Assessing Levels of Urban Public Electric Vehicle Charging Service in Different-level Cities: A Case Study of the 35 Cities of the Chengdu–Chongqing Urban Agglomeration, China

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Abstract: Urban public electric vehicle charger (PEVC) plays a vital role in meeting the sustainable development needs of countries with low single-family home ownership rates, promoting vehicle electrification, and achieving SDGs. There are significant variations in the provision of PEVC across regions and cities in China, particularly among cities of different levels, which, yet, has not received sufficient attention, hindering targeted PEVC development planning in the cities. To clarify these disparities, this study combines an analysis of the supply and usage costs of PEVCs, which are the main factors affecting vehicle electrification, and evaluate the disparities in PEVC service among 35 cities of varying levels in Chengdu–Chongqing Urban Agglomeration. The results indicate that mega-cities exhibit the highest service levels, attributed to their strong supply capacity and well-developed pricing mechanisms. Medium-sized and small cities show intermediate PEVC service, while large cities unexpectedly demonstrate the lowest supply levels and highest usage costs due to the mismatch between PEVC and population size. Additionally, the study highlights the priority of PEVC station scale in enhancing the supply. These findings provide practical insights for policymakers to formulate targeted policies and strategic planning based on the current status of PEVC services in cities of different levels.

Keywords: Vehicle electrification, PEVC service, PEVC supply, PEVC usage costs, city levels, SDGs

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1 Introduction

Vehicle electrification can significantly reduce greenhouse gas and hazardous substance emissions at a much lower cost. During the year 2021, the electric vehicles (EV) worldwide have consumed 50 TWh of electricity, accounting for only 0.5% of the world’s total electricity consumption and replacing 0.3 Md/d of oil consumption, which will take 7 Md/d to achieve the global Net Zero Scenario (NES) by 2030 (IEA, 2022), aligning with the objectives of the Sustainable Development Goals (SDGs) in promoting sustainable development and environmental protection. In the long run, EV infrastructure development is the primary driving force for vehicle electrification (Hagem et al., 2023). Electric vehicle charger (EVC) is an essential EV infrastructure and is divided into home-based and public-based electric vehicle charger (HEVC&PEVC). Compared to HEVCs, PEVCs are irreplaceable (Yi et al., 2023) due to the fulfillment of intercity travel electricity demand and urban EV users’ demand, including low- and middle-income EV users who cannot afford HEVCs and users of urban transportation services, such as cabs (Yang et al., 2018), intra-city freight, shared EVs, etc. Therefore, countries around the world are sparing no effort to promote the construction of urban PEVCs. As early as 2020, China set out its ambitious "Dual Carbon Goal", which is China's commitment to peak its carbon dioxide emissions before 2030 and achieve carbon neutrality by 2060, and the construction of PEVCs is regarded as an important initiative to promote the transformation of energy structure. In 2021, China accounted for 85% of the world’s total number of fast PEVCs and 55% of slow PEVCs (IEA, 2022), cementing its front-runner status in the world’s three major EV markets, including Europe, the US and China.

In comparison to the US and Europe, China exhibits a more pressing demand for the
development of PEVCs. Boasting the world's largest urban population of 900 million, China surpasses the United States by 3.4 times and Europe by 1.57 times (UN, 2018). However, Chinese cities face more constrained conditions in terms of HEVCs deployment when compared to their European and American counterparts. Notably, HEVCs remain the prevailing mode of charging in the United States and the European Union, constituting approximately 75% to 80% of the total charging infrastructure (Engel, 2018; Smart and Schey., 2012). In contrast, relying on the case of Shanghai, China, a mere 5.3% of users have access to private charging facilities (Ou et al., 2018). This limited availability can be attributed to lower single-family home penetration in China (Engel, 2018). Consequently, the promotion of public charging infrastructure construction better aligns with China's requirements for vehicle electrification.

According to China Electric Vehicle Charging Infrastructure Promotion Alliance (http://www.nea.gov.cn/2023-03/20/c_1310703965.htm), the construction of urban PEVCs is extremely unbalanced between regions and cities in China. The number of PEVC in the top 10 regions in China accounts for 71.2%, while the remaining 24 regions only account for 28.8%. In Sichuan Province, Chengdu (a mega-city) alone accounts for 48.7% of the total number of PEVCs in the province, while the remaining 20 small and medium-sized cities account for 51.3%. The research conducted by Li et al. (2022) also indicates a significant disparity in the PEVCs development among the top ten cities in China, concluding that cities of varying levels exhibit distinct capacity and characteristics of PEVCs service provision. In order to systematically explore the differences and commonalities in PEVC service among cities of different levels, it is necessary to characterize the PEVC service in the cities as a way to provide a broader range of decision-making guarantees for promoting vehicle electrification in China.
To assess the PEVC service, a rich literature has measured the service capacity from the perspective of PEVC supply, as detailed in Section 2. In fact, the supply of charging infrastructure plays a crucial role in the EV adoption and early EV market formation, which is positively correlated with potential users' willingness to adopt EVs (Narassimhan and Johnson, 2018). In addition, there are also some scholars have proposed that cost factors play a more pivotal role compared to the supply of PEVCs in the promotion process of EV adoption (Miele et al., 2020). The usage cost of EVCs is a significant component of EV users' total cost of ownership (TCO) (Hagman et al., 2016). The usage cost of EVCs is negatively correlated with users' willingness to adopt EVs (Ghasri et al., 2019). Therefore, the supply and usage cost of a particular city's PEVCs determine the convenience in using PEVCs and EV purchasing intentions for users in that city, serving as a direct reflection of the city's PEVCs service. Nonetheless, the lack of analysis of city's PEVCs service from the comprehensive perspective of PEVCs supply and usage cost, which represents the promoting and inhibiting factors of EV adoption, especially the perspective of usage cost, is witnessed. In addition, existing research has limitations in terms of the study scope, as both single-city and multi-city studies on PEVC tend to focus on major cities, neglecting the attention towards small and medium-sized cities. This results in a narrow research scope that fails to reflect the broader status of PEVC service in cities.

To address the gaps, this study aims to compare the PEVC service of cities of different levels from the perspectives of PEVCs supply and usage costs. Specifically, we select 35 cities of varying levels in the Chengdu-Chongqing urban agglomeration in China as research subjects. Through web scraping and commercial map interfaces, the study obtains attributes such as the characteristics of usage, fees, location of PEVCs, as well as the PEVCs’ accessibility time. The PEVC supply in cities
are analyzed by using the Two-Step Floating Catchment Area (2SFCA) method, shortest travel time, average travel time, and isochronous circle analysis. The variations in PEVCs usage costs in cities are measured by analyzing the all-day cost changes of PEVC in each city.

The remainder of the paper is organized as follows: Section 2 provides a literature review on the research topic. Section 3 presents the data and methods, including the selection of the study area, data collection on PEVCs, calculation and analysis of spatial accessibility. Section 4 presents the main findings of this study, which will be further discussed in Section 5. Finally, Section 6 presents the main conclusions and corresponding policy recommendations.

