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Characterizing Mobility Patterns of Private Electric Vehicle Users with Trajectory Data

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Abstract

Human mobility pattern analysis has received rising attention. However, little is known about the mobility patterns of private Electric Vehicle (EV) users. In response, this paper characterized mobility patterns of private EV users using a unique one-month dataset containing moving trajectories of 76,774 actual private EVs in January 2018 in Beijing. Specifically, we first explored the diversity, regularity, spatial extent, and uniqueness of EV users' mobility patterns. The results suggested that most EV users had both regular travel and activity patterns (the mean travel and activity entropies were 2.17 and 1.83, respectively) with special preferences towards some specific activity locations relative to all the locations they visited (the mean number of activity locations visited was 13.57 in one month). Furthermore, they tended to perform activities within a small geographical area (the mean radius of gyration was 7.60 km) and have a short daily travel distance (the mean value was 37.35 km) relative to their electric driving range. Further, we associated EV users' mobility patterns with the built environment through ordinary least squares and geographically weighted regression models, particularly considering the so-called modifiable areal unit problem (MAUP). Due to the MAUP, most of the statistically significant built environment variables varied across spatial analysis units (SAUs). Gymnasia was the only variable statistically associated with the mobility patterns for all SAUs; while the variables related to residence and workplace were not statistically associated.

Keywords: Electric Vehicle; Mobility Patterns; Trajectory Data; Built Environment

1 Introduction

The popularization of electric vehicles (EVs) helps to develop a more sustainable transportation system [1-3]. Both adoption and usage rates have increased significantly over the past few years with various supportive policies, such as subsidies and tax exemption [4-6]. At the end of 2020, there were more than 10 million EVs globally, as reported in “Global EV Outlook 2021” by International Energy Agency (IEA) [7]. However, conventional vehicles (CVs), such as petrol cars, are still dominant in the vehicle market. To further promote the adoption and usage of EVs, understanding mobility patterns of EV users is essential, as EV-related policy making, infrastructure planning and technology investment need to take EV users’ mobility patterns into account [8-10].

On the other hand, human mobility pattern analysis has received increasing attention over the past decade, in part due to the emergence of various urban big data sources, such as mobile phone data, trajectory data and smart card data, which contain rich information on individual movements. Many empirical studies have been conducted to characterize mobility patterns of mobile phone users [11-13] and the travelers using different transport modes, such as active transport modes [14, 15], public transport [16, 17], shared modes [18], and private conventional cars [19, 20]. Further, some of them explored the relationship between mobility patterns and the built environment.

Meanwhile, many attempts have been made to investigate mobility patterns of EV users, with a focus on their travel, parking and charging patterns or behaviors [21-23]. However, most of these EV studies used traditional questionnaire survey data or small EV GPS datasets, and the samples from such small datasets could not be representative enough and the mobility patterns revealed were very likely to be biased.

To better characterize the mobility patterns of private EV users, which would be helpful for the EV-related policy making, infrastructure planning and technology investment, this study will use a unique one-month GPS dataset containing moving trajectories of 76,774 private EVs in January 2018 in Beijing. Beijing had 113,280 private New Fuel Vehicles (NFVs) at the end of 2017, which made it possible to generate such a large GPS dataset on actual private EV users. Specifically, there are two main contributions of this study:

- We will characterize private EV users' mobility patterns with a large real EV trajectory dataset through spatial big data analysis; while previous studies tended to use traditional questionnaire survey data or small EV GPS datasets, which could not well represent mobility patterns of EV users.
- We will also explore the potential association between the EV users' mobility patterns and the built environment, which has not been well understood.

The rest of this paper is organized as follows: Section 2 conducts an extensive review of mobility patterns and their association with the built environment. Then, Section 3 describes study area and the datasets used, and further introduces the methods to characterize mobility patterns and explore the association between mobility patterns and the built environment. Next, Section 4 presents and discusses the results about private EV users' mobility patterns. Finally, Section 5 summarizes the key research findings and discusses further work.

2 Literature Review

2.1 Mobility Indicators

Mobility analysis with various indicators portrays individual activity space through measuring activity locations and movements between them, so as to reveal the inherent properties and mechanism in mobility patterns [24-26]. Typical mobility indicators include the number of activity locations, activity entropy, travel entropy, radius of gyration, k-radius of gyration, and unicity, which can be used to characterize the diversity, regularity, spatial extent and uniqueness of individual mobility patterns [26]. These typical mobility indicators are reviewed below.

Indicators of the number of activity locations, activity entropy, and travel entropy are used to quantify the diversity and regularity of individual mobility patterns. Xu et al. [26] found that mobile phone users in Singapore and Boston exhibited similar level of mobility regularity characterized by activity entropy and travel entropy, although users in Boston generally visited more diverse activity locations. Xu et al. [27] used these three indicators to measure and compare the mobility patterns of tourists traveling to three different Korean tourism cities, i.e., Jeonju, Gangneung and Chuncheon. Zhao et al. [28] displayed an underestimation of individual activity entropy only using the call detail records (CDR) dataset that has a low temporal sampling rate, compared to the estimates using a complete and more granular mobile phone location dataset. Pappalardo et al. [29] aggregated mobile phone users' travel entropy at the municipality level and related it to sociodemographic indicators, revealing the strong relationship between them. The concept of entropy has also been used to measure the evolution of electric taxis' mobility and charging patterns. According to the indicator, Entropy of Charging Location Evolution, Wang et al. [30] found that electric taxis drivers in Shenzhen, China had stable charging locations over time. In addition to the number of activity locations, the number of unique origin-destination trips [31, 32] can also be used to measure the diversity of individual mobility patterns.

Indicators of radius of gyration and k-radius of gyration can be used to measure the spatial extent of individual mobility patterns. Ahmouda et al. [33] used radius of gyration to measure the variation of individual activity space under harsh weather conditions (e.g., hurricane). Using mobile phone data and GPS trajectory data of conventional vehicles (CVs) separately, Pappalardo et al. [13] delineated the probability distributions of radius of gyration and k-radius of gyration and found that they both generally fit the truncated power-law with different parameters. Tian et al. [34] used radius of gyration as an indicator to compare the operating coverage of electric and conventional taxis in Shenzhen, China. The results showed that the operating coverage of conventional taxis tented to be larger than that of electric taxis. Diameter of convex hull [31, 32] is another indicator that can be used to measure the spatial extent of individual activity space.

As for unicity, it is a measure of re-identifiability, characterizing the uniqueness of individual mobility traces [11]. Xu et al. [26] and de Montjoye et al. [11] both found out around 95% of mobile phone users can be uniquely identified only using top 4 frequently visited 500×500 m grids. The results from Xu et al. [26] also suggested that the re-identifiability power would, to some extent, decline when conducting the empirical analysis at a coarser spatial unit (e.g., 1×1 km grid).

2.2 Mobility Patterns of Electric Vehicle Users

It is of paramount importance to analyze real-world EV operating data to facilitate the understanding of the mobility patterns of EV users. Up to the present, researchers have put noticeable efforts into investigating the mobility patterns of EV users at the trip level but mostly with a small sample of EVs. Some specific examples are reviewed below:

Zhang et al. [21] collected the operating data of 41 private EVs in Beijing, China and statistically characterized the travel patterns of EV users with seven trip-related indexes, such as the trip distance, trip start time, daily distance travelled and the number of trips per day. Similar investigations were conducted using EV-generated datasets collected from different regions of the global. For example, Corchero et al. [22] analyzed 140,000 EV trips extracted from a fleet of 503 monitored EVs spreading eight European countries. Kessler and Bogenberger [35] analyzed 54,000 trips generated from the one-year travel history of 40 BMW i3 (one common EV model) users in Germany and found that the average EV trip distance was 11.1 km. Weldon et al. [36] collected the real data of 15 EVs in Ireland and utilized both analysis of variance (ANOVA) and interquartile range (IQR) to investigate the trip characteristics of EV users. Habla et al. [23] accessed private and shared electric and conventional fleets (among which 16 private EVs and 91 shared EVs were included) and their usage patterns (e.g., single-day and annual distance travelled) in Germany in which they discovered that EVs drove shorter distances comparing to conventional vehicles, on average. One exceptional case was that Sun et al. [9] tried to uncover trip, parking and charging patterns of private EV users using a unique dataset which contained moving trajectories of over 76,000 private EVs collected in January 2018 in Beijing. However, it only looked at statistical and spatiotemporal distributions of these three typical events of EV users (i.e., travel, parking and charging events), with little regular patterns observed. This study will also use this unique dataset, but will take one step forward: specifically, we will characterize mobility patterns of private EV users at the individual level using typical mobility indicators and further associate the mobility patterns with different built environment factors. These two aspects have not been explored in the previous study by Sun et al. [9], and thus are the contributions of our study.

In addition to measuring descriptive and statistical trip characteristics of EV users, a few previous studies have strived for a deeper understanding of EV users' mobility patterns. However, these studies were mostly focused on non-private vehicles, such as taxis. Tian et al. [34] employed Centriod and Radius of Gyration to characterize the operating coverage of electric taxis using GPS records data of around 600 electric taxis in Shenzhen, China. The results showed that the operating coverage of electric taxis was smaller than that of conventional taxis. Chen et al. [37] incorporated the theory of entropy to capture the vehicle usage stability with a one-week GPS trajectory data of 8,000 EVs collected in Shanghai, China. Using a multi-source dataset comprising the five-year GPS data of 427 electric taxis in Shenzhen, China, Wang et al. [38] estimated the evolution of mobility patterns of electric taxis network with three indicators, namely coverage density, daily distance travelled and overhead after charging.

2.3 Association between Mobility Patterns and the Built Environment

Compared with other factors (e.g., socioeconomic and sociodemographic factors), the built environment has been commonly considered as potentially influential factors and incorporated to examine their relationships with travel demand/patterns, due to the acknowledgement that they could heavily influence travelers' behavior [39, 40]. Also, easily acquirable point of interest (POI) data containing high accuracy land use information had commonly been used to measure the built environment in relevant studies [15, 40-42]. For example, Shen et al. [20] used geographically and temporally weighted regression (GTWR) models to analyze the relationship between a variety of POIs and the travel demand of car users and total persons. They found that the influence of various POIs varied spatially and temporally. Liu et al. [43] employed the GWR model to explain the spatial heterogeneity of taxi ridership in Xiamen, China with collected POI data. The results showed that the density of residential buildings and transport infrastructure would generally induce more taxi use demand.

There is a considerably large literature on exploring the association between different built enviroment factors and mobility patterns (or travel demand/patterns) of the travelers using different means of tranport, including active transport modes [14, 44], public transport [16, 45], and vehicle-related transport mode (e.g., private conventional car, taxi ridership, ride-sourcing, and ride-hailing) [19, 20, 46, 47]. Taking those studies focusing on vehicle-related transport modes as an example, Bi et al. [18] investigated the effects of the built enviornment on car-hailing ridership with geographically weighted regression (GWR) uisng Chengdu, China as the study area. Wang and Noland [46] extended the understanding of the association between car-hailing ridership in Chengdu, China and the built environment factors by additionally considering other factors, such as population density and housing price, using both ordinary least-squares (OLS) and GWR models. Tu et al. [16] and Qian and Ukkusuri [48] leveraged GWR models to explain the spatial variation of taxi ridership by relating it to various sociodemographic and built eneviroment variables. Moreover, Tu et al. [16] conducted the comparion of the similarities and differences between the taxi ridership and public transport ridership regarding the effects of their exploratory factors. Soltani et al. [19] investigated the relationships between the mobility patterns of older private CV users in Iran and the sociodemographic and built environment variables. Among these studies reviwed the above, OLS and GWR tended to be the most-commonly used global and local regression models, respectively.

