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Unraveling influencing factors of public charging station utilization

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ABSTRACT

Accelerating EV adoption is crucial in reducing carbon emissions. To support EV penetration and minimize waste, we analyzed real-world charging status big data in a high-density city heavily reliant on public charging infrastructure. Using a two-part spatial lag of X model, we investigated the impact of charging station attributes and the surrounding built environment on the utilization rates, defined as the ratio of occupied (fast/slow) charging piles to the total available (fast/slow) piles at each station. Our findings reveal that fast charging stations located outdoors, sheltered, and near major roads attract more users, while these factors do not significantly affect the slow utilization rate. Utilization rates are higher for fast charging stations surrounded by a diverse land use mix, while the opposite is observed for slow charging stations. These findings provide valuable insights for the effective operation of charging infrastructure, furthering the development of the new-energy market and sustainable transportation.

1. Introduction

As a key technology for decarbonizing road transport and improving energy efficiency, electric vehicle (EV) promotion has gained significant attention. To align with the goal of achieving net-zero CO_2 emissions by 2050, the International Energy Agency projects that EVs must account for 60% of new light-duty vehicle sales by 2030, with advanced economies aiming for a 75% adoption rate (International Energy Agency, 2021). Governments worldwide have adopted various strategies and policies to increase EV penetration. Notably, countries such as Norway, the United Kingdom, and Germany have committed to phasing out fossil-fuel vehicles between 2025 and 2040 (Bennett & Vijaygopal, 2018; Dugdale, 2018; He et al., 2022). Additionally, countries like China, France, Germany, the Netherlands, Norway, and Sweden have launched EV subsidy schemes, including purchase rebates, tax credits, and sales tax waivers (Hao et al., 2014; Shang et al., 2024; Stephens et al., 2018; Zhou et al., 2016).

Promoting public charging stations to mitigate drivers' range anxiety and ensure adequate power support is crucial (Avci et al., 2015; Guo et al., 2018; Lutsey et al., 2015). Despite increased promotion of public charging infrastructure, a disparity persists between the rising demand for charging and the low utilization of public charging stations, especially in high-density Asian regions. This may lead to wasted land, equipment, and capital investment. For instance, as of 2022, China has built about 1,800,000 public chargers; however, in cities such as Shenzhen, Beijing, and Shanghai, the average time utilization rate[1] of public charging stations is below 8%,

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[1] Time utilization rate: The percentage of time that a charging pile is in use compared to the total time it is available for use.

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the average pile utilization rate[2] is less than 40%, and the average turnover rate[3] is under 2.0 (China Academy of Urban Planning and Design, 2023). Therefore, understanding the factors influencing the (low) utilization rates is crucial for effectively constructing and managing these facilities.

Recent studies have examined public charging station utilization from various perspectives, including mapping temporal and spatial charging demand hotspots using data mining techniques (Helmus et al., 2020; Morrissey et al., 2016), optimizing charging station allocations (He et al., 2022; Wang et al., 2019), and exploring user charging preferences through surveys and interviews (Philipsen et al., 2018; Wang et al., 2021). However, factors influencing the utilization from a facility supply perspective remain insufficiently understood. A comprehensive, macro-level view based on real-world datasets is still lacking. While expanding and optimizing the distribution of charging stations is necessary, understanding the underlying relationships is also crucial.

Using charging status big data from a densely populated Asian city with extensive public charging station coverage, we define the utilization rate as the ratio of occupied (fast/slow) charging piles to the total available (fast/slow) piles at each station. Through a systematic and empirical approach, we focus on the supply side and analyze the spatial and temporal distribution of public charging station utilization. Then, based on a two-part spatial lag of X (TP-SLX) model, we investigate the influence of station attributes and the surrounding built environment on the (dis)use of charging stations. Additionally, we assess the impact of nearby competing charging stations on local utilization rates.

This study distinguishes itself from previous studies in three aspects: First, we collect and analyze real-world charging big data in a high-density Asian city heavily reliant on public charging infrastructure, which is unique compared with previous studies. Second, starting from the supply side, the study explores the factors affecting utilization rates at the macro level, providing valuable insights for operational recommendations. Finally, this study includes surrounding charging stations as potential competitors, which previous studies overlooked and therefore failed to provide a more comprehensive assessment.

The rest of the paper is structured as follows: Section 2 reviews related literature and outlines the research questions. Section 3 describes the methodology employed in this study. Section 4 presents the regression results. Section 5 concludes the paper and provides further discussions.

2. Literature Review

Recent studies on the utilization of EV charging stations can be broadly categorized into three types.

Charging resource allocation: This category focuses on overall resource allocation, including studies on accessibility, placement, and optimization (Cai et al., 2014; He et al., 2015; Wagner et al., 2014; Wang et al., 2019; Xu & Meng, 2020). These studies aim to identify inadequate charging facilities through accurate demand modeling. Using heuristic algorithms or spatial analysis to predict or maximize resource allocation (Andrenacci et al., 2016; Bai et al., 2019; He et al., 2015; He et al., 2016; Tu et al., 2016), some researchers emphasize temporally and spatially varying demand, including predictions of charging durations (Ullah et al., 2022), waiting time, and energy consumption (Hoehne & Chester, 2016; Tu et al., 2016), as well as optimizing station locations (He et al., 2022).

Charging behavioral perspectives: In this category, studies adopt a behavioral perspective, utilizing questionnaires or structured interviews to understand charging preferences and experiences (Daina et al., 2015; Philipsen et al., 2015, 2018; Schmalfuß et al., 2015; Will & Schuller, 2016). These studies have provided valuable insights for the allocation and design of public charging stations prior to their construction.

Data mining on charging decisions: In addition to traditional methods, several studies employ data mining techniques to uncover factors influencing charging decisions (Gnann et al., 2018). Some of these investigations analyze charging records data to examine preferences based on vehicle characteristics and user types, etc. (Helmus et al., 2020; Kim et al., 2017; Siddique et al., 2022; Song & Hu, 2023; Wolbertus et al., 2018; Xydas et al., 2016). Emerging research also utilizes vehicle trajectory data to estimate dwell time as charging time and to analyze its impact on station attributes (Cai et al., 2023; Guo et al., 2022; Lei et al., 2022). These studies aim to accurately describe spatio-temporal patterns from collected information in a scalable and cost-effective manner, complementing traditional charging behavior analysis.

Based on the existing research (Potoglou et al., 2023), factors influencing charging decisions can be broadly categorized into several domains: temporal factors (charging time of day, charging days of the week, charging frequency), user factors (socio-economic background), vehicle factors (battery capacity, state of charge, vehicle types), and station factors (station capacity, charging costs, locations, supporting facilities). While limited studies have examined the impact of the built environment, it is evident that the surroundings of public charging stations significantly influence charging behavior. Studies into land use types and amenities indicate a substantial effect on charging preferences (Cai et al., 2023; Guo et al., 2022), though further investigation is required to fully understand this potential impact.

We identify research gaps from both supply and demand perspectives. On the demand side, existing studies primarily assess individual preferences through questionnaires or analyze fleet charging patterns via trajectory data. However, these micro-level studies provide limited information for charging station operations and management as they focus more on fleet rather than stations themselves. To gain real-world insights, it is crucial to incorporate a macro and long-term perspective at the charging station level. From the supply-side perspective, several studies have utilized charging records in European and American contexts to analyze factors

[2] Pile utilization rate: The ratio of charging piles that are in use to the total number of piles in a public charging infrastructure.

[3] Turnover rate: The number of EVs served per charging pile per day.

influencing charging utilization. However, there is a notable lack of empirical studies addressing group differences between actual choices and preferences in the Asian context, characterized by high density and substantial public charging station dependence.