2 literature review

2.1 PEVC supply

The supply capacity of PEVC is typically defined as its ability to meet the demand for electric vehicles (EVs) within a given region (Dong et al., 2019), and it has been empirically established as a primary driver for vehicle electrification, exerting a positive impact on consumers' EV choices (Narassimhan and Johnson, 2018; Zhou, 2016). Moreover, this impact is particularly pronounced within urban areas (Mersky et al., 2016; Zhang et al., 2016). Studies pertaining to the supply of PEVC predominantly revolve from the perspective of quantity and spatial pattern.

Top-down data has been employed to quantitatively measure the PEVC supply at the regional scale. IEA (2022) and Engel (2018) have relied on data such as regional PEVC energy demand, the number of PEVC installations, types of PEVCs, total electricity supply, and investment to objectively assess the PEVC supply in major EV markets worldwide. However, such data have only
reflected the quantity-based PEVC service at the regional level and have not provided a spatial assessment of PEVC supply.

Spatial analysis can further quantify the PEVC service, facilitating PEVC development and planning. The optimizing of public electric vehicle charging stations (PEVCS) locations is a key focus in current PEVC research. These studies have utilized bottom-up spatial data to spatialize PEVC demand by using a series of indicators and overlaid them with PEVCS locations. It is considered that PEVC supply can be ensured when the PEVCSs are within a certain distance from demand points (Yi et al., 2022). For instance, Yi et al. (2023) have used the CMCLP model to assess the optimal PEVC deployment pattern in Salt Lake City, where the PEVC supply is characterized by information such as PEVC locations, quantity, charging status, and real-time power. In fact, the location optimization research for PEVCS, based on the principle of measuring PEVC supply through the proximity of supply and demand, shares similarities with the computation principle of opportunity accessibility, which directly aggregates the number of supply points reachable within a given travel time or distance to measure the fulfillment of demand by the supply (Chen et al., 2019).

Based on this principle, Li et al. (2022) have highlighted the role of opportunity accessibility in evaluating the spatial patterns of PEVCS and applied it in the study of spatial equity of urban PEVCs. The study has examined the spatial equity of PEVC supply in 10 major cities of China through the analysis of opportunity accessibility. However, the supply analysis based on opportunity accessibility primarily focuses on depicting the coverage of supply to demand, while overlooking the spatial reverse impact of demand on supply (Chen and Jia, 2019). Taking into account the interaction between supply and demand and the influence of distance decay, the two-step floating catchment area (2SFCA) method effectively measures the supply and demand of public service...
facilities and provides a more comprehensive assessment of the supply of public service facilities (Luo and Wang, 2003). Park et al. (2022) has employed the 2SFCA method to calculate the PEVCS supply-demand ratio in Seoul within a 24-hour period, thereby assessing the spatial accessibility variation of PEVCSs in Seoul throughout the day. By considering the PEVC quantity, spatial distribution, and population supply-demand ratio, the 2SFCA method offers a comprehensive evaluation of PEVC supply in Seoul.

The spatial alignment of PEVC location optimizing and the analysis of PEVC accessibility offer a more realistic approach to matching PEVC quantity with demand, moving beyond a simplistic calculation of PEVC numbers for demand fulfillment. Moreover, travel time reflects the ease for the demand to access the supply. The study conducted by Park et al. (2022) have depicted isochronous circle of PEVC travel time coverage, evaluating the transportation coverage capability of PEVCSs in Seoul. Falchetta and Noussan. (2021) focused on the shortest travel time of PEVCs, addressing the question of "how long it takes for EV users to reach the nearest PEVC," using the minimum travel time it takes for users to reach PEVCs as a measure of regional PEVC supply capacity.

In general, studies employing spatial analysis to assess the PEVC service predominantly focus on examining the spatial patterns rather than specifically addressing the supply of PEVC or evaluating the overall supply capacity in urban areas, due to research objectives. To address these gaps, this study employs the 2SFCA method to evaluate the supply capacity of urban PEVC and utilizes travel time and isochronous circle to depict the accessibility between supply and demand. This approach aims to provide a more comprehensive characterization of the PEVC supply. Detailed methods are presented in Section 3.
2.2 PEVC Usage Cost

Fuel prices have a significant impact on consumer preferences (Javid and Nejat, 2017) for EVs due to the lower total cost of ownership (TCO) compared to gasoline and hybrid vehicles (Hagman et al., 2016). Charging costs play a vital role in EV users' TCO (Wu et al., 2015), and the usage cost of PEVC in cities directly influences the charging expenses incurred by EV users, thereby influencing the EV adoption rate in the region. Therefore, the usage cost of PEVC in urban areas serves as an important indicator for assessing the quality of PEVC services. Previous studies on urban PEVC costs have primarily explored factors affecting PEVC costs and strategies for optimizing cost mechanisms.

Muratori et al. (2019) have conducted a study on the electricity cost of 7,500 PEVCs in the United States and found notable variations in electricity costs, primarily driven by the uncertainty associated with power plant design and usage. The study also reveals that lower utilization rates lead to higher electricity costs for PEVCs. Flores et al. (2016) has further demonstrated that increasing utilization rates can significantly reduce PEVC electricity costs. Additionally, Schroeder and Traber (2012) showed that lower utilization rates decrease the profitability potential for PEVC suppliers. These studies extensively investigate the factors influencing PEVC costs and to some extent reflect the level of PEVC electricity prices in the study area.

Different from the aforementioned studies, some researches focus on the dynamic pricing variation of PEVC. Zhou et al. (2020) have developed a dynamic charging scheduling model to optimize costs. Their research reveals that the lowest electricity prices occur during the non-peak hours of 2 am-8 am, at approximately 50% of the daytime rates, while the peak hours of 8 pm-11 pm exhibit a cost increase of about 16% compared to the non-peak hours. This finding is similar to
the results obtained by Di Giorgio and Liberati (2014), who have observed price peaks during the evening hours due to fluctuations in daytime usage rates. The fluctuation of dynamic pricing reflects the varying usage frequency of urban PEVC throughout the day, providing valuable insights into the service characteristics of PEVC in cities of different scales. By comparing the dynamic pricing characteristics of PEVC in cities of various levels, it is possible to depict the usage pressure experienced by urban PEVC systems.

However, constrained by the research objectives, the aforementioned studies have not utilized the cost characteristics of PEVC usage to delineate the PEVC service in cities, let alone comparing them. Therefore, it is imperative to analyze the variations and commonalities in PEVC service across cities of different levels from the perspective of usage costs.

2.3 Scale of PEVC Research

A systematic review of existing PEVC researches reveals that the current studies can be broadly categorized into three scales: macro, meso, and micro perspectives (Table 1).

The macro perspective focuses on large-scale regional PEVC studies, which primarily aim to explore the overall development of PEVC in a region and the variations within the region. Examples of such research include analysis of major PEVC markets worldwide (IEA, 2022), analysis of PEVC accessibility in Europe (Falchetta and Noussan, 2021), research on PEVC costs in the United States (Muratori et al., 2019), and studies on the factors influencing PEVC adoption in California (Javid and Nejat, 2017). These studies provide valuable insights into the overall development of PEVC at the regional level but may overlook the specific characteristics of urban PEVC.