2.4 Research Gaps and Aims

We conducted a comprehensive review of mobility patterns, in terms of mobility indicators, mobility patterns of EV users, and the association between mobility patterns and the built environment, and identified three research gaps below:

- A collection of mobility indicators has been commonly used to characterize human mobility patterns, but were not used to characterize mobility patterns of EV users, particularly for private EV users.
- Most existing studies of EV mobility patterns were focused on EV users' travel patterns (e.g., travel distance and duration). In general, they used a small dataset (e.g., questionnaire survey datasets and GPS trajectory datasets with a small number of participants), and the samples were not representative enough and the results could be

largely biased.

- The association between mobility patterns and the built environment has been explored extensively for travelers using different transport modes, including active transport modes, shared modes, and private conventional cars. However, little is done for private EV users, in part due to the lack of proper EV datasets for the association analysis.

To overcome the limitations above, this paper will characterize mobility patterns of private EV users using a unique one-month dataset which contains moving trajectories of 76,774 actual private EVs in January 2018 in Beijing (with a sample rate of 68%) [9]. Specifically, we will first explore the diversity, regularity, spatial extent, and uniqueness of EV users' mobility patterns using eight typical mobility indicators, namely the number of activity locations, activity entropy, travel entropy, radius of gyration, k-radius of gyration, unicity, average daily travel distance, and proportion of travel distance on different road types, which will be computed with activity and travel information extracted from the EV trajectory dataset. Further, we will explore the potential association between the EV users' mobility patterns and the built environment using two classical methods, namely ordinary least squares (OLS) and geographically weighted regression (GWR) models.

3 Methodology

3.1 Study Area and Datasets

3.1.1 Study Area: Beijing

As the capital of China, Beijing was one of the first batch of demonstration cities which tried to promote the adoption and usage of New Fuel Vehicles (NFVs) with various supportive policies [21], and it has experienced the rapid development of NFVs. By the end of 2019, there were 324,828 NFVs, among which passenger NFVs and private NFVs accounted for 95% and 69%, respectively [49]. Fig. 1 shows the number of private NFVs owned per 1,000 permanent residents at the district level in 2019, suggesting that central districts tended to have relatively more NFVs. It is worth noting that nearly all NFVs in Beijing were EVs [9].

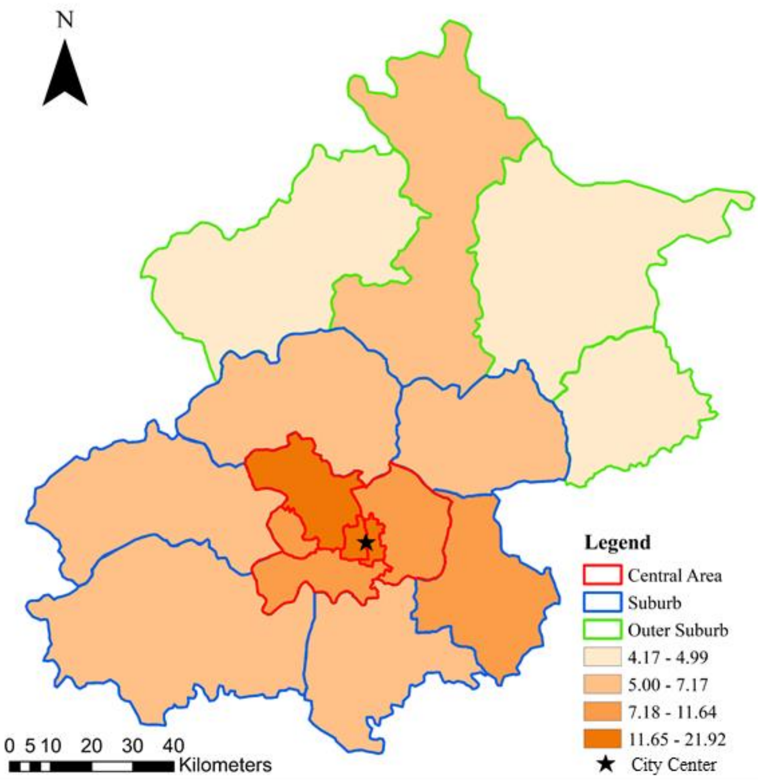
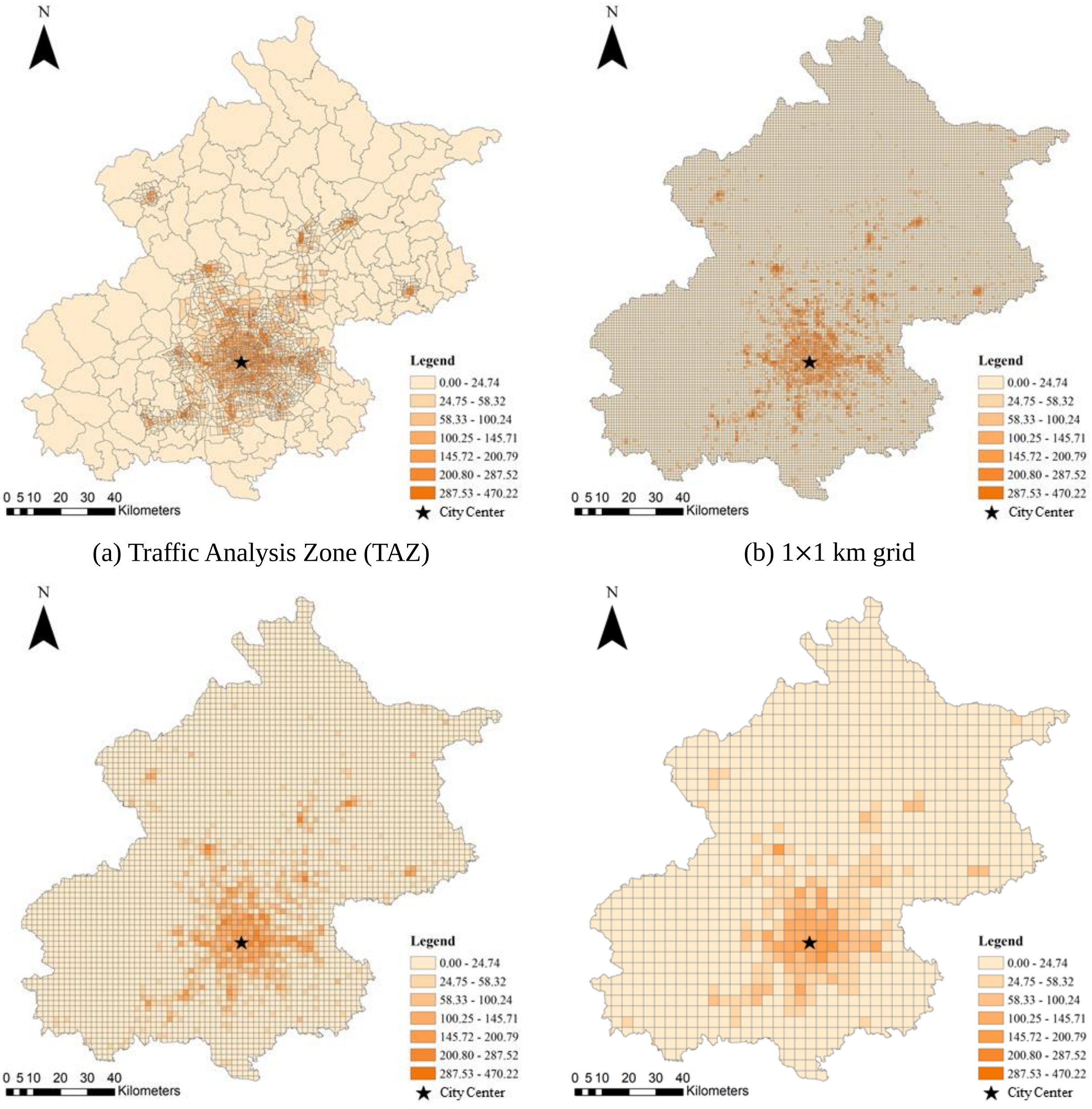


Fig. 1 The numbers of private NFVs owned per 1,000 permanent residents in the 16 administrative districts in Beijing in 2019

Fig. 2 characterizes the built environment in Beijing with point of interest (POI), which is a typical data type for the description of the built environment [15, 40-42], using different spatial analysis units, including traffic analysis zone (TAZ) and grids with different spatial scales (i.e., 1×1 km, 2×2 km, and 4×4 km). In this study, the POI data was from the Baidu Map (https://map.baidu.com/), which is one of the largest Chinese online mapping applications. In total, the dataset contains several POI types with a total number of over 230,000 POIs, including Residential Buildings, Companies/Enterprises, Government Agencies, Educational Institutions, and Financial Facilities (see Appendix A in the Supplementary Materials for more details about the POI types). It can be found from Fig. 2 that the spatial patterns of POI were different from each other when different spatial analysis units were used, which is known as the modifiable areal unit problem (MAUP), as introduced by Openshaw [50]. Therefore, we will consider the MAUP when exploring the potential association between mobility patterns of private EV users and the built environment.



(a) Traffic Analysis Zone (TAZ)

(b) 1×1 km grid

(c) 2×2 km grid

(d) 4×4 km grid

Fig. 2 Spatial patterns of POIs (unit: the number of POI per km^2)

3.1.2 GPS Trajectory Data on Private EVs

We used a unique one-month GPS dataset, which was provided by the Beijing Transport Institute. The dataset contains moving trajectories of 76,774 actual private EVs (i.e., those EVs for personal use) in Beijing, which was collected from January 1, 2018 to January 31, 2018 through on-board diagnostics (OBD) devices [9]. The dataset only contains private EVs and does not contain those EVs used by businesses (e.g., delivery service). To protect private of the EV users, the records in the dataset were not linked to any specific persons, and their sociodemographic characteristics (e.g., age and income) were not collected, either. But it contains several fields reflecting vehicle's real-time status, such as vehicle ID, timestamp, location (comprising latitude and longitude) and instantaneous speed (see Table 1), which are sufficient for mobility pattern analysis.

Table 1 An example for the key fields in the trajectory dataset for one private EV

Vehicle ID	Timestamp	Latitude	Longitude	Instantaneous Speed (km/h)
…	…	…	…	…
F1FD123743	2018-01-02 12:44:14	40.06231	116.335045	44.7
F1FD123743	2018-01-02 12:44:24	40.062344	116.3337	29
F1FD123743	2018-01-02 12:44:34	40.06238	116.332405	45.8
F1FD123743	2018-01-02 12:44:44	40.06274	116.331535	38.1
F1FD123743	2018-01-02 12:44:54	40.063835	116.331215	31.2
F1FD123743	2018-01-02 12:45:04	40.064114	116.330765	13
…	…	…	…	…

With this trajectory dataset, we can identify travel and parking events through the EV trajectory data analytical framework proposed by Sun et al. [9] and Yang et al. [51], based on which we can further characterize private EV users' mobility patterns in this study. Fig. 3 shows how an EV trajectory can be segmented into a series of connected travel and parking events using the EV trajectory data analytical framework.