In light of the identified gaps, this study aims to address the following questions: (1) Does charging station occupancy exhibit spatial or temporal variability? (2) Which factors affect the utilization rates of fast and slow charging stations?

3. Methodology

3.1. Research area

As a densely populated city in Asia, Shenzhen had 17.66 million permanent residents at the end of 2022, with a total coverage of 1997.47 km^2. Renowned for its innovative and inclusive culture, Shenzhen actively embraces environmental protection and emission reduction measures, positioning itself as a pioneer city in vehicle electrification in China. Beginning in 2010, the Shenzhen government initiated and promoted taxi electrification, and by the end of 2018, public vehicles, including the bus or taxis, had been almost completely electrified. In the private car sector, EV sales in 2022 amounted to 239,000, marking a 22.3% year-on-year increase, with a penetration rate of new vehicles reaching 61.8%. By the end of June 2023, the number of EV ownership had reached 862,600, accounting for 21% of the total ownership in the city.[4]

The rapid expansion of the EV market also generates significant demand for charging infrastructure, particularly in Shenzhen. Restrictions on parking lot purchases in the city impede the widespread adoption of private home charging stations. EV charging in Shenzhen heavily relies on public charging infrastructure. Consequently, Shenzhen is recognized for its extensive network of public charging and battery-swapping stations. In 2022, 23,000 new public charging piles were added, with a cumulative total of 128,000 public charging piles, which is the highest in China (China Academy of Urban Planning and Design, 2023).

3.2. Data preparation

The primary dataset utilized in this study comprises charging status data collected from a prominent Chinese mobile application designed for aggregating charging station information. This platform collaborates with various charging station providers, including infrastructure companies (e.g., StarCharge and TELD), EV manufacturers (e.g., NIO and Xiaopeng), and third-party platforms (e.g., YKC Charging and Orange Charging). Utilizing a self-developed web scraping tool, we collected the charging status of 17,540 piles across 626 charging stations from July 25 to August 25, 2023, including both fast and slow charging modes. Specifically, we recorded real-time statuses (i.e., charging, plugged-in, off-grid, malfunctioning and available) for each pile at each charging station on an hourly basis. In addition, we extracted station details from the platform, including address, number of charging piles, charging fees, and service costs.

Supplementary information regarding the stations, such as parking fees during charging and station attributes (e.g., indoor or outdoor, sheltered or not, and location type such as residential, office, public area, or large charging hub), was obtained from the two major online map companies, Baidu and Gaode Map, and further corroborated through field research.

The geospatial data employed in this paper primarily include urban land use parcels and points of interest (POIs). Land use parcels were sourced from Shenzhen Municipal Bureau of Planning and Natural Resources and subsequently reclassified into categories including commercial areas, green spaces, industrial and logistics land, non-constructed areas (encompassing reserved areas and white zones), public service areas, residential areas, transportation areas, and water bodies for analytical purposes. While parcel data provides large-scale contextual information, POIs are essential for complementing the socio-economic context and detailing the surrounding built environment. These POIs were collected from Gaode Map according to official categories, including bus and subway stops, shopping malls, grocery stores, restaurants, offices, residential buildings, recreational facilities, etc.

Following data collection, we conducted data preprocessing. Due to network issues, the charging status of some piles was missing during specific periods. To ensure data quality, records from affected stations on these days were excluded. Ultimately, only stations with over 60% valid days were retained for analysis. Furthermore, we geocoded station addresses into geographic coordinates to enable more effective integration and analysis with other datasets.

3.3. Variable Definition

3.3.1. Dependent variable

The dependent variable in this study is defined as the utilization rate at a station for a specific hour, averaged over the research period. Fig. 1 presents the distribution of average hourly charging pile occupancy across charging stations. The vertical axis represents the hourly utilization rate, while the horizontal axis denotes the time intervals. The graph indicates that diurnal fluctuations in utilization rates are more significant than the variations observed between weekdays and weekends. Additionally, the utilization rates for fast charging stations exhibit greater variability throughout the day compared with slow charging mode. Notable utilization peaks of fast charging mode occur at 1:00, 7:00, 13:00, and a minor peak around 20:00, with troughs primarily observed between 10:00–11:00 and 15:00–16:00. In contrast, slow charging mode peaks predominantly during nighttime hours. Therefore, in the subsequent analysis,

[4] *Shenzhen Accelerates the Creation of "A New Generation of World-Class Automobile City".* (2023, August 4). Eye Shenzhen. https://www.sz.gov.cn/cn/xxgk/zfxxgj/zwdt/content/post_10764684.html.

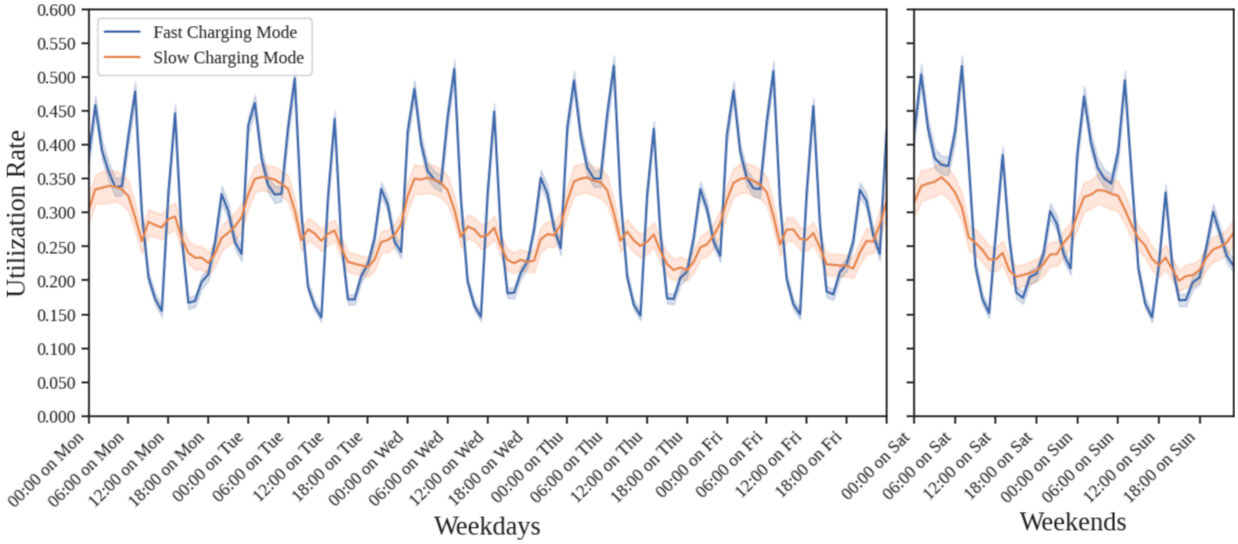

Fig. 1. Distribution of Hourly Utilization Rate.

greater emphasis is placed on diurnal differences rather than weekday versus weekend variations. Thus, the dependent variable in this study is described as the hourly average share of occupied (fast/slow) piles at each (fast/slow) station during the specified time period. Detailed statistical information is provided in Table S1.

Regarding spatial distribution, the average utilization of each charging station is depicted in Fig. 2. Fig. 2(a) represents the average utilization rate of fast charging stations, while Fig. 2(b) depicts that of slow charging stations. Fast charging stations generally exhibit a higher utilization rate, with values concentrated in the medium range of 0.301–0.600, particularly in non-urban areas. In contrast, slow charging stations display a low utilization rate, predominantly located in urban areas.

3.3.2. *Charging station attribute*

Considering practical insights and the literature on charging behavior and preferences, we identified station capacity, charging cost, station design, and station location as key station-level characteristics.