The meso perspective focuses on comparative studies of PEVC at a multi-city scale. These
studies analyze cities as individual units and compare the development levels of PEVC among different cities to identify commonalities and characteristics in urban PEVC development. Examples include studies on the spatial patterns of PEVC in 41 major Chinese cities (He et al., 2022) and the spatial equity of PEVC services in 10 major Chinese cities (Li et al., 2022).

The micro perspective examines PEVC researches at the scale of individual cities. These studies uncover the mechanisms driving the development of PEVC within a specific city. Examples of such researches include optimization of PEVC location selection in cities (He et al., 2016; Yi et al., 2023), analysis of spatial accessibility of PEVC within cities (Park et al., 2022), and the identification of optimal pricing strategies for PEVC in urban areas (Zhou et al., 2020).

However, both the meso and micro perspectives of the researches have primarily focused on mega-cities and large cities, neglecting the development characteristics of PEVC in small and medium-sized cities, which is unavoidable emerging markets of EVs. This oversight has resulted in a limited perspective in existing research, which hampers the provision of comprehensive policy references for policymakers and planners. Therefore, this study selects 35 cities of different levels as research objects to investigate the commonalities and differences in PEVC services.
Table 1. PEVC Studies of Different Scales

<table>
<thead>
<tr>
<th>Scale</th>
<th>Citation</th>
<th>Case Study</th>
<th>Objective</th>
</tr>
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<tbody>
<tr>
<td>Macroscale</td>
<td>IEA (2022)</td>
<td>Global</td>
<td>Analysis of the EV market</td>
</tr>
<tr>
<td></td>
<td>Falchetta and Noussan (2021)</td>
<td>Europe</td>
<td>PEVC accessibility</td>
</tr>
<tr>
<td></td>
<td>Muratori et al. (2019)</td>
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<tr>
<td></td>
<td>Di Giorgio and Liberati (2014)</td>
<td>Italy</td>
<td>Rate optimization for PEVC</td>
</tr>
<tr>
<td></td>
<td>Wu et al. (2015)</td>
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<td>TCO comparative</td>
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<tr>
<td></td>
<td>Javid and Nejat (2017)</td>
<td>California</td>
<td>Impacts of EV adoption</td>
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<td></td>
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<td>Mesoscale</td>
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<tr>
<td>Microscale</td>
<td>Yi et al. (2023)</td>
<td>Salt Lake City</td>
<td>PEVC location optimization</td>
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<td></td>
<td>Park et al. (2022)</td>
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<td>PEVC Spatial accessibility</td>
</tr>
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<td></td>
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<td></td>
<td>He et al. (2016)</td>
<td>Beijing</td>
<td>Institution and spatial factors in PEVC location optimization</td>
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3 Materials and methods

The methodology framework comprises three main components: data process, PEVC supply, and PEVC cost, as illustrated in Figure 1. In the data processing phase, demand grids for urban PEVC are created based on population and urban built-up area (Fig 1.a), while the supply points are derived from PEVC data collected through web scraping (Fig 1.b). The travel time between supply points and demand points is then computed using the Baidu Maps API, resulting in a travel time matrix (Fig 1.c). In the supply analysis (Fig 1.d,e,f,g), metrics such as shortest reachable time (MTT), average reachable time (ATT), isochronous circles, and supply-demand ratio are calculated using the matrix to assess the PEVC supply in cities. In the cost analysis (Fig 1.h), the PEVC costs for different time periods in each city are computed using the PEVC data collected through web scraping. The following subsections elaborate on the specific details of these three components.
3.1 Data Resources

This study focuses on the urban built-up areas within the Chengdu-Chongqing City Cluster, encompassing 35 administrative districts, to investigate the PEVC service across cities of varying scales. The Chengdu-Chongqing City Cluster, situated in the southwestern region of China, serves as a prominent economic hub in the western part of the country. However, there exists a significant disparity in internal PEVC infrastructure development, as discussed in section 1. Consequently, fostering the development of the PEVC infrastructure within the Chengdu-Chongqing City Cluster contributes to the pursuit of regional equilibrium. The cluster comprises mega-cities (Chengdu, Chongqing), large cities (Mianyang, Yibin, etc), medium-sized cities (Fuling, Ziyang, etc), and small...
cities (Zhongxian, Nanchuan, etc), ensuring the comprehensive representation of the research scale. According to the Chinese Urban Level Classification Standard (https://www.gov.cn/zhengce/content/2014-11/20/content_9225.htm), the cities in the study area are categorized as follows: there are two mega-cities with a population of over 10 million, namely Chengdu (CD) and the main urban area of Chongqing (CQ). 13 large cities with a population between 5 million and 10 million, including Dazhou (DZ), Deyang (DY), Guang'an (GA), Leshan (LS), Luzhou (LZ), Meishan (MS), Mianyang (MY), Nanchong (NC), Neijiang (NJ), Suining (SN), Wanzhou (WZ), Yibin (YB), and Zigong (ZG). 9 medium-sized cities with a population between 1 million and 5 million, namely Bishan (BS), Dazu (DU), Fuling (FL), Hechuan (HC), Jiangjin (JJ), Kaizhou (KZ), Ya'an (YA), Yongchuan (YC), and Ziyang (ZY). There are 11 small cities with a population below 500,000, including Changshou (CS), Dianjiang (DJ), Fengdu (FD), Liangping (LP), Nanchuan (NH), Qijiang (QA), Rongchang (RC), Tongliang (TL), Tongnan (TN), and Zhongxian (ZX).

![Fig.2 Cities of different levels: megacities (black line), large cities (blue line), medium-sized cities (green line), and small cities (red line).](image)

The city boundary data (Fig.1.a) used in this study is derived from the 2020 China Urban
Impervious Layer Data published by Sun et al. (2021). This dataset provides vector data of the built-up areas for 433 cities in China with a population greater than 300,000. However, as some small cities in the study area are not included in this database, we supplemented the data using the annual China Land Cover Dataset (CLCD) developed by Yang and Huang (2021). The city boundaries were determined by vectorizing the built-up areas of these cities using Google Earth.

We utilized the WorldPop (www.worldpop.com) dataset (Fig. 1.a) for the year 2020 at a resolution of 100 meters to obtain population distribution data. To align with the accessibility grids, we employed ArcGIS software to merge and downscale the grids to a resolution of 200 meters.

3.2 Public Electric Vehicle Charging Stations (PEVCS)

The PEVC data (Fig. 1.c) utilized in this study was obtained from a commercial source, namely the "Charging Bar (www.bjev520.com)" , which serves electric vehicle users across all cities in mainland China. This application allows users to geolocate the nearest PEVCS based on their preferences, and the data is continuously updated in real-time. Unlike non-profit international databases such as Open Charge Map (OCM), which may exhibit delays in site establishment and data entry, as well as potential underreporting of technical issues at certain stations (Falchetta and Noussan, 2021), commercially-driven PEVC service applications benefit from active user engagement, providing a wealth of real-time feedback and error correction. Consequently, these localized commercial databases offer higher levels of accuracy and timeliness. Nonetheless, it is important to note that the advantages of “Charging Bar” lacks empirical verification in the absence of supporting evidence.