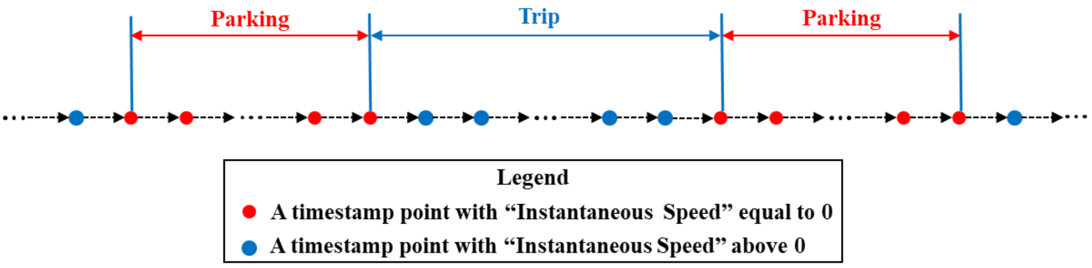


Fig. 3 An illustration of trajectory segmentation (Source: Adapted from [51])

The one-month (i.e., January 2018) trajectory dataset will be used to characterize EV users' mobility patterns. However, it was argued that different ambient temperatures in different months (or seasons) could influence the real-world driving range of EVs significantly (e.g., a low temperature could lead to a much shorter driving range) [52, 53], and thus might have indirect effects on EV users' mobility patterns.

In practice, the current EV battery capacity is larger enough to meet most EV users' mobility demand in one single day, even when EVs suffer from a shorter real-world driving range in the cold weather. This means that EV users do not have to change their activity schedule due to the decrease in the driving range. The statistical evidence extracted from the EV trajectory dataset shows that there were only 1.06% of travel days in which the EVs' cumulative percentage of consumed charge is over 100% (in such cases, EVs have to get recharged at some of their trip destinations in daytime, and could not just rely on overnight charging). On the other hand, the changes in the real-world EV driving range caused by the variation of ambient temperatures in different months (or seasons) could directly influence EVs' charging patterns (e.g., charging frequency and charging duration), but its further influence on EV users' mobility patterns (reflecting how EV users move around within their activity space) would be limited. Also, some studies indicated that the seasonal effects on EV charging patterns were not significant. For example, Hao et al. [52] found that the charging events at workplace for private EVs in Beijing only increased by 4% in winter, compared with other seasons. For these two reasons above, we would expect that the monthly or seasonal effects on EV users' mobility patterns tend to be limited. Therefore, using one-month trajectory data in this study should be adequate and could well uncover EV users' mobility patterns.

3.2 Analytical Framework

Fig. 4 shows the analytical framework for characterizing mobility patterns of private EV users and further associating mobility patterns with the built environment. Specifically, we first use the EV trajectory analysis method by Sun et al. [9] to extract individual mobility information (i.e., travel and parking events of private EVs). Then, we further infer each private EV user's activity locations with the mobility information (see Appendix B in the Supplementary Materials for the approach that we used), based on which we calculate several typical mobility indicators (including the number of activity locations, activity entropy, travel entropy, radius of gyration, k-radius of gyration, unicity, average daily travel distance, and proportion of travel distance on different road types) to characterize private EV users' mobility patterns, i.e., diversity, regularity, spatial extent, and uniqueness (see Section 3.3). Furthermore, we explore the potential association between mobility patterns of private EV users and the built environment (described with POIs) at multiple scales, particularly considering the modifiable areal unit problem (MAUP) (see Section 3.4).

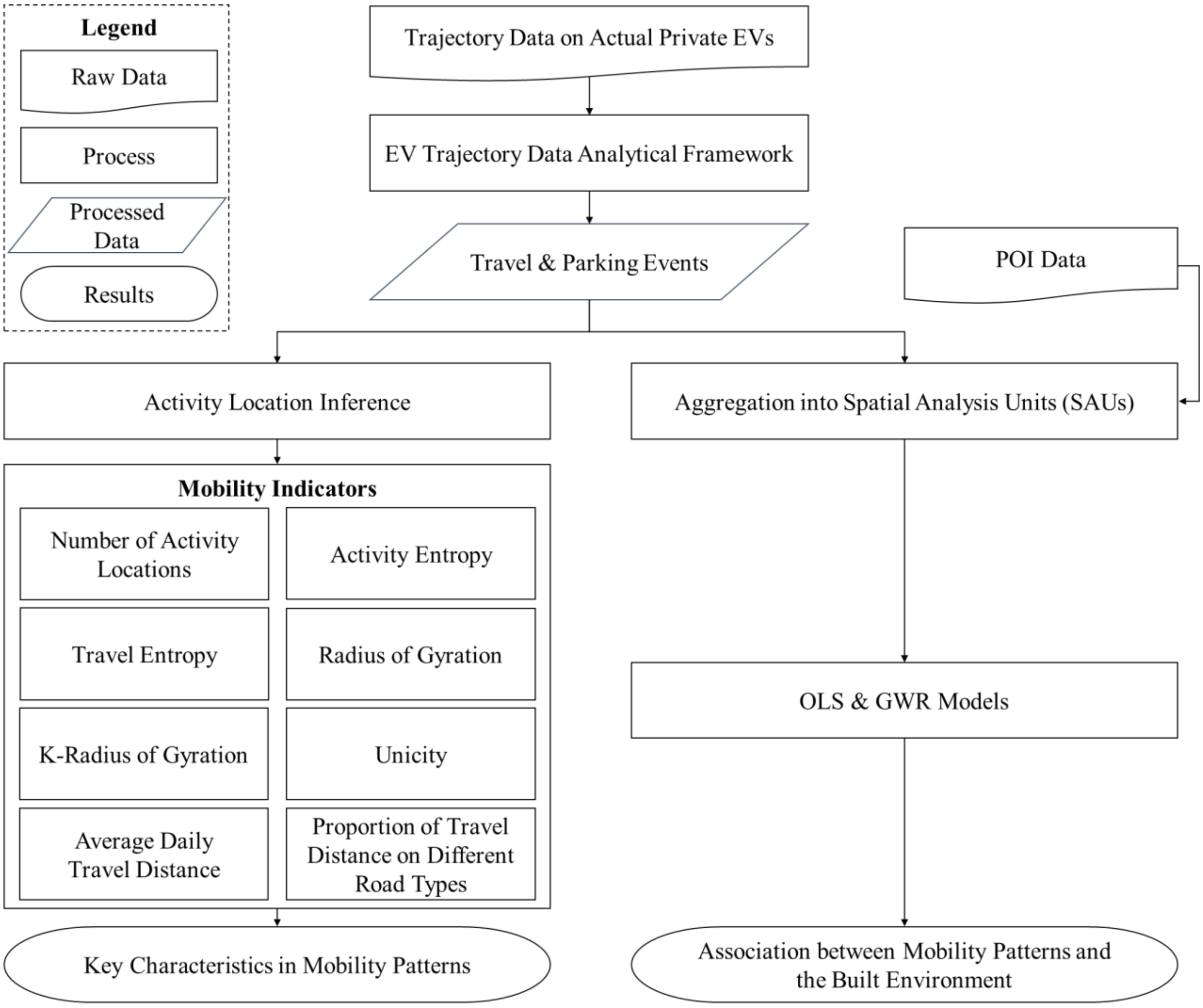


Fig. 4 Analytical framework

3.3 Characterizing Mobility Patterns of Private EV Users

We used eight typical mobility indicators which have been widely used in human mobility analysis (see Section 2.1 for a review), to characterize mobility patterns of private EV users, namely the number of activity locations (N_a), activity entropy (E_a), travel entropy (E_t), radius of gyration (R_g), k-radius of gyration (R_g^k), unicity (U_k), average daily travel distance (ADTD), and proportion of travel distance (PTD) on different road types.

(1) The Number of Activity Locations (N_a)

N_a quantifies the total number of activity locations visited by a private EV user during a specific period of time, reflecting whether the user tends to perform activities at more diverse locations or not. A large value suggests the user tends to perform activities at a wider variety of places [26, 32]. N_a can be calculated with Equation (1). Here, we used the number of parking lots which an EV user used as the number of activity locations visited with an assumption that EV users perform their activities around the parking lots where their EVs are parked.

$$N_a = |\{al_1, al_2, \cdots, al_N\}| = |set\{pl_1, pl_2, \cdots, pl_n\}| \quad (1)$$

Where, al_i denotes the i_{th} activity location; $\{al_1, al_2, \cdots, al_N\}$ denotes a collection of a private EV user's activity locations referred from the parking events sequence by the user $\{(pl_1, pt_1^s, pt_1^e), (pl_2, pt_2^s, pt_2^e), \ldots, (pl_n, pt_n^s, pt_n^e)\}$, in which, pl_j denotes the parking location of the j_{th} parking event; pt_j^s and pt_j^e denote the starting and ending times of the parking event.

(2) Activity Entropy (E_a)

Compared with the indicator Number of Activity Locations (N_a), which only considers the number of activity locations visited by an EV user, the indicator, Activity Entropy (E_a), takes a further step and additionally considers the visitation frequency at each activity location. If an EV user performs its activities more frequently at some specific locations (rather than visiting all the locations with an equal frequency), it tends to have a more regular mobility pattern [12, 26, 28]. Given the number of activity locations N_a, the visitation probability at each activity location for a private EV user can be described with a vector $\{p_1^a, p_2^a, \cdots, p_N^a\}$, where $p_i^a = \frac{af_i}{\sum_{i=1}^{N} af_i}$ denotes the ratio of the visitation frequency at the i_{th} activity location to the total number of visitations. Thus, $\sum_{i=1}^{N} af_i = 1$. Based on the calculated visitation probability at each activity location, the activity entropy E_a can be calculated with Equation (2). A small value indicates the user has preferences towards some particular activity locations and thus perform activities more frequently at these locations. Therefore, the user has a more regular mobility pattern.

$$E_a = -\sum_{i=1}^{N} p_i^a \times \log(p_i^a) \tag{2}$$

(3) Travel Entropy (E_t)

Similar to activity entropy E_a, travel entropy E_t also measures the regularity of human mobility behavior but with a focus on the link (or relation) between paired activity locations, rather than individual activity locations. Specifically, it quantifies the extent to which a private EV user' travels were uniformly distributed across paired activity locations (see Equation (3)). A large value suggests more evenly distributed (or less laterality) [27, 29].

$$E_t = -\sum_{trv \in T} p(trv) \times \log(p(trv)) \tag{3}$$

Where, trv denotes the travel between two specific activity locations (i.e., an origin-destination pair); T denotes a set of unique origin-destination pairs without considering direction; $p(trv)$ is the ratio of the number of observed travel events between an origin-destination pair to the total number of travel events by the user. Thus, $\sum_{trv \in T} p(trv) = 1$.