Prior studies have demonstrated the positive impact of station capacity (Visaria et al., 2022) and the negative impact of charging cost (Guo et al., 2022; Ma et al., 2022; Sun et al., 2016) on charging decisions. We used the number of piles in the station to represent station capacity. The prevalent chargers used in Shenzhen charging stations are fast (direct current) chargers and slow (alternative current) chargers. Typically, an EV can replenish approximately 200 km of range by charging for one hour at a fast charging station, while charging at a slow charging station often requires 6 to 8 h. This difference also explains the driver's willingness to take a detour to reach a fast-charging location with more chargers (Visaria et al., 2022). Consequently, the number of charging piles in a station can be seen as an indicator of service efficiency, potentially influencing utilization at the station level.

The expenses involved in the charging process consist of charging costs (including the electricity costs and platform service fees at public stations) and parking fees. Previous research examining user charging behavior has demonstrated a negative impact of both charging costs (Ma et al., 2022; Wang et al., 2021) and parking costs (Pan et al., 2019) on charging utilization. However, while higher charging costs are often associated with a better charging experience, many public parking lots offer subsidized parking fees to promote EVs. Thus, at the station level, the impact of different expenses on utilization remains unclear. To address this complexity and account for discounts, we separated the electricity and service fees from overall charging costs, and incorporated the parking fee required for the first hour of charging at the selected station into our analysis.

In terms of station design, we incorporated factors such as the distance to the major road, whether the station is indoors, and whether it is sheltered, as shown in Fig. S1. These factors can influence safety, accessibility, and convenience for users, which are highly ranked in the criteria for charging station evaluation (Philipsen et al., 2015).

The location of charging stations, including their site host and their positioning within the city, is also a key consideration. Drawing from the classification in the annual report on electric charging infrastructure in major Chinese cities (China Academy of Urban Planning and Design, 2023), as well as insights from previous research (Funke et al., 2019) and field investigations, we categorized the charging stations in Shenzhen into four types based on their installation sites: offices, residences, large charging hubs, and public facilities (including all other facilities such as educational and scientific research institutes, shopping centers, etc.). In our regression analysis, public facilities served as the reference category. Furthermore, the locations of charging stations within the city may also play a significant role. Prior studies have shown that residential proximity to the city center significantly influences car ownership, travel modes, and trip distances (Berrill et al., 2024). Shenzhen's non-monocentric urban structure, a result of its historical development as a Special Economic Zone (SEZ) (Li et al., 2021), affects spatial accessibility and the uneven distribution of public and private services. This, in turn, influences travel patterns, accessibility, EV adoption, and charging behavior (Du et al., 2024; Philipsen et al., 2016). In

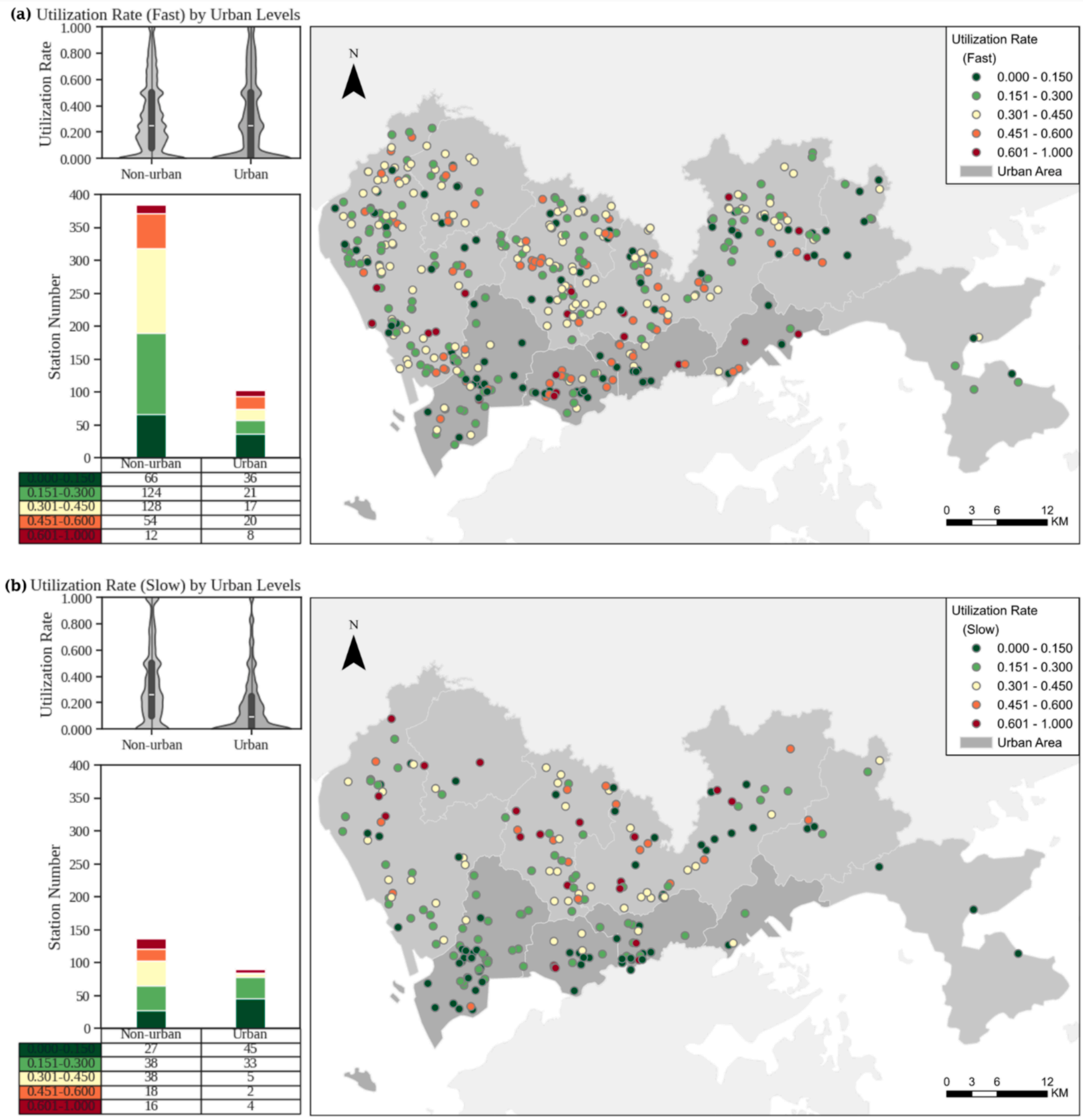

Fig. 2. Average Utilization Rate Distribution of Public Charging Stations (a) Fast Charging Mode (b) Slow Charging Mode.

this study, former SEZ areas including Nanshan, Futian, Luohu, and Yantian are identified as urban areas (Zhou et al., 2022).

3.3.3. Built environment

The influence of the built environment on travel demand has been extensively examined (Ewing & Cervero, 2010). However, the specific attributes of the built environment surrounding charging stations remain underexplored in the context of charging behavior. Notably, several studies suggest that users value the ability to integrate charging with their daily activities (Philipsen et al., 2015). Additionally, distance to public transit has been found to have either an inverse or negligible effect on charging preferences (Guo et al., 2022; Philipsen et al., 2015).

In this study, we analyzed three dimensions related to the built environment: land use mix, access to public transit, and various types of POIs. Land use mix is quantified using entropy in Eq. (1), which ranges from 0 (indicating a single land use type and no diversity) to 1 (indicating an even distribution among all land use types):

$$entropy = -\sum_{k=1}^{K} p_k \times \frac{ln(p_k)}{ln(K)} \quad (1)$$

where K represents the number of land use categories, and p_k denotes the proportion of land area dedicated to each land use type k. For this analysis, eight distinct land use types were included.

