Dominant Charging Location Choice of Commuters and Non-commuters: A Big Data Approach

Xiong Yang[1], Chengxiang Zhuge[1,2,3,4*], Chunfu Shao[5], Runhang Guo[1], Andrew Tin Chak Wong[1], Xiaoyu Zhang[5], Mingdong Sun[5], Pinxi Wang[6], Shiqi Wang[1]

[1] Department of Land Surveying and Geo-Informatics, The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong, China

[2] Research Institute for Sustainable Urban Development, The Hong Kong Polytechnic University, Hong Kong, China

[3] The Hong Kong Polytechnic University Shenzhen Research Institute, Shenzhen, China

[4] Smart Cities Research Institute, The Hong Kong Polytechnic University, Hong Kong, China

[5] Key Laboratory of Transport Industry of Big Data Application Technologies for Comprehensive Transport, Beijing Jiaotong University, 3 Shangyuancun, Xizhimenwai, Beijing, China

[6] Beijing Transport Institute, No. 9 LiuLiQiao South Lane, Fengtai District, Beijing, China

Email addresses: Xiong Yang (xiong.yang@connect.polyu.hk); Chengxiang Zhuge* (Corresponding Author, chengxiang.zhuge@polyu.edu.hk); Chunfu Shao (cfshao@bjtu.edu.cn); Runhang Guo (runhaguo@polyu.edu.hk); Andrew Tin Chak Wong (18055859d@connect.polyu.hk); Xiaoyu Zhang (xiaoyuzhang@bjtu.edu.cn); Mingdong Sun (sunmd@bjtu.edu.cn); Pinxi Wang (wangpinxi@bjtrc.org.cn); Shiqi Wang (shiqi-anya.wang@connect.polyu.hk)

Dominant Charging Location Choice of Commuters and Non-commuters: A Big Data Approach

Abstract

This paper is focused on electric vehicle (EV) users' dominant charging locations, where they get their EVs recharged more frequently. We particularly compared the dominant charging location choice of commuters and non-commuters using a unique one-month trajectory dataset collected from 76,774 actual private EVs in Beijing in January 2018. Specifically, we first grouped EV users for both commuters and non-commuters according to their dominant charging locations and then characterized and compared their charging patterns. Further, we associated the dominant charging location choice of EV users with their characteristics using a mixed logistic regression model. The results suggested that over 50% of the EV users were the Home Dominated (HD) users with most charging events occurring around home. Further, there were significant differences in charging patterns of EV users from different groups by dominant charging location, and also between commuters and non-commuters. Commuters tended to have a lower SOC than non-commuters when they got their EVs recharged. Moreover, the dominant charging location choice of EV users was significantly associated with their characteristics, including charging opportunities available and mobility patterns, and the association is different for commuters and non-commuters. The results are expected to be useful for deploying charging infrastructure.

Keywords: Electric Vehicle; Commuters; Dominant Charging Location; Trajectory Data; Mixed Logistic Regression Model

1 Introduction

Electric vehicles (EVs) have widely been deemed as a promising alternative to internal combustion engine vehicles (ICEVs), advancing the transition to a more sustainable and environmental-friendly transport system (Kang et al., 2022; Sun et al., 2015; Xu et al., 2017). To promote the EV market share, the EV-related stakeholders (e.g., automakers and government agencies) have contributed a lot in, for example, battery and vehicle technology innovation, charging infrastructure deployment and planning, and EV-related policymaking (Chakraborty et al., 2019). It is projected by International Energy Agency (IEA) that the penetration rate of EVs in the road vehicle fleet will reach around 7% by 2030 and the adoption rate of EVs in 2030 will be around 15% (IEA, 2021).

To further promote the adoption and usage of EVs, it is of great importance to understand existing EV users' charging behavior, such as charging location choice behavior (van der Kam et al., 2020). Charging location choice characterizes how EV users get their EV recharged at different locations. In general, there are three different types of locations for EV users to charge their EVs, namely home, workplace, and other places. Charging at home is the most common option for the majority of EV users, followed by charging at workplace and other places (Chakraborty et al., 2019; Lee et al., 2020). Understanding charging location choice and its influential factors could not only help to estimate the influence of EV charging demand and electricity consumption on the local power grid load but also inform the future charging infrastructure planning and investment, which are two pressing challenges for welcoming the era of massive EV adoption (Chakraborty et al., 2019; Xu et al., 2017).

There are a number of studies shedding light on EV users' charging location choice (Chakraborty et al., 2019; Lee et al., 2020; Sun et al., 2016; Xu et al., 2017; Yun et al., 2019). Most of them tended to use datasets collected from a small number of participants (e.g., hundreds of EV users) and over a short observation period (e.g., one week) to analyze and model charging location choice of each charging event or charging events in one day. However, few of them have been conducted to reveal EV users' long-term habit and preferences towards charging location choice (e.g., dominant charging location, where EV users get their EVs recharged more frequently). Also, little is known about charging location choice of both commuters and non-commuters, in terms of their similarity and differences.

To overcome these limitations, we will particularly look at the dominant charging location of EV users (where EV users get their EVs recharged more frequently) and compare the dominant charging location choice of commuters and non-commuters, using a unique one-month trajectory dataset collected from 76,774 actual private EVs in Beijing in January 2018. Specifically, we will first use a clustering algorithm to group EV users for both commuters and non-commuters according to their dominant charging locations and then characterize charging patterns of EV users from different groups by dominant charging location. Further, we will associate the dominant charging location choice of EV commuters and non-commuters with their characteristics, including vehicle attributes, individual- and household- level attributes, charging opportunities available, and mobility patterns. The findings from this paper are expected to shed light on EV user's charging behavior, particularly charging location choice behavior of commuters and non-commuters, which could inform future EV-related policymaking, infrastructure planning, and the management of power demand from the local grid.

2 Literature Review

2.1 Charging Location Choice of Electric Vehicle (EV) Users

Understanding EV users' charging behavior (e.g., when, where, and how EV users charge their EVs) plays a significant role in promoting the adoption and usage of EVs through informing, for example, the launch of successful charging infrastructure initiatives and the rollout of effective and efficient charging strategies (van der Kam et al., 2020). Three main types of charging behavior have received increasing attention, including charging decisions (i.e., whether to charge) (Ge et al., 2018; Wen et al., 2016; Yu & MacKenzie, 2016; Zoepf et al., 2013), time-related charging choices (e.g., when and how often to get EVs recharged) (Kim et al., 2017; Sun et al., 2015; Sun et al., 2018; Wolbertus et al., 2018) and charging location choice (Chakraborty et al., 2019; Lee et al., 2020; Sun et al., 2016; Xu et al., 2017; Yun et al., 2019). As this paper aims to explore EV users' dominant charging location (where EV users get their EVs recharged more frequently), the following review will be focused on those studies related to charging location choice of EV users.

The low penetration of EVs in the automobile market makes it difficult to collect real EV usage data. Consequently, the stated preference (SP) survey has become the dominant approach to gathering charging location choice of the general public or EV users in given scenarios. For example, Jabeen et al. (2013) studied charging preferences of 54 EV users in Western Australia with four sets of stated choice experiments. It was observed that EV users preferred to charge at home or work rather than at public charging stations in general. EV users with solar panels installed at home preferred to get their EVs charged at home; while EV users picking up their friends or family members preferred not to charge at home but to use public charging facilities. Chakraborty et al. (2019) used the charging location choice data of more than 3,000 plug-in electric vehicle (PEV) users in California, which were collected over 7 consecutive days, to explore the factors influencing the daily charging location choice. The results showed that factors related to sociodemographic attributes, charging cost and vehicle technology could influence daily charging location choice. Lee et al. (2020) examined the 7-day charging patterns of 7,979 PEV users in California, in terms of their charging locations and levels. Results revealed that PEV users relied heavily on home charging, with more than half of them merely charging with home chargers. Also, PEV users' choices of charging locations were significantly influenced by various factors, such as PEV users' sociodemographic attributes, the characteristics of owned PEVs, and the availability of charging infrastructure at workplace. However, there is still a debate on whether such SP data could well characterize charging location choice of EV users, because, on the one hand, the survey sample is usually small and the survey data is collected in a fixed short period (e.g., one day); on the other hand, the respondents in a SP survey do not always share the real information (for example, as they cannot remember clearly what happened).

Compared to the SP data, the revealed preference (RP) data, which could realistically reflect how EV users used their EVs, is more suitable for exploring EV users' charging location choice. For example, using a two-year long revealed preference data of 500 commercial and private battery electric vehicles (BEVs) in Japan, Xu et al. (2017) studied what and how factors affected the joint choice of charging mode and location for BEV users. The mixed logit estimation results showed that the battery capacity, midnight indicator, initial SOC and number of past fast charging events were the main predictors that determined BEV users' joint choice of charging mode and location. To determine the location of people charging their plug-in hybrid electric vehicles (PHEVs), Yun et al. (2019) investigated the GPS trajectory data of 700 PHEVs and the charging infrastructure data in Shanghai. The result indicated that PHEV users were more inclined to charge at home or workplace than at public charging stations. the main factors influencing users' decisions on charging location included charging price and tariffs, the initial SOC, dwell time, charging power, and vehicle kilometer travel (VKT) of the current trip and current day. Although these studies did contribute to the studies of EV charging location choice, there are two main limitations. On the one hand, for a few of the studies, the sample size was small (e.g., hundreds). As a result, the samples used may not be well representative, and the results may not be reliable. On the other hand, most studies investigated charging location choice over a short period (e.g., one-time charging or daily charging choice), and paid almost no attention to EV users' long-term habit or preferences towards charging location (e.g., dominant charging location, where EV users get their EVs recharged more frequently).

2.2 Travel and Charging Behavior of EV Commuters

Commuters are generally expected to be suitable early EV adopters considering the matching between their rather fixed travel patterns with a short daily driving distance and the limited range of most EVs (Brady & O'Mahony, 2011). Though there is an increasing number of studies providing insights into EV user's travel and charging behavior/patterns, limited knowledge is known particularly for EV commuters.