The three indicators, namely Number of Activity Locations (N_a), Activity Entropy (E_a), and Travel Entropy (E_t), are used to reveal whether private EV users tend to perform activities at a small number of specific activity locations and to move between these locations more frequently, relative to all the activity locations they visited, so as to characterize the diversity and regularity of private EV users' mobility patterns. The empirical findings are expected to be helpful for transport planners and infrastructure companies to better deploy charging facilities according to EV users' specific activity and travel patterns.

(4) Radius of Gyration (R_g)

R_g measures the range of activity space of a private EV user. A large value suggests that the user prefers to drive his/her EV to perform activities over a broad geographical area [13, 26, 54]. R_g can be calculated by Equation (4).

$$R_g = \sqrt{\frac{\sum_{i=1}^{N}(af_i \times ((x_i - \bar{x})^2 + (y_i - \bar{y})^2))}{\sum_{i=1}^{N} af_i}} \quad (4)$$

Where, (x_i, y_i) denotes spatial coordinates of the i_{th} activity location; $(\bar{x}, \bar{y})$ is the center of mass of all activity locations, which can be calculated by $(\frac{\sum_{i=1}^{N}(af_i \times x_i)}{\sum_{i=1}^{N} af_i}, \frac{\sum_{i=1}^{N}(af_i \times y_i)}{\sum_{i=1}^{N} af_i})$. In the calculation, those frequently visited locations would contribute more to the result than those locations with less visitations.

(5) K-Radius of Gyration (R_g^k)

Instead of measuring all visited activity locations, R_g^k, which was proposed by Pappalardo et al. [13], could help understand the role of the k most important locations in determining the mobility range of an individual. Here, we treated the top k most frequented visited activity locations of a private EV user as the k most important locations (called top k locations hereafter). R_g^k can be calculated by Equation (5). A large value of R_g^k suggests that the top k

locations can explain individual activity space to a large extent, while a small value indicates that the top k locations play an insignificant role in determining one's range of movements. Furthermore, the ratio of R_g^k to R_g can be used to group EV users into k-returners and k-explorers [13]. Specifically, k-returners (defined as $R_g^k \geq R_g/2$) are those individuals who have a propensity to intensively perform their activities at the top k locations and the space covered by these locations approximates the overall activity space; while k-explorers (defined as $R_g^k < R_g/2$) prefer to explore outer space besides the given top k locations.

$$R_g^k = \sqrt{\frac{\sum_{i=1}^{k}(af_i \times ((x_i - \overline{x_k})^2 + (y_i - \overline{y_k})^2))}{\sum_{i=1}^{k} af_i}} \tag{5}$$

Where, $(\bar{x}_k, \bar{y}_k)$ denotes the center of mass of top k locations.

The two indicators, namely Radius of Gyration (R_g) and K-Radius of Gyration (R_g^k), are used to characterize the spatial extent of private EV users' activity space. The insights would inform the design of EVs (particularly, the EV battery capacity). In general, a larger activity space indicates a need for a larger EV on-board battery.

(6) Unicity (U_k)

U_k is used to measure the uniqueness of mobility traces of private EV users. An EV user is considered as unique when at least one of the activity locations visited by the user had never been accessed by the others. Since activity locations are a collection of spatial points and it is difficult to define a spatial relationship between points, we quantified the uniqueness at the level of spatial analysis units (SAUs), including grid and traffic analysis zone [11, 26].

Given a collection of an EV user's activity locations $\{al_1, al_2, \cdots, al_N\}$ and a set of SAUs $\{sau_1, sau_2, \cdots, sau_z\}$, we mapped activity locations into SAUs, counted the visitation frequency at each SAU, sorted the SAUs in a descending order according to visitation frequency, and extracted the top k SAUs for further analysis. We applied this procedure to all private EV users and described the uniqueness of EV users with their top k SAUs. A private EV user was labeled as unique if at least one of the SAUs the user visited had never been accessed by the others. U_k was defined as the ratio of the number of unique private EV users to the total number of users, as presented by Equation (6).

$$U_k = \frac{number\ of\ unique\ private\ EV\ users\ with\ top\ k\ SAUs}{total\ number\ of\ private\ EV\ users} \tag{6}$$

Understanding the uniqueness of mobility traces of private EV users relative to others with the indicator Unicity (U_k) would inform the suitable development strategies for public charging facilities. For example, it could help us to figure out whether it would be better to deploy large charging stations at a few places than to deploy small charging stations at many places (so as to extend the coverage of charging network).

In addition, two indicators (namely Average Daily Travel Distance and Proportion of Travel Distance on Different Road Types) were particularly used to characterize driving patterns of private EV users [55].

(7) Average Daily Travel Distance (ADTD)

Given a set of EV travel distances from different travel days $\{TD_1, TD_2, \cdots, TD_{N_d}\}$ for a private EV user, its ADTD can be calculated by Equation (7). A larger value indicates that the private EV user needs to travel a longer distance for its daily activities.

$$ADTD = \frac{\sum_{i=1}^{N_d} TD_i}{N_d} \tag{7}$$

Where, N_d denotes the total number of travel days in one month for a private EV user; TD_i denotes the travel distance in the i_{th} travel day for the user.

(8) Proportion of Travel Distance (PTD) on Different Road Types

For private EV users, they may have heterogenous preferences in planning a route from one activity to another. Here, we used the indicator, Proportion of Travel Distance on Different Road Types, to indicate EV users' preferences toward different levels of road links, namely, arterial road and above (with three lanes and above for one direction), secondary road (with two lanes for one direction), and branch (with one lane for one direction), in route choice. This can be mathematically represented by a vector (see Equation (8)). It is worth noting that the level of road links chosen is closely associated with electricity consumption of EVs [56, 57].

$$(PTD_a, PTD_s, PTD_b) = (\frac{TD_a}{TD_a + TD_s + TD_b}, \frac{TD_s}{TD_a + TD_s + TD_b}, \frac{TD_b}{TD_a + TD_s + TD_b}) \tag{8}$$

Where, PTD_a, PTD_s, and PTD_b denote the proportions of distances travelled on arterial roads and above, secondary roads, and branches, respectively; TD_a, TD_s, and TD_b denote the total distances travelled on arterial roads and above, secondary roads, and branches, respectively.

3.4 Exploring the Association between Mobility Patterns and the Built Environment: OLS and GWR Models

It has been commonly accepted that human mobility patterns are associated with the built environment [14, 20, 40]. Particularly for EV users, their interaction with the built environment involves the influence of vehicles' energy consumption and the availability of charging facilities. Therefore, we could observe that EV users' mobility patterns are similar to their charging patterns (see Appendix C in the Supplementary Materials for more details).

Here, we will explore how mobility patterns of private EV users may be associated with the built environment, using two typical regression models, i.e., ordinary least squares (OLS) and geographically weighted regression (GWR). For the spatial regression analysis, the OLS estimation is usually a good start point, as it is simple but could provide a global understanding of the association between mobility patterns and the built environment [15]. Further, since the spatial autocorrelation is found for mobility patterns of private EV users (described with the daily number of visitations to SAUs) and the built environment variables based on the Moran' I test (see Appendix D in the Supplementary Materials for more details), GWR, which takes the spatial correlation into consideration, can be used to model the local (i.e., spatially varying) relationship between mobility patterns and the built environment [46, 58]. Compared with other similar local regression models, such as Multi-Scale GWR, GWR tends to be the most popular one and has been widely used in geographical [59] and transportation [40] studies.

(1) Ordinary Least Squares (OLS) Model

OLS is a global model and uses least square approach to estimate the value of a dependent variable with one or more exploratory variables in a linear function form, as presented by Equation (9). The term global implies that the effect of exploratory variables on the dependent variable remains the same over space, and thus it fails to capture spatial non-stationarity [14, 20]. Although OLS does not account for spatial variability, it could examine the global effects of the built environment variables on mobility patterns of EV users.

$$y_i = \beta_0 + \sum_{k=1}^{m} \beta_k x_{ik} + \varepsilon_i, i \in \{1,2,\cdots z\} \tag{9}$$

Where, $i \in \{1,2,\cdots z\}$ denotes a SAU; k denotes an exploratory variable; x_{ik} denotes the value of the k_{th} exploratory variable in the i_{th} SAU; β_k denotes the estimated coefficient for x_{ik}; β_0 denotes the intercept; ε_i denotes the error term; y_i denotes the daily number of visitations to the i_{th} SAU by all private EV users in the trajectory dataset.

(2) Geographically Weighted Regression (GWR) Model

GWR [60] is particularly designed to model spatially heterogeneous data, explicitly considering the spatial effect of variables with incorporation of spatial locations of SAUs, as presented by Equation (10). As a local regression model, GWR can be viewed as an extension of OLS [14, 48]: specifically, it develops a regression model for each SAU only considering nearby observations (rather than all observations); meanwhile, those closer observations would have a greater influence on the targeted SAU compared to those further ones.

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{m} \beta_k(u_i, v_i)x_{ik} + \varepsilon_i, i \in \{1,2, \cdots n\} \quad (10)$$

Where, (u_i, v_i) denotes the spatial location of the i_{th} SAU; $\beta_0(u_i, v_i)$ denotes the intercept; $\beta_k(u_i, v_i)$ denotes the regression coefficient for x_{ik}. Unlike fixed β_k in an OLS model, $\beta_k(u_i, v_i)$ varies spatially in a GWR model, so as to measure spatial variation of observations. The spatially varying coefficient for each exploratory variable can be estimated using the weighted least square approach, in which the Gaussian kernel function is usually employed to calculate the spatial weight matrix [15, 61, 62].

4 Results and Discussion

4.1 Characterizing Mobility Patterns of Private EV Users in Beijing

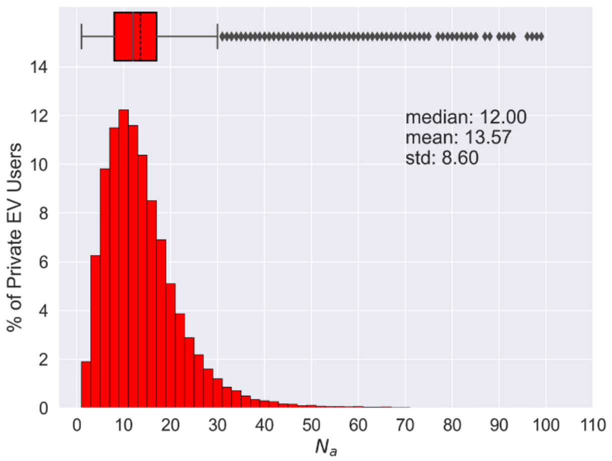
The calculation of eight mobility indicators for private EV users in Beijing was implemented through the programming language Java and was conducted on a desktop computer with a "Intel(R) Core (TM) i7-10700 CPU @ 2.90GHz" processor and 16 GB RAM. The total running time for calculating the mobility indicators was 49.2 minutes.