To assess the built environment surrounding the charging stations, we utilized a buffer with a radius of 500 m (Guo et al., 2022; Wolbertus, 2024; Zheng et al., 2024). Detailed statistics for the independent variables are presented in Table 1.

In addition to the characteristics of charging stations and their surrounding built environment, we accounted for the number of nearby charging piles by employing an inverse distance spatial weight matrix. While direct evidence regarding the potential influence of nearby charging piles on local station utilization remains limited, analogous findings from bike-sharing systems provide valuable insights (El-Assi et al., 2017; Faghih-Imani et al., 2014; Faghih-Imani & Eluru, 2015; Zhang et al., 2017). Specifically, the proximity of nearby bike stations has been shown to influence local station usage, though the direction of this effect varies among studies. Some research points to an agglomeration effect, whereas other studies suggest that once a station reaches its capacity, users tend to shift to nearby alternatives. This variability underscores the need for further investigation. Furthermore, as illustrated by the spatial distribution in Fig. 2, incorporating the spatial lag of the X term is essential for mitigating potential spatial autocorrelation effects. This approach also enables a more comprehensive analysis of the combined influence of different nearby charging modes (both fast and slow charging modes) on local utilization rates.

3.4. Modeling approach

Existing research on the factors influencing charging station utilization primarily employs two analytical methods: clustering and regression. The first type of study performs cluster analysis on large datasets of charging records or driving trajectories, correlating category outcomes of charging behavior or demand preferences with station attributes (Cai et al., 2024; Helmus et al., 2020). The second type conducts analysis on charging behavior or demand with station attributes, using ordinary linear regression (Du et al., 2024), quantile regression (Guo et al., 2022), multinomial logistic regression (Wolbertus et al., 2018) or machine learning methods such as random forest regression (Cai et al., 2023) to explore potential linear and nonlinear effects. While these methods are effective in analyzing the factors influencing charging station utilization, a more appropriate model is required to accurately quantify their impact, particularly given that many stations currently experience low usage or remain idle.

Additionally, existing models often overlook potential spatial autocorrelation, which may introduce bias into the results. The spatial lag of X (SLX) model offers a simplified analytical framework (Halleck Vega & Elhorst, 2015) without incurring severe econometric issues such as endogeneity or regularity conditions. The SLX model's advantage over other spatial econometric models lies in its compatibility with non-spatial econometric techniques. To better address our research questions and account for station utilization characteristics, we employed a two-stage estimation approach designed for mixed discrete–continuous outcomes (Min & Agresti, 2002) incorporating a spatial lag of X term based on charging piles in the neighborhood.

Table 1
Variable Definitions and Descriptive Statistics.

Variable	Defination	unit	mean	std	min	max
Charging station attribute (Independent variable)						
Fast Pile	number of fast piles at the station	–	21.081	28.488	0.000	252.000
Slow Pile	number of slow piles at the station	–	7.526	19.227	0.000	259.000
Charging Cost	hourly charging cost	yuan/kWh	0.838	0.352	0.010	2.000
Service Cost	hourly service cost	yuan/kWh	0.439	0.226	0.000	1.500
Parking Cost	parking cost (for the first hour) at the charging station	yuan	2.408	4.319	0.000	20.000
Road Distance	Euclidean distance to the main road	km	0.078	0.073	0.001	0.496
Is Indoor	1 if the station is indoor, 0 otherwise	–	yes = 17.521%		no = 82.479%	
With Shelter	1 if the station has the shelter, 0 otherwise	–	yes = 41.157%		no = 58.843%	
At Residence	1 if the station is installed in a residential community, 0 otherwise	–	yes = 11.074%		no = 88.926%	
At Office	1 if the station is installed in a office building or company, 0 otherwise	–	yes = 17.521%		no = 82.479%	
Is Charging Hub	1 if the station is a large charging hub, 0 otherwise	–	yes = 23.802%		no = 76.198%	
Urban	1 if the station is located inside the previous special economic zone, 0 otherwise	–	yes = 26.612%		no = 73.388%	
Built environment within 500-m radius of the selected charging station (Independent variable)						
Land Use Mix	entropy index for land use mix	–	0.618	0.138	0.000	0.916
Distance to Bus Station	Euclidean distance to the nearest bus station	km	0.166	0.103	0.005	0.580
Distance to Subway Station	Euclidean distance to the nearest subway station	km	1.037	0.875	0.031	5.453
Shop	number of shops within the neighborhood	*100	1.908	2.063	0.000	24.890
Restaurant	number of restaurants within the neighborhood	*100	1.456	1.350	0.000	7.480
Office	number of offices and companies within the neighborhood	*100	1.481	1.388	0.000	14.160
Leisure	number of leisure places within the neighborhood	*100	0.216	0.224	0.000	1.810

3.4.1. Two-part framework

As shown in Fig. 3, the utilization rate is nonnegative but exhibits a substantial proportion of zero values. While numerous studies have proposed estimation techniques to handle zero-inflation, the key to model selection lies in distinguishing between actual and potential outcomes—specifically, whether a systematic difference exists between these outcomes (Dow & Norton, 2003). In this study, zero utilization rates are treated as true zeros, with no indication of selection bias related to the utilization rate. Thus, the two-part model is deemed appropriate. One of the primary advantages of the two-part model is that it avoids the assumption of an underlying normal distribution, while also tending to produce lower mean square errors when analyzing actual outcomes compared to other estimators (Duan et al., 1983).

The two-part model first employs a binary choice model to estimate the probability of observing a positive outcome versus zero. Conditional on a positive outcome, a regression model is then applied to the continuous positive dependent variable (Belotti et al., 2015; Duan et al., 1983). This approach framework can be represented as follows:

$$Pr(y > 0|X) = \phi(X\beta_1, \varepsilon_1) \tag{2}$$

$$E(y|y > 0, X) = X\beta_2 + E(\varepsilon_1|y > 0, X) = X\beta_2 \tag{3}$$

where y represents the utilization of the charging station, β is the coefficient vector associated with the explanatory variables, X is the vector of independent variables, including charging station attributes, built environment, competitive charging piles and temporal factors, and ε is a random error term.

The primary main outcome of interest, $E(y|X)$, can be derived using the decomposition equation: $E(y|X) = Pr(y > 0|X) \times E(y|y > 0, X)$ incorporating both Eq.(2) and Eq.(3). Specifically, the marginal effects for the combined model in this study can be represented as:

$$\frac{\partial E(y)}{\partial x_k} = \frac{\partial[Pr(y > 0) \times E(y|y > 0)]}{\partial x_k} = \left[Pr(y > 0) \times \frac{\partial E(y|y > 0)}{\partial x_k}\right] + \left[E(y|y > 0) \times \frac{\partial Pr(y > 0)}{\partial x_k}\right] = \beta_{2k}\phi(X\beta_1) + \beta_{1k}\phi(X\beta_1)[X\beta_2] \tag{4}$$