Compared with other types of EV users (e.g., ride-hailing drivers), commuters have heterogeneous travel patterns and charging behavior. Using a dataset comprising the real-world data of 2,500 BEVs in Shanghai, Hu and Sun (2019) characterized BEV users' travel and charging behavior with six metrics (e.g., travel distance and start time of charging event), based on which three groups of BEV users (namely commuters, ride-hailing drivers, and other users) with distinct travel patterns and charging behavior were identified. Also, commuters owning different types of EV models may have different travel and charging behavior. Based on an online survey of 3,500 PEV users in California, Tal et al. (2014) explored the differences in travel (e.g., commuting distance and daily travel distance) and charging (e.g., workplace charging) behavior of PEV owners with different types of PEV models. It was found that drivers with larger-battery PHEVs and BEVs travelled a longer distance and had more battery charge than smaller-battery PHEVs because of the larger battery size and easier access to charging opportunities.

Understanding commuters' travel/mobility patterns could inform, for example, the design of EVs and the rollout of EV-related policies (Björnsson & Karlsson, 2015; Hu et al., 2016; Smith et al., 2011; Xu et al., 2018). Using the dataset collected from a fleet of 76 vehicles in Winnipeg, Canada, Smith et al. (2011) constructed a commuter driving cycle presenting city commuting on weekdays, based on which an energy-based simulation was conducted to explore the optimal battery storage for a commuter sedan car. The results showed that with a 2.4-hour daytime charge, the reduction in the battery size of such a vehicle can be around 40% without losing functionality. Through combining three unique datasets from the Bay Area, including fine-scale mobile phone data, census data and PEV charging session data, Xu et al. (2018) presented a method coupling PEV users' mobility patterns and charging profiles to optimize electricity planning and management. The authors recommended commuters to change their start and end times of PEV charging session at workplace to ease the power demand for the power grid at peak charging hours. Also, the monetary gains from such a recommendation were quantified.

Several studies have contributed to characterize EV commuters' charging patterns and the potential association between commuters' characteristics and their charging behavior (Chakraborty et al., 2019; Daina et al., 2015; Lee et al., 2020; Lee et al., 2019). For example, Chakraborty et al. (2019) collected the dataset comprised of characteristics and history charging activities of more than 3,000 PEV commuters in California and developed error component logit models to associate commuters' daily charging location choices with their characteristics. The results showed these driving factors on daily charging location choice include charging costs, commuter's sociodemographic attributes (e.g., gender) and the technological attributes of PEVs owned (e.g., electric range). Lee et al. (2020) revealed the differences in the relationship between commuting distance and the mixed use of charging infrastructure of BEV and PHEV users using two multinomial logit models conducted based on a survey on 7,979 PEV users in California. It was found that for BEV users, commuting distance was not a significant factor influencing their choices on charging locations; while for PHEV users, those who resided farther away from their workplace preferred to get their PHEVs charged at more diverse charging locations. Although these studies have made efforts to understand charging behavior of commuters, they failed to explore charging behavior of non-commuters and further reveal the similarity and differences between commuters and non-commuters in terms of charging behavior, such as charging location choice.

2.3 Research Gaps and Aims

We conducted a comprehensive review on charging location choice of EV users and travel and charging behavior of EV commuters, and identified the following research gaps:

- SP and RP data have been used to explore charging location choice of EV users. However, most studies tended to use the datasets with a small sample size (e.g., hundreds) or collected over a short observation period (e.g., one week), and thus there is a big concern about the representativeness of the samples.
- Most studies of EV charging location choice tried to model EV users' charging location

choice over a short period (e.g., one-time charging or daily charging choice), and little is known about the long-term habit or preferences towards charging location of EV users (e.g., dominant charging location, where EV users get their EVs recharged more frequently).

- A number of studies characterized charging behavior of commuters, but few of them involved the charging behavior of non-commuters. Furthermore, it remains unclear about how commuters and non-commuters behave similarly or differently regarding charging behavior, in particular for charging location choice.

To fill these gaps, this paper will use a unique one-month trajectory dataset which was collected from 76,774 actual private EVs in Beijing in January 2018 to provide insights into private EV users' charging behavior with a focus on the dominant charging location choice of EV users (where they get their EVs recharged more frequently). Furthermore, we will explore the possible association between EV users' dominant charging location choices with their characteristics. In particular, we will conduct a comparative study of commuters and non-commuters, revealing their different dominant charging location choice behaviors.

3 Study Area and Dataset

3.1 Study Area: Beijing

Beijing, the capital of China, is one of the Chinese cities acting actively to promote the uptake of electric vehicles (EVs) and the development of charging infrastructure (Gong et al., 2018;

Kang et al., 2022). According to the 2021 Beijing Transport Annual Report by Beijing Transport Institute (BTI), the number of passenger New Energy Vehicles (NFVs, nearly all of them were EVs) in Beijing has reached 389,000 at the end of 2020, with an increase rate of 26.6% (BTI, 2021). Meanwhile, as reported by Beijing Municipal Commission of Urban Management (BMCUM), an EV charging infrastructure network comprised of more than 200,000 charging posts has been developed. Among them, private charging posts accounted for more than two-thirds, and the remaining (around 50,000 charging posts) were open and partially open to the public (BMCUM, 2021). From a spatial perspective, these charging facilities were mostly located in the central area of Beijing with a dense population, and were expected to ensure that EV users can, on average, find charging infrastructure within 5 km (excluding those mountainous areas in Beijing) (BMCUM, 2021).

3.2 GPS Trajectory Data on Private EVs

We used a unique one-month trajectory dataset which was collected from 76,774 actual private EVs in Beijing in January 2018, as detailed in the work by Sun et al. (2021). Table 1 is an example about the key fields in the dataset, including EV identification, timestamp, latitude and longitude (reporting an EV's real-time location), distance travelled, instantaneous speed, and state of charge (SOC).

Table 1 An example about the key fields in the EV trajectory dataset

Vehicle ID	Timestamp	Latitude	Longitude	Distance Travelled (km)	Instantaneous Speed (km/h)	SOC (%)
…	…	…	…	…	…	…
P1G4024922	2018-1-2 20:52:47	39.762900	116.377450	56056	21.7	68
P1G4024922	2018-1-2 20:53:17	39.763380	116.382540	56057	26.8	68
P1G4024922	2018-1-2 20:53:47	39.763380	116.382540	56057	26.8	68

P1G4024922	2018-1-2 20:54:17	39.764305	116.393000	56058	49.6	66
P1G4024922	2018-1-2 20:54:47	39.764305	116.393000	56058	49.6	66
P1G4024922	2018-1-2 20:55:17	39.758217	116.395325	56058	29.3	66
P1G4024922	2018-1-2 20:55:47	39.758217	116.395325	56058	29.3	66
P1G4024922	2018-1-2 20:56:17	39.761368	116.398445	56059	39.1	65
…	…	…	…	…	…	…

With the EV trajectory dataset, we need to identify travel, parking and charging events of EVs. Fig. 1 illustrates how an EV trajectory can be segmented into a series of connected travel, parking and charging events using an EV trajectory data analytical framework by Sun et al. (2021) and Yang et al. (2021).

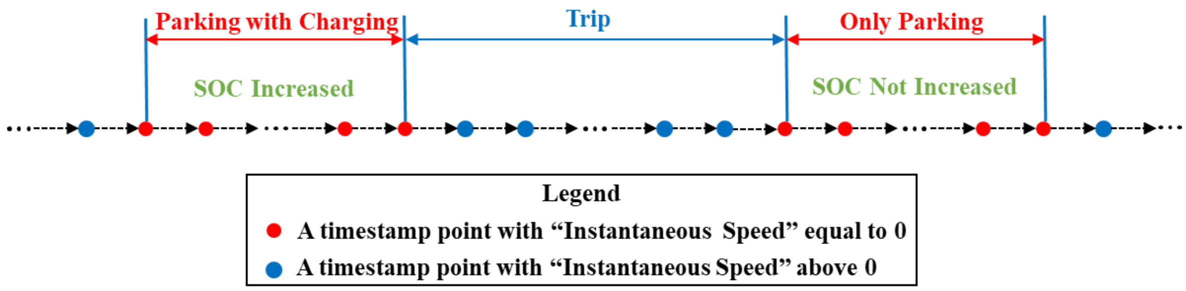


Fig. 1 An illustration of trajectory segmentation (Source: Adapted from Yang et al. (2021))

4 Methodology

4.1 Inferring Commuters and Non-Commuters

Since the EV trajectory dataset does not contain sociodemographic characteristics of EV users (e.g., age and employment statue), we need to infer their employment statue (i.e., commuter or non-commuter, defined as whether having a fixed workplace) and residential location, so as to further conduct a comparative study of commuter and non-commuters on dominant charging location (see Section 4.2). Generally, residential location and workplace are conceptualized as the places where a commuter most visits and stays for substantial amounts of time during nighttime and working hours, respectively (Alexander et al., 2015; Lv et al., 2016; Tu et al., 2017; Wang et al., 2018; Zhou et al., 2017). Following this concept, we proposed a two-step procedure below for home and workplace inference using the travel and parking events of EV users extracted from EV trajectory data:

Step 1: Identify potential home/workplace visiting events. Specifically, those parking events within a period from 7 pm to 7 am (the next day) and lasting for more than 3 hours are considered as potential home visiting events; while those parking events within a period from 7 am to 7 pm on weekdays and lasting for more than 3 hours are considered as potential workplace visiting events. Similar rules have been widely used for inferring residential location and workplace with big data (e.g., mobile phone data and vehicle trajectory data) in the previous work (Alexander et al., 2015; Çolak et al., 2015; Tu et al., 2017; Xiong et al., 2021; Zhou et al., 2017). It is worth mentioning that the rules above are designed to identify potential home/workplace visiting events (i.e., candidates for home/workplace inference), and thus these rules should be applicable to most cases (both individuals not driving EVs and EV users). There is a chance that some actual non-home/workplace visiting events are included as candidates for inference. For example, when compared to the individuals not driving EVs, EV users may have more parking events longer than 3 hours (due to EV charging) outside home/workplace, and these events could be selected as candidates. Nonetheless, given that the place with few visitations cannot be inferred as home/workplace (see Step 2) in this study, including these events as candidates would have little influence on the inference of residential locations and workplace, as their size is rather small and also they are geographically dispersed.