4.1.1 Diversity and Regularity of Private EV Users' Mobility Patterns

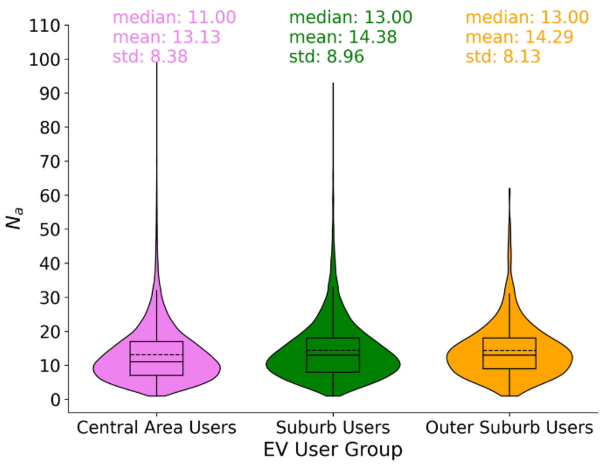
We will first present the diversity and regularity in private EV users' activity and travel patterns with three indicators, i.e., the number of activity locations (N_a), activity entropy (E_a), and travel entropy (E_t).

(1) The Number of Activity Locations (N_a)

It can be found from Fig. 5-(a) that the distribution of N_a is skewed to right, suggesting that a significant proportion of private EV users tended to perform activities at a small number of locations (with an average N_a of 13.57 per month). Similar mobility patterns were observed for mobile phone users in Singapore (the average N_a was 14.24) in the work by Xu et al. [26], which used a 50-day mobile phone dataset. Further, Fig. 5-(b) shows the differences between EV users from the three district categories (namely center area, suburb, and outer suburb, as shown in Fig. 1) in the number of activity locations visited, N_a. It can be found that private EV users from the suburb and outer suburb of Beijing were slightly prone to visit more activity locations than those from the central area. For example, the average numbers for EV users from the suburb and outer suburb were 14.38 and 14.29, respectively; while the average number was 13.13 for those from the central area. A possible reason might be that the central area tended to have a higher density of activity facilities (see Fig. 2), which allowed EV users to get access more easily to different activity facilities in one place. As a result, EV users could visit fewer places.



(a) The distribution of N_a for all private EV users

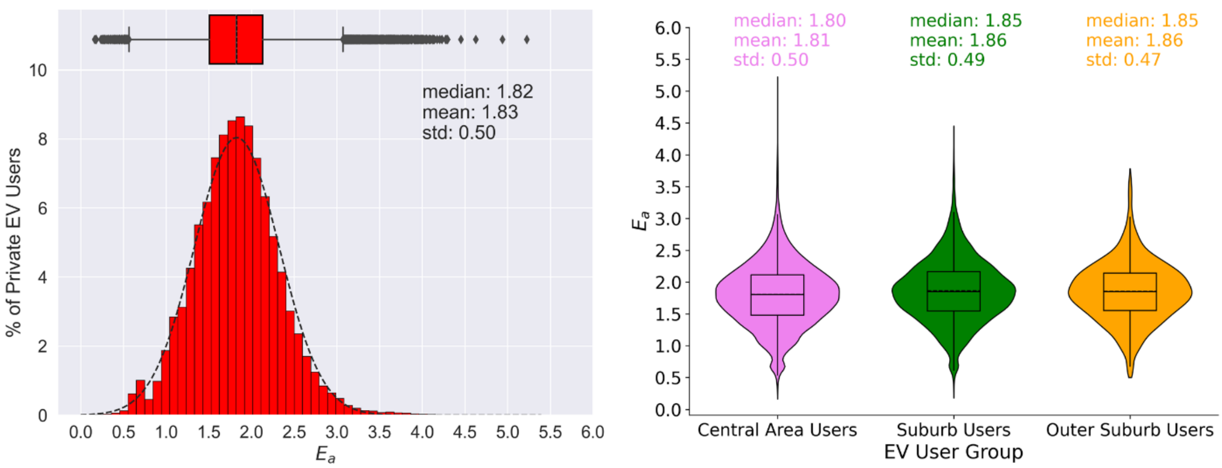


(b) N_a distributions for EV users from three different district categories

Fig. 5 The number of activity locations (N_a)

(2) Activity Entropy (E_a)

Fig. 6-(a) shows the distribution of E_a for overall private EV users, generally following a normal distribution (with a $mean = 1.83$ and $std = 0.50$). It can be found that private EV users tended to prefer to perform activities at a small number of activity locations relative to the number of all the locations visited (indicating regularity to some extent). Take the median value of N_a (which is equal to 12) as an example, it can be estimated that a user's random visitation at 12 activity locations (see Fig. 5-(a)) would result in a median value of 2.48 for E_a, which is higher than the actual median value of 1.82. Compared with mobile phone users in Singapore (the mean E_a was 1.10) [26], the private EV users in Beijing tended to have a less regular activity pattern (with an average E_a of 1.83), though the average numbers of activity locations visited are close to each other for private EV users in Beijing and mobile phone users in Singapore. Meanwhile, Fig. 6-(b) reveals that the regularity of activity patterns of the EV users from the three district categories was highly similar, probably because most of the EV users had a much higher frequency of performing their activities at a small number of locations, such as home and workplace.

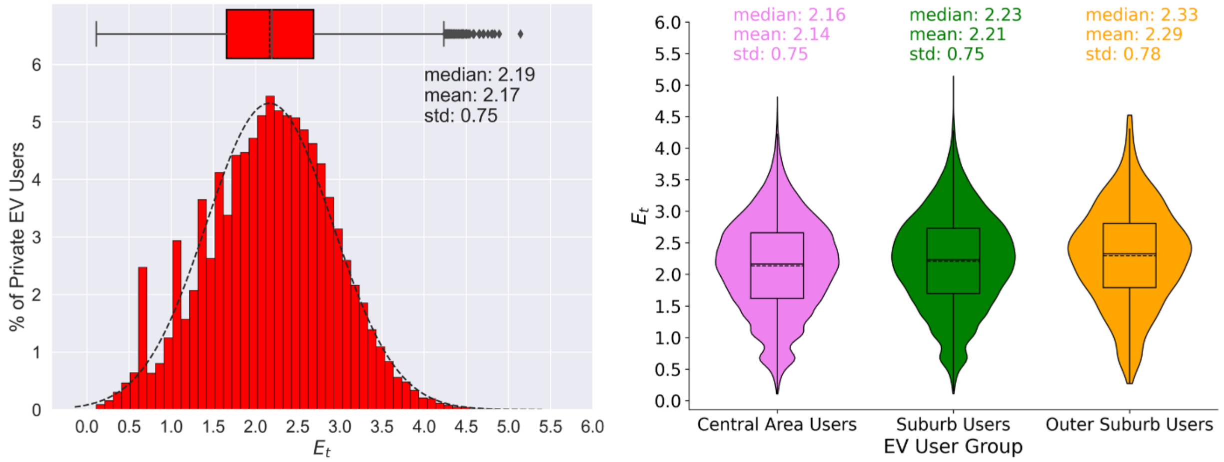


(a) The distribution of E_a for all private EV users (b) E_a distributions for EV users from three different district categories

Fig. 6 Activity entropy (E_a)

(3) Travel Entropy (E_t)

E_t measures the regularity of travel patterns of private EV users. Fig. 7-(a) shows that the distribution of E_t generally follows a normal distribution (with a $mean = 2.17$ and $std = 0.75$), revealing that private EV users did have regular travel patterns. The distribution of E_t is similar to that of E_a (see Fig. 6-(a)), because travel is commonly considered as a derived demand for performing activities, which is the essential concept of activity-based travel demand modelling [63]. Aa a result, we would expect that private EV users' travel events were mostly associated with those frequently visited activity locations, rather than all the visited locations. Since EVs' charging demand is closely associated with their mobility behavior, we could further speculate that the distribution of charging demand was likely to be spatially uneven and there was a higher charging demand at those activity locations that were visited frequently. Such empirical findings would be helpful for deployment of charging infrastructure: we could deploy charging facilities at those locations that EV users tend to visit more frequently. The regularity of travel patterns of private EV users in Beijing (with an average E_t of 2.17) is similar to that of mobile phone users in Singapore (with an average E_t of 2.28) [26]. In addition, we did not find significant differences between the three district categories in the regularity of travel patterns, as shown in Fig. 7-(b).



(a) The distribution of E_t for all private EV users

(b) E_t distributions for EV users from three different district categories

Fig. 7 Travel entropy (E_t)

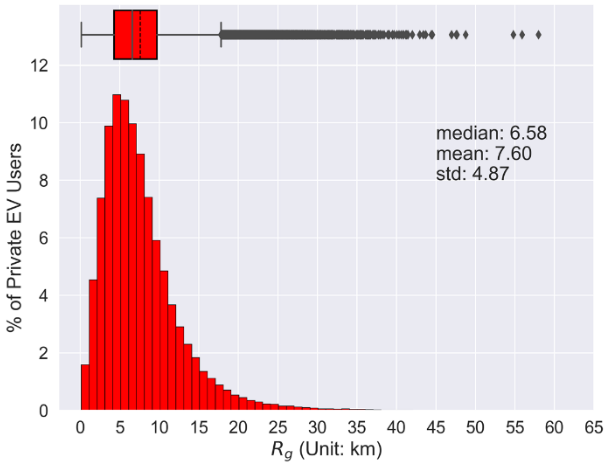
Furthermore, we also examined the temporal difference between working and non-working days in the diversity and regularity of private EV users' mobility patterns (see Appendix E in the Supplementary Materials). The results suggest that a larger proportion of private EV users tended to have less diverse activity locations and more regular activity and travel patterns on working days. This might be because private EV users tended to have more mandatory activities (e.g., work) generally with a fixed location on working days.

4.1.2 Spatial Extent of Private EV Users' Mobility Patterns

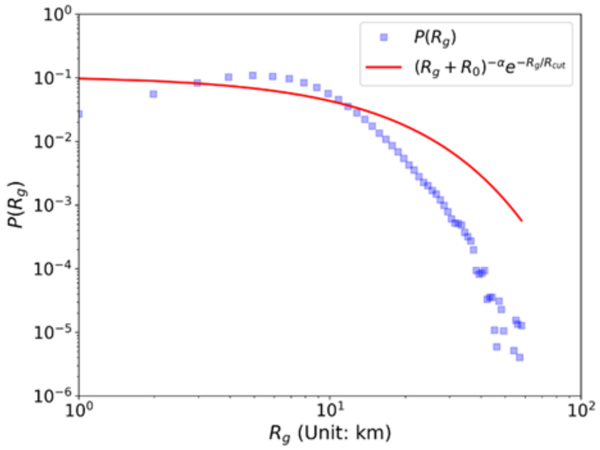
We used another two indicators, namely radius of gyration (R_g) and k-radius of gyration (R_g^k), to describe the spatial extent of private EV users' overall activity space and the EV users' activity space that was only made up of top k activity locations, respectively.