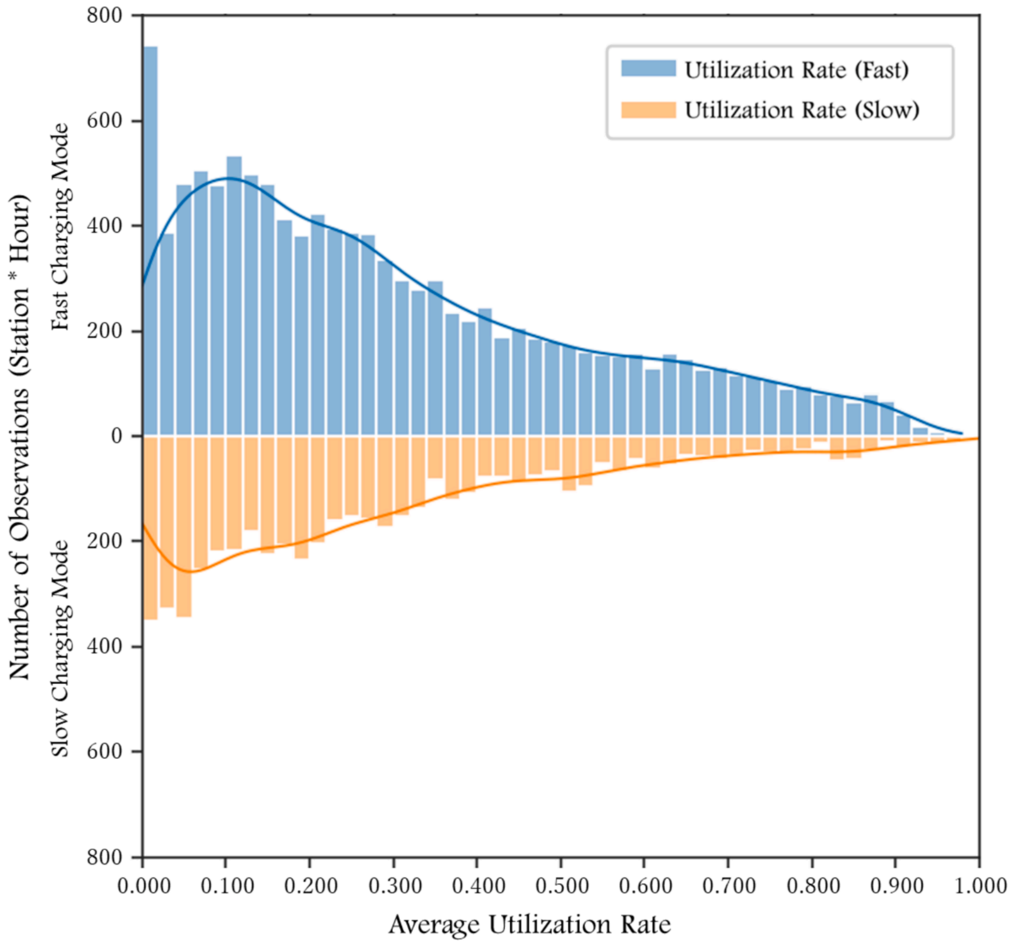

Fig. 3. Distribution of Average Utilization Rate.

3.4.2. Spatial lag of X term and spatial weight matrix Specification

Spatial econometrics is fundamentally grounded in Tobler's First Law of Geography, which states that near things are more related to each other (Tobler, 1970). This principle is operationalized through the use of a spatial weight matrix in econometric models. The choice of this matrix profoundly influences both estimation and inference (Halleck Vega & Elhorst, 2015), underscoring its critical role in spatial econometric analysis (Yamagata & Seya, 2019). Given that charging stations were represented as point vector data, a geographic distance matrix was the most suitable matrix to analyze the spillover effect. To approximate the geographic proximity between charging stations, we employed an inverse distance spatial weight matrix (W_D), where the weights are defined as $w_{ij} = 1/d_{ij}$, with d_{ij} representing the Euclidean distance between charging stations i and j.

$$
\begin{aligned}
y_{it}^{*} &= X\beta \\
&= \alpha_0 + \alpha_1 StationCapacity_i + \alpha_2 ChargingCost_{it} + \alpha_3 StationDesign_i + \alpha_4 StationLocation_i + \alpha_5 LandUseMix_i \\
&\quad + \alpha_6 AccesstoPublicTransit_i + \alpha_7 VariousDestinations_i + \alpha_8 \sum\nolimits_j w_{ij} StationCapacity_j + \gamma_t
\end{aligned} \tag{5}
$$

Following row normalization of the spatial weight matrix, a standard practice in spatial econometrics, subsequent calculations are conducted. Unlike other spatial models, the direct and spillover effects do not necessitate additional computation. As shown in Eq.(5), direct effects correspond to the coefficient estimates of the non-spatial variables, while spillover effects relate to the spatially lagged explanatory variables (Halleck Vega & Elhorst, 2015). Consequently, this model is more straightforward in terms of estimation and interpretation, and it is compatible with a non-spatial econometric framework, specifically two-part estimation in this case.

4. Results

4.1. Regression results

As shown in Table 2, columns (1) and (2) present the regression coefficients resulting from fitting the TP-SLX regression model for fast charging, while columns (3) and (4) focus on the slow charging mode. The estimation results consist of two parts, including utilization probability (Adoption) and conditional utilization rate (Magnitude).

4.1.1. Charging station attribute

The impact of station capacity on adoption and utilization magnitude is statistically significant. Specifically, station capacity influences adoption at slow charging stations and their utilization magnitude, both significant at the 1% level. The probability of using a fast charging station increases with its capacity. At each level of fast charging utilization, the magnitude rises with the number of fast charging piles, while the number of slow charging piles has no significant effect. The likelihood of using slow charging stations increases as the number of fast charging piles decreases and the number of slow charging piles increases. Conversely, regardless of charging utilization rate, the magnitude of slow charging modes rises with an increase in fast charging piles and a decrease in slow charging piles.

Charging costs play a critical role in determining the utilization of fast charging stations. Charging fees, service fees, and parking charges significantly influence charging decisions. Regardless of fast charging utilization rates, both adoption and overall utilization magnitude decline as associated costs increase. However, the adoption of slow charging stations differs. Specifically, charging fees negatively influence the probability of utilizing slow charging stations, while service fees do not have a significant effect. Conversely, parking charges exert a positive influence. In terms of utilization magnitude, the impact of costs on slow charging is similar to that on fast charging.

Outdoor sheltered fast charging stations are more likely to be utilized, with higher utilization magnitude when located near major roads. Additionally, distance from major roads significantly affects the utilization of slow charging stations. Sheltered slow charging stations situated farther from major roads tend to have higher utilization potential, though those near major roads also experience increased utilization magnitude.

The location of charging stations is crucial for determining their utilization. Fast charging stations in residential and office settings are less likely to be adopted than those in public facilities. Conversely, fast stations within charging hubs demonstrate higher utilization magnitudes. Slow charging stations in residences and offices are less likely to be utilized than those in public facilities. Similarly, slow charging stations in urban areas consistently face lower probabilities of adoption. Regarding slow charging utilization rates, while stations in residential areas and large charging hubs show lower magnitudes compared to public facilities, those in office settings present relatively higher utilization rates. Urban slow charging stations exhibit lower usage levels.

4.1.2. Built environment

Regarding land use mix, the overall utilization of fast charging is higher at stations with more mixed land uses in the surrounding area, while the opposite trend is observed for slow charging stations. All these coefficients are statistically significant at the 1% level.

Distance to the nearest transit station significantly influences fast charging mode utilization at the 1% level. Fast charging stations near bus stops but farther from subway stations are more likely to be used. Conversely, those positioned farther from public transit stations exhibit increased utilization magnitude. For slow charging mode, greater distance from a subway station is associated with a higher likelihood of adoption, while stations situated farther from bus stops and closer to subway stations demonstrate higher utilization magnitude.

Table 2
Preliminary Regression Result Using TP-SLX Model.