Step 2: Infer the location for home/workplace. Given a list of potential home/workplace visiting events (obtained from Step 1), we used the mean shift clustering algorithm (Cheng, 1995) to find the place which has the most potential home/workplace visiting events within a specific distance (set to 400 m in this study). If the located place was visited less than 4 times per month (once a week, on average) by the EV user, we inferred this place as other locations rather than home/workplace considering the uncertainty to infer a place as home/workplace with infrequent visitations (Alexander et al., 2015). Then, we defined EV users with an inferred workplace as commuters; otherwise, non-commuters. Note that 1) the inference of home location was conducted firstly and those parking events within the specific distance of the inferred home location were removed before inferring workplace; 2) we filtered out those EV users without an inferred home (Alexander et al., 2015; Çolak et al., 2015).

It should be pointed out that there is no ground truth to verify our inferences from EV trajectory data, in terms of the exact residential location and workplace for each EV user and whether a specific EV user is a commuter (defined as having an inferred workplace) or not. Indeed, this is a common concern (i.e., no ground truth for result verification) when working with big data, such as trajectory data, mobile phone data, and smart card data. However, there is a growing trend of using big data to conduct behavior-related research, particularly when it comes to understanding the travel and charging behavior of EV users. This is because big data has several advantages over traditional survey data, such as larger sample sizes, longer observation periods, and lower data collection costs, which make it more promising for studying individuals' behavior, habits, and preferences (Sun et al., 2021). On the other hand, inferring residential locations and workplace for individuals using big data (e.g., trajectory data) and conducting further research based on these inferences are quite common and well-established practice in literature (Alexander et al., 2015; Wang et al., 2018; Xu et al., 2018; Yan et al., 2019), as the rather rhythmic activity patterns of individuals at residential locations and workplace could lead to the high reliability of residential location and workplace inferences. Further, we compared the ownership of all private New Energy Vehicles (NFVs, nearly all of them were EVs) in Beijing in 2018 to the private EVs used in this study at the district level (see Appendix A in the Supplementary Materials and note that the visualization for the private EVs used in this study was based on the inferred residential locations). The comparison shows that their spatial distributions at the district level are rather similar, to some extent implying that our inferences should be reliable.

4.2 Grouping EV users by Dominant Charging Location

4.2.1 Classifying Charging Events by Charging Location

According to the location where a charging event occurs, we classified the event into three different types:

- **Home-based charging events**: refer to those charging events occurring within the specific distance of the EV user's home location. In this study, the distance is set to 400

m. There are two reasons for us to use 400 m as the threshold. First, Huang et al. (2020) who used the trajectory data on private conventional vehicles found that 400 m was the most appropriate radius to cluster parking events to a specific activity location, considering the drift of GPS trajectory points and the change of exact parking locations around a specific activity location. Second, we did a sensitivity analysis to explore how the threshold would influence the quantities of those charging events that are considered as home-based charging events and workplace-based charging events, respectively. The results show that when the distance is larger than 400 m, the number of events to be further considered as home-based charging events or workplace-based charging events becomes much smaller (see Appendix B in the Supplementary Materials).

- **Workplace-based charging events**: refer to those charging events occurring within the specific distance of the EV user's workplace location.
- **Other charging events**: refer to those charging events occurring outside the specific distance of the EV user's home and workplace locations.

For EV commuters, they could have all of the three charging event types, i.e., home-based, workplace-based and other charging events; while non-commuters only have home-based and other charging events (without workplace-based ones).

4.2.2 Grouping EV users

To characterize EV users' charging location patterns and further group them into different categories according to their dominant charging locations, we made a charging event portfolio for each user, based on the percentage of the three charging event types (i.e., home-based, workplace-based, and other charging events). Accordingly, commuters and non-commuters can be represented by 3-tuples and 2-tuples, respectively, as workplace-based charging is only applicable to commuters (see Equation (1) and (2)). Here, each tuple represents the percentage of a specific charging event type.

$$C_n = \left(\frac{N_{nh}}{N_{nh}+N_{nw}+N_{no}}, \frac{N_{nw}}{N_{nh}+N_{nw}+N_{no}}, \frac{N_{no}}{N_{nh}+N_{nw}+N_{no}}\right) \tag{1}$$

$$NC_n = \left(\frac{N_{nh}}{N_{nh}+N_{no}}, \frac{N_{no}}{N_{nh}+N_{no}}\right) \tag{2}$$

Where, C_n and NC_n denote the n_{th} EV commuter and non-commuter, respectively; N_{nh}, N_{nw}, and N_{no} denote the numbers of home-based, workplace-based, and other charging events which the n_{th} commuter/non-commuter has, respectively (note: N_{nw} is only applicable to commuters).

Based on the calculation above, we further clustered EV users into different groups for commuters and non-commuters, respectively, using the k-means++ clustering algorithm (Vassilvitskii & Arthur, 2006). Note that we filtered out those EV users (including both commuters and non-commuters) with less than 4 charging events per month (i.e., charging once a week, on average), as their charging patterns were unlikely to be representative. Totally, we got 33,625 commuters and 4,784 non-commuters for subsequent analyses.

In order to explore the proper number of groups to be clustered, we first tried the automatic way informed by two commonly used clustering quality indexes (namely Silhouette Score and

Davies Bouldin Index) (Helmus et al., 2020). The results (see Appendix C in the Supplementary Materials) show that the number of groups to be clustered should be 3 for EV commuters, and then the three groups would be Home Dominated (HD), Workplace Dominated (WD), and Other Dominated (OD). However, these three groups cannot well represent those commuters frequently charging their EVs at more than one location (such as both home and workplace, both home and other places, and both workplace and other places) found in our preliminary analysis of the dataset used for clustering. Therefore, to better represent those commuters frequently charging their EVs at more than one location, we set the number of groups to be clustered as 6 in the k-means++ clustering algorithm with an expectation that EV commuters could be clustered into six groups, i.e., Home Dominated (HD), Workplace Dominated (WD), Other Dominated (OD), Home-Workplace (H-W), Home-Other (H-O), and Workplace-Other (W-O) (see Table 2 for a detailed description). It is worth mentioning that we did try 7 for the number of groups, with an expectation that there might be a group of EV users who equally rely on home-based, workplace-based, and other-based charging facilities. However, no such a group could be found, and thus we eventually set the number of groups to be clustered as 6. For the same reason (i.e., to better represent those non-commuters frequently charging their EVs at more than one location), we set the number of groups to be clustered as 3 for non-commuters (with an expectation that EV non-commuters could be clustered into three groups, namely HD, OD, and H-O, see Table 2), instead of two groups informed by the indicators Silhouette Score and Davies Bouldin Index (see Appendix C in the Supplementary Materials). The clustering results showed in Section 5.1.1 verified the reasonability of clustering six groups for commuters and three groups for non-commuters.

Table 2 Clustering EV users based on their dominant charging locations

Group	Description	Applicable to Commuters	Applicable to Non-Commuters
Home Dominated (HD)	Most charging events occurred around home	Yes	Yes
Workplace Dominated (WD)	Most charging events occurred around workplace	Yes	No
Other Dominated (OD)	Most charging events occurred at other places (i.e., non-home and -workplace)	Yes	Yes
Home-Workplace (H-W)	Charging events occurred frequently around both home and workplace	Yes	No
Home-Other (H-O)	Charging events occurred frequently around home and at other places	Yes	Yes
Workplace-Other (W-O)	Charging events occurred frequently around workplace and at other places	Yes	No

4.3 Associating EV Users' Dominant Charging Locations with their Characteristics: A Mixed Logistic Regression Model

After clustering EV users into different groups according to their dominant charging locations, we further explored whether the grouping results (i.e., EV users' dominant charging location choice) were associated with EV users' characteristics. We used the mixed logistic regression model for the association analysis, which is a typical type of discrete choice model (DCM) and considers the differences in preference across individuals (McFadden & Train, 2000). Mixed logistic regression models have been widely used in modelling of charging behavior of EV users (Sun et al., 2015; Xu et al., 2017; Yu & MacKenzie, 2016; Zoepf et al., 2013).

4.3.1 Mixed Logistic Regression Model Specification

Let J denote a set of alternatives (i.e., dominant charging location choices) available for commuters/non-commuters. To be specific, there are six alternatives for commuters, namely HD, WD, OD, H-W, H-O, and W-O, while there are three alternatives for non-commuters, namely

HD, OD, and H-O (see Table 2). The utility (U_{ni}) that a commuter/non-commuter n obtains from choosing the alternative $j \in J$ is defined as Equation (3).

$$U_{nj} = \beta_{nj} X_n + \varepsilon_{nj} \tag{3}$$

Where, $\beta_{nj} X_n$ defines the observed utility, in which X_n denotes a vector of observed variables related to individual n (i.e., characteristics of an EV user in this case, see Section 4.3.2) and β_{nj} denotes a vector of coefficients estimated to characterize the effects of the observed variables; ε_{nj} denotes the unobservable error term. It should be pointed out that the dominant charging location choice (j) of an EV user is individual specific, characterizing the long-term habit or preferences towards charging location (rather than one-time charging location choice for a specific charging event). Thus, those attributes related to the charging location choice of a specific charging event were not considered in this study. Instead, those factors related to characteristics of the EV user that could potentially influence the dominant charging location choice were included as explanatory variables (X_n) in the regression model. All the explanatory variables were extracted from the EV trajectory data on private EVs and introduced in Section 4.3.2 in a detailed way.

