00	0.35	0.6	0.95
2	8:00–12:00	0.88	0.52	1.4
3	12:00–15:00	0.6	0.6	1.2
4	15:00–21:00	0.88	0.52	1.4
5	21:00–24:00	0.6	0.6	1.2

It is evident that there was a 47% variation in the price of kWh charging between the lowest of the initial time segments and the highest of the subsequent time segments. Additionally, there was a 17% difference in the kWh charging price between the highest of the subsequent time segments and the middle of the following time segments.

Based on the analysis of time period variables through frequency density, the data indicate that the highest charging frequency within a 24 h period occurs between 6:00 pm and 12:00 am, during the 4th and 5th time segments. Both charging prices of 1.4 and 1.3 show no preference in price during these time periods.

A total of 1,039,602 cases of EV usage in logistics distribution were analyzed for time period variables. The analysis revealed that the highest charging frequency occurs between 0:00 and 7:00 in Figure 12, with the first time period having the lowest charging price of 0.95. This indicates a distinct preference for pricing during specific time periods in Figure 13.

Table 11 presents a summary of the frequency of single-price charging periods by categorizing and consolidating the data. The analysis shows that a majority (52.1%) of charging activities take place during the period with the lowest price of 0.95.

Table 11. Summary table of single price frequency in charging period.

Time Period Price	N	% of Total N	Frequency Sum	% of Total Sum
0.95	539,723	51.9%	7,684,891.44	52.1%
1.2	187,706	18.1%	2,619,382.24	17.8%
1.4	312,173	30.0%	4,451,317.88	30.2%
Total	1,039,602	100.0%	14,755,591.56	100.0%

We examine the interrelationships between fare amount, charging time, and charging amount across four distinct classes of EVs. Analysis of the test results depicted in Figures 14–16 reveals evident heterogeneity in the logistic distribution EV model, with these variations ultimately manifesting in pricing decisions.

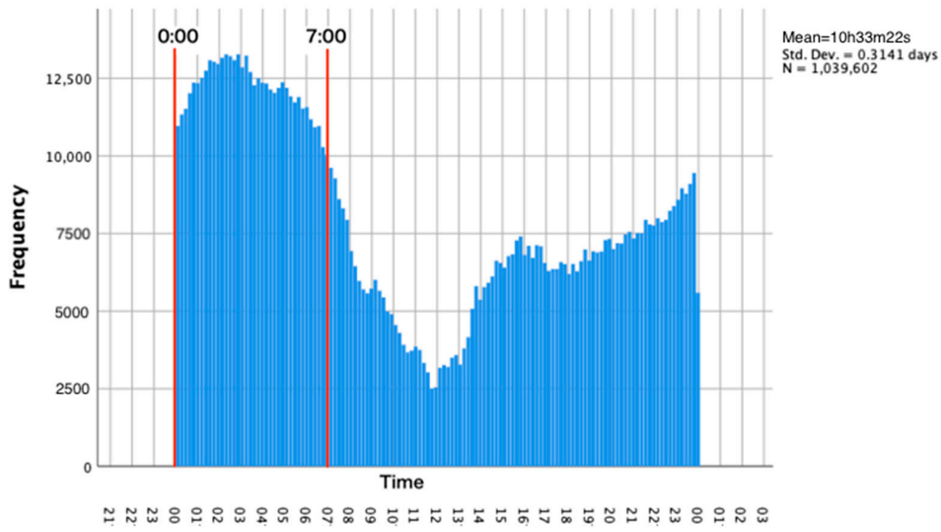

Figure 12. Frequency density of charging time periods for all cases.