	Fast Charging Mode		Slow Charging Mode	
	(1) Adoption	(2) Magnitude	(3) Adoption	(4) Magnitude
Charging station attribute				
Fast Pile	0.0431	0.0002	−0.1247	0.0014
	(5.6111)***	(2.5684)**	(−7.0195)***	(5.1568)***
Slow Pile	0.0126	0.0002	0.4942	−0.0008
	(1.9536)*	(1.5304)	(7.6230)***	(−8.9431)***
Charging Cost	−1.7158	−0.2133	−2.1164	−0.2637
	(−9.5012)***	(−23.3750)***	(−4.1337)***	(−26.8638)***
Service Cost	−0.5650	−0.1350	−1.6139	−0.0994
	(−1.9333)*	(−13.0262)***	(−1.4283)	(−6.2305)***
Parking Cost	−0.0866	−0.0115	0.2037	−0.0040
	(−7.5354)***	(−17.4355)***	(4.8190)***	(−6.0807)***
Road Distance	−0.5047	−0.0844	13.9528	−0.0925
	(−0.8475)	(−3.1583)***	(4.6542)***	(−2.3825)**
Is Indoor	−1.0148	−0.0747	−0.5777	0.0024
	(−3.7269)***	(−7.9531)***	(−0.6657)	(0.1776)
With Shelter	0.5225	0.0462	1.8229	−0.0116
	(2.8371)***	(10.4997)***	(3.6929)***	(−1.0084)
At Residence	−0.9835	−0.0222	−4.6016	−0.0293
	(−7.0539)***	(−2.7449)***	(−10.6320)***	(−4.2330)***
At office	−0.7615	−0.0380	−2.5227	0.0133
	(−5.4307)***	(−6.9067)***	(−6.7368)***	(1.7147)*
Is Charging Hub	−0.6687	0.0140	−0.3692	−0.0581
	(−4.6953)***	(3.0128)***	(−1.2068)	(−5.3528)***
Urban	−1.1306	0.0317	−3.3344	−0.1055
	(−8.0879)***	(5.4839)***	(−6.0716)***	(−14.4501)***
Built environment within 500-m radius of the selected charging station				
Land Use Mix	1.2483	0.0892	−4.9049	−0.1159
	(3.3596)***	(6.3685)***	(−2.7114)***	(−5.4936)***
Distance to Bus Station	−3.5790	0.1467	1.0392	0.2941
	(−7.3949)***	(7.3397)***	(0.9786)	(9.7622)***
Distance to Subway Station	0.2704	0.0098	0.3689	−0.0081
	(4.3852)***	(4.7818)***	(1.8086)*	(−2.2409)**
Shop	0.1535	0.0027	1.3553	−0.0066
	(3.3045)***	(1.7443)*	(6.7535)***	(−3.6355)***
Restaurant	−0.4449	0.0172	−1.0935	0.0210
	(−6.8738)***	(6.2240)***	(−4.5662)***	(5.9322)***
Office	−0.1537	0.0052	−1.0375	0.0143
	(−3.1917)***	(2.6624)***	(−6.0557)***	(5.4374)***
Leisure	3.1535	0.0309	2.0114	−0.0132
	(8.1177)***	(2.0175)**	(1.1561)	(−0.9245)
Control for competitive stations				
W * Fast Pile	0.0210	−0.0008	−0.0734	0.0004
	(2.6239)***	(−3.8208)***	(−3.8959)***	(1.8559)*
W * Slow Pile	0.0837	−0.0004	0.3772	0.0013
	(5.6443)***	(−1.0646)	(3.8338)***	(3.9634)***
Temporal factor				
Hour = 01:00	−0.1911	0.0696	0.0000	0.0251
	(−0.5376)	(4.6012)***	(0.0000)	(1.2607)
Hour = 02:00	−0.1911	−0.0119	0.0000	0.0285
	(−0.5350)	(−0.8034)	(0.0000)	(1.4346)
Hour = 03:00	−0.3061	−0.0527	−0.2819	0.0312
	(−0.8727)	(−3.6099)***	(−0.3715)	(1.5552)
Hour = 04:00	−0.2496	−0.0690	−0.2819	0.0306
	(−0.7071)	(−4.7138)***	(−0.3715)	(1.5203)
Hour = 05:00	−0.5606	−0.0657	−0.5339	0.0269
	(−1.6290)	(−4.4129)***	(−0.6988)	(1.3387)
Hour = 06:00	−0.4635	0.0179	−0.7633	0.0184
	(−1.3561)	(1.1263)	(−0.9924)	(0.9304)
Hour = 07:00	−0.3391	0.1038	−0.7616	0.0048
	(−0.9821)	(6.5619)***	(−0.9910)	(0.2505)
Hour = 08:00	0.1695	−0.0068	−0.0539	0.0207
	(0.4941)	(−0.5043)	(−0.0724)	(1.1546)

(*continued on next page*)

Table 2 (*continued*)

	Fast Charging Mode		Slow Charging Mode	
	(1) Adoption	(2) Magnitude	(3) Adoption	(4) Magnitude
Hour = 09:00	0.3894	−0.1291	0.1859	0.0408
	(1.0734)	(−10.0675)***	(0.2469)	(2.1846)**
Hour = 10:00	0.8835	−0.1090	0.5610	0.0772
	(2.3589)**	(−7.8682)***	(0.7249)	(4.0561)***
Hour = 11:00	0.9859	−0.1230	0.7193	0.0712
	(2.6102)***	(−8.8537)***	(0.8853)	(3.7357)***
Hour = 12:00	0.4581	−0.0272	−0.0553	0.0144
	(1.2519)	(−1.9998)**	(−0.0765)	(0.7743)
Hour = 13:00	0.4550	0.0901	−0.0553	0.0228
	(1.2465)	(6.2738)***	(−0.0765)	(1.2273)
Hour = 14:00	0.8201	−0.0122	0.3242	0.0543
	(2.2287)**	(−0.8563)	(0.4220)	(2.9089)***
Hour = 15:00	0.7988	−0.0969	0.2481	0.0409
	(2.1857)**	(−6.9475)***	(0.3112)	(2.2012)**
Hour = 16:00	0.7987	−0.0979	0.7232	0.0371
	(2.1783)**	(−6.9154)***	(0.8967)	(2.0075)**
Hour = 17:00	0.9735	−0.0724	0.5625	0.0218
	(2.5410)**	(−5.0466)***	(0.7263)	(1.1959)
Hour = 18:00	0.7808	−0.0601	0.3228	0.0225
	(2.1041)**	(−4.2118)***	(0.4357)	(1.2481)
Hour = 19:00	0.6505	−0.0746	−0.2681	−0.0027
	(1.6999)*	(−5.4974)***	(−0.3891)	(−0.1489)
Hour = 20:00	0.6501	−0.0041	−0.2681	0.0191
	(1.7172)*	(−0.2885)	(−0.3891)	(1.0313)
Hour = 21:00	0.5926	−0.0310	0.4526	0.0136
	(1.5686)	(−2.2560)**	(0.6004)	(0.7283)
Hour = 22:00	0.2759	−0.0764	0.4524	0.0204
	(0.7748)	(−5.7387)***	(0.6001)	(1.0571)
Hour = 23:00	0.3460	−0.1032	0.1837	0.0245
	(0.9566)	(−7.7617)***	(0.2450)	(1.2410)
Constant	3.5271	0.4681	8.7886	0.6008
	(7.7989)***	(26.8439)***	(4.4499)***	(24.3441)***
N	11,640	11,160	5,400	5,245
(Pseudo) R^2	0.2219	0.3598	0.5297	0.3181

z-statistics in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The proximity of various destinations significantly influences the utilization of fast charging stations. Specifically, the presence of nearby shops and leisure facilities increases the likelihood of charging at these stations, whereas a greater number of restaurants and offices reduces this likelihood, with these effects being statistically significant at the 1% level. Moreover, a diverse range of POIs enhances the overall utilization rate of fast charging stations. Users show a greater propensity to use slow charging stations located near a higher density of shops, as opposed to those situated in areas with more restaurants and offices. Notably, slow charging stations in areas with more restaurants and offices and fewer shops tend to experience higher utilization rates. Furthermore, leisure facilities do not significantly influence the utilization of slow charging stations.