The PEVCS data was obtained through a Python program that sent requests to “Charging Bar”
for web scraping. The data retrieval process was conducted on October 21, 2022, and it included PEVCS data from 35 cities. Each PEVCS data entry consists of the following information:

- **PEVCS Name:** The name of the PEVC and its open status (the open status is indicated within parentheses after the name, including "Open to the Public," "Internal Use Only," or "Not Open").
- **Location:** Administrative region, latitude, and longitude.
- **Available PEVC Count:** The number of fast chargers and slow chargers.
- **Rate Information:** Electricity rate, service rate, and parking fees. Parking fees are constant, while charging fees and service fees are divided into multiple time periods, each with different prices. These time periods cover the 24 hours of a day.
- **Opening Hours:** The opening hours of each PEVC within a day.

These parameters were used for all the analyses in this study. However, it should be noted that this study does not encompass all the information types displayed on the website, and other parameters were not selected for analysis.

After obtaining the latitude and longitude of PEVCSs in each city, we spatially overlaid the points of interest (POI) with the urban built-up areas to exclude PEVCS data outside the city boundaries, particularly in rural areas and highway service areas. Only PEVCSs in the "open" state were included in the analysis, excluding those not accessible to the public or limited for internal use. Among the obtained PEVCSs, 99.7% were classified as "open all day," resulting in the exclusion of PEVCs not meeting this criterion. Due to software limitations, the study only displayed the quantities of "fast charging stations" and "regular charging stations," without distinguishing between different power levels (DC and AC). Consequently, a weighted combination of fast charging stations and regular charging stations was performed, as explained in section 3.4.
Regarding cost information, each PEVC’s cost was presented in time intervals. To address this, a 24-hour cost table was created, allocating the corresponding interval costs of each charging station to specific time points.

3.3 Travel time matrix

The travel time between nodes is the core of accessibility calculations. Internet map APIs can directly facilitate this process, as internet maps based on big data and AI algorithms provide more realistic real-time traffic data and more accurate route planning capabilities. Additionally, they offer convenience by simply inputting the origin and destination coordinates, along with the chosen mode of transportation, to obtain accurate travel time data.

Based on this, the calculation of travel time in this study consists of two main parts (Fig.1.c): the origin-destination pair table and API data retrieval. The origin-destination pair table includes the coordinates of the starting points (grids) and the destination points (PEVCSs). Specifically, the study divides the urban built-up area vector data of each city into 200m x 200m grids, represented as square-shaped grids. The central point of each grid is considered as the starting point coordinate. While previous studies, such as those by Liao et al. (2020), have utilized hexagonal grids to better consider the directional aspects of spatial calculations and improve accuracy in traditional simulation methods, internet map APIs do not require such considerations and are capable of guaranteeing accuracy by directly calculating point-to-point travel time.

After obtaining the origin and destination coordinates, the pandas library is used to concatenate them and create an origin-destination correspondence table. This table is then inputted into the Baidu Maps API (https://lbsyun.baidu.com), where the route planning function is called with the

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transportation mode set to "driving." This process allows for obtaining the travel time between each origin and destination pair, resulting in a travel time matrix (Fig.1.c).

Using the travel time matrix, we calculate the average travel time, shortest travel time, and isochronous circle for each grid. Then, at the city scale, the average travel time (ATT), minimum travel time (MTT), and average size of PEVCs isochronous circles are calculated for each city.

The average travel time (ATT) calculates the average time it takes for each grid to reach all PEVCs (Fig.1.e).

\[ T_i = \frac{\sum_{j=1}^{n} T_{ij}}{n} \]  

In the equation, \( T_i \) represents the average travel time for grid \( i \), \( T_{ij} \) represents the travel time from grid \( i \) to PEVCs \( j \), and \( n \) represents the number of PEVCs.

As shown in Fig.1. (d) and Fig.1. (f), the calculation of the minimum travel time (MTT) and isochronous circle is performed using the “groupby” function in the Python library Pandas. The MTT is obtained by applying the “groupby” function to the matrix, which calculates the minimum travel time for each grid corresponding to a PEVC. For the isochronous circle, different travel time thresholds are set, and the “groupby” function is used to count the number of grid cells that satisfy the criteria for each PEVC in the matrix.

### 3.4 Two-Step Floating Catchment Area (2SFCA)

The Two-Step Floating Catchment Area (2SFCA) method measures the spatial efficiency of urban services by considering two aspects: the interaction between supply and demand and distance decay (Chen and Jia, 2019; Dai, 2011; Wang, 2012). Due to the publicness of PEVCs, our study prioritizes fairness when defining supply and demand (Tsou et al., 2005). It emphasizes that all
residents, regardless of their location, educational attainment, income, living conditions, and age structure, should have equal access to urban services. Therefore, this research uses population distribution to characterize demand and PEVCSs locations and scales to represent supply. The 2SFCA method consists of two steps. The first step calculates the supply-to-demand ratio for each supply point (PEVC) within a certain travel range, and the calculation method is shown in the following formula:

$$R_j = \sum_{k \in \{d_{kj} \leq d_o\}} \frac{S_j}{D_k f(d_{ij})}$$

(2)

In the equation, $R_j$ represents the supply-to-demand ratio at point j, $S_j$ represents the supply scale at point j, which is represented by the number of PEVCs in each PEVCS. As mentioned in section 3.2, due to the unavailability of precise data on the power of each PEVC, this study refers to the research conducted by Falchetta and Noussan (2021) and takes the average power of fast charging stations and regular charging stations in a broad sense. The power of fast charging stations is standardized to 30 kW, and the power of regular charging stations is standardized to 15 kW. Based on this power, we set the weight of the fast charging station count to 1 and the weight of the regular charging station count to 0.5. We then sum up the weighted number of PEVCs for each PEVCS to represent $S_j$. $D_k$ represents the demand scale at point k, which is represented by the population count. $d_{kj}$ represents the cost of accessing PEVC services between point k and point j, which is represented by travel time. $d_o$ is the search radius, and $f(d_{ij})$ represents the general form of the distance decay function. The calculation of $f(d_{ij})$ is explained in detail in formula 4 and 5.

The second step involves searching for all PEVCS points within a certain travel range of each grid point i. The $R_j$ values of the PEVCSs are then summed up to obtain the supply-demand level $A^f_i$ for point i. The calculation method is as follows:
\[ A_i^f = \sum_{j \in \{d_{ij} \leq d_0\}} R_i f(d_{ij}) = \sum_{j \in \{d_{ij} \leq d_0\}} \sum_{k \in \{d_{kj} \leq d_0\}} S_{ij} f(d_{ij}) D_{kj} f(d_{kj}) \] (3)

In the equation, \( A_i^f \) represents the supply-demand level PEVCS at point \( i \), \( d_{ij} \) represents the travel time between point \( i \) and point \( j \) to access PEVC services. The function \( f(d_{ij}) \) is the general form of the distance decay function, which incorporates Tobler's first law of geography stating that spatial entities have mutual influences that diminish as distance increases (Tobler, 1970). The function \( f(d_{ij}) \) quantifies this principle, and its calculation method is as follows:

\[
f(d_{ij}) = \begin{cases} g(d_{ij}) & d_{ij} \leq d_0 \\ 0 & d_{ij} > d_0 \end{cases}
\] (4)

\[
g(d_{ij}) = \frac{e^{-\frac{1}{2}d_{ij}^2/d_0^2}}{1-e^{-1/2}}
\] (5)

In the equation, \( d_0 \) represents the specified search radius, \( d_{ij} \) represents the travel time between point \( i \) and point \( j \), and \( g(d_{ij}) \) represents the distance decay function when \( d_{ij} < d_0 \). When \( d_{ij} > d_0 \), \( f(d_{ij}) \) is set to 0, meaning that points outside the search range are not included in the calculation.