(1) Radius of Gyration (R_g)

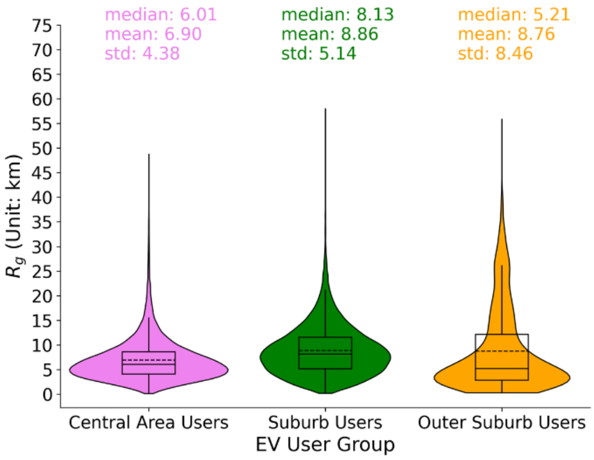
As shown in Fig. 8-(a), the distribution of R_g is highly skewed to right, indicating that most of the private EV users tended to move around in a small geographical area. The mean R_g (specifically 6.90 km) for private EV users in Beijing is larger than the value (specifically 4.78 km) for mobile phone users in Singapore [26]. Meanwhile, Pappalardo et al. [64] and Pappalardo et al. [13] found that the probability distribution of R_g for CV users in the central Italy generally followed the truncated power-law (i.e., $(R_g + R_0)^{-\alpha} exp^{-R_g/R_{cut}}$), which cannot be found in our case for private EV users in Beijing, as shown in Fig. 8-(b). Fig. 8-(c) compares the differences between the three district categories in the range of private EV users' activity space: (1) the EV users from the central area tended to have a smaller R_g (specifically 6.90 km on average) than those from the suburb users (specifically 8.86 km on average); (2) the proportion of EV users with R_g ranging from 20 to 35 km was more remarkable for the outer suburb, and also a larger proportion of EV users from the outer suburb had a rather small R_g with a median value of 5.21 km. This may be attributed to different degrees of development in the three district categories, as well as the unique geographic relationships between them. Specifically, the central area has a much higher density of activity facilities (see Fig. 2), which generates more activity opportunities (e.g., employment opportunities) for the EV users not only from the central area but also from the suburb and outer suburb. As a result, the EV users particularly from the outer suburb had a longer travel distance if they need to travel to the central area. However, the long travel distance might also discourage some of the EV users to perform activities in the central area. Instead, they might just use activity facilities in the outer suburb. Note that we also explored the temporal difference in R_g (see Appendix E in the Supplementary Materials).



(a) The distribution of R_g for all private EV users



(b) The probability distribution of R_g for all private EV users

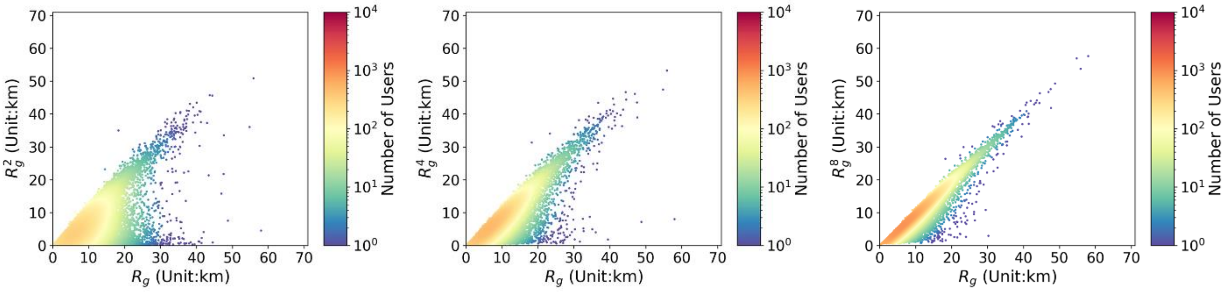


(c) R_g distributions for EV users from three different district categories

Fig. 8 Radius of gyration (R_g)

(2) Radius of Gyration (R_g) versus K-Radius of Gyration (R_g^k)

Fig. 9 shows the relationship between R_g^k ($k = 2, 4, 8$) and R_g. Each point in the figure represents a specific pair of R_g^k and R_g, and we used the color to indicate the number of private EV users at a specific point. The location of a point in the coordinate space provides insights into the extent to which the EV user's top k locations could represent the user's overall activity space. Specifically, for those points located along the diagonal (i.e., R_g^k is close to R_g), the EV users' top k locations could well explain their overall activity space; while for those points located along the x-axis, the EV users' top k locations could not represent their overall activity space. By comparing the subfigures (a)-(c), we found that with an increase in the number of top k locations used, more points move away from the x-axis, but move towards the diagonal, indicating that using a higher number of top k locations could help to better present the EV users' overall activity space. This was also observed in the work by Pappalardo et al. [13], which explored the CV users' mobility patterns in the central Italy.



(a) $k = 2$ (b) $k = 4$ (c) $k = 8$

Fig. 9 R_g versus R_g^k for all private EV users

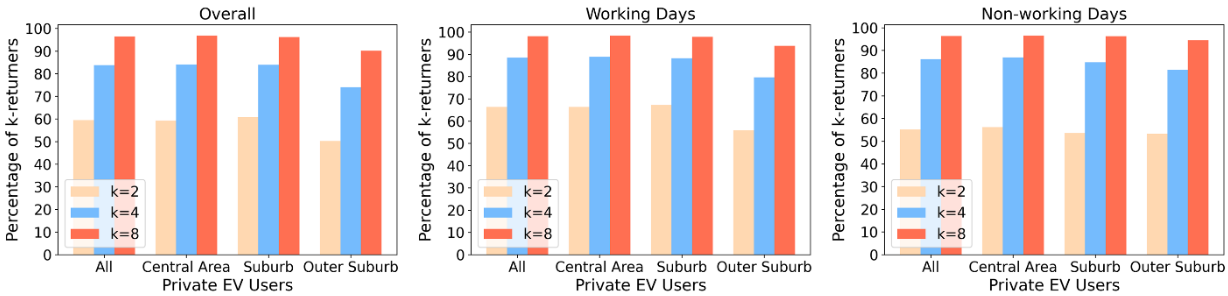
(3) K-Returners/K-Explorers

Private EV users can be defined as k-returners or k-explorers according to the ratio of R_g^k to R_g (see Section 3.3 for the definitions). Fig. 10 shows the percentage of k-returners ($k = 2, 4, 8$) by day and geographical region. The following conclusions can be drawn:

- There were around 60% of all private EV users were 2-returners, meaning that more than half of overall activity space can be explained by the top 2 locations (most likely home and workplace) for around 60% of private EV users. While in the work by Xu et al. [26], more than 70% of mobile phones users in Singapore were 2-returners. Furthermore, the proportion of k-returners would rise to around 95% when the k is set to 8 (see Fig. 10-(a)).
- There were less returners (i.e., more explorers) in the outer suburb for $k = 2, 4, 8$ than the

central area and suburb, indicating that more EV users from the outer suburb were more likely to explore the outer space beyond their top k activity locations. As a result, some EV users from the outer suburb had very large activity space (see Fig. 8-(c)).

- There was a higher proportion of 2-returners on working days. This might be because the general top 2 locations would be home and workplace for the majority of private EV users on working days. However, there was no significant difference between working days and non-working days in the proportions of 4-returners and 8-returners.



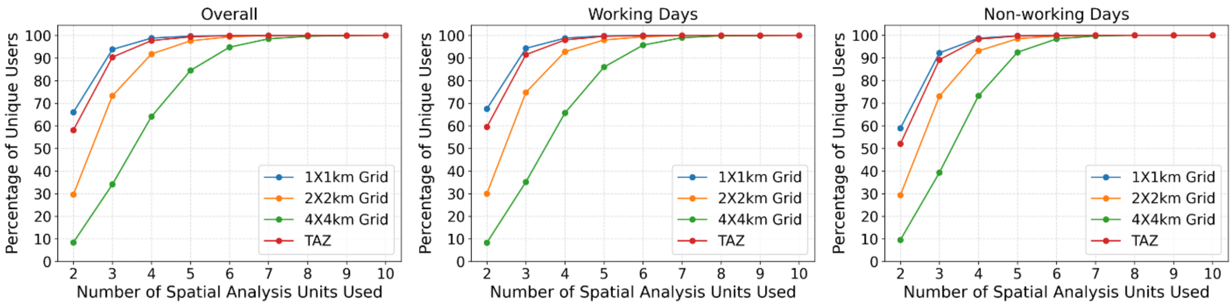
(a) Overall mobility patterns (b) Mobility patterns on working days (c) Mobility patterns on non-working days

Fig. 10 Percentages of k-returners ($k = 2, 4, 8$) by day and geographical region. Note that the percentage of k-explorers can be calculated by subtracting the percentage of k-returners from 100%.

4.1.3 Uniqueness of Private EV Users' Mobility Patterns

We further explored the uniqueness of private EV users' mobility patterns with a typical indicator, i.e., Unicity (U_k), particularly considering the modifiable areal unit problem (MAUP). Specifically, we used the four types of spatial analysis unit (SAU) in quantification of uniqueness, namely 1×1 km grid, 2×2 km grid, 4×4 km grid, and traffic analysis zone (TAZ). Fig. 11 shows the percentage of uniquely identified private EV users when the top 2 to 10 SAUs were used to extract from EV users' mobility. As found by Xu et al. [26], over 90% of mobile phone users could be uniquely identified in Singapore with only five 1×1 km grids visited;

while our results reveal a higher level of uniqueness for private EV users in Beijing at the same spatial scale: the uniqueness degree in our case was almost 100%, see Fig. 11-(a). Also, we found that the uniqueness could remain at an extremely high level (specifically, above 95%) even a lower-resolution spatial analysis unit (e.g., 2×2 km grid or TAZ) was used. Compared with 1×1 km and 2×2 km grids, 4×4 km grids would significantly weaken the ability to uniquely distinguish between EV users, especially when a small number of SAUs visited (e.g., from 2 to 5) was used. Besides, there was no significant difference between working days and non-working days in the uniqueness of private EV users' mobility patterns (see subfigures (b) and (c)).