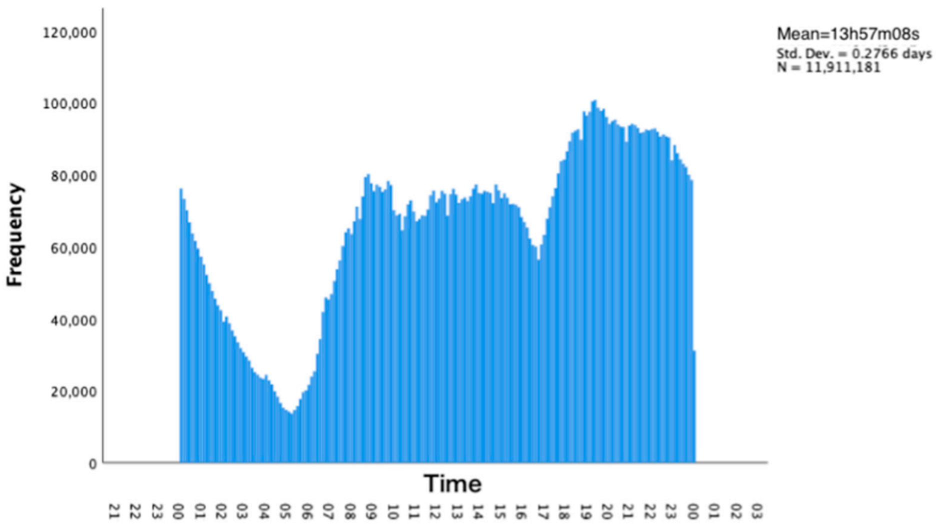

Figure 13. Logistic distribution EV cases distribution of 24h.

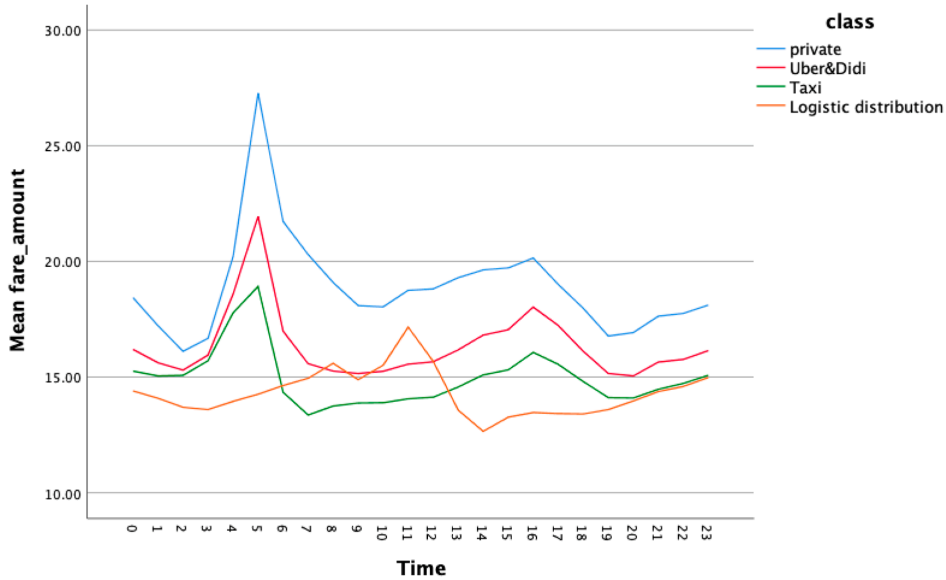

Figure 14. Mean fare amount over 24 h.

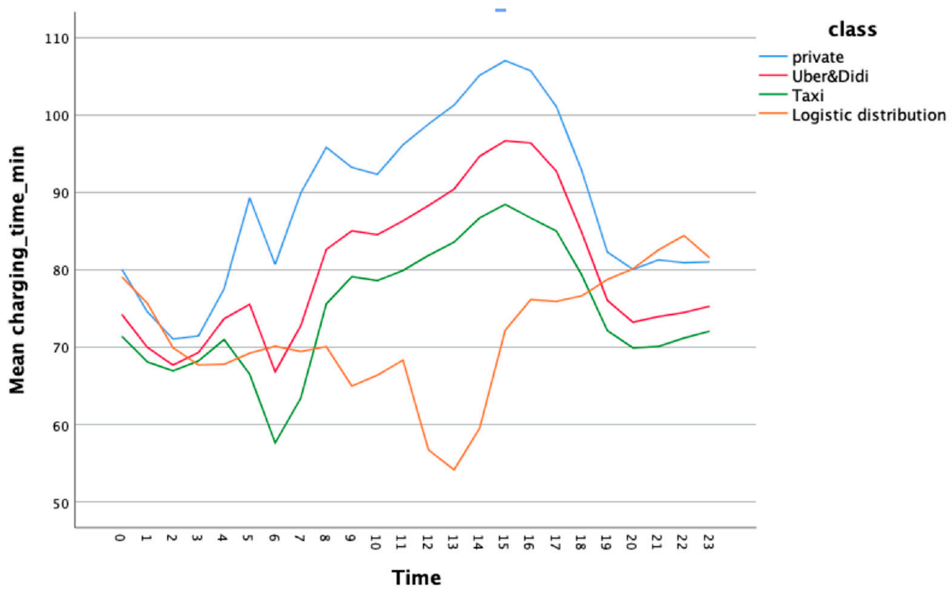

Figure 15. Mean charging time over 24 h.