Unlike the conventional multinominal logistic regression model (MNL) with fixed β_j (i.e., the same to all individuals), β_{nj} in the mixed logistic regression model is assumed to be randomly distributed (following a specific continuous distribution $f(\beta|\theta)$) to accommodate the preference heterogeneity across individuals, such that the probably (P_{ni}) for commuter/non-commuter n to choose alternative i can be defined as Equation (4) by integrating MNL choice probabilities

(Train, 2009) over the continuous probability distribution $f(\beta|\theta)$ (Hess & Polak, 2005).

$$P_{ni} = \int \frac{e^{\beta_{ni}X_n}}{\sum_{j\in J} e^{\beta_{nj}X_n}} f(\beta|\theta)d\beta \tag{4}$$

Where, θ is a vector of parameters of the distribution $f(\beta|\theta)$ that can be assumed to be, for example, normal or lognormal. In this study, we assumed it to be normal, and the assumption has been widely used (Sun et al., 2015; Wen et al., 2016).

For the determination of random parameters in this study, we assumed all parameters as random to test whether the standard deviation for each parameter is statistically significant or not. Those parameters with a statistically significant standard deviation were kept as random parameters and the others were set as non-random parameters (Hensher et al., 2005).

4.3.2 Exploratory Variables

We used 12 exploratory variables to describe EV users' characteristics, which can be categorized into 4 groups, namely Vehicle Attributes, Individual- and Household- Level Attributes, Charging Opportunities Available, and Mobility Patterns. Table 3 shows the definitions of the 12 exploratory variables (see Appendix D in the Supplementary Materials for a detailed description).

Table 3 Definitions of exploratory variables

Index	Group	Variable Name	Definition	Applicable to Commuters	Applicable to Non-Commuters
1	Vehicle Attributes	Battery Capacity	The battery capacity of the EV owned by an EV user.	Yes	Yes
2	Individual- and Household-Level Attributes	Socioeconomic Status	The socioeconomic status of an EV user, characterized by the housing price around the user' home location (Xu et al., 2018).	Yes	Yes
3		Home in Central Area	Whether an EV user lives in the central area of Beijing.	Yes	Yes
4		Workplace in Central Area	Whether an EV user works in the central area of Beijing.	Yes	No
5	Charging Opportunities Available	Charging Opportunities around Home	The number of charging stations within the specific distance of an EV user's home. In this study, the distance is set to 400 m.	Yes	Yes
6		Charging Opportunities around Workplace	The number of charging stations within the specific distance of an EV user's workplace.	Yes	No
7		Charging Opportunities at Other Places	The average number of charging stations within the specific distance of the activity locations (except home and workplace) visited by an EV user.	Yes	Yes
8	Mobility Patterns	Commuting Distance	The Euclidean distance between an EV user' home and workplace.	Yes	No
9		Ratio of Non-Working Days Having EV Travel	The ratio of the number of non-working days that an EV user travelled with his/her EV to the total number of days that an EV user travelled with his/her EV in a month.	Yes	Yes
10		Diversity of Activity Locations Visited Daily	The average number of unique activity locations (including home and workplace) visited by an EV user per travel day.	Yes	Yes
11		Daily Travel Distance	The average distance travelled by an EV user by EV per travel day.	Yes	Yes
12		Standard Distance Centered at Home	One mobility indicator measures the range of an EV user's activity space with the user's home as the reference point (Xu et al., 2015). A small value reflects that the EV user tends to perform activities near home.	Yes	Yes

5 Results

5.1 Comparing Commuters and Non-Commuters' Dominant Charging Locations

5.1.1 Descriptive Analysis of EV User Groups

We grouped commuters and non-commuters according to their dominant charging locations. As expected (see Section 4.2.2), we identified 6 groups of commuters and 3 groups of non-commuters with distinct dominant charging location patterns.

(1) Percentage of Charging Events by Location for each EV User Group

Fig. 2 shows the percentage of charging events by location, based on which we identified each EV user group (6 groups for commuters and 3 groups for non-commuters). We can find similar dominant charging location patterns for commuter and non-commuters: in terms of HD, OD, and H-O, the percentages of home-based (95% vs. 96%), other-based (93% vs. 95%) and home- & other- based (36% & 61% vs. 39% & 61%) charging events are quite close to each other. For WD commuters, 90% of charging events took place around their workplaces; For H-W commuters, 49% and 43% of charging events occurred around their homes and workplaces, respectively; For W-O commuters, 52% and 44% of charging events occurred around their workplaces and at other places, respectively.

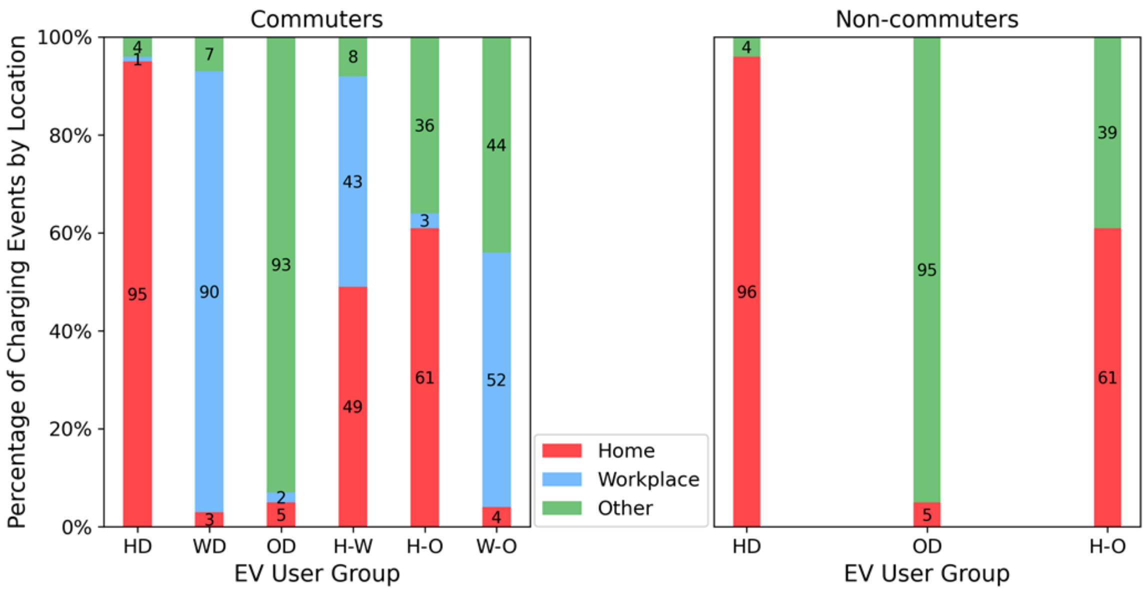


Fig. 2 The percentage of charging events by location for each EV user group

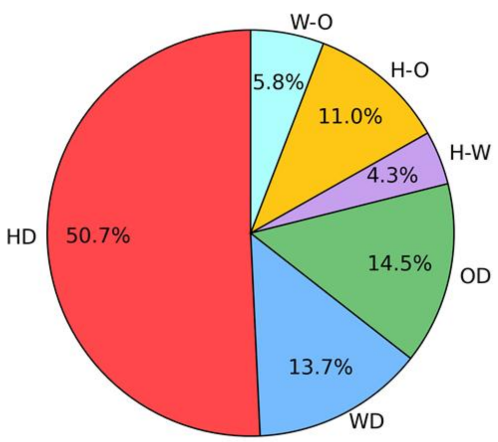
(2) Proportions of EV User Groups for Commuters and Non-commuters

Fig. 3 shows the proportions of EV user groups for commuters (see subfigure (a)) and non-commuters (see subfigure (b)). Key findings are listed as follows:

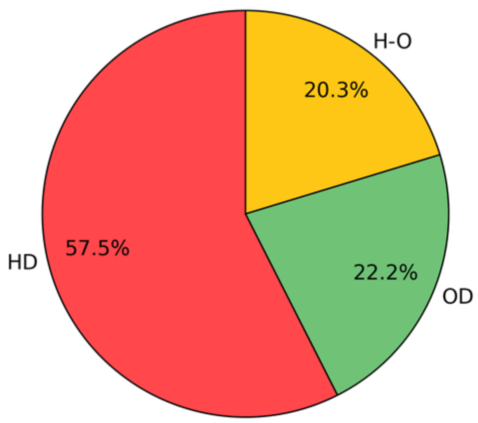
- More than half of commuters (50.7%) and non-commuters (57.5%) were HD users with most charging events occurring around home. In total, 66.0% of commuters (including the groups HD, H-O, and H-W) and 77.8% of non-commuters (including the groups HD and H-O) charged frequently around their homes. This suggests that home is the most common charging location for the majority of commuters and non-commuters.
- More than two-thirds of commuters (78.9%) and non-commuters (79.7%) tended to charge their vehicles mainly at one single type of charging location (e.g., home, workplace (only applicable to commuters), or other places), indicating that EV users (including both commuters and non-commuters) might be used to get their EVs charged

at those places with which they are familiar.

- Since workplace charging is not applicable to non-commuters, the fractions of HD, OD, and H-O non-commuters were larger than those of commuters. For commuters, workplace-based charging opportunities may be available though, the fractions of WD, H-W, and W-O commuters were small, only accounting for 24.8% totally. This finding is consistent with what have been pointed out in others' work: the charging at workplace is far less popular than that at home (Chakraborty et al., 2019; Lee et al., 2020). Also, the group H-W accounted for the least proportion of commuters (4.3%), likely because there is no need for the majority of EV commuters to get their EVs charged around both home and workplace frequently due to a short commuting distance relative to the EV driving range (for example, only 4.6% of EV commuters in Beijing had a commuting distance longer than 20 km).



(a) Commuters



(b) Non-commuters

Fig. 3 The proportions of EV user groups for commuters and non-commuters

Further, we compared the proportions of EV user groups in Central and Non-Central Areas from a spatial perspective. As shown in Fig. 4, commuters and non-commuters have similar spatial patterns: central areas tended to have a smaller fraction of EV users with home-based charging included (i.e., HD, H-W, and H-O). This suggests that EV users (both commuters and non-commuters) in the central areas tended to rely less on home-based charging but more on workplace-based and other-based charging than those in the non-central area. It may be because that in the central area, the EV users tended to access to less private charging facilities, due to the limited land and less private parking spaces (Kang et al., 2022). On the other hand, a higher density of public charging infrastructure in the central area (BMCUM, 2021) provides more charging opportunities at non-home activity locations. Note that workplace-based charging and EV user groups with workplace-based charging included (i.e., WD, H-W, and W-O) are only applicable to commuters.