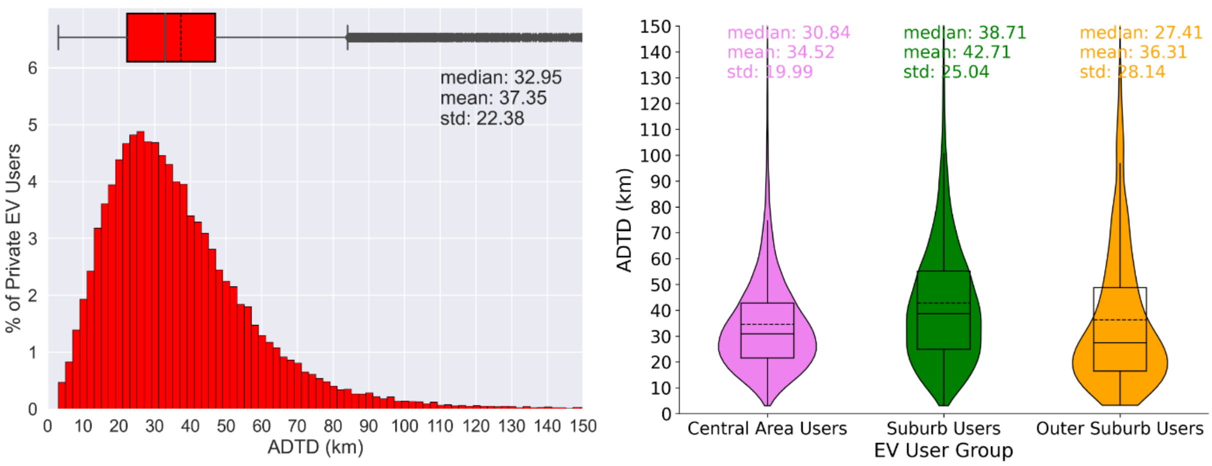
(a) Overall mobility patterns (b) Mobility patterns on working days (c) Mobility patterns on non-working days

Fig. 11 Percentages of unique private EV users

4.1.4 Driving Patterns of Private EV users

(1) Average Daily Distance Travelled (ADDT)

Fig 12-(a) shows the distribution of ADTD. It can be found the mean ADTD for private EV users was 37.35 km (the ADTD for car travelers in Beijing in 2018 was 31.30 km [65]) and there were only 1.79% of private EV users having the ADTD over 100 km, suggesting that for most private EV users, only a short travel distance (relative to their electric driving range) was needed to meet their daily activity demand. Compared with the previous work by Hao et al. [52], which used a dataset containing only 58 private EV users in Beijing, the ADTD in our study was much shorter than that (i.e., 44.8 km) from their study. This indicates the advantage of using a much larger dataset and more representative samples (over 76,000 EV users) in our study: the dataset could more accurately characterize EV mobility patterns. Also, we compared ADTDs of private EV users from the three different district categories, as shown in Fig. 12-(b). It can be found that the private EV users from the central area tended to have a shorter ADTD (specifically 34.52 km on average) than those from the suburb users (specifically 42.71 km on average). Meanwhile, the proportion of EV users with an ADTD longer than 100 km was more remarkable for the outer suburb, and also a large proportion of EV users from the outer suburb had a rather short ADTD with a median value of 27.41 km. Similar patterns were observed for the indicator Radius of Gyration (R_g). This may be because that a large activity space usually results in a longer travel distance.



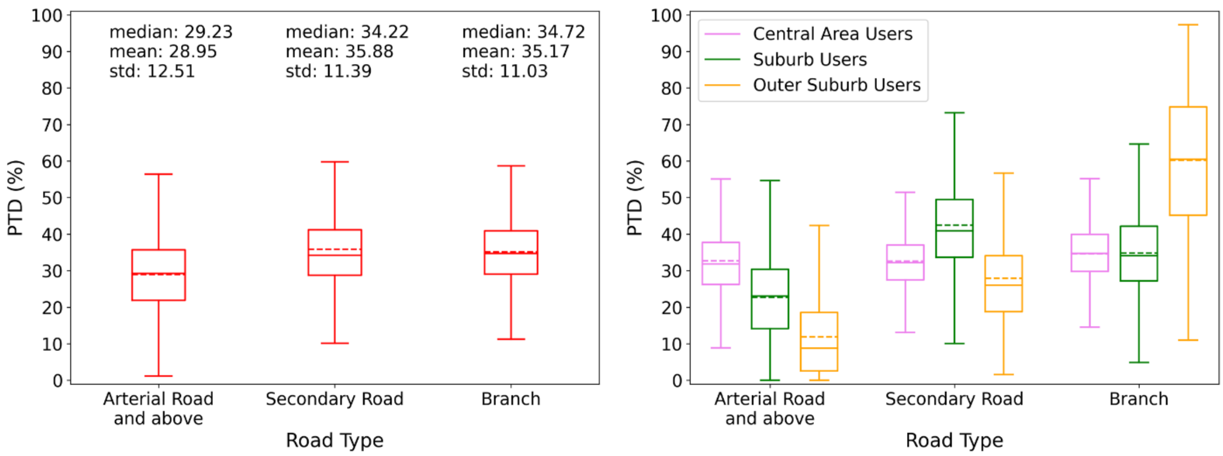
(a) The distribution of ADTD for all private EV users

(b) ADTD distributions for EV users from three different district categories

Fig. 12 Average daily travel distance (ADTD)

(2) Proportion of Travel Distance (PTD) on Different Road Types

As shown in Fig. 13-(a), the PTDs on arterial roads and above, secondary roads, and branches for private EV users were 28.95%, 35.88%, and 35.17%, on average. Compared with the actual proportions of these three levels of road links in Beijing (i.e., 8.45%, 34.94% and 56.61%, respectively), it can be found that in general, private EV users had preferences towards arterial roads and above in their route choice. This may be attributed to a higher driving speed allowed and less traffic congestion on arterial roads and above. Also, we compared PTD distributions for private EV users from the three different district categories, as shown in Fig. 13-(b). The results show that the private EV users from the central area tended to use more arterial roads and above in their journeys than those from the suburb and outer suburb. This is likely because that there was a larger proportion of higher level of road links (e.g., express ways and arterial roads) in the central area.



(a) The distributions of PTDs for all private EV users

(b) PTD distributions for EV users from three different district categories

Fig. 13 Proportion of travel distance (PTD) on different road types

4.2 Association between Mobility Patterns and the Built Environment

We estimated OLS and GWR models within ArcMap 10.2 software package on a desktop computer with a "Intel(R) Core (TM) i7-10700 CPU @ 2.90GHz" processor and 16 GB RAM to explore the possible association between mobility patterns of private EV users and the built environment. Before applying these two categories of models, we first examined the multi-collinearity issue, and eliminated those exploratory variables with a variance inflation factor (VIF) above 7.5 [45, 66]. Furthermore, all the remaining variables passed the test of Moran's I (see Appendix D in the Supplementary Materials for more details) and were used in both OLS and GWR models. The running time for estimating the OLS models varied from 3 to 12 seconds depending on the type of SAUs used (namely, 1×1 km grid, 2×2 km grid, 4×4 km grid, and TAZ), while the running time for estimating the GWR models varied from 5 to 30 seconds.

4.2.1 OLS Model Results

Table 2 shows the estimated OLS models by SAU for both working days and non-working days. The statistically significant variables are almost the same for working days and non-working days with few exceptions. However, we found the classical modifiable areal unit problem (MAUP) [46, 66] in the model estimation. Specifically, we identified different statistically significant variables with different SAUs used. For example, the variable, Scenic Spots, had a significantly positive association with the generation of EV trips according to the OLS model for the 4×4 km gird, while there was a significantly negative association according to the OLS model for TAZ. Therefore, we will only look at those variables which are statistically significant in all the models so as to reduce the influence of MAUP. Gymnasia is found as the only variable which is statistically significant in all the eight models; while previous studies identified Companies/Enterprises and Residential Buildings as statistically significant variables to the travel demand with vehicle-related transport modes used (e.g., car-hailing, taxi and bus) [66-69].

Table 2 OLS model estimation results

Variables	Estimated Coefficients of Exploratory Variables							
	Working Days				Non-working Days			
	1×1 km grid	2×2 km grid	4×4 km grid	TAZ	1×1 km grid	2×2 km grid	4×4 km grid	TAZ
Intercept	0.447	-2.941	-7.154	**16.126**	**0.580**	-0.803	-3.019	**9.619**
Transport Infrastructure	**0.829**	**1.059**	−	0.125	**0.803**	**1.070**	−	0.086
Educational Institutions	**2.174**	**4.138**	−	**2.112**	**1.524**	**2.911**	−	**1.677**
Financial Institutions	0.651	0.513	1.142	**1.280**	**0.591**	0.706	1.102	**1.024**
Scenic Spots	0.020	0.335	**1.232**	**-0.261**	-0.064	0.056	0.378	**-0.306**
Culture/Media Facilities	**1.503**	**2.609**	1.513	0.819	0.108	0.222	-1.001	-0.261
Health Care Facilities	-0.165	-1.133	−	0.422	-0.117	-0.295	−	0.300
Gymnasia	**4.423**	**7.237**	**16.133**	**4.750**	**3.396**	**6.396**	**13.036**	**3.719**
Government Agencies	-0.119	-0.108	-0.291	-0.083	-0.240	-0.013	0.643	-0.062
Service Facilities	**0.963**	−	−	**0.636**	**0.810**	−	−	**0.639**
Commercial Establishments	-0.074	−	−	-0.088	0.053	−	−	0.027
Companies/Enterprises	**-0.390**	-0.323	1.033	**-0.766**	**-0.725**	**-0.725**	0.291	**-0.754**
Residential Buildings	**-0.722**	**-1.237**	-1.230	**-0.731**	**-0.419**	**-0.639**	-0.424	**-0.447**

Note: (1) coefficients highlighted in bold are statistically significant at the 0.05 level; (2) " − ": denotes the variables that have been eliminated from the final models due to the multi-collinearity issue.

4.2.2 GWR Model Results

We first compared the performance of OLS and GWR models using three typical indictors, AIC_c, R^2, and Adjusted R^2, as shown in Table 3. Overall, GWR models outperform OLS models on both working days and non-working days, and also at all the SAU levels.

Table 3 OLS and GWR model performance

Indicators		Working Days				Non-working Days			
		1×1 km grid	2×2 km grid	4×4 km grid	TAZ	1×1 km grid	2×2 km grid	4×4 km grid	TAZ
AIC_c	**OLS**	54777.281	23482.249	9020.954	19205.775	49930.436	22331.401	8832.484	18159.874
	GWR	48690.980	21478.639	8609.670	17824.261	44949.342	20696.010	8447.149	17022.199
R^2	**OLS**	0.666	0.791	0.878	0.510	0.701	0.815	0.888	0.581
	GWR	0.914	0.958	0.949	0.808	0.922	0.941	0.951	0.813
Adjusted R^2	**OLS**	0.665	0.790	0.877	0.507	0.700	0.814	0.887	0.579
	GWR	0.891	0.937	0.938	0.779	0.893	0.924	0.940	0.786

Tables 4 shows the estimated GWR models on working days (see Appendix F in the Supplementary Materials for the estimated GWR models on non-working days). We found similar patterns on working days and non-working days: for nearly all exploratory variables, their local coefficients varied from a negative value to a positive one. This can be found even for those variables that are positively associated with EV travel demand at the global level, such as Gymnasia (see Table 2). This means that most of the built environment variables had spatially varying relationships with the EV users' mobility patterns.