The distance decay function used in this study is the Gaussian distance decay function.

Determining the search radius \( (d_0) \) for public service facilities is crucial in the 2SFCA method and depends on the utilization patterns of services and the activity space of consumers (Wang, 2012). Rooted in Tobler's theory, it is assumed that the benefits of spatial interactions must outweigh the travel costs between demand and supply, and a reasonable search radius is determined within this threshold (Chen and Jia, 2019). However, current research on PEVCs is still in its early stages, and these criteria have not been thoroughly investigated (Park et al., 2022). Park et al. (2022) determined the search radius for 2SFCA as 15 minutes by examining the time taken by EV users in Seoul to reach the nearest charging station. However, we have considered that different user preferences, such as differences in commuting distances, commuting times, and transportation modes, may lead...
to variations in the preferred PEVC service radius (Pan et al., 2020). Therefore, this study sets different thresholds as service radius in intervals of 5 minutes within the range of 5 minutes to 60 minutes, aiming to explore variations in PEVC supply within multiple search ranges and differences in PEVC supply across the city.

In the first step of the 2SFCA, the individual $R_j$ of a PEVCS is mainly determined by two factors: $S_j$ and $D_k$. $S_j$ represents the number of EV chargers per station (NECS). A higher NECS indicates a stronger supply capacity of the individual PEVCS. Secondly, the population covered by a single PEVCS within the $d_0$ represents the demand scale of the PEVCS, denoted as $D_k$, which refers to the population density. A higher average population density in a city implies a larger demand scale for each PEVCS within the search range.

In the second step, the $R_j$ values of all PEVCSs within the $d_0$ for each grid are aggregated. Therefore, a city with a higher PEVCS density will have a greater number of PEVCSs within the $d_0$. This results in higher $A^F$ values for the grids, indicating a higher level of accessibility, and a larger overall $A^F$ value for the city. To measure the overall $A^F$ and characteristics of a city, this study calculates the average $A^F$ value for all grids within each city. Additionally, by comparing the average NECS, average PEVCS density, and city population density, the $A^F$ of different cities can be characterized.

### 3.5 PEVC cost

The usage cost of PEVC primarily consists of three components: electricity cost, service cost, and parking cost. Among these, the “Charging Bar” provides the electricity rate and service rate for PEVC throughout the 24-hour period, measured in $/kilowatt-hour, allowing for the direct
calculation of costs based on a pre-defined charging amount. The calculation method is as follows:

\[ C_E = R_E \times TCC \]  
\[ C_S = R_S \times TCC \]  

In the equation, \( C_E \) represents electricity cost, \( R_E \) represents the electricity rate, \( C_S \) represents service cost, \( R_S \) represents the service rate. \( TCC \) represents the total charging capacity. According to the 2022 China New Energy Vehicles Outlook Report, the average battery capacity of new energy vehicles in China in 2021 was 45 kWh. This study assumes a single charging session with 90% capacity utilization, thus TCC is set to 40.5 kWh to calculate the electricity and service costs.

The parking price remains constant throughout the day and is determined by the specific parking lot where the PEVC is located. The obtained parking fee pricing information includes a total of five charging modes, in which the mode I and mode II embody the subsidy of PEVC costs:

I. EVs are exempt from parking fees.

\[ C_P = 0 \]  

II. EVs are free for parking within the designated time limit, and fees are charged according to the parking lot's regulations for exceeding the time limit.

\[ C_P = \begin{cases} 0 & \frac{TCC}{CP} < T \\ \left( \frac{TCC}{CP} - T \right) \times R_P \frac{TCC}{CP} > T \end{cases} \]  

III. EVs are subject to a one-time fixed fee for parking within the designated time period. If the parking duration exceeds this time period, an additional hourly fee is charged on top of the fixed fee.

\[ C_P = \begin{cases} C_P, & \frac{TCC}{CP} < T \\ C_P + \left( \frac{TCC}{CP} - T \right) \times R_P \frac{TCC}{CP} > T \end{cases} \]  

IV. EVs are charged for parking on an hourly basis.
\[ C_P = \frac{TCC}{CP} * R_P \] (11)

V. EVs are charged a one-time fixed fee for parking, regardless of the duration of parking.

\[ C_P = C_{P2} \] (12)

In the equations, \( C_P \) represents Parking Cost, \( CP \) represents charging power, \( T \) represents the designated time limit set by the PEVC parking facility, \( C_{P1} \) represents the one-time fee within the designated time limit, \( C_{P2} \) represents the one-time fee, and \( R_P \) represents the hourly parking rate. In section 3.5, we applied a weighted approach to slow EV chargers, so we use a standardized charging power of 30 kW for all charging stations. Therefore, \( T = 1.35 \) h.

After calculating the Electricity cost, service cost, and parking cost for each PEVC, the total cost of the PEVC can be calculated using the following formula:

\[ C_t = C_E + C_S + C_P \] (13)

The cost components \( C_E \) and \( C_S \) vary dynamically throughout the day due to the different rates \( R_E \) and \( R_S \) in each time period. On the other hand, the \( C_P \) remains constant throughout the day. By calculating the average value of \( C_t \) for all PEVCs in a city, the overall cost level of the PEVCs in that city can be characterized.

4 Result

4.1 PEVC supply capability

4.1.1 PEVC supply-demand level of PEVC

Figure 3 presents the average \( A^E \) (supply-demand level) across cities, Figure 4 displays the \( A^E \) values for different travel time thresholds, and Figure 5 illustrates the characteristics of the
NECS, EVCS density, and population density for cities at different $A^F$. The results indicate that mega-cities exhibit the highest PEVC supply-demand level, followed by medium-sized and small cities, while large cities show the weakest supply-demand level. The PEVC supply proportion in each city is determined by NECS, EVCS density, and population density, leading to the categorization of $A^F$ into four types based on their distinct distribution patterns. Furthermore, the PEVC supply-demand level decreases with increasing travel time threshold, with the highest supply-demand level observed within the short travel time range (travel time less than 5 minutes).

Fig.3 PEVC supply-demand level of 35 cities: the supply-demand levels of mega-cities, large cities, medium-sized cities, and small cities were arranged in descending order (vertical bar charts), and their average values were calculated (horizontal dotted lines).

There are substantial variations in the supply-demand levels of PEVCS among different city types. Fig.3 illustrates that mega-cities demonstrate the highest overall PEVC supply-demand levels, with Chongqing and Chengdu leading the rankings. In contrast, large cities exhibit comparatively
lower supply-demand levels, accounting for only one-fifth of the mega-cities, and half of the supply-demand levels observed in medium-sized and small cities. Notably, significant differences in PEVC supply-demand levels are observed among cities such as Zigong, Luzhou, Suining, Dazhou, Neijiang, and Nanchong. Medium-sized cities like Fuling, Jiangjin, and Dazu, as well as small cities including Qijiang, Qianjiang, and Tongnan, demonstrate remarkably high PEVC supply.