4.1.3. Control for competitive stations

In terms of potential competition, a higher number of nearby chargers increases the likelihood of using local fast stations. Conversely, fewer fast charging piles and more slow charging piles in a neighborhood increase the adoption of local slow charging stations. However, the presence of nearby fast piles could potentially reduce local fast station utilization rates due to competition. Slow charging stations with a greater number of surrounding piles experience higher utilization magnitudes.

4.1.4. Temporal factor

Consistent with the temporal distribution in Fig. 1, the utilization of charging stations is influenced by the time of day. Fast charging mode has an overall larger diurnal variation than slow charging mode. Additionally, the utilization level of charging stations is more affected by time than whether they are used.

4.2. Marginal effect

The coefficients in Table 2 are the results of the separate parts of the two-part model and are insufficient to capture the overall impact of the independent variables. Only the calculation of the marginal effects that integrates both parts of the model can present coefficients and sign directions that fully reveal how the independent variables affect utilization rate.

Based on the further calculation, Table 3 presents the total marginal effects of the different variables. Note that these effects are for the whole sample, as opposed to calculation based on the second (magnitude) part of the model, which is typically for the conditional sample of those with positive values (Belotti et al., 2015). Columns (5) and (6) show the results of calculating the total marginal effects for fast charging and slow charging rates, respectively.

4.2.1. Charging station attribute

Station capacity: The marginal effects of fast and slow charging piles at the station are 0.0005 and 0.0003, respectively. This implies that for each additional fast and slow charging pile installed at the station, the fast utilization rate increases by 0.05% and 0.03%. Similarly, the effects on slow charging utilization are 0.0008 and 0.0017, resulting in increases of 0.08% and 0.17% per additional pile.

Charging Cost: Charging costs have a negative and significant impact on utilization at the 1% statistical level. The marginal effects for fast charging utilization in response to increases in charging, service, and parking fees are at −0.2184, −0.1340, and −0.0118, respectively. This indicates that a 1 RMB increase in these fees leads to reductions of 21.84%, 13.40%, and 1.18% in fast charging utilization rates. For slow charging, the marginal effects are −0.2665, −0.1045, and −0.0029, reflecting decreases of 26.65%, 10.45%,

Table 3
Marginal Effect of TP-SLX Model.

	(5) Fast Charging Mode	(6) Slow Charging Mode
Charging station attribute		
Fast Pile	**0.0005**	**0.0008**
	(5.7533)*	**(2.6534)***
Slow Pile	**0.0003**	**0.0017**
	(2.2143)	**(4.1518)***
Charging Cost	**−0.2184**	**−0.2665**
	(−24.8456)*	**(−27.1473)***
Service Cost	**−0.1340**	**−0.1045**
	(−13.1215)*	**(−6.3645)***
Parking Cost	**−0.0118**	**−0.0029**
	(−18.4204)*	**(−4.2907)***
Road Distance	**−0.0850**	−0.0210
	(−3.2615)*	(−0.5164)
Is Indoor	**−0.0805**	−0.0009
	(−8.7094)*	(−0.0600)
With Shelter	**0.0484**	−0.0035
	(10.9164)*	(−0.3019)
At Residence	**−0.0314**	**−0.0678**
	(−4.0772)*	**(−9.3629)***
At office	**−0.0432**	−0.0040
	(−8.0023)*	(−0.5094)
Is Charging Hub	0.0066	**−0.0581**
	(1.4026)	**(−5.4845)***
Urban	**0.0213**	**−0.1189**
	(3.7765)*	**(−15.6189)***
Built environment within 500-m radius of the selected charging station		
Land Use Mix	**0.0956**	**−0.1367**
	(6.9567)*	**(−6.1824)***
Distance to Bus Station	**0.1117**	**0.2908**
	(5.7110)*	**(9.7838)***
Distance to Subway Station	**0.0116**	**−0.0061**
	(5.7173)*	**(−1.6546)***
Shop	**0.0038**	0.0003
	(2.5033)	(0.1251)
Restaurant	**0.0129**	**0.0150**
	(4.7681)*	**(4.0979)***
Office	**0.0037**	**0.0087**
	(1.9588)*	**(3.2290)***
Leisure	**0.0552**	−0.0029
	(3.6813)*	(−0.1778)
Control for competitive stations		
W * Fast Pile	**−0.0006**	0.0001
	(−2.8860)*	(0.2902)
W * Slow Pile	0.0003	**0.0031**
	(0.9852)	**(5.0138)***

z-statistics (t-statistics) in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

and 0.29% in slow utilization rates due to a 1 RMB increase in the respective fees.

Station design: For fast charging mode, a 1 km increase in the Euclidean distance from a major road decreases utilization by 8.50%. Indoor stations show an 8.05% lower utilization rate compared with outdoor stations, whereas sheltered stations experience a 4.84% increase. However, these design factors do not significantly influence the overall slow utilization rates.

Station location: Stations in residential areas and offices exhibit 3.14% and 4.32% lower fast utilization rates compared with those in public facilities. And charging stations installed in residential areas and large charging hubs demonstrate 6.78% and 5.81% lower slow utilization rates than those in public areas. As for urban level, stations in urban areas show a 2.13% higher fast utilization rate, although the slow utilization rate is 11.89 % lower, compared with non-urban areas.

4.2.2. Built environment

Land use mix: The marginal effect of land use mix on fast charging utilization is 9.56%, while a significant negative effect on slow charging utilization is estimated at −13.67%.

Access to public transit: Each 1 km increase in distance from a charging station to the nearest bus stop or metro station correlates with increases in fast charging utilization rates of 11.17% and 1.16%, respectively. Conversely, for slow charging, a 1 km increase in distance to a bus stop and a decrease in distance to a metro station lead to utilization increases of 29.08% and 0.61%, respectively.

Various destinations: Destinations within a 500-meter radius of the charging station have a significantly positive but limited impact on fast charging utilization. An increase of 100 shops, restaurants, offices, and leisure facilities in the neighborhood results in fast utilization rate increases of 0.38%, 1.29%, 0.37%, and 5.52%, respectively. Additionally, the presence of 100 more restaurants and offices corresponds to increases of 1.50% and 0.87% in slow station utilization.

4.2.3. Control for competitive stations

The increase in nearby charging piles of another mode does not significantly affect the overall utilization of a particular mode. The marginal effect of additional fast charging piles in the neighborhood corresponds to a 0.06 % decrease in fast utilization rate, while slow charging piles lead to a 0.31% increase. This implies that fast charging primarily exhibits a competitive effect, whereas slow charging demonstrates agglomeration effects.

5. Discussion

Our results indicate the significant impact of charging station attributes, surrounding built environment, potential competitive stations and temporal factors on charging utilization rate.

Stations with greater capacity tend to have higher utilization rates, as the number of piles may affect drivers' perception of charging availability, a critical factor in their decision-making process (Lim et al., 2022). Consequently, drivers often prefer stations equipped with more piles to ensure successful charging, leading to increased utilization of those stations. However, the overall impact of the number of piles is relatively minor, which aligns with findings from prior studies (Guo et al., 2022).

Expenses have a substantial negative impact on both charging utilization (Pan et al., 2019; Wang et al., 2021). Among these expenses, charging fees significantly influence both fast and slow charging utilization rates, followed by service fees, with parking fees having the least impact. This finding is not unexpected, as EV owners tend to be price-sensitive consumers. Many choose EVs due to their perceived lower costs for both the vehicles and fuel compared to fossil-fuel alternatives.