Table 4 GWR model estimation results on working days

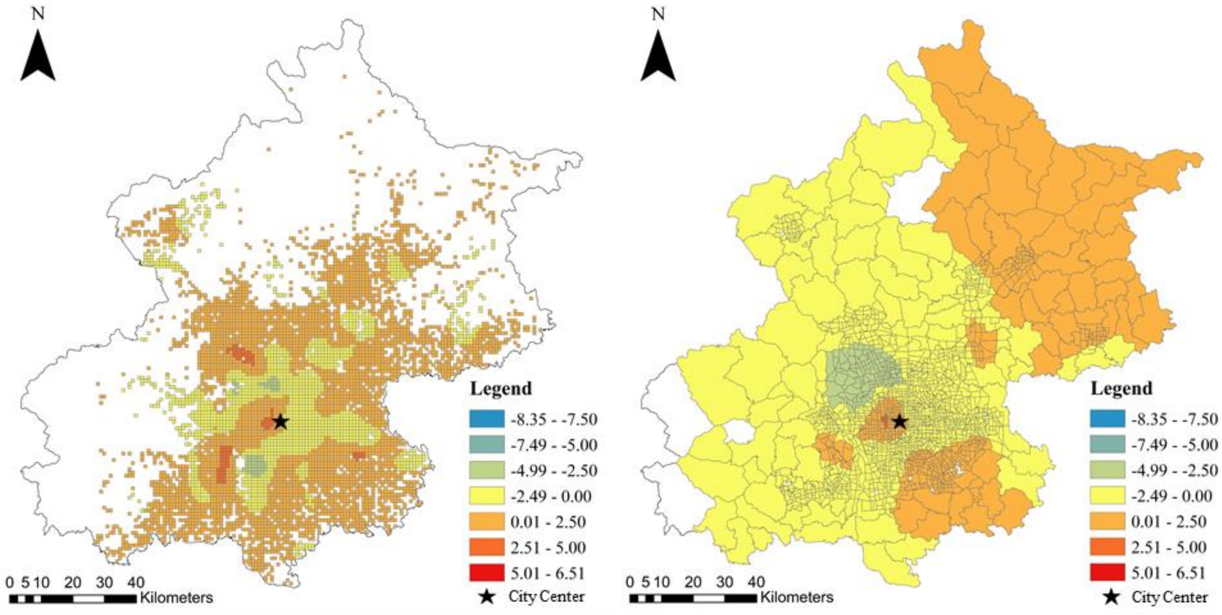
Variables	Estimated Coefficients of Exploratory Variables							
	1×1 km grid		2×2 km grid		4×4 km grid		TAZ	
	Min	Max	Min	Max	Min	Max	Min	Max
Intercept	-3.481	95.808	-25.059	307.393	-233.740	97.703	2.313	40.152
Transport Infrastructure	-0.434	4.850	-3.052	7.448	−	−	-0.728	4.263
Educational Institutions	-1.129	5.132	-2.385	7.141	−	−	0.208	3.085
Financial Institutions	-5.354	6.810	-9.933	10.562	-3.557	12.882	-0.962	5.094
Scenic Spots	-4.104	3.647	-14.981	6.029	-2.956	4.116	-1.187	1.417
Culture/Media Facilities	-6.450	7.603	-17.411	13.722	-2.328	20.385	-3.331	9.157
Health Care Facilities	-3.297	7.738	-13.456	15.247	−	−	-1.624	8.170
Gymnasia	-4.331	9.323	-7.041	14.463	0.239	22.157	0.646	8.093
Government Agencies	-2.361	3.291	-5.815	5.949	-4.958	3.685	-2.752	1.940
Service Facilities	-1.233	1.767	−	−	−	−	-2.696	4.898
Commercial Establishments	-0.856	0.884	−	−	−	−	-0.857	0.955
Companies/Enterprises	-3.935	9.124	-5.364	12.334	-1.267	6.506	-0.336	0.506
Residential Buildings	-4.336	3.500	-8.357	6.505	-5.616	4.343	-4.457	2.666

Note: " − ": denotes those variables were eliminated from the final models due to the multi-collinearity issue.

We further explore the spatial variances in the local coefficients for two typical variables, namely Residential Buildings and Companies/Enterprises (which are generally associated with home and work activities of travelers, respectively), using GWR models for 1×1 km grid and TAZ on working days for example. Note that we found similar patterns on working days and non-working days, and for GWR models for 2×2 km grid and 4×4 km grid (as presented in Appendix G in the Supplementary Materials). We particularly looked at Companies/Enterprises and Residential Buildings, as these variables were generally expected to be associated with EV users' commuting patterns, but were found not statistically significant at the global level according to the OLS models (see Table 2). To avoid the possible influence of the modifiable areal unit problem (MAUP) [66], our discussion below will be focused on the common patterns observed in both 1×1 km grid and TAZ.

(1) Spatial Variance in the Local Coefficients for Residential Buildings

For those positive coefficients, they were mostly located in city center and those central areas of the suburb, as shown in Fig. 14. This was likely because a large proportion of private EV users lived in these areas, which generated more EV trips originated from or destinated to their homes. For those negative coefficients, they mostly appeared in the areas around the city center where we can find many large residential communities. For instance, two of the most famous ones called Hui-Long-Guan and Tian-Tong-Yuan were located in the northwest and north areas away from the city center, in which we could observe significantly negative local coefficients for Residential Buildings (see Fig. 14). This may be attributed to the competition between EV and the other transport modes (e.g., metro). It is generally easy to access to public transit in these large residential communities [40], and the residents (especially for commuters) would prefer to travel through subway system if there is a subway station nearby [16], which could help to get rid of traffic congestion and save travel time.

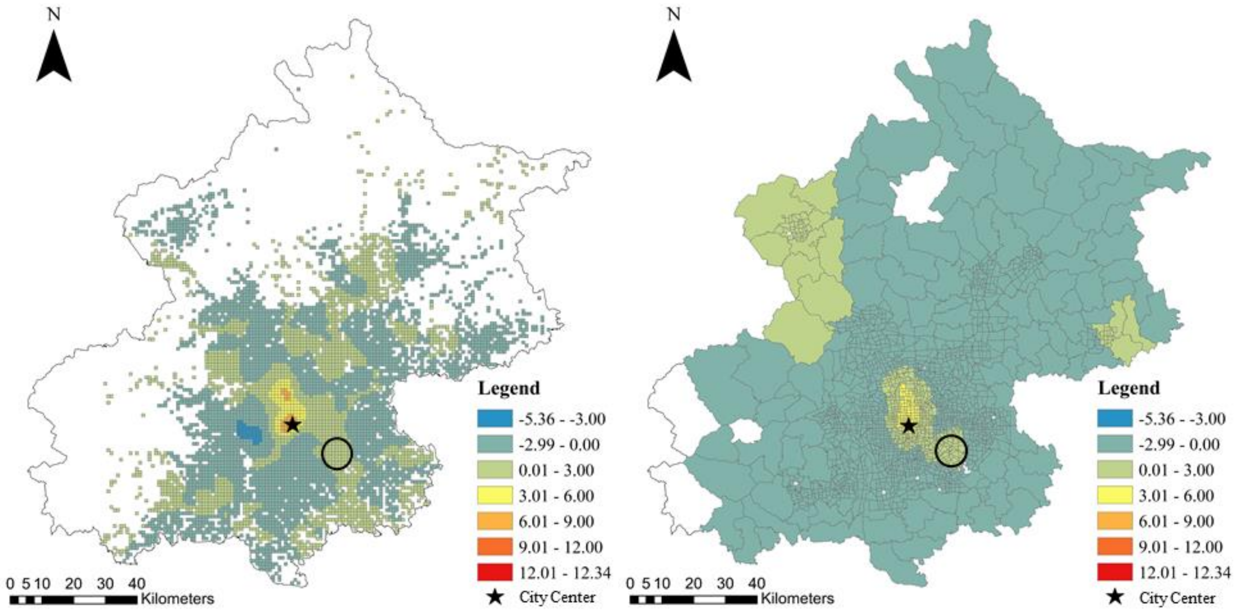


(a) 1×1 km grid (b) TAZ

Fig. 14 Spatial distribution of coefficients estimated for the variable Residential Buildings on working days (Note that those SAUs with no private EV visitation were eliminated from the GWR estimation)

(2) Spatial Variance in the Local Coefficients for Companies/Enterprises

For both 1×1 km grid and TAZ, the positive coefficients were mostly located in the city center (where CBD and Beijing Financial Street are located) and the northwest area adjacent to the city center (e.g., Xi-Er-Qi, where many high-tech companies are clustered), as shown in Fig 15. In addition, the areas which is southeast away from the city center (highlighted with a black circle in the figure) also had positive coefficients, as it is located in the economic development zone of Beijing. All the areas above have a high density of workplaces.



(a) 1×1 km grid (b) TAZ

Fig. 15 Spatial distribution of coefficients estimated for the variable Companies/Enterprises on working days (Note that those SAUs with no private EV visitation were eliminated from the GWR estimation)

5 Conclusions and Future Work

This paper characterized mobility patterns of private EV users using a unique one-month dataset comprising moving trajectories of 76,774 actual private EVs in January 2018 in Beijing. Specifically, we used eight mobility indicators, namely the number of activity locations (N_a), activity entropy (E_a), travel entropy (E_t), radius of gyration (R_g), k-radius of gyration (R_g^k), unicity (U_k), average daily travel distance (ADTD), and proportion of travel distance (PTD) on different road types, to characterize the diversity, regularity, spatial extent and uniqueness of private EV users' mobility patterns. The statistical distributions of these indicators show that most private EV users had both regular travel and activity patterns with special preferences towards some specific activity locations relative to all the activity locations they visited. Also, they tended to perform activities within a small geographical area and have a short daily travel distance (relative to their electric driving range). Furthermore, private EV users' mobility traces tended to be highly unique to each other. In addition, we used the ordinary least squares (OLS) and geographically weighted regression (GWR) models to explore the potential association between mobility patterns of private EV users and the built environment (described with POIs), particularly considering the modifiable areal unit problem (MAUP). Overall, GWR models outperformed OLS models, as the former captured the spatially varying relationships between mobility patterns and the built environment variables. Due to the MAUP, most of the statistically significant built environment variables varied across spatial analysis units (SAUs). Gymnasia was found as the only variable with the significantly positive coefficient in all the global models.

Our findings on private EV users' mobility patterns have several important implications for EV-related policymaking and infrastructure planning. First, private EV users tended to perform activities more frequently at some specific activity locations among all the locations they visited. Since EVs' charging demand is closely associated with their mobility behavior, there was a higher charging demand at these activity locations with more frequent visitations. Therefore, it is of significant importance to prioritize the deployment of charging facilities at these activity locations that were visited frequently (e.g., the residential places and workplaces of private EV users). Second, most private EV users tended to move around within a small activity space and have a short daily travel distance (relative to their electric driving range), and thus the current EV battery capacity (64% of battery EVs produced in China in 2018 had a range of over 300 km [70]) is large enough to meet their daily mobility demand. Therefore, instead of over-emphasis on the provision of those long-range EVs, more supportive policies (e.g., fiscal subsidy and free parking) and charging infrastructure should be developed to promote the uptake of EVs [52].

Third, considering that the high uniqueness of private EV users' mobility traces, it would be better to deploy small charging stations across the city, rather than to deploy large charging stations at a few places. This would help extend the coverage of charging network and thus provide more charging opportunities.

Our future work will be focused on the following several aspects: first, only a one-month trajectory dataset was used in this study to characterize private EV users' mobility patterns and it would be interesting to further examine whether the monthly or seasonal effects on private EV users' mobility patterns exist, for example, using a one-year dataset. Second, since there may be a nonlinear relationship between mobility patterns of private EV users and the built environment variables, advanced machine learning techniques, such as the Interpretable Memristive LSTM Network [71] and Gradient Boosting Decision Trees [72], could be used to capture the possible nonlinear impacts and further to predict the future mobility patterns of private EV users. Third, the empirical findings about the mobility patterns of private EV users could be further used in modelling of private EV users' mobility behaviors. For example, we could use the mobility patterns to define behavioral rules in an agent-based travel behavior model for private EV users.

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