The $A_F$ values at different thresholds reveal a decreasing trend as the travel time coverage expands, as depicted in Figure 4. Consequently, PEVCS exhibits greater supply capacity within smaller travel ranges. Moreover, as the threshold value increases, the rate of supply decline for the four city types gradually diminishes. Mega-cities tend to stabilize at a 40-minute threshold, while medium-sized cities stabilize at 20 minutes, and small and large cities stabilize around 15 minutes. This suggests that mega-cities can sustain their supply over a wider travel range, thereby effectively meeting the demands of EV users for medium to long-distance trips within the urban areas. Conversely, large, medium-sized, and small cities have a more limited coverage range for maintaining their supply.
Fig. 4 $A^F$ in Different Thresholds: The bold lines represent the average $A^F$ values for cities of different levels.

The differentiation of NECS, PEVCS density, and population density reveals distinct supply characteristics of PEVC across different cities (Fig. 5). The supply characteristics of cities can be categorized into four groups: A1, A2, B1, and B2. Cities with $A^F$ values exceeding the average level are further classified into A1 and A2 categories (Fig. 6(a) and Fig. 6(b)). A1 cities exhibit a "high supply-high demand" pattern, including Chongqing, Jiangjin, and Qijiang. These cities possess PEVCS density and NECS values above the average, effectively meeting the higher-than-average population density demands and resulting in elevated $A^F$. A2 cities showcase a "high supply-low demand" pattern. They demonstrate either high PEVCS density, high NECS values, or both, while simultaneously exhibiting lower population density. Consequently, their supply adequately meets the demand. Chengdu and Dazu, for instance, demonstrate NECS and PEVCS density values exceeding the average, with lower population density, resulting in favorable $A^F$. On the other hand, Wanzhou, Fuling, Qianjiang, and Changshou exhibit lower PEVCS density but higher NECS, indicating a larger PEVCS scale compensating for the lower PEVCS density and ensuring a satisfactory $A^F$. Conversely, Tongnan has a smaller PEVCS scale, yet its higher PEVCS density compensates for this limitation.
Fig. 5 Cities with 4 supply-demand characteristics, where the x-axis represents PEVCS density, the y-axis represents NECS, and the z-axis represents population density.

Cities with low supply-demand levels can be further classified into two categories: B1 and B2.

B1 cities exhibit a "low supply-high demand" pattern (Fig. 6(a) and Fig. 6(b)). These cities have lower PEVCS density and NEPS values, while their population density is higher than the average level, resulting in lower $A_F$ values. Examples include Guang'an, Nanchong, Suining, Zigong, Kaizhou, and Ziyang. On the other hand, B2 cities demonstrate a "low supply-low demand" pattern. These cities have lower PEVCS density, NEPS, and population density compared to the average level. Consequently, the supply of PEVCS cannot meet the corresponding population demand, resulting in a low $A_F$. B2 cities include Meishan, Leshan, Luzhou, Bishan, Hechuan, Yongchuan, Dianjiang, Tongliang, Fongdu, Zhongxian, Rongchang, and Liangping.

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4.1.2 Travel time and isochronous circle of PEVC

Figure 7 presents the average minimum travel time (MTT) and average travel time (ATT) from grids to PEVCs in different cities. Figure 8 illustrates the proportion of city area covered by isochronous circles of varying travel times. Figure 9 displays the area enclosed by the 5-minute isochronous circle for each city. The findings reveal that cities exhibit comparable levels of MTT, typically within 4 minutes to reach the nearest PEVC. However, there are substantial variations in ATT, with mega-cities exhibiting the highest value (14.04 minutes), surpassing large cities (5.18 minutes), medium-sized cities (5.11 minutes), and small cities (4.16 minutes). Concerning PEVC coverage within specified travel times, mega-cities require longer travel durations to encompass the same proportion of city area compared to large, medium-sized, and small cities, which experience shorter and relatively similar travel times. When considering a uniform travel time of 5 minutes, mega-cities exhibit a larger coverage area, while large, medium-sized, and small cities display smaller and relatively comparable coverage areas.

Regarding the MTT (Fig.7), cities exhibit a comparable level of efficiency, with all cities able
to reach the nearest PEVC within 4 minutes. This indicates a prompt access to PEVC services across the cities. Among them, Yibin (3.89 minutes), Dazhou (3.37 minutes), Ziyang (3.16 minutes), Hechuan (3.43 minutes), and Tongnan (3.82 minutes) show slightly higher values. Conversely, cities such as Chengdu, Deyang, Fuling, Dazu, Bishan, Yongchuan, Changshou, Qianjiang, Fengdu, Tongliang, Qijiang, Liangping, Rongchang, and Dianjiang demonstrate an impressive performance, as they can reach the nearest PEVC within a mere 2 minutes.

In terms of ATT (Fig.7), mega cities exhibit higher values, with an average of 14.04 minutes. Specifically, the largest city, Chengdu, has a value of 15.34 minutes, while Chongqing has an ATT of 12.74 minutes. Large, medium, and small cities show similar average values, with Yibin (8.08 minutes), Fuling (8.56 minutes), Zhongxian (7.48 minutes), and Changshou (6.93 minutes) slightly higher in this regard.

Beyond travel time, assessing the accessibility of PEVC in cities requires considering the
coverage within a certain travel time. This study employed isochronous circle for various travel time ranges to investigate the coverage range of PEVC. Additionally, a 5-minute isochronous circle was selected to compare the coverage capabilities of PEVC in different cities within the same travel time (Fig.8).

Figure 8 illustrates that small cities exhibit a higher proportion of urban coverage by PEVC within a shorter time period, followed by medium-sized and large cities. In contrast, mega cities require more time to achieve a comparable coverage proportion. To achieve full coverage of the urban area, small cities require an average of 11.54 minutes, medium-sized cities require 12.79 minutes, and large cities require 12.89 minutes, while mega cities need 32.5 minutes. For a 25% coverage, small cities average 1.78 minutes, medium-sized cities average 2.61 minutes, large cities average 3.13 minutes, and mega cities require 8.25 minutes.

However, relying solely on the coverage proportion of isochronous circle is limited to assessing
the capability of PEVCs to fulfill the specific demands within each city, thereby failing to provide an objective measure of the overall PEVC traffic coverage capacity across cities. Therefore, using a 5-minute travel time range allows for an objective comparison of PEVC coverage area, reflecting differences in PEVC accessibility among cities. As shown in Figure 9, mega cities demonstrate superior PEVC accessibility, with an average coverage area of 63.65 km² within 5 minutes. Large, medium-sized, and small cities have average coverage areas of 29.21 km², 23.80 km², and 21.33 km², respectively. Among mega cities, Chengdu boasts the largest coverage area (79.00 km²), followed by Chongqing (48.30 km²). Zigong, Deyang, Mianyang, Yongchuan, Ziyang, and Changshou also exhibit relatively large coverage areas, while Yibin, Dazu, Ya'an, Zhongxian, Qianjiang, and Qijiang have smaller coverage areas.

Fig. 9. The isochronous circle area of PEVCs within a 5-minute travel time range in cities of different sizes.
4.2 PEVC usage cost

Figure 10 illustrates the PEVC usage costs across different city sizes during distinct time periods within a 24-hour cycle. Meanwhile, Figures 11 and 12 depict the corresponding electricity costs, service costs, and parking costs. The findings reveal that the PEVC usage costs are subject to the influence of electricity costs and service costs, displaying discernible fluctuations throughout the day. Notably, this trend is most conspicuous within mega and large cities, while smaller cities exhibit less pronounced variability. Moreover, off-peak periods entail reduced PEVC usage costs compared to peak-demand intervals, with prominently lower fees observed during the early morning hours (11 pm to 7 am) in contrast to daytime and evening hours (8 am to 10 pm). During off-peak hours, small and medium-sized cities register the highest utilization costs, followed by large cities, whereas mega cities exhibit the lowest costs. However, during non-peak hours, large cities incur the highest costs, trailed by mega and medium-sized cities, with small cities experiencing the lowest expenditure. In terms of parking fees, mega cities command the highest costs, succeeded by medium-sized cities and small cities, while large cities display the most economical costs. Furthermore, research indicates that urban PEVC systems’ preferential policies for new energy vehicle parking significantly mitigate the associated costs for electric vehicle owners, which is evident in both mega cities and large cities.
Fig. 10 The PEVC usage costs for each city within a 24-hour period, with bold lines representing the average cost values for each city type at each time point.

During the period of 11 pm to 6 am, cities exhibit lower cost levels, while experiencing distinct peak variations from 6 am to 11 pm. Mega cities show an upward trend in PEVC total costs starting at 7 am, reaching the first peak at 12 am ($8.69). After a brief decline, a second peak is observed at 4 pm ($8.88), followed by a third peak at 8 pm ($8.69). The costs gradually decrease to the lowest point at 12 pm ($3.97) and remain at this level until 7 am the next day. Large cities display an ascending trend in PEVC costs from 6 am, with two peaks occurring at 9 am ($8.22) and 12 am ($9.54). Costs remain relatively high from 3 pm ($10.63) until 9 pm ($10.86), then decline to the lowest point at 12 pm ($5.41). Medium-sized cities show moderate variations, with comparable costs during daytime and nighttime. The first peak is observed at 8 am ($6.62), and relatively higher levels are maintained from 12 am to 5 pm ($7.38-$7.83). A higher level is noted from 9 pm to 10 pm ($7.61-$7.70), followed by a decline to the lowest level ($5.67). Small cities exhibit minimal
fluctuations in costs, ranging from $5.06 to $5.84 throughout the day, with subtle peaks during the hours of 8-9 am and 3-4 am.

Fig.11 The electricity costs (a) and service fees (b) for each city within a 24-hour period, with bold lines representing the average values for each city type at each time point.

Fluctuations in electricity and service costs contribute to the variability in total costs, displaying similar trends across different city levels throughout the day. Electricity costs exhibit a consistent pattern, increasing from 7 am and peaking between 11 am and 10 pm. Service fees show minimal fluctuations. Mega cities have slightly higher daytime service fees (8 am to 9 pm) ranging from $1.85 to $2.20 compared to nighttime fees (10 pm to 7 am) ranging from $1.61 to $1.82, with a peak observed at 4 pm. Large cities demonstrate relatively stable service fees, except for peaks at 9 am and 8 pm. Medium-sized cities experience modest service fee changes throughout the day without distinct peaks, while small cities exhibit a noticeable peak during 8-9 am. Mega cities generally have higher daytime service fees, with a peak occurring at 4 pm.

Regarding service fees, large cities have the highest average fees, followed by medium-sized cities and small cities, with mega cities having the lowest fees. The fluctuations in service fees throughout the day are minimal, with only one or two peaks observed. Large cities typically
experience peaks around 9 am and 8 pm, while medium-sized cities show less prominent peaks. Small cities exhibit a distinct peak during 8-9 am, and mega cities generally maintain higher daytime levels with a peak at 4 pm.

In terms of parking costs, there is a clear distinction among city levels (Fig.12). On average, mega cities exhibit the highest average parking costs, followed by medium and small cities, with large cities having the lowest. Moreover, the availability of parking subsidies for electric vehicles varies across city levels. Mega and large cities offer higher proportions of subsidies, while medium and small cities provide relatively lower proportions. Significant variations in parking costs exist within each city level. In mega cities, Chongqing and Chengdu demonstrate similar PEVC parking costs. Large cities display a divergence, with cities like Dazhou, Meishan, Nanchong, Wanzhou, and Zigong imposing significantly higher costs compared to Mianyang, Suining, and Yibin. Medium-sized cities show relatively smaller differences in parking costs, though certain cities stand out, such as Kaizhou with the highest costs, and Ya'an and Ziyang with lower costs. Small cities, on average, tend to have higher parking costs, with outliers like Liangping, Rongchang, and Fengdu having particularly high costs, while cities like Qijiang and Tongnan have lower costs.

The components of parking charges reveal that subsidies for electric vehicle parking substantially reduce the costs. Cities like Deyang, Leshan, Mianyang, Neijiang, Luzhou, Suining, Yibin, Ziyang, and Tongnan exhibit higher proportions of Class I and Class II parking costs, resulting in lower PEVC parking costs. Conversely, cities such as Dazhou, Zigong, Hechuan, Kaizhou, Fengdu, and Liangping lack Class I and Class II fees, leading to higher parking costs. The accompanying figure illustrates the distribution of parking fee categories across the four city types, with mega and large cities having higher proportions of Class I and Class II fees at 47% and 45%.
respectively, while medium and small cities have lower proportions at 9% and 15% respectively.

Fig. 12 The parking costs and components of charges in cities of different levels.

5 Discussion

5.1 PEVC supply level and characteristic

Previous studies have indicated that regions with higher per capita income and population density tend to have a greater number of charging stations, facilitating the development of the electric vehicle market (He et al., 2022). While the findings of this study align with this trend in terms of PEVC quantity, revealing a positive correlation between the number of charging facilities and city levels, the analysis of PEVC supply-demand ratio \( A_F \) demonstrates that large cities have a lower \( A_F \) compared to mega cities, medium-sized cities, and small cities. This outcome is primarily attributed to an inadequate level of PEVC infrastructure development that fails to meet the higher demand in large cities relative to medium-sized and small cities. Additionally, the study explores the influence of different searching threshold on the \( A_F \), demonstrating that PEVC exhibits
a stronger supply within shorter travel distances. This finding offers insights for threshold selection in the 2SFCA method employed in PEVC research.

This study identifies four types of cities with different PEVC supply and confirms that both the number of EV chargers per station (NECS) and PEVCS density have positive effects, albeit with different characteristics. A higher PEVCS density allows users to access more PEVC options within a given range, resulting in faster service availability and an overall increase in PEVC supply. A larger NECS enables individual PEVCS to accommodate more demand, thereby enhancing the overall supply capacity. Therefore, improving both PEVCS density and NECS effectively boosts the PEVC supply in cities. However, achieving higher PEVC supply requires a balanced consideration of cost and efficiency. Establishing a new PEVCS is significantly costlier than expanding existing it due to the additional soft costs involved in constructing and operating a new PEVCS (Rogers, 2019). Hence, policymakers should deliberate on the prioritization between scaling up the magnitude of PEVCS and augmenting the quantity of PEVCS, weighing their respective merits. The analysis of shortest travel time to PEVCS reveals that all cities have an MTT of less than 4 minutes. This demonstrates that the existing PEVC density ensures prompt access to the nearest PEVC for EV users. Increasing PEVCS construction solely expands the range of PEVC choices for users within a specific area, but for the purpose of enhancing accessibility, it is unnecessary. Therefore, when planning PEVC infrastructure, emphasis should be placed on expanding existing PEVCS scale and improving NECS. Furthermore, enhancing PEVC efficiency through technological advancements can elevate the overall level of PEVC services (C. et al., 2021).

The results of isochronous circles and average travel time indicate that smaller cities have an advantage in terms of transportation coverage compared to larger cities. Mega cities, with their
larger area and congested traffic (Hanson and Giuliano, 2004), struggle to meet the demand for PEVC services across the entire city within a short travel time, the PEVC of which can only cater to specific areas. Although the isochronous circle area of PEVCS in mega-cities is larger and can ensure a higher level of PEVC supply over a wider range, as the limited radiating capacity of PEVCS results in the division of mega-cities into multiple central places (Berry et al., 1967) of PEVC service. To improve the overall PEVC service in the urban area, the construction of PEVCS needs to be enhanced in each central place. However, public financial resources are limited, which can easily lead to inequality in PEVC service provision in mega-cities. Research conducted by Li et al. (2022) also demonstrates this phenomenon. On the other hand, due to smaller city size and less congested traffic, the construction of PEVCS in small cities can directly cover the entire city. This leads to stronger marginal effects and more evident impacts in medium and small cities, even with an equal level of investment.

5.2 Usage cost of PEVC

Based on cost analysis, the fluctuation in PEVC's daily electricity and service fees reflects changes in usage rates. Consistent with Zhou et al. (2020)’s findings, mega-cities and large cities show lower fees at night and higher fees during the day. Our study identifies peak hours of electricity and service fees in these cities, indicating that operators employ dynamic pricing strategies to maximize profits, optimize costs, and reduce strain on the power grid during periods of high PEVC usage (Di Giorgio and Liberati, 2014; Kumar and Revankar, 2017). However, this phenomenon is less prominent in medium-sized and small cities due to their lower PEVC utilization rates, which do not drive operators to implement pricing strategies for peak usage. PEVC electricity pricing is
determined by operational costs, strongly influenced by usage rates (Flores et al., 2016). This is supported by off-peak PEVC electricity prices, which are lower in mega-cities and large cities with higher usage rates, while small and medium-sized cities have higher off-peak prices due to lower usage rates. However, large cities have the highest overall electricity prices, as their lower supply fail to meet the higher demand, particularly during peak daytime usage. Regarding parking fees, subsidies lead to lower PEVC parking costs in large cities and mega-cities, especially noticeable in large cities. In contrast, medium-sized and small cities, lacking policy subsidies, have higher PEVC parking fees despite lower land prices.

5.3 Policy implications for PEVC development

The disparities in PEVC service among cities resulting from variations in PEVC supply capacity and usage costs should be a concern for policymakers. To promote the adoption of EVs, policymakers should focus on city-level PEVC planning and cost subsidies to enhance the corresponding PEVC service. However, advancing PEVC infrastructure and the adoption of electric vehicles pose a chicken-and-egg dilemma (Shi et al., 2021). In the early stages of market development, the low adoption and usage rates of electric vehicles increase operational costs, creating significant barriers for operators to enter the market (Flores et al., 2016). Thus, initial public funding participation is necessary (Falchetta and Noussan, 2021). This study suggests that for medium-sized and small cities, which are still in the early stages of EV market development, increased public funding should be allocated for PEVC investments to facilitate the development of PEVC infrastructure. On the one hand, when considering PEVC construction plans, prioritizing the expansion of existing PEVCS to improve efficiency and cost savings is crucial. On the other hand,
policy subsidies should be provided to PEVC operators in medium-sized and small cities, such as benchmark electricity price subsidies and parking fee subsidies, to significantly reduce PEVC usage costs and encourage the adoption of EVs by users in these cities. For mega-cities where the EV market has already formed and is continuously developing, encouraging the participation of more private operators and improving the local market mechanisms for PEVC will enhance the PEVC service. For large cities that have initial EV market formation but lack corresponding infrastructure, a combination of public and private funding should be utilized to jointly promote PEVC facility construction and facilitate the local electrification of automobiles.

6 Conclusion

This study investigates the PEVC service levels and characteristics of cities of different levels, focusing on two key factors influencing vehicle electrification: supply capacity and usage costs. The results indicate that mega-cities have the highest service levels, with superior PEVC supply capacity. Higher usage cost contribute to a more refined pricing mechanism, and ample policy subsidies reduce usage costs. However, the larger population base and longer average travel time within the city result in higher marginal costs for enhancing PEVC service in mega-cities. Medium-sized and small cities exhibit intermediate service levels. The lower demand in these cities, driven by their smaller population size, contributes to less developed pricing mechanisms and higher usage costs. Additionally, due to lower demand and shorter average travel time within the city, the marginal costs for improving PEVC service are lower in medium-sized and small cities. Large cities demonstrate the lowest service levels primarily due to insufficient supply to meet demand. This mismatch is reflected in the pricing mechanism of large cities, where higher usage costs and policy
subsidies have led to an improved pricing mechanism, but overall higher prices persist due to the supply-demand imbalance.

The study confirms the positive impact of PEVCS scale and deployment density on the PEVC supply level in cities. Through the application of the minimum travel time (MTT) analysis, it is demonstrated that the existing deployment density of PEVCS can meet the city's PEVC accessibility demands, highlighting the efficiency of expanding the scale of existing PEVCS as a means to enhance the PEVC supply.

The novelty of this study lies in several aspects. Firstly, it provides a comparative analysis of the PEVC service in different cities from the perspective of city level, depicting the characteristics of PEVC service in various cities. Secondly, it incorporates spatial analysis, particularly accessibility analysis, into the characterization of PEVC supply, and optimizes the threshold selection issue in the 2SFCA method used in PEVC research. Thirdly, it introduces the concept of PEVC usage costs, a crucial factor influencing users' EV choices, to characterize the service of PEVC in cities. Overall, this research offers new comparative perspectives and methodological approaches for measuring PEVC service levels in cities, assisting policymakers in formulating targeted policies and strategic planning based on the current status of PEVC services in cities of different levels, providing concrete policy-making strategies to advance the SDGs and achieve the NES.

One limitation of this study is the limited availability of data, which prevents the classification and discussion of PEVCs with multiple power levels. Although the study addresses this issue by weighting the PEVCs. Additionally, users' charging behavior varies depending on the power level of the PEVC (Pan et al., 2020), which further affects the diversity of the PEVC cost analysis in this
study. As the PEVC information service industry develops in the future, data availability is expected to improve, allowing for more comprehensive research on PEVCs with different power levels in subsequent studies.

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