Regarding station design, outdoor, sheltered fast charging stations close to major roads attract more users, while such attributes do not significantly affect slow charging usage. This indicates that users prioritize convenience and accessibility when utilizing fast charging stations (Anderson et al., 2018).

In terms of station location, fast charging stations situated in residential and workplace areas, and slow charging stations in residential areas and charging hubs, are less utilized compared to stations in public spaces. A study in the Netherlands showed that most charging sessions were not primarily driven by insufficient range to complete the trip but time left and the possibility to charge (Wolbertus & Van den Hoed, 2019). Thus, decentralized charging may attract higher usage than at a destination at specific times each day. Stations in urban areas exhibit higher fast utilization and lower slow utilization. This could be due to the fact that urban areas have a higher EV concentration, leading to greater demand for fast charging to accommodate busy schedules and frequent usage. And as fast chargers enable quicker turnover, which allows more vehicles to charge in a shorter time, which is crucial in densely populated areas (International Energy Agency, 2024).

Concerning the built environment, fast charging usage tends to be higher for stations surrounded by a diverse land use mix (Cai et al., 2023), while slow charging usage is higher in areas with a more homogeneous land use type. This difference may be due to the fact that fast charging mode requires a shorter time, enabling drivers to combine charging with a daily transaction or activity, such as shopping and dining. Areas with more diverse land use provide them with more opportunities for these activities during charging. In contrast, drivers who prefer slow mode are more likely to charge at the trip destinations. They typically conclude their trips first and allocate more time for charging (Philipsen et al., 2016). In this case, drivers are less concerned about whether they could complete subsequent trips when deciding to charge (Pan et al., 2020), thereby placing less emphasis on dual-use of charging time and routes for slow charging mode.

Stations located away from public transit show significantly higher use of fast charging, while those situated farther from buses but near subways experience higher use of slow charging. And the impact of proximity to buses is more substantial than that to subways. Residents with more sufficient public transportation options may rely less on cars, especially in urban areas (Saeidizand et al., 2022; Wiersma et al., 2017), and further reduce the use of charging stations. Moreover, the number of destinations in different site categories positively affects fast charging usage, highlighting the role of density in promoting fast charging usage at a site. In contrast, for slow charging sites, a higher number of nearby restaurants and offices correlates with higher slow charging rates, while the number of other types of POIs does not significantly affect slow charging utilization. Similarly, previous research (Philipsen et al., 2016), based on questionnaires, also emphasized the importance of dual-use and accessibility in evaluating charging station sites, while the connection to the public transportation network was ranked as less significant.

When considering the surrounding charging stations, fast charging primarily exhibits a competitive effect, while slow charging demonstrates agglomeration effects. This distinction likely arises from differences in charging behavior and station characteristics. Drivers typically seek fast charging stations when the battery is low or during time-sensitive multitasking. For example, a study in Japan reveals that fast-charger users are generally willing to charge at stations requiring a shorter detour (Sun et al., 2016). As a result, they often choose the nearest or most accessible station to minimize waiting times, resulting in increased competition between stations as the number of fast charging stations in an area grows. Conversely, slow charging stations are usually located where EV owners can leave their vehicles for extended periods. A study of electric taxi drivers' choice of public charging stations shows that drivers are willing to tolerate a longer driving time when they expect a longer charging duration (Guo et al., 2022). Thus, drivers may gravitate towards areas with multiple slow chargers, fostering a network effect that attracts more users to charge in the neighborhood. These findings further prove that fast and slow charging stations cannot be used interchangeably in planning charging infrastructure.

We could draw the following policy implications based on the above findings. On the one hand, investors need to adopt a more rational approach. In selecting station sites, they should avoid indiscriminate expansion and instead choose locations based on appropriate charging modes. At the same time, since capacity is often limited by factors such as grid availability and construction costs, these constraints should be addressed during the planning process, as they are challenging to adjust during the operational phase. On the other hand, efforts could be made to reduce charging and service fees and possibly offer free parking incentives to attract more vehicle owners. And given the peak and off-peak usage times of public charging stations, operators could implement a pricing strategy to encourage "off-peak charging". By attracting price-sensitive drivers to charge during off-peak hours, this strategy could extend the overall usage time of charging stations and enhance utilization rates.

This study has several limitations. First, while considering the impact of neighboring piles of different modes, it remains challenging to fully address the potential spatial autocorrelation issue considering the spatial interaction of two different charging modes. Currently, there is no comprehensive spatial autoregressive model that is able to fully capture the effects of different charging modes in neighboring areas on local usage of a particular charging mode. Additionally, as an exploratory study, the research primarily focuses on the quantification of the potential impacts of various factors on charging station utilization, without digging deeply into underlying mechanisms. Therefore, follow-up research needs to consider employing qualitative research methods, such as in-depth interviews with EV drivers and charging station operators to look into the mechanisms. Moreover, since the study focuses on the influences on charging station utilization, an important caveat is that any policy measures based on the found associations need to be further examined carefully because they might improve utilization rates but do not account for other objectives such as accessibility. Subsequent studies on spatial layout optimization need to comprehensively consider the charging service and demand, in order to improve the allocation of charging resources and enhance the charging experience for EV drivers. Additionally, it would be valuable for future research to compare results across different user types, such as private vehicle owners, taxi drivers, or urban logistics drivers. Different user profiles and locations may exhibit varying charging preferences and patterns. Lastly, with the emergence of new technologies like supercharging and battery switching, more charging modes and behaviors require further exploration.

6. Conclusion

This study presents findings from utilization patterns in public charging stations and their influencing factors in an Asian dense city from a supply side. Through descriptive statistics, we identified: (1) temporal distribution and differences in utilization between fast and slow charging modes; (2) spatial patterns of station utilization. Moreover, through a two-part regression analysis, we quantified the correlation between charging station (dis)utilization and station attributes, as well as the built environment.

Key findings include: (1) The diurnal variation in utilization rate is more pronounced than the difference between weekdays and weekends. Additionally, fast charging utilization varies more throughout the day compared to slow charging. (2) Fast charging stations exhibit higher average utilization rates, particularly in the medium charging rate range. Stations with low average slow utilization rates are more concentrated in urban areas. (3) Stations with greater capacity tend to have higher utilization, although this impact is relatively minor. The number of fast piles in the neighborhood decreases fast station utilization, while an increase in slow piles enhances slow charging utilization rates. Charging fees have the most significant influence on both fast and slow mode, followed by service fees, with parking fees having the least impact. Outdoor, sheltered fast stations near major roads attract more users, while these attributes do not significantly affect slow charging usage. Fast charging stations in residential areas and workplaces, and slow charging stations in residential areas and charging hubs, are less utilized compared to those in public facilities. (4) Fast charging utilization is higher in stations surrounded by a diverse mix of land uses, whereas slow charging shows the opposite trend. Stations farther from public transit exhibit significantly higher use of fast charging, and those away from buses or near the subway experience significantly higher use of slow charging. The distance to the nearest bus has a greater impact than to the subway. The number of destinations in different site categories contributes to increased fast charging usage, indicating that higher density boosts fast charging activity at the site. Conversely, more nearby restaurants are associated with higher slow charging rates, while other types of POIs do not significantly affect slow charging utilization. These findings provide insights for the allocation, evaluation, and optimization of charging infrastructures, thereby further advancing the development of the new-energy market and sustainable transportation.

CRediT authorship contribution statement

Mushu Zhao: Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Dawei Wang:** Methodology, Data curation. **Weifeng Li:** Writing – review & editing, Supervision, Methodology. **Jianzheng Liu:** Writing – review & editing, Methodology.

Declaration of competing interest

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

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.trd.2024.104506.

Data availability

Data will be made available on request.

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