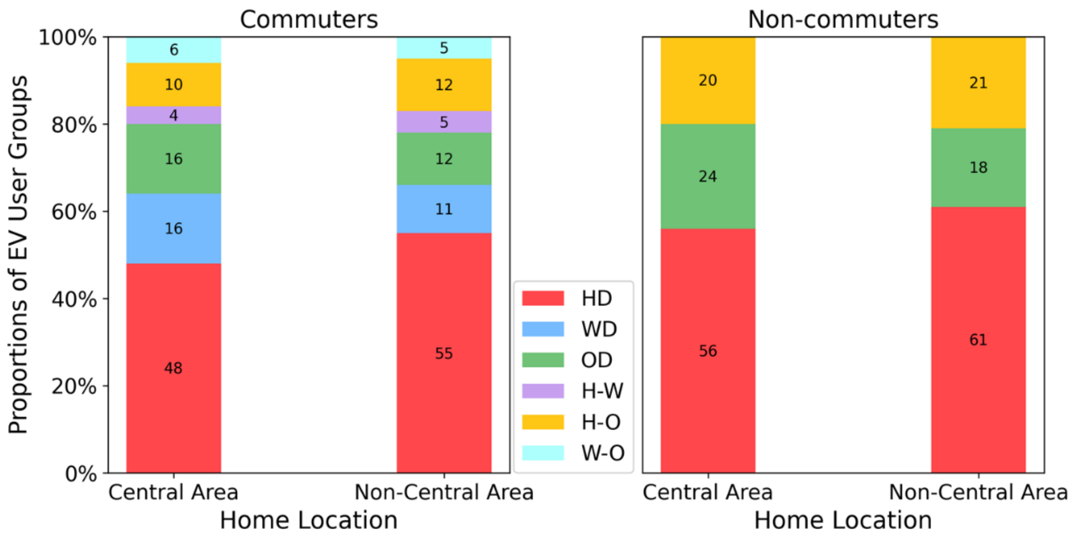


Fig. 4 The proportions of EV user groups in Central Area and Non-Central Area

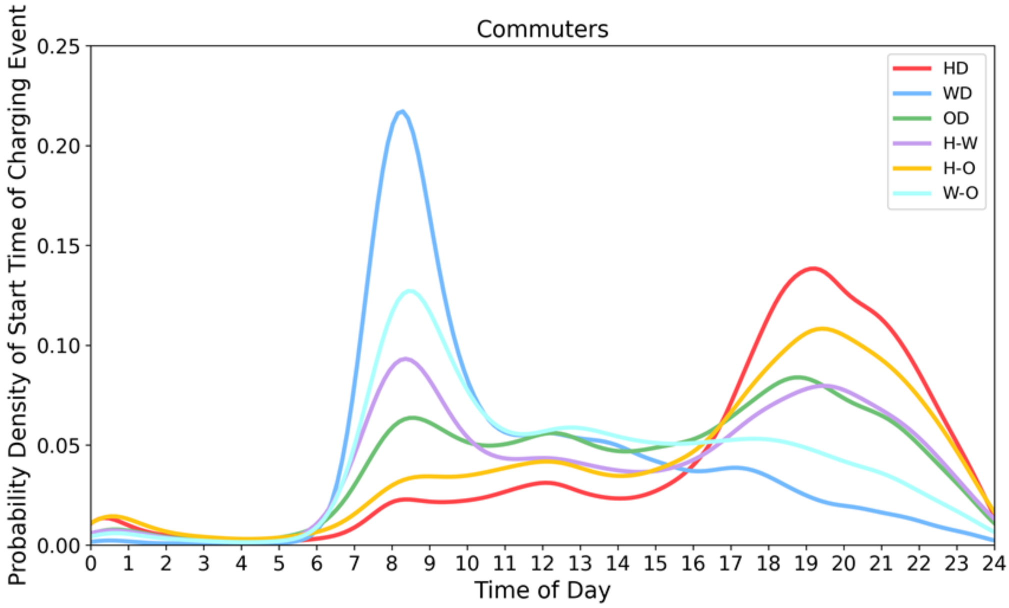
5.1.2 Charging Patterns of EV Users from Different Groups

We further characterized and compared charging patterns of EV users from different groups for commuters and non-commuters using two indicators, namely start time of a charging event and EV's start state of charge (SOC) in a charging event. Also, we compared charging patterns for commuters and non-commuters on working and non-working days (see Appendix E in the Supplementary Materials).

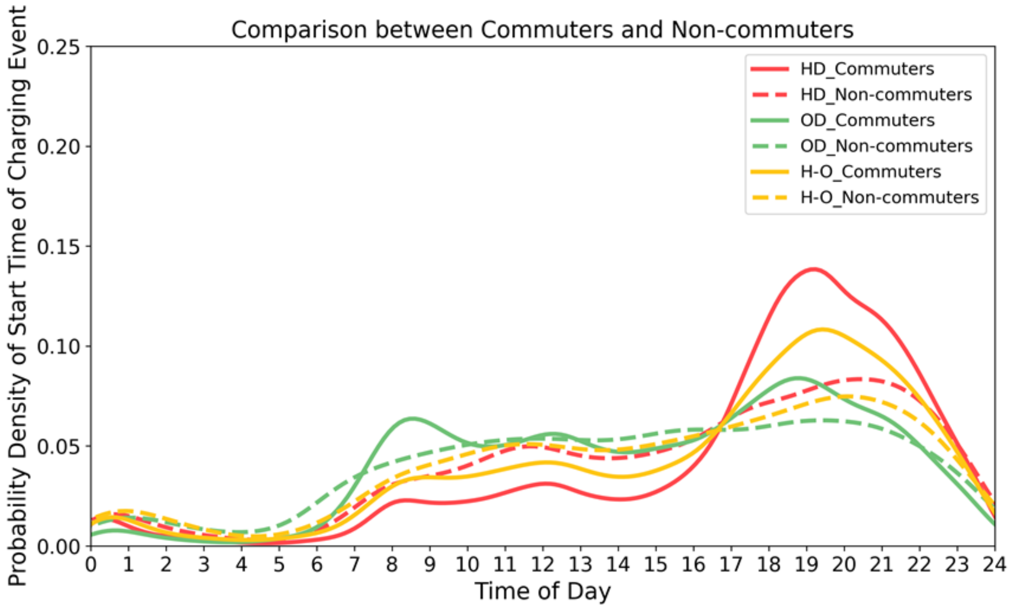
(a) Start Time of Charging Event

Fig. 5 shows the probability density (estimated using the kernel density estimation) of start time of charging event for different EV user groups. It can be found from the subfigure (a) that for commuters from those groups with workplace-based charging included (i.e., WD, H-W, and W-O), their charging events mostly started during the working hours and charging demand peaked in the morning peak (specifically from 8 to 9 AM); while for those commuters from the groups with home-based charging included (i.e., HD, H-W, and H-O), their charging events mostly started during the nighttime and charging demand peaked in the evening peak (specifically, from 7 to 8 PM). Also, the group HD had the sharpest evening peak (as their charging events were mostly home-dominant), the group WD had the sharpest morning peak (as their charging were mostly workplace-dominant), and the group H-W had both the morning and evening peaks (as their charging event were mostly both home- and workplace-dominant). Moreover, the commuters from the group OD tended to have a flatter distribution of start time than those from the other 5 groups, as their charging events were mostly associated with those flexible activities (e.g., shopping and leisure) with a flexible start time.

In addition, the comparison of start time between commuters and non-commuters from groups HD, OD, and H-O (see the subfigure (b)) suggests that non-commuters tended to have flatter distributions of start time. This may be because non-commuters did not need to commute and thus had more flexible time for recharging their EVs.



(a) Commuters



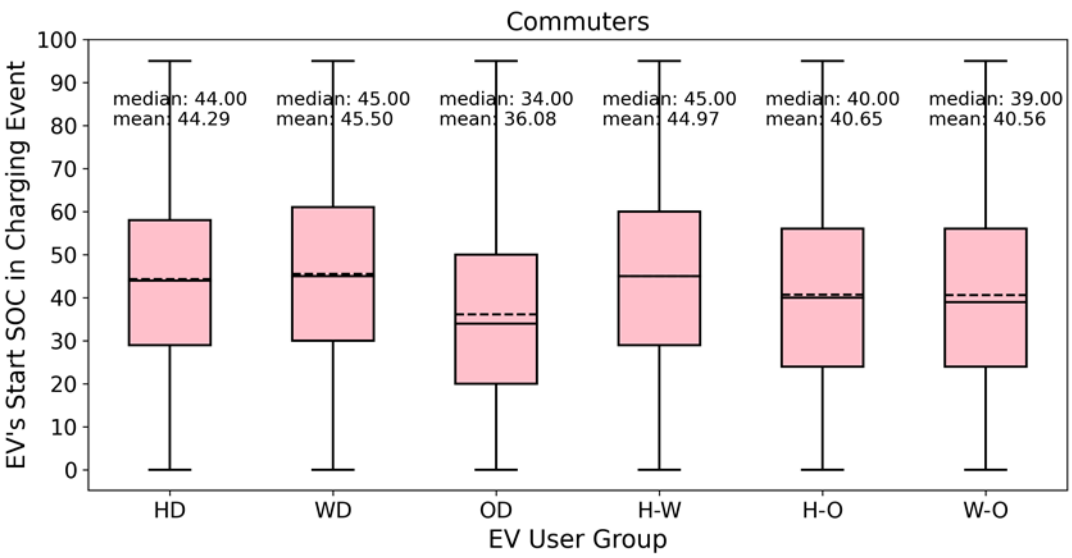
(b) Comparison between commuters and non-commuters