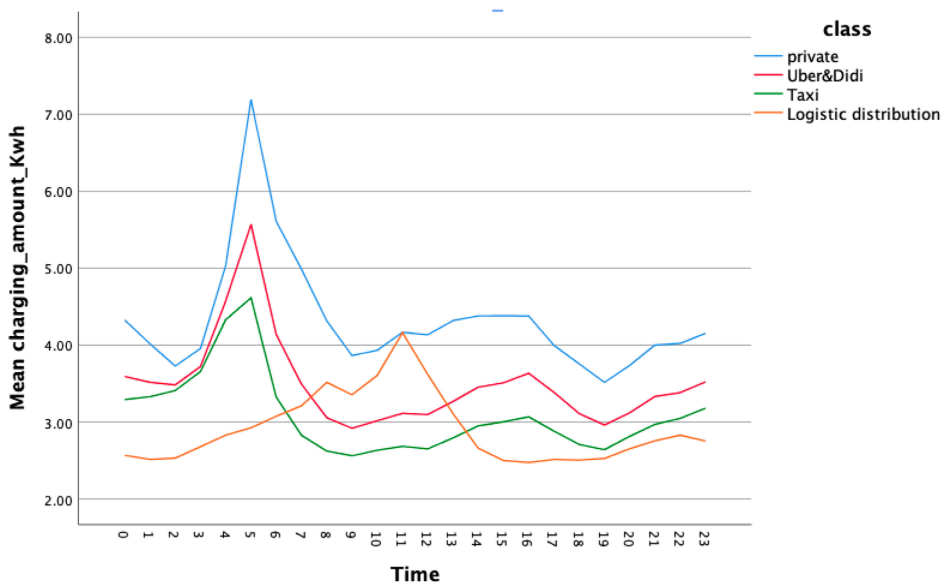

Figure 16. Mean charging amount over 24 h.

In summary, the charging preference of a logistic distribution EV is charging price.

5. Conclusions and Limitations

The purpose of this study is to establish a dynamic charging behavior model to accommodate various roles of EV users. Real operational data from the 5gRTS-ET platform in China were utilized. The following different methods were used to conduct the study. The findings indicate that different roles of EV users show unique preferences in terms of charging behavior.

(1) The charging behavior of a private EV was analyzed using the frequency density method, utilizing 5gRTS-ET data. This approach considered charging time as a primary factor.
(2) The mathematical model was developed using nonlinear regression, discrete selection theory, and constraint analysis. The validity of the data was tested using K–S. Subsequently, the charging behavior of the passenger operating EV mode with a preference for charging speed was analyzed and addressed.

(3) This study utilizes numerical modeling, numerical analysis methods, and constraint analysis to construct a model for analyzing and addressing the charging behavior in the logistics distribution EV mode, considering charging price preferences.

In contrast with conventional research, this study examines EV charging behaviors through the lens of diverse user roles, moving beyond simplistic predictions based on factors like charging prices, station locations, and speeds. The insights, gleaned from actual EV operational data, provide a more realistic and precise depiction of user behaviors. The diverse charging preferences under various operational models enhance the adaptability of EVs to the dynamic roles they play, particularly as current sharing platforms encompass EVs and their users globally.

EV charging is a complex chicken-and-egg problem. While this study has achieved its research goals, the insightful findings can provide valuable guidance for practical applications. Nevertheless, it is crucial to acknowledge that both methods and models utilized in this study are subject to certain limitations that warrant further investigation.

(1) The model formulated in this study for the charging behavior of an EV during operation is established using important parameters and variables from the 5gRTS-ET platform. Future research opportunities include the conducting of cluster analysis by integrating subjective behavioral preferences and performing adjustment analysis of the charging behavior model by incorporating urban traffic information variables.
(2) With the advancement and increasing economic viability of vehicle-to-grid (V2G) technology, its adoption is expected to grow [43]. Consequently, the focus for future research will be on establishing real-time interaction systems aligning 5G connectivity among vehicles, charging stations, power grid, and transportation networks, alongside an examination of the site selection and business models for new charging stations incorporating updated technologies like V2G.

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