Fig. 5 Probability density of start time of charging event for different EV user groups

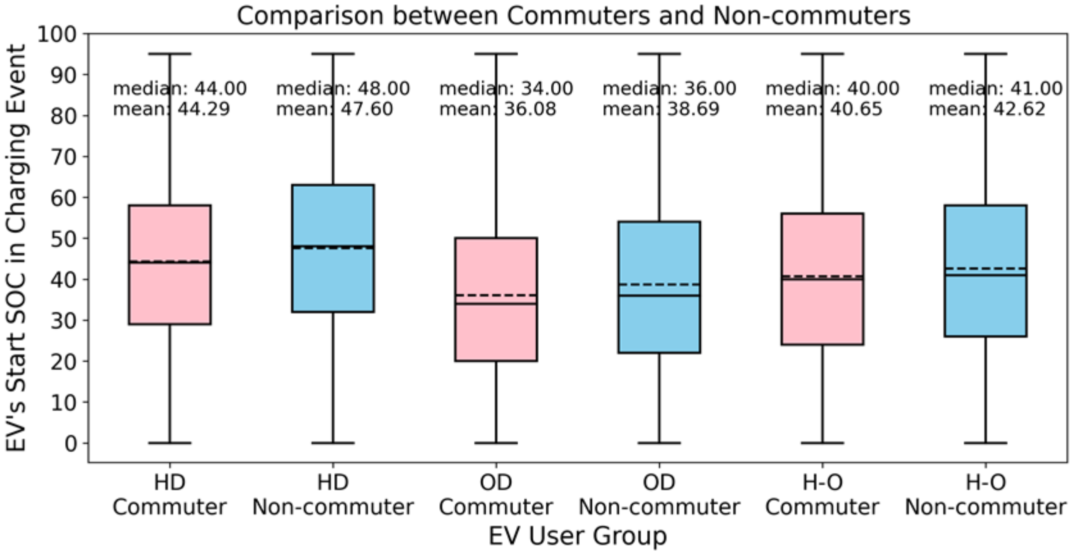
(b) EV's Start State of Charge (SOC) in Charging Event

Fig. 6 shows the statistical distributions of EV's start SOC in charging event for different EV user groups, suggesting that those EV users (including both commuters and non-commuters) from the groups with other-based charging included (i.e., OD, H-O, and W-O) tended to get their EVs recharged with a lower SOC. In particular, the group OD had a much lower SOC (specifically, the average SOCs were 36.08% and 38.69% for commuters and non-commuters, respectively). This may be because the EV users from these groups (particularly the group OD) tended to have an urgent need to get their EVs recharged (when their SOC is running low); while for the EV users from other groups (e.g., HD, WD, and H-W), they usually did not have an urgent need to get their EVs recharged and could get EVs recharged as long as they have access to charging facilities (e.g., around their homes and workspaces).

As shown in subfigure (b), commuters, on average, tended to have a lower SOC than non-commuters when they got their EVs recharged for all the three EV user groups, i.e., HD, OD, and H-O. This might be because non-commuters tended to have a more flexible time and thus could recharge their EVs more frequently and for a longer time. Another possible reason could be that compared against non-commuters, commuters tended to visit some fixed locations and to be less likely to visit those activity locations they were less familiar with (e.g., those activity locations other than home and workplace). The familiarity with the activity locations they visited could reduce their range anxiety, and thus they tended to have a lower SOC than non-commuters when they got their EVs recharged. This can be somewhat evident from the information extracted from the trajectory data: after excluding those activity locations commuters/non-commuters were more familiar with (i.e., home and workplace for commuters and home for non-commuters), the diversity of activity locations visited daily (i.e., the number of unique activity locations visited daily) for commuters was less than that for non-commuters (1.39 vs. 1.91).



(a) Commuters



(b) Comparison between commuters and non-commuters

Fig. 6 Distributions of EV's start SOC in charging event for different EV user groups (Unit: %)

5.2 Mixed Logistic Regression Model for Associating EV Users' Dominant Charging Locations with their Characteristics

To consider the multicollinearity problem, we conducted the Pearson correlation coefficient test for explanatory variables firstly (see Appendix F in the Supplementary Materials for the results and discussion). The variable Standard Distance Centered at Home is closely related to both Commuting Distance and Daily Travel Distance, with the correlation coefficients of 0.720 and 0.651, respectively, and thus it was eliminated from the model estimation for commuters. Also, since a comparative study was conducted for commuters and non-commuters, the variable Standard Distance Centered at Home was also not included in the model estimation for non-commuters.

Table 4 shows the coefficient estimation results of two mixed logistic regression models, which were used to explore the possible association between EV users' dominant charging locations and their characteristics for both commuters and non-commuters. Also, Appendix G in the Supplementary Materials reports and discusses the results of marginal effects derived from the estimated mixed logistic regression models for both commuters and non-commuters.

The unobserved heterogeneity among individuals were captured and represented using random parameters with standard deviation values in parentheses (see Table 4). It can be found that in general, EV users evaluated several variables (e.g., Battery Capacity and Daily Travel Distance) differently in dominant charging location choice. For example, commuters with a dominant charging location choice of H-W or H-O had heterogeneous tastes of Battery Capacity; non-commuters with a dominant charging location choice of OD valued Daily Travel Distance differently.

Table 4 Mixed logistic regression model estimation results for commuters and non-commuters

Group	**Variable**	**Alternative Estimates**						
		Commuters					**Non-commuters**	
		WD	**OD**	**H-W**	**H-O**	**W-O**	**OD**	**H-O**
Vehicle Attributes	Battery Capacity	**0.005**	**0.022**	**-0.040** **(0.019)**	**-0.022** **(0.014)**	-0.004	**0.007**	**-0.013**
Individual- and Household-Level Attributes	Socioeconomic Status	**0.076**	**0.065**	**0.053**	0.014	**0.067**	**-**	**-**
	Home in Central Area	**0.333**	**0.314**	0.087	0.074	**0.386**	**0.393**	0.052
	Workplace in Central Area	**-0.381**	0.101	**-0.363**	0.053	**-0.199**	×	×
Charging Opportunities	Charging Opportunities around Home	**0.111**	**0.114**	0.015	**0.090**	0.066	**-**	**-**

Available	Charging Opportunities around Workplace	**-0.114**	0.049	-0.038	-0.019	0.004	×	×
	Charging Opportunities at Other Places	-0.083	**-0.906**	0.047	**-0.443**	**-0.446**	**-0.755**	**-0.395**
Mobility Patterns	Commuting Distance	**0.019**	**0.035**	**0.040**	-0.006 **(0.025)**	**0.020**	×	×
	Ratio of Non-working Days Having EV Travel	**-2.480 (1.882)**	**0.505**	**0.722**	0.319	0.118	**1.110**	**0.632**
	Diversity of Activity Locations Visited Daily	0.001	**1.094 (0.230)**	**0.175**	**0.450**	**0.484**	**0.921**	**0.318**
	Daily Travel Distance	**-0.017 (0.008)**	**-0.038 (0.013)**	**0.006**	**0.007**	-0.001	**-0.017 (0.012)**	**0.007**
	Alternative-specific Constant	**-0.630**	**-3.750**	**-2.849**	**-2.104**	**-3.380**	**-2.551**	**-1.431**

Note: (1) The reference alternative is the group HD for both commuters and non-commuters; (2) coefficients highlighted in bold are statistically significant at the 0.05 level; (3) the random parameters are presented with standard deviation values in parentheses; (4) "-" denotes the exploratory variables that are not statistically significant and thus were eliminated from the final model; (5) "×" denotes the exploratory variables that are not applicable to non-commuters.

5.2.1 Implications of Vehicle Attributes

(1) Battery Capacity

For commuters, the significantly negative estimates for groups H-W and H-O, and the significantly positive estimates for groups WD and OD indicate that those commuters with a larger EV battery (i.e., a longer driving range) were more likely to have a less complex charging location choice behavior and preferred to get their EVs charged at one single type of charging location (i.e., home, workplace, or other places). This may be because that a larger battery capacity could mitigate range anxiety of EV users to some extent, allowing them to choose those charging stations where they usually get their EVs recharged. Moreover, those commuters with a larger EV battery were more likely to choose charging stations around workplaces or at other places and thus become WD or OD commuters (compared to the reference alternative, HD commuters). This may be attributed to a higher charging efficiency at non-home based charging stations where fast charging facilities are more accessible (Xu et al., 2017). This allows EV users to get their larger batteries recharged at a higher rate. The finding reflects the significant role of fast charging infrastructure particularly in the future EV market where the EV models with a high-storage battery (i.e., a long driving range) will become more common. In addition, the association between the variable Battery Capacity and the dominant charging location choice of non-commuters is similar to that of commuters. Specifically, for non-commuters with a high-storage EV battery, they were more likely to become OD non-commuters but were less likely to become H-O non-commuters, compared to the reference alterative, HD non-commuters.

5.2.2 Implications of Individual- and Household- Level Attributes

(1) Socioeconomic Status

For commuters, the significantly positive coefficients of the variable Socioeconomic Status for most alternatives (i.e., the groups WD, OD, H-W, and W-O) suggest that those commuters with a lower socioeconomic status (described with housing price in this case study) were more likely to become HD commuters (i.e., relying mainly on home-based charging). A possible reason may be that these commuters were more sensitive to charging costs. Home-based charging allows EV users to have more opportunities to get their EVs charged during the offpeak time slots (e.g., the period from 9:00 PM to 7:00 AM (the next day) in Beijing) with the lowest charging fee. This is consistent with the charging patterns of HD commuters, as shown in Fig. 5-(a): a considerable number of charging events were initialized by HD commuters after 9:00 PM. For non-commuters, we found the variable Socioeconomic Status is not statistically associated with their dominant charging locations.

(2) Home or Workplace in Central Area

For both commuters and non-commuters, the coefficients of the variable Home in Central Area are significantly positive for those EV user groups without home-based charging included (namely WD, OD, and W-O). Meanwhile, the coefficients of the variable Workplace in Central Area (only applicable to commuters) are significantly negative for those EV user groups with workplace-based charging included (namely WD, H-W, and W-O). These results suggest that EV users living or working in the central area were less willing to rely on home- or workplace-based charging, respectively. The reason is discussed as follows: compared with the city periphery of Beijing, the buildings of residential neighbors and job gathering places in the central area tend to be much high-density (limiting the availability of parking infrastructure) and older (increasing the difficulty to renovate the circuits) (Kang et al., 2022). Because of this, the installation of private and workplace charging infrastructure become less feasible. As a result, those EV users living or working in the central area have less access to charging at home or workplace.

5.2.3 Implications of Charging Opportunities Available

(1) Charging Opportunities around Home or Workplace

For commuters, the coefficients of the variable Charging Opportunities around Home are estimated positively for all alternatives listed in Table 4, and significantly for three alternatives (namely WD, OD, and H-O). Meanwhile, the estimate of the variable Charging Opportunities around Workplace is only significantly negative for the group WD. These results suggest that those commuters with more charging opportunities (i.e., accessing a higher number of charging stations) around home or workplace were less likely to become HD or WD commuters. In other words, commuters with more charging opportunities around home tended to not mainly rely on home-based charging facilities, but tried to get their EVs recharged at other places rather than home. Similarly, commuters with more charging opportunities around workplace tended to not mainly rely on workplace-based charging facilities, but tried to get their EVs recharged at other places rather than workplace. This may be because more charging opportunities around home or workplace could potentially attract more EVs with home- or workplace- based charging demand. On the one hand, this could increase the competition for using charging facilities. On the other hand, home- or workplace- based charging is usually along with long parking duration (and thus long occupation of charging facilities), which could decrease the turnover of charging facilities. These two reasons may make commuters with more charging opportunities around home or workplace not to mainly rely on home- or workplace- based charging, but to try charging facilities at other places rather than home or workplace, as well. In addition, for non-commuters, we found that their dominant charging location choices are not statistically associated with the variable Charging Opportunities around Home. These findings for commuters and non-commuters suggest that how EV users chose their dominant charging locations was not simply determined by the number of charging opportunities.

(2) Charging Opportunities at Other Places

For both commuters and non-commuters, the significantly negative estimates of the variable Charging Opportunities at Other Places for those EV user groups with other-based charging included (namely OD, H-O, and W-O) indicate that EV users with more charging opportunities (i.e., accessing a higher number of charging stations) at other places tended not to get their EVs recharged at other places. Similar finding was obtained in the work by Yun et al. (2019): for plug-in hybrid electric vehicle (PHEV) users in Shanghai, China, a higher average number of charging posts in public charging stations (i.e., higher public charging opportunities) would reduce the likelihood for public charging. In addition, previous studies have found that with the growth of charging facilities, EV users' range anxiety decreases (Dong et al., 2014; Zhang et al., 2021). Therefore, EV users accessing a higher number of charging stations at other places may have less range anxiety. Consequently, they tended to get their EVs recharged at more fixed and familiar locations (i.e., home and workplace for commuters and home for non-commuters), and thus less likely to be those groups with other-based charging included (namely OD, H-O, and W-O).

5.2.4 Implications of Mobility Patterns

(1) Commuting Distance

The significantly positive association between the variable Commuting Distance (only applicable to commuters) and the dominant charging location choice of EV users from the groups WD, H-W, and W-O (i.e., those groups with workplace-based charging included) suggests that for those EV users with a longer commuting distance, they were more likely to get their EVs recharged around workplace. This finding reveals that a longer commuting distance could increase the possibility of EV charging around workplace for commuters.

(2) Ratio of Non-working Days Having EV Travel

The significantly negative estimates for those commuters from the group WD suggests commuter with a higher ratio of non-working days having EV travel were less likely to mainly rely on workplace-based charging facilities. This may be because most commuters would not commute to work on non-working days, decreasing the possibility of charging around workplace. Meanwhile, in order to support daily travel activities on both working and non-working days, there would be more charging activities conducted around home and at other places. On the other hand, the significantly positive estimates for those commuters from the group OD and for those non-commuters from the groups OD and H-O indicate that EV users with a higher ratio of non-working days having EV travel tended to get their EVs recharged more at other places. This may be because non-working days usually involves more leisure activities away from home, increasing the reliance on charging facilities located at sites for entertainment.

(3) Diversity of Activity Locations Visited Daily

As expected, the variable, Diversity of Activity Locations Visited Daily, is significantly and positively associated with the dominant charging location choice of EV users from the groups OD, H-W, H-O, and W-O for commuters and from the groups OD and H-O for non-commuters. This is likely to be because visiting more diverse activity locations (which means that the chance of accessing to charging infrastructure located at different locations is increased) may allow EV users to charge their EVs at more diverse locations. On the other hand, the intention to get EV recharged at different locations could potentially increase the diversity of activity locations visited daily for EV users.

(4) Daily Travel Distance

For commuters, the coefficients of the variable Daily Travel Distance are estimated significantly negative for the alternatives WD and OD and significantly positive for the alternatives H-W and H-O. A longer daily travel distance means a higher charging demand when returning home, resulting in more charging around home, and thus there was less likely for commuters to be WD or OD users. Meanwhile, A longer daily travel distance could induce a higher range anxiety outside home, leading to charging outside home as a supplement to charging around home, and thus there was more likely for commuters to be H-W and H-O users. Similar to commuters, the estimates are significantly negative for non-commuters from the group OD and significantly positive for non-commuters from the group H-O.

6 Conclusions

This paper used a unique trajectory dataset collected from 76,774 actual private electric vehicles (EVs) in Beijing in January 2018 to explore EV users' dominant charging locations (where EV users get their EVs recharged more frequently), within a comparative study of commutes and non-commuters. The results showed that more than half of commuters and non-commuters were the HD users with most charging events occurring around home. Moreover, there were significant differences in charging patterns of EV users from different groups by dominant charging location, and also between commuters and non-commuters. In addition, the dominant charging location choice of EV users was significantly associated with their characteristics, such as charging opportunities available and mobility patterns. Particularly, we found several unexpected results about those variables related to charging opportunities available. For example, those commuters with more charging opportunities around their home or workplace were less likely to become the HD or WD users with home or workplace dominant charging. These findings suggest that how EV users chose their charging locations was not simply determined by the number of charging opportunities. Also, the association between the same factor and dominant charging location choice for commuters and non-commuters is different. For example, Socioeconomic Status was estimated as a significant factor to influence commuters' dominant charging location choice, but not significant for non-commuters.

The findings of this study could be helpful for the EV-related stakeholders in their decision-making. First, smart charging (e.g., time of use and V2G) is a good way to alleviate the load pressure of the local power grid. To encourage greater participation in such an advanced program, tailored incentives and schemes should be devised based on EV users' dominant charging location choice, as EV users with different dominant charging location choices exhibited distinct preferences regarding the commencement time of charging their EVs. Second, both EV commuters and non-commuters with a larger EV battery (i.e., a longer driving range) were more likely to be OD users (i.e., with most charging activities at other places rather than home and workplace), highlighting the significance of further developing charging infrastructure at public locations (e.g., leisure complex and shopping mall) in the near future with more EV models available with a larger battery. Third, EV commuters with a longer commuting distance tended to be WD, H-W, and W-O users with workplace-based charging included. In order to meet their charging demand at workplace, it is of great importance to promote the deployment of workplace-based charging facilities for those job gathering places with more commuters from the periphery of the city (and thus with a longer commuting distance).

The future work will be focused on the following two aspects: first, we will try to collect more exploratory variables (such as EV users' sociodemographic attributes and charging price of charging facilities located at different locations) that are generally expected to influence the dominant charging location choice of EV users and model their relationship. This could further deep our understanding of EV users' charging location choice. Second, the unique large-scale trajectory dataset actually contains rich charging information. We will further investigate other charging choice behaviors of EV users with this dataset, such as charging decision and time-related charging behavior, in addition to the dominant charging location choice behavior.

Acknowledgements

This research was supported by the National Natural Science Foundation of China (52002345), and the RISUD Joint Research Fund (Project ID: P0042828), Funding Support to Small Projects (Project ID: P0038213) and SCRI IRF-SC (Project ID: P0041230) at the Hong Kong Polytechnic University.

References

Alexander, L., Jiang, S., Murga, M., & González, M. C. (2015). Origin–destination trips by purpose and time of day inferred from mobile phone data. Transportation Research Part C: Emerging Technologies, 58, 240-250.

Björnsson, L.-H., & Karlsson, S. (2015). Plug-in hybrid electric vehicles: How individual movement patterns affect battery requirements, the potential to replace conventional fuels, and economic viability. Applied Energy, 143, 336-347.

BMCUM. (2021). 2020 Charging infrastructure construction and operation data analysis brief. Beijing Municipal Commission of Urban Management (BMCUM), Beijing, China.

Brady, J., & O'Mahony, M. (2011). Travel to work in Dublin. The potential impacts of electric vehicles on climate change and urban air quality. Transportation Research Part D: Transport and Environment, 16(2), 188-193.

BTI. (2021). 2021 Beijing transport annual report. Beijing Transport Institute (BTI), Beijing, China.

Calvo, F., Eboli, L., Forciniti, C., & Mazzulla, G. (2019). Factors influencing trip generation on metro system in Madrid (Spain). Transportation Research Part D: Transport and Environment, 67, 156-172.

Chakraborty, D., Bunch, D. S., Lee, J. H., & Tal, G. (2019). Demand drivers for charging infrastructure-charging behavior of plug-in electric vehicle commuters. Transportation Research Part D: Transport and Environment, 76, 255-272.

Çolak, S., Alexander, L. P., Alvim, B. G., Mehndiratta, S. R., & González, M. C. (2015). Analyzing cell phone location data for urban travel: Current methods, limitations, and opportunities. Transportation Research Record, 2526(1), 126-135.

Daina, N., Polak, J. W., & Sivakumar, A. (2015). Patent and latent predictors of electric vehicle charging behavior. Transportation Research Record, 2502(1), 116-123.

Dong, J., Liu, C., & Lin, Z. (2014). Charging infrastructure planning for promoting battery electric vehicles: An activity-based approach using multiday travel data. Transportation Research Part C: Emerging Technologies, 38, 44-55.

Ge, Y., MacKenzie, D., & Keith, D. R. (2018). Gas anxiety and the charging choices of plug-in hybrid electric vehicle drivers. Transportation Research Part D: Transport and Environment, 64, 111-121.

Gong, H., Zou, Y., Yang, Q., Fan, J., Sun, F., & Goehlich, D. (2018). Generation of a driving cycle for battery electric vehicles: A case study of Beijing. Energy, 150, 901-912.

Helmus, J. R., Lees, M. H., & van den Hoed, R. (2020). A data driven typology of electric vehicle user types and charging sessions. Transportation Research Part C: Emerging

Technologies, 115, 102637.

Hensher, D. A., Rose, J. M., Rose, J. M., & Greene, W. H. (2005). Applied choice analysis: A primer. Cambridge university press.

Hess, S., & Polak, J. W. (2005). Mixed logit modelling of airport choice in multi-airport regions. Journal of Air Transport Management, 11(2), 59-68.

Hu, Y., Yang, L., Yan, B., Yan, T., & Ma, P. (2016). An online rolling optimal control strategy for commuter hybrid electric vehicles based on driving condition learning and prediction. IEEE Transactions on Vehicular Technology, 65(6), 4312-4327.

Hu, Z., & Sun, Y. (2019). An analysis of travel patterns and charging behaviors of battery energy vehicles owners using real-world data. Nineteenth COTA International Conference of Transportation Professionals, 670-682.

Huang, Y., Xiao, Z., Wang, D., Jiang, H., & Wu, D. (2020). Exploring individual travel patterns across private car trajectory data. IEEE Transactions on Intelligent Transportation Systems, 21(12), 5036-5050.

IEA. (2021). Global EV Outlook 2021. Retrieved on on 23rd January 2022 from https://www.iea.org/reports/global-ev-outlook-2021.

Jabeen, F., Olaru, D., Smith, B., Braunl, T., & Speidel, S. (2013). Electric vehicle battery charging behaviour: Findings from a driver survey. Proceedings of the Australasian Transport Research Forum.

Kang, J., Kong, H., Lin, Z., & Dang, A. (2022). Mapping the dynamics of electric vehicle charging demand within Beijing's spatial structure. Sustainable Cities and Society, 76, 103507.

Kim, S., Yang, D., Rasouli, S., & Timmermans, H. (2017). Heterogeneous hazard model of PEV users charging intervals: Analysis of four year charging transactions data. Transportation Research Part C: Emerging Technologies, 82, 248-260.

Lee, J. H., Chakraborty, D., Hardman, S. J., & Tal, G. (2020). Exploring electric vehicle charging patterns: Mixed usage of charging infrastructure. Transportation Research Part D: Transport and Environment, 79, 102249.

Lee, Z. J., Li, T., & Low, S. H. (2019). ACN-Data: Analysis and applications of an open EV charging dataset. Proceedings of the Tenth ACM International Conference on Future Energy Systems.

Leo, Y., Fleury, E., Alvarez-Hamelin, J. I., Sarraute, C., & Karsai, M. (2016). Socioeconomic correlations and stratification in social-communication networks. Journal of The Royal Society Interface, 13(125), 20160598.

Lv, M., Chen, L., Xu, Z., Li, Y., & Chen, G. (2016). The discovery of personally semantic places based on trajectory data mining. Neurocomputing, 173, 1142-1153.

McFadden, D., & Train, K. (2000). Mixed MNL models for discrete response. Journal of Applied Econometrics, 15(5), 447-470.

Qian, X., & Ukkusuri, S. V. (2015). Spatial variation of the urban taxi ridership using GPS data. Applied Geography, 59, 31-42.

Smith, R., Shahidinejad, S., Blair, D., & Bibeau, E. L. (2011). Characterization of urban commuter driving profiles to optimize battery size in light-duty plug-in electric vehicles. Transportation Research Part D: Transport and Environment, 16(3), 218-224.

Sun, M., Shao, C., Zhuge, C., Wang, P., Yang, X., & Wang, S. (2021). Uncovering travel and charging patterns of private electric vehicles with trajectory data: Evidence and policy implications. Transportation.

Sun, X.-H., Yamamoto, T., & Morikawa, T. (2015). Charge timing choice behavior of battery electric vehicle users. Transportation Research Part D: Transport and Environment, 37, 97-107.

Sun, X.-H., Yamamoto, T., & Morikawa, T. (2016). Fast-charging station choice behavior among battery electric vehicle users. Transportation Research Part D: Transport and Environment, 46, 26-39.

Sun, X.-H., Yamamoto, T., Takahashi, K., & Morikawa, T. (2018). Home charge timing choice behaviors of plug-in hybrid electric vehicle users under a dynamic electricity pricing scheme. Transportation, 45(6), 1849-1869.

Sun, X., Yamamoto, T., & Morikawa, T. (2014). The timing of mid-trip electric vehicle charging. Transportation Research Board 93rd Annual Meeting.

Tal, G., Nicholas, M. A., Davies, J., & Woodjack, J. (2014). Charging behavior impacts on electric vehicle miles traveled: Who is not plugging in? Transportation Research Record, 2454(1), 53-60.

Train, K. E. (2009). Discrete choice methods with simulation. Cambridge university press.

Tu, W., Cao, J., Yue, Y., Shaw, S.-L., Zhou, M., Wang, Z., Chang, X., Xu, Y., & Li, Q. (2017). Coupling mobile phone and social media data: A new approach to understanding urban functions and diurnal patterns. International Journal of Geographical Information Science, 31(12), 2331-2358.

van der Kam, M., van Sark, W., & Alkemade, F. (2020). Multiple roads ahead: How charging behavior can guide charging infrastructure roll-out policy. Transportation Research Part D: Transport and Environment, 85, 102452.

Vassilvitskii, S., & Arthur, D. (2006). k-means++: The advantages of careful seeding. Proceedings of the Eighteenth Annual ACM-SIAM Symposium on Discrete Algorithms.

Wang, Y., Correia, G. H. d. A., van Arem, B., & Timmermans, H. J. P. (2018). Understanding travellers' preferences for different types of trip destination based on mobile internet usage data. Transportation Research Part C: Emerging Technologies, 90, 247-259.

Wen, Y., MacKenzie, D., & Keith, D. R. (2016). Modeling the charging choices of battery electric vehicle drivers by using stated preference data. Transportation Research Record, 2572(1), 47-55.

Wolbertus, R., Kroesen, M., van den Hoed, R., & Chorus, C. (2018). Fully charged: An empirical study into the factors that influence connection times at EV-charging stations. Energy Policy, 123, 1-7.

Xiong, Q., Liu, Y., Xie, P., Wang, Y., & Liu, Y. (2021). Revealing correlation patterns of individual location activity motifs between workdays and day-offs using massive mobile phone data. Computers, Environment and Urban Systems, 89, 101682.

Xu, M., Meng, Q., Liu, K., & Yamamoto, T. (2017). Joint charging mode and location choice model for battery electric vehicle users. Transportation Research Part B: Methodological, 103, 68-86.

Xu, Y., Belyi, A., Bojic, I., & Ratti, C. (2018). Human mobility and socioeconomic status: Analysis of Singapore and Boston. Computers, Environment and Urban Systems, 72, 51-67.

Xu, Y., Çolak, S., Kara, E. C., Moura, S. J., & González, M. C. (2018). Planning for electric vehicle needs by coupling charging profiles with urban mobility. Nature Energy, 3(6), 484-493.

Xu, Y., Li, J., Xue, J., Park, S., & Li, Q. (2021). Tourism geography through the lens of time use: A computational framework using fine-grained mobile phone data. Annals of the American Association of Geographers, 111(5), 1420-1444.

Xu, Y., Shaw, S.-L., Zhao, Z., Yin, L., Fang, Z., & Li, Q. (2015). Understanding aggregate human mobility patterns using passive mobile phone location data: A home-based approach. Transportation, 42(4), 625-646.

Yan, L., Wang, D., Zhang, S., & Xie, D. (2019). Evaluating the multi-scale patterns of jobs-residence balance and commuting time–cost using cellular signaling data: A case study in Shanghai. Transportation, 46(3), 777-792.

Yang, X., Shao, C., Zhuge, C., Sun, M., Wang, P., & Wang, S. (2021). Deploying battery swap stations for shared electric vehicles using trajectory data. Transportation Research Part D: Transport and Environment, 97, 102943.

Yizong, C. (1995). Mean shift, mode seeking, and clustering. IEEE Transactions on Pattern Analysis and Machine Intelligence, 17(8), 790-799.

Yu, H., & MacKenzie, D. (2016). Modeling charging choices of small-battery plug-in hybrid electric vehicle drivers by using instrumented vehicle data. Transportation Research Record, 2572(1), 56-65.

Yun, B., Sun, D., Zhang, Y., Deng, S., & Xiong, J. (2019). A charging location choice model for plug-in hybrid electric vehicle users. Sustainability, 11(20), 5761.

Zhang, B., Niu, N., Li, H., Wang, Z., & He, W. (2021). Could fast battery charging effectively mitigate range anxiety in electric vehicle usage? Evidence from large-scale data on travel and charging in Beijing. Transportation Research Part D: Transport and Environment, 95, 102840.

Zhou, L., Ji, Y., & Wang, Y. (2017). Analysis of public transit trip chain of commuters based on mobile phone data and GPS data. Fourth International Conference on Transportation Information and Safety.

Zoepf, S., MacKenzie, D., Keith, D., & Chernicoff, W. (2013). Charging choices and fuel displacement in a large-scale demonstration of plug-in hybrid electric vehicles. Transportation Research Record, 2385(1), 